Volumetric Image Visualization

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In order to visualize the image content, the simplest methods are

- the extraction of axial, coronal, and sagital slices,

- the adjustments of brightness and contrast by **radiometric transformations**, when presenting the images of those slices,

- the use of **color compositions** to further enhance nuances in those images, given that humans can perceive 7 millions of colors and only 30 tones of gray.

Radiometric Transformation

For an image $\hat{I} = (D_I, I)$ with voxel intensities $I(p) = l$ in the range $[l_{\min}, l_{\max}]$ for any $p \in D_I$, a radiometric transformation is a mapping $\mathcal{T}(l) = k$ that creates another image $\hat{J} = (D_I, J)$ with values $J(p) = k \in [k_{\min}, k_{\max}]$.
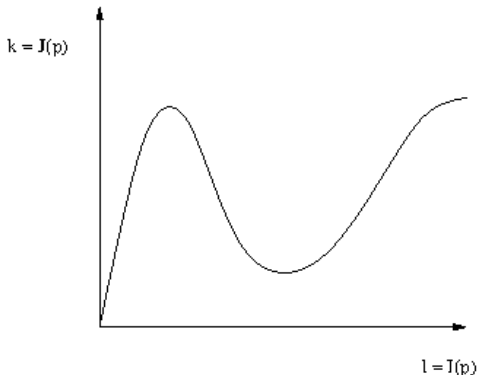
Radiometric Transformation

Given that $\mathcal{T}$ changes the image's intensity interval, it affects the distribution of its gray values, named **histogram**. A normalized histogram $h(I)$, for instance, is defined as

$$h(I) = \frac{1}{|D_I|} \sum_{\forall p \in D_I} \delta(I - I(p)),$$

where $\delta(x) = 1$, for $x = 0$, and $\delta(x) = 0$, otherwise.

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- It reveals that dark (bright) images with low contrast present higher concentration of voxels with low (high) values.

- A radiometric transformation can improve brightness and contrast by distributing those values within the possible range $[0, 2^b - 1]$, for a depth b bits per voxel.

Linear Stretching

A linear stretching is the simplest way to map intensities from $[l_1, l_2]$, $l_{\min} \leq l_1 \leq l_2 \leq l_{\max}$ into $[k_1, k_2]$, when transforming $\hat{I} = (D_I, I)$ into $\hat{J} = (D_I, J)$.

$$
k = \begin{cases}
k_1, & \text{for } I < l_1, \\
\frac{(k_2 - k_1)}{(l_2 - l_1)}(I - l_1) + k_1, & \text{for } l_1 \leq I < l_2, \\
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- window & level, when $k_2 = 2^b - 1$, $k_1 = 0$, and $l_1 < l_2$, such that the **level** $\frac{l_1 + l_2}{2}$ affects brightness and the **window** $l_2 - l_1$ affects contrast; and
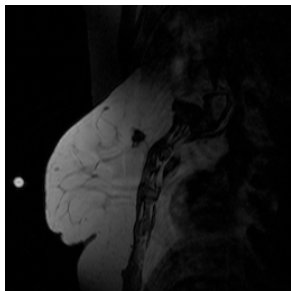
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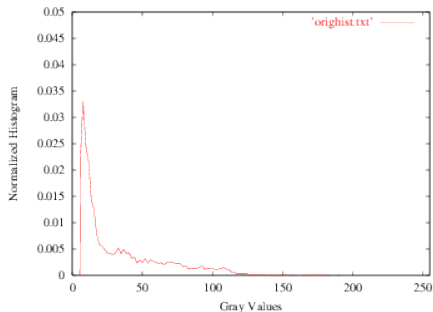k_2, & \text{for } I \geq l_2.
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- limiarization (binarization, thresholding), when $k_2 = 2^b - 1$, $k_1 = 0$, and $l_1 = l_2$.

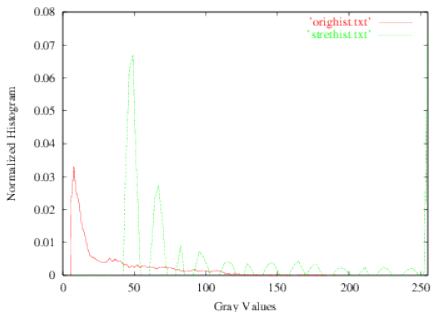# Dark image with low contrast

(a)   (b)

(a) Image $\hat{I}$ of an MR slice of a breast with carcinoma and (b) its normalized histogram.
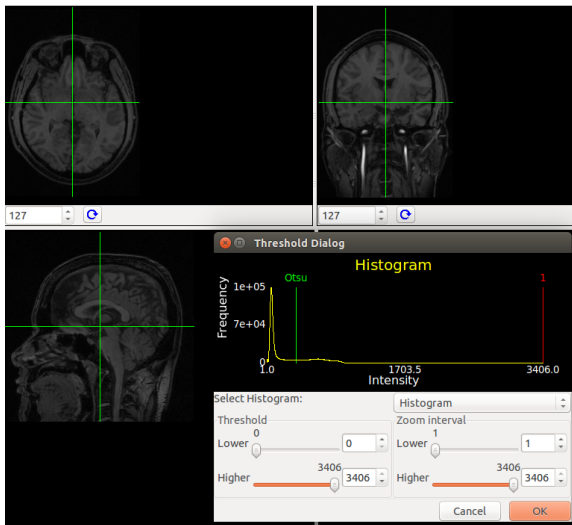
(a)   (b)

(a) Image $\hat{J}$ after linear stretching and (b) the comparison between the previous and the resulting normalized histograms.

Dark images in practice

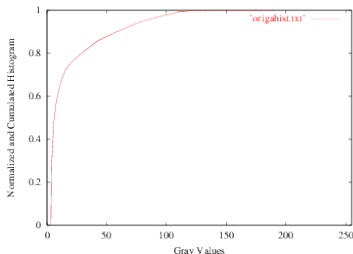The presence of blood flow in MR can often create dark images.

Dark images in practice

Those brightest voxels from the blood flow can be easily detected based on the **cumulative histogram**
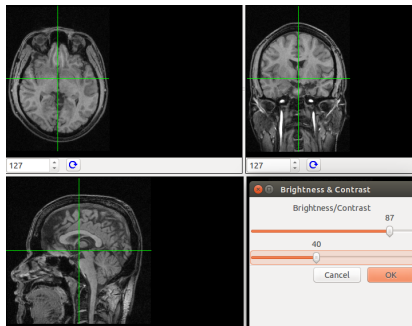
$$h_a(l) = \sum_{l'=l_{\min}}^{l} h(l'),$$

which corresponds to the area below the normalized histogram $h(l)$.

An example of $h_a(l)$, when $h(l)$ is the normalized histogram of the MR-breast slice.

Dark images in practice

- In the case of the MR image of the brain, we may then assume that 2% of the brightest voxels are blood flow and suppress their intensities by linear stretching with l_2 as the highest value for $h_a(l) < 0.98$, $l_1 = l_{min}$, $k_1 = 0$, and $k_2 = 2^b - 1$.
- Another option is to interactively adjust the percentages of window and level in the user interface.

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- Most of the visible colors can be produced by a combination of monochromatic light in the wavelengths of the blue, red, and green.

- One can also decompose a color into three independent components: **intensity** (brightness perception), **hue** (the most predominant color perception), and **saturation** (perception of color purity related to the white).

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- When an image $\hat{I}$ is a color image $(D_I, \vec{I})$ with $\vec{I}(p)$ being a vector with the three color components assigned to each voxel $p \in D_I$, radiometric transformations can only be applied to the intensity component.

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- This requires to convert the image from RGB to YCgCo, for instance, apply the radiometric transformation to Y, and convert the image from YCgCo to RGB.

Color space conversion

For $H = 2^b - 1$, assuming an image with depth b bits per color channel, the conversions between RGB and YCgCo involve, for every $p \in D_I$,

$$
\begin{bmatrix} Y(p) \\ Cg(p) \\ Co(p) \\ 1 \end{bmatrix} = \begin{bmatrix} 0.25 & 0.50 & 0.25 & 0.0 \\ -0.25 & 0.50 & -0.25 & \frac{H}{2} \\ 0.50 & 0.00 & -0.50 & \frac{H}{2} \\ 0.00 & 0.00 & 0.00 & 1.00 \end{bmatrix} \begin{bmatrix} R(p) \\ G(p) \\ B(p) \\ 1 \end{bmatrix}
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\begin{bmatrix} R(p) \\ G(p) \\ B(p) \\ 1 \end{bmatrix} = \begin{bmatrix} 1.00 & -1.00 & 1.00 & 0.00 \\ 1.00 & 1.00 & 0.00 & -\frac{H}{2} \\ 1.00 & -1.00 & -1.00 & H \\ 0.00 & 0.00 & 0.00 & 1.00 \end{bmatrix} \begin{bmatrix} Y(p) \\ Cg(p) \\ Co(p) \\ 1 \end{bmatrix}
$$

Color Composition

We can also create a color composition $\hat{J} = (D_I, \vec{J})$,
$\vec{J}(p) = (R(p), G(p), B(p))$, $p \in D_I$, from a grayscale image
$\hat{I} = (D_I, I)$ by using its values $I(p)$ to index the corresponding RGB
mapping in a **color table** (e.g. *a rainbow color table*).

| Red | Orange | Yellow | Green | Blue | Indigo | Violet |
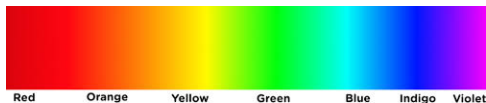
$$V \leftarrow \frac{I(p)}{H}$$
$$V \leftarrow (6 - 2)V + 1$$
$$R(p) \leftarrow H \max\{0, (3 - |V - 4| - |V - 5|)/2\}$$
$$G(p) \leftarrow H \max\{0, (4 - |V - 2| - |V - 4|)/2\}$$
$$B(p) \leftarrow H \max\{0, (3 - |V - 1| - |V - 2|)/2\}$$

where $H = 2^b - 1$ for b bits per channel.

Color Composition

- We may also create a color table with **random colors** by generating $V \in [0, 1]$ randomly.
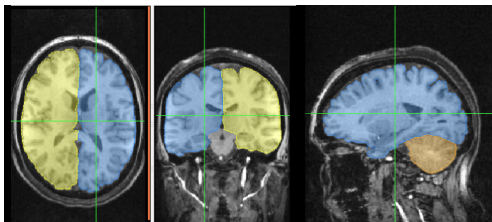
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- If $\hat{I} = (D_I, I)$ is a **label image**, $I(p) \in \{0, 1, \dots, c\}$, $p \in D_I$, for c objects, being 0 the background label, we may combine the original and the color composition of a label image as follows.
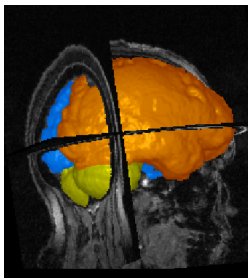
Color Composition with Transparency

It is also possible to combine the original image and the color composition of the label image with **transparency**.

This can be done by converting the color of the object from RGB to YCgCo, substitute Y by $I(p)$ for pixels p inside the object, and return it to the RGB color space.

Color Composition

We may also combine two grayscale images in the same image domain by assigning one of them to the channel R, the other to the channel G, and their average to the channel B.
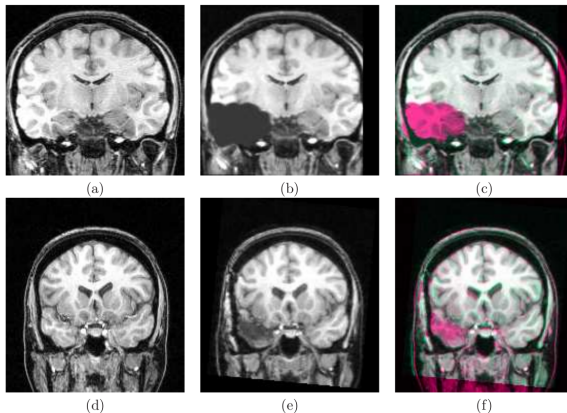

(a) (b) (c)

(d) (e) (f)

Figure 7. Visualization of registration using color-coding. The last column shows the combination between the fixed image (first column) and the registered moving image (second column). The first row shows an example of a synthetic lesion case. The second row is an example of clinical image (pre- and post-surgery).