Page No.
Date

Consider an image with L different intensity value let R be a random variable denoting the different intensities in this image (assume R lies from 0 to L-1)

The normalized histogram of this image is

$$P_R(r_k) = \frac{n_k^r}{H*W}$$

Where r_k is the k^{th} intensity value and n_k^r is the number of pixels with that intensity and H, W are the image dimensions

After applying Histogram equalization to this image we get a new image (Image 2) with

$S = T(R)$, where S is a transform Random variable denoting the different intensities of this new image

$$s_k = (L-1) \times cdf_R = (L-1) \times \sum_{j=0}^{k} P_R(r_j)$$

Ignoring some errors, we can say that almost all ~~imag~~ pixels in the original image having intensities r_j now have the intensity s_j in the new image

This means $n_j^r = n_j^s$

[n_j^s is the number of pixels having intensity s_j]

~~Eo~~ $cdf_R^k = \sum_{j=0}^{k} p_R(r_j) = \sum_{j=0}^{k} n_R^j / HW = \sum_{j=0}^{k} n_S^j / HW$

$$cdf_R^k = cdf_S^k \quad - (1)$$

Now if we apply histogram equalization on this new Image (Image 2) we get a new image (Image 3)

$U = T(S)$ where U is a transform Random Variable denoting the intensities of image 3

~~$U = T(S)$~~

Since $0 \leq r \leq L-1 \Rightarrow 0 \leq S \leq L-1$, S is also of ~~length L~~ ranging from 0 to $L-1$

$U_k = T(S) = (L-1) \times cdf_S^k = (L-1) \times cdf_R^k$ (From (1))

$\therefore U_k = S_k$

This shows that another round of histogram equalization will produce the exact same result as the first round