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Comparison of Image Fusion Technique with Special reference to Information Content

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Abstract- ***There is many image fusion methods which are used to produce high resolution multispectral images from high resolution panchromatic image and low resolution multispectral images. This paper deals with review on the different image fusion technique for a remote sensed image and the information content of image. In this paper the different image fusion techniques used are HIS transform, BROVEY transform and Principal Component Analysis (PCA) transform. And the information quantification methods of the image are Entropy, Spectral Similarity index and Feature Similarity index.***

Keywords*:* HSI, Brovey, PCA, FSIM, SSIM

1. Introduction

Image fusion basically refers to the combination of image data from different sources with the aim of increasing the information content of the resulting merged image in accordance with the principle that the whole is greater than the sum of the parts. There are few important requirements for image fusion process:

- The fused image should be able to preserve all relevant information from the input images.
- Image fusion should not introduce artifacts which can lead to wrong diagnosis.

The image fusion between low resolution multispectral (MS) images and high resolution panchromatic (Pan) images has importance in variety of remote sensing application. Many methods have been proposed for image fusion such as HSI transform, PCA transform, BROVEY transform Multiplicative transform, and Wavelet based transform. Among such methods in this paper HSI transform, PCA transform and BROVEY transform methods are comparatively studied to extract the information content in it and brief comparison on quantitative assessment is performed. Among numerous quantitative evaluation indicators (indexes) we will be dealing with Entropy, Spectral Similarity Indexes and Feature Similarity Indexes.

2. Literature Survey

Image Fusion is used widely in image processing systems. In other words, we can say that Image fusion is used to enhance the quality of image by removing the noise and blurriness of the image. Therefore fusion algorithm should be robust and reliable to imperfections such as mis-registration, noise. Image fusion is branch which deals with data fusion where data appear in the form of arrays of numbers representing temperature, distance, brightness, color, and other scene properties. Such data can be two-dimensional (still images), three-dimensional or higher dimensions. In recent years, multivariate imaging techniques have become an important source of information in many medical fields. Early work in it can be traced back to the mid-eighties. Burt [1] was the one to be the first to report the use of Laplacian pyramid techniques in binocular image fusion and later on Burt and Adelson[2] introduced a new approach to image fusion which was based on hierarchical image decomposition at the same time Adelson disclosed the use of a Laplacian technique in construction of an image with an extended depth of field from a set of images taken with a fixed camera but with different focal lengths. Later Toet [3] used different pyramid schemes in image fusion which were mainly applied for fusion of visible and IR images for surveillance purposes. Some other early image fusion work are due to Lillquist[4] which disclose an apparatus for composite visible/thermal infrared imaging, Ajjimarang[5] suggested the use of neural networks in fusion of visible and infrared images, Nandhakumar and Aggarwal [6] provided an integrated analysis of thermal and visual images for scene interpretation, and Rogers et al. [7] described fusion of LADAR and passive infrared images for target segmentation. Use of the discrete wavelet transform (DWT) in image fusion was also simultaneously proposed by Li and Chipman et al. [8] and at the same time Koren et al. [9] described a steerable dyadic wavelet transform for image fusion and also at the same time Waxman and colleagues developed a computational image fusion methodology based on biological models of color vision and used opponent processing for fusion of visible and infrared images. The need of combining visual and range data in robot navigation and to merge images captured at different locations and modalities for target localization and tracking in defense applications prompted further research in image fusion. In the last decade many other fusion techniques have been developed. Today, image fusion algorithms are used as effective tools in remote sensing, medical, surveillance, industrial, and defense applications that require the use of multiple images of a scene.

3. Image Fusion Techniques

Image fusion techniques can be used to enhance a digital image without spoiling it. The enhancement methods are of two types namely Spatial domain methods and Frequency domain methods**.** Spatial domain techniques, directly deal with the image pixels. The pixel values are controlled to achieve desired enhancement. Whereas in frequency domain methods the Fourier Transform of the image is computed first. All the enhancement operations are performed on the Fourier transform of the image and then the Inverse Fourier transform is performed to get the resultant image. The fusion methods, such as averaging, the BROVEY method, principle component analysis (PCA), and HSI based methods fall under the spatial domain approaches.

In this paper we are dealing with three different image fusion techniques and the information quantification methods comprises of Entropy, Spectral Similarity Indexes and Feature Similarity Indexes. To compute the fusion techniques we can use different software's such as ERDAS, ENVI and PRIMEWIN. In this paper we are using PRIMEWIN software to compute fusion techniques on remote sensed image.

3.1 Brovey Transform

The Brovey Transformation (BT) is very old method of image fusion this was established and promoted by an American scientist, Brovey, is also called the color normalization transform because it involves a red-green-blue (RGB) color transform method. It is a simple method for combining data from different sensors. It is a combination of arithmetic operations and normalizes the spectral bands before they are multiplied with the panchromatic image. In the mathematical formula of the Brovey transform each multispectral image is multiplied by a ratio of the pan image divided by sum of the multispectral image. It retains the corresponding spectral feature of each pixel, and transforms all the luminance information into a panchromatic image of high resolution.
The formulae used for the Brovey transform can be described as follows:
Red = (band1/Σ band n)∗ High Resolution Band
Green = (band2/Σ band n)∗ High Resolution Band
Blue = (band3/Σ band n)∗ High Resolution Band
High resolution band = PAN

3.2 HSI Transform*:*

Hue, Saturation and Intensity are the three basic properties of a color that give controlled visual representation of an image. Hexcone model is used to represent Hue- Saturation - Intensity. The co-ordinates of hexcone model will consist of (i) Hue expressed as an angle between 0 and 360◦. (ii) Saturation and intensity on a 0-1 scale. Hue is the dominant wavelength of color; Saturation gives the degree of purity of color whereas Intensity is the brightness or dullness of the color. In the HSI space, hue and saturation need to be carefully controlled because it contains most of the spectral information. HSI transform method is the oldest method of image fusion. The HSI transform is useful in two ways: First, as a method of image enhancement and Second, as a means of combining co-registered images from different sources. In terms of image fusion applications the forward transform of the geometrically rectified and resampled multispectral image is computed and the HSI components are extracted. The intensity components are replaced by the registered panchromatic (PAN) image and the result back transformed to RGB color space. The method is easy to understand and is widely used.

3.3 PCA Transform

Principal Component Analysis is similar to IHS transform, but the advantage of PCA method over IHS method is that an arbitrary number of bands can be used. This is one of the most popular methods for image fusion. Principal component analysis (PCA) is a vector space transform often used to reduce multidimensional data sets to lower dimensions for analysis. PCA is the simplest and most useful of the true eigenvector-based multivariate analyses, because its operation is to reveal the internal structure of data in an unbiased. Basically Principal component analysis is a technique in which numbers of correlated variables are transformed into number of uncorrelated variables called principal components. Uncorrelated Principal components are formed from the low resolution multispectral images. The first principal component (PC1) has the information that is common to all bands used. It contains high variance such that it gives more information about panchromatic image. A high resolution PAN component is stretched to have the same variance as PC1 and replaces PC1. Then an inverse PCA transform is employed to get the high resolution multispectral image. The second principal component is made to be in the subspace perpendicular to the first and the third one to be in the subspace perpendicular to the first two and so on. PCA and HIS transforms provide good results at the cost of color distortion.

4. Information Quantification Method:

Image quantity is the important assessment parameter of an image that measures the information content of the image. The motivation for employing image fusion techniques is to provide a suitable image map for import into a GIS. Therefore along with visual appearance the information quantity is also important. For quantitative evaluation, different quantitative measures or indicators are selected for the evaluation and thus we get different evaluation results. Among numerous quantitative evaluation indicators, the Mean Bias (MB), Variance Difference (VD), Standard Deviation Difference (SDD), Correlation Coefficient (CC), Spectral Angle Mapper (SAM), Relative Dimensionless Global Error (ERGAS), and Q4 Quality Index (Q4) have been often used in image fusion publications. In this paper we are dealing with Entropy, Spectral similarity Index and Feature Similarity Index for quantitative evaluation.

4.1 Entropy

Entropy is used to evaluate the information quantity contained in an image. The higher value of entropy implies that the fused image is better than the reference image.
Entropy is defined as

$$\mathrm{E} = -\sum_{i=0}^{L-1} pi \log_2 pi \quad \ldots\ldots\ldots\ldots (1)$$

Where L = total of grey labels,
P = {p0, p1, …….…. pL-1} is the probability distribution of each labels.

4.2 Structural similarity index measure (SSIM)

The structural similarity (**SSIM**) index is a method for measuring the similarity between two images. The Structural similarity index measures follows that a measure of structural information change provides a good approximation to perceived image distortion. SSIM considers image degradation as perceived change in structural information. Structural information gives the idea that the pixels have strong inter-dependencies especially when they are spatially close. And these dependencies carry important information about the structure of the objects in the visual scene. To calculate SSIM first luminance and contrast are measured. The SSIM compares local patterns of pixel intensities which have been normalized such as luminance, contrast and structure. It is an improved version of traditional methods like PSNR and MSE. The SSIM index is a decimal value between 0 and 1. A value of 0 would mean to be zero correlation with the original image, and 1 means to be the exact same image.

- Symmetry: S(x, y) = S(y, x)
- Boundedness: S(x, y) <= 1
- Unique maximum: S(x, y) = 1 if and only if x = y (in discrete representations $x_i = y_i$, for all i = 1, 2,…………,N)

SSIM can be calculated using SSIM =Mean

$$\left(\frac{(2\,\mu_x\ \ \mu_y + C1)\ (2\,\sigma_{xy}\ + C2\,)}{(\mu_x^2\ + \mu_y^2 + C1\,)\,(\,\sigma_x^2 + \sigma_y^2 + C1\,)}\right) \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ (2)$$

Where

σ_x^2 the variance of x

σ_y^2 the variance of y

σ_{xy}^2 the covariance of x and y

μ_1 the average of x

μ_2 the average of y

$C1= (K_1 * L)^2$

$C2= (K_2 * L)^2$

where L =255 and value of k varies from K = [0.01 to 0.03]

4.3 Feature Similarity Index (FSIM)

Image quality assessment is used for computational models to measure the image quality consistently with subjective evaluations. The very well known structural similarity index (SSIM) brings image quality assessment from the pixel based stage to the structure based stage. The SSIM was successful with result which owes to the fact that human visual system (HVS) is adapted to the structural information in images. But it has limitations that the salient low level features in image convey crucial information for the HVS to interpret the scene. Accordingly, this perceptible image degradations will lead to perceptible changes in image low level features and hence will give a good image IQA metric which could be devised by comparing the low level feature sets between the reference image and distorted image. Based on the above analysis a low level feature similarity induced IQA metric, whose name is FSIM was proposed.

Based on the physiological and psychophysical evidence, it can be seen that visually discernable features coincide with those points where the Fourier waves at different frequencies have congruent phases [10-13]. This means that, at points of high phase congruency (PC) we can extract highly informative features. Therefore, PC is used as the primary feature to compute FSIM. Meanwhile, it is also considered that PC is contrast invariant but image local contrast does affect HVS's perception on the image quality, the image gradient magnitude (GM) is computed as the secondary feature to encode the contrast information. Also PC and GM are complementary and they reflect different aspects of the HVS in assessing the input image.

- **Phase Congruency (PC)**

As given in the definition of PC in [11], there can be different implementations from which we can compute the PC map of a given image. In this paper we adopt the method developed by Kovesi in [13], which is widely used in literature. In this method Pc of 1D image is calculated and then to compute the PC of 2D grayscale image, then we can apply the 1D analysis over several orientations and then combine the results using some rule. The 1D log-Gabor filters can be extended to get 2D ones by simply applying some spreading function across the filter perpendicular to its orientation. By using Gaussian as the spreading function, the 2D log-Gabor function has the following transfer function

$$G_2(\omega\,,\theta_j) = \exp\left(-\frac{(\log(\,\omega\,/\,\omega_0))^2}{2\sigma_r^2}\right).\exp\left(-\frac{(\theta-\,\theta_j)^2}{2\sigma_\theta^2}\right) \ldots\ldots\ldots\ldots\ldots(3)$$

where $\theta j = j\pi\,/\,J, j = \{0,1,\ldots, J\text{-}1\}$ is the orientation angle of the filter, J is the number of orientations and σ_θ determines the filter's angular bandwidth.

By modulating ω_0 and θ_j and convolving G_2 with the 2D image, we will get a set of responses at each point **x** as $[e_{n,\theta j}\,(X),\ o_{n,\theta j}\,(X)]$. The local amplitude at scale n, orientation θ_j is given by $A_{n,\theta j}\,(X) = \sqrt{e_{n,\theta j}\,(X)^2 + o_{n,\theta j}\,(X)^2}$, and the local energy along orientation θj is given by $E_{\theta j}\,(X) = \sqrt{F_{\theta j}\,(X)^2 + H_{\theta j}\,(X)^2}$, where $F_{\theta j}\,(X) = \sum_n e_{n,\theta j}\,(X)$ and $H_{\theta j}\,(X) = \sum_n o_{n,\theta j}\,(X)$. The 2D PC at **x** is defined as

$$PC_{2D}\,(x) = \frac{\sum_j E_{\theta j}\,(x)}{\varepsilon + \sum_n \sum_j A_{n,\theta j}\,(x)} \ldots\ldots(4)$$

It should be noted that $PC_{2D}(x)$ is a real number within 0 ~ 1.

- Gradient Magnitude (GM)

To compute Image gradient is a traditional topic in image processing. For expressing Gradient operators convolution masks are used. Some commonly used gradient operators are Laplace operator, Robert operator, Sobel operator, Prewitt operator, etc. In this paper, we simply use the Sobel operator to compute the gradient of an image. The partial derivatives of image $f(\mathbf{x})$ along horizontal and vertical directions are

$$G_X = \frac{1}{4}\begin{bmatrix}1 & 0 & -1\\ 2 & 0 & -2\\ 1 & 0 & -1\end{bmatrix} * f(x)$$

$$G_y = \frac{1}{4}\begin{bmatrix}1 & 2 & 1\\ 0 & 0 & 0\\ -1 & -2 & -1\end{bmatrix} * f(x)$$

Then, the gradient magnitude (GM) of $f(\mathbf{x})$ can be defined as $G = \sqrt{G_x^2 + G_y^2}$.

With the extracted PC and GM features, we will calculate Feature SIMilarity (FSIM) index for IQA. Suppose that we will be calculating the similarity between images f_1 and f_2. Denote by PC_1 and PC_2 the PC maps extracted from f_1 and f_2, and G_1 and G_2 the GM maps extracted from them. FSIM will be computed based on PC_1, PC_2, G_1 and G_2 which is calculated.

For the easy of calculation we separate the feature similarity measurement between $f_1(\mathbf{x})$ and $f_2(\mathbf{x})$ into two components, each for PC or GM. First, we find the similarity measure for PC values $PC_1(\mathbf{x})$ and $PC_2(\mathbf{x})$ which is given as

$$S_{PC}(x) = \frac{2PC_1(x).PC_2(x) + T_1}{PC_1^2(x) + PC_2^2(x) + T_1} \qquad \ldots\ldots\ldots\ldots(5)$$

Here the constant T_1 is introduced to increase the stability of S_{PC}. Generally, the determination of T_1 depends on the dynamic range of PC values. Similarly, the GM values $G_1(\mathbf{x})$ and $G_2(\mathbf{x})$ are compared and the similarity measure is given as

$$S_G(x) = \frac{2G_1(x).G_2(x) + T_2}{G_1^2(x) + G_2^2(x) + T_2} \qquad \ldots\ldots\ldots\ldots\ldots(6)$$

Here T_2 is a constant depending on the dynamic range of GM values. In experiments, both T_1 and T_2 will be fixed to all databases so that the proposed FSIM can be conveniently used. $S_{PC}(\mathbf{x})$ and $S_G(x)$ are then combined as follows to get the similarity measure $SL(\mathbf{x})$ of $f_1(\mathbf{x})$ and $f_2(\mathbf{x})$:

$$S_L(x) = S_{PC}(x) * S_G(x) \qquad \ldots\ldots\ldots\ldots(7)$$

After obtaining the similarity $S_L(\mathbf{x})$ at each location of $\mathbf{x}$, the overall similarity between f_1 and f_2 can be obtained easily. For a given location $\mathbf{x}$, if anyone of $f_1(\mathbf{x})$ and $f_2(\mathbf{x})$ has a significant PC value, then it gives that this position $\mathbf{x}$ will have the high impact on HVS to evaluate the similarity between f_1 and f_2. Therefore, we use $PC_m(\mathbf{x}) = \max(PC_1(\mathbf{x}), PC_2(\mathbf{x}))$ to weight the importance of $S_L(\mathbf{x})$ in the overall similarity between f_1 and f_2, and according to this the FSIM index between f_1 and f_2 is given as

$$FSIM = \frac{\sum_{x \in \Omega} S_L(x).\, PC_m(x)}{\sum_{x \in \Omega} PC_m(x)} \qquad \ldots\ldots\ldots\ldots(8)$$

Where Ω means the whole image spatial domain.

5. Software and data sets used

For comparison and implementation of different fusion technique for increasing the information content of the resulting merged image PRIMEWIN software is used. Sample data set is also taken from PRIMEWIN which is of the type GeoTiff file.

6. Result and Discussion

Multi-sensor image fusion seeks to combine information from different images to obtain more inferences than can be derived from a single sensor. It is widely recognized as an efficient tool for improving overall performance in image based application. Among the hundreds of variations of image fusion techniques, methods which had be widely used including IHS, PCA, Brovey transform, wavelet transform, and Artificial Neural Network (ANN). Methods like HIS, PCA and Brovey transform, has lower complexity and faster processing time, the most significant problem is color distortion. Figure 1 LISS4-TEST-FUSION. TIF which is RGB file and figure 2 CARTO-TEST-FUSION.TIF which is High Resolution Data shows the input image for Brovey and HSI transform.

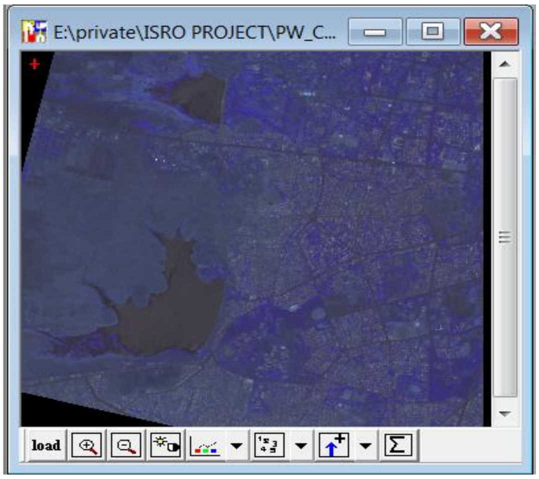

Figure 1: LISS4-TEST-FUSION. TIF (RGB file)

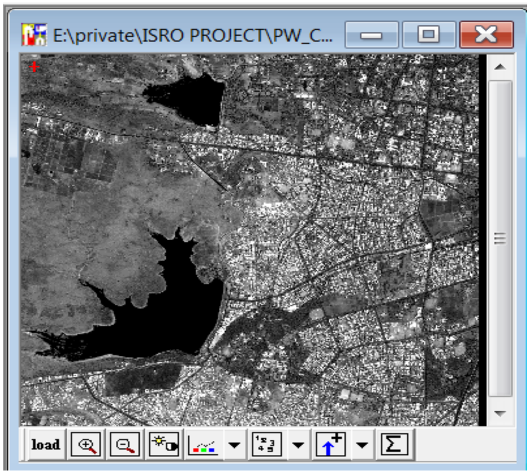

Figure 2: CARTO-TEST-FUSION. TIF (High Resolution Data)

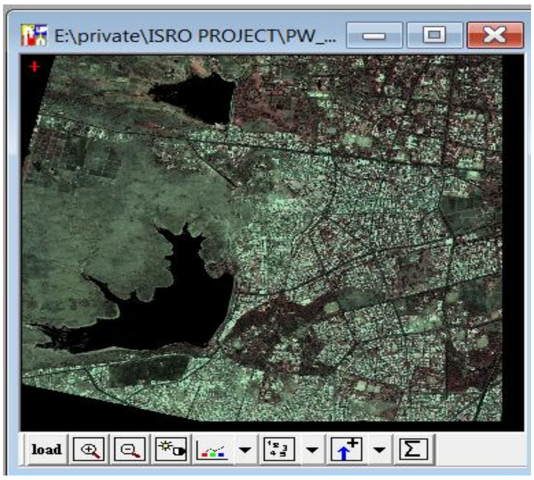

Figure 3: Output of Brovey transform

Now by using PRIMEWIN software the output image we obtain is given in figure 3 and 4 for Brovey and HSI transform respectively.

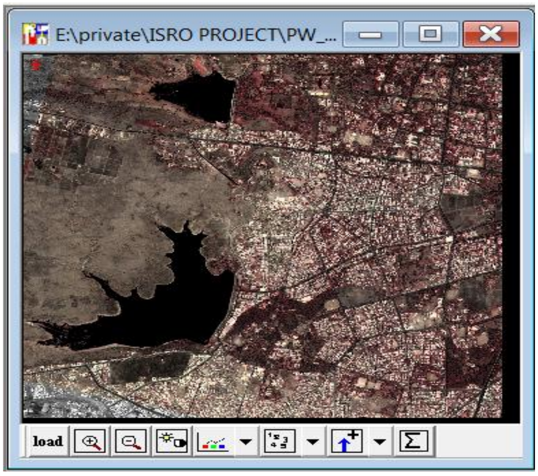

Figure 4: Output of HSI transform

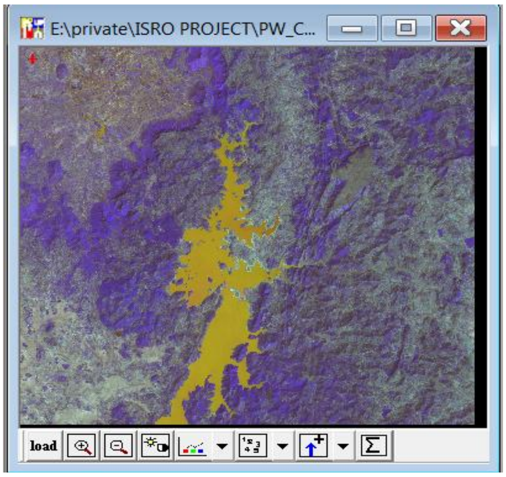

Figure 5: IRS-L3-TEST-UNSUP-CLASSIF.TIF (GeoTiff file) input for PCA transform

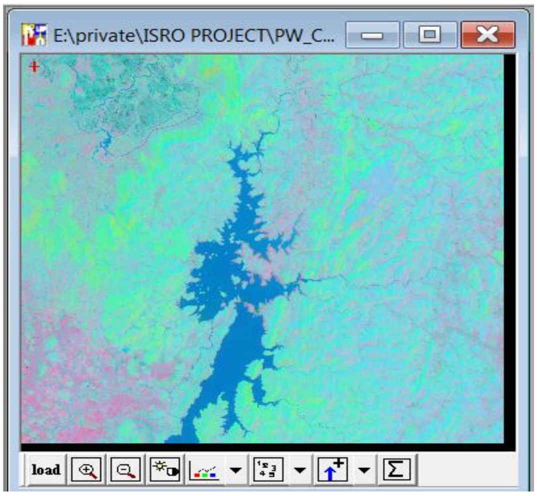

Figure 6: Output of PCA Transform

We use Principal Components to produce uncorrelated output bands, to segregate noise components, and to reduce the dimensionality of data sets. Because multispectral data bands are often highly correlated, the Principal Component (PC) Transformation is used to produce uncorrelated output bands. This is done by finding a new set of orthogonal axes that have their origin at the data mean and that are rotated so the data variance is maximized. For this the input image used is given in figure 5 IRS-L3-TEST-UNSUP-CLASSIF.TIF which is GeoTiff file. And the output of PCA transform is given in figure 6.

7. Conclusion

The purpose of Image Fusion is for the integration of disparate and complementary data for enhancement of the information content in the images as well as for the increment of the reliability of the interpretation. This brings to more accurate data and increased utility in application fields like segmentation and classification. In remote sensing it found immense application as the reduced amount of data in the multispectral images can be fused through efficient fusion techniques with the high informative panchromatic (PAN) images to yield better high spectral and spatial resolution images. These high quality fused images can be used for landmass classification or for military purposes like target localization etc. The quality of the fused image greatly affects the classification accuracy. For this a good registration technique is required which greatly affects the quality of fused image. The entropy based MI based registration technique which is applied only quite recently to the remote sensing field is found to be giving better results for the classification purposes in this field.

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