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Efficient Image Segmentation using Curve let and Contour let Transform for Bio-Medical Applications

Y.Hima Deepthy[1], G.Amjad Khan [2]
[1] *PG Scholar, Dept Of ECE, G.Pulla Reddy College Of Engineering, Kurnool, Andhra Pradesh.*
[2]*AssistantProfessor, Dept Of ECE, G. PullaReddy Collegeof Engineering, Kurnool, Andhra Pradesh.*

Abstract: *The goal of image fusion is to integrate complementary info from multifocus information such the new pictures area unit additional appropriate for the aim of human beholding and computer-processing tasks like segmentation, feature extraction, and beholding. This paper presents a picture fusion theme that is predicated on the Curveletmodel (DCT). The curvelet transforms of the input pictures area unit fittingly combined, and therefore the new image is obtained by taking the inverse Curvelet remodel of the united rippling coefficients. Associate in Nursing area unita-based most choice rule and a consistency verification step are used for feature choice. The projected theme performs higher than the Transform strategies as a result of the compactness, directional property, and orthogonality of the curvelet remodel. A performance live mistreatment specially generated check pictures is usually recommended and is employed within the analysis of various fusion strategies, and in examination the deserves of various rippling remodel kernels.intensive experimental results together with the fusion of multifocuspictures, Landsat and Spot pictures, Landsat and Seasat SAR pictures, IR and visual pictures, and magnetic resonance imaging and PET pictures area unit bestowed within the paper.*

I. Introduction

IMAGE fusion is a very important technique for varied image processing and pc vision applications like feature extraction and target recognition [1]. Through image fusion, different pictures of a similar scene may be combined into a single consolidated image. The consolidated image will offer additional comprehensive info regarding the scene that is additional useful for human and machine perception. As an example, the performance of feature extraction algorithms may be improved by fusing multi-spectral remote sensing pictures. The fusion of multi-exposure pictures may be used for photography. In these applications, a decent image fusion methodology has the subsequent properties. First, it will preserve most of the useful info of various pictures. Second, it doesn't produce artifacts. Third, it's strong to imperfect conditions such as miss registration and noise. A large variety of image fusion ways have been planned in literature. Among these ways, multi-scale image fusion and data-driven image fusion are terribly winning ways[2].

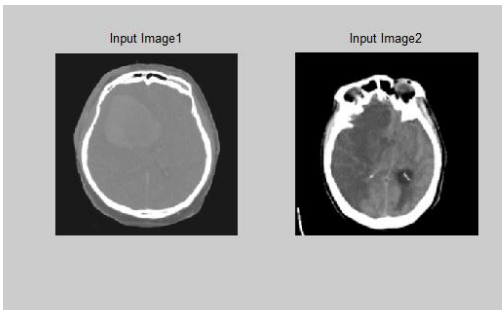


Figure.1:-Input Images

Segmentation of brain tissues in gray matter, white matter and tumour on medical images is not only of high interest in serial treatment monitoring of “disease burden” in oncologic imaging, but also gaining popularity with the advance of image guided surgical approaches[3]. Outlining the brain tumour contour is a major step in planning spatially localized radiotherapy (e.g., Cyber knife, I MRT) which is usually done manually on contrast enhanced T1-weighted magnetic resonance images (MRI) in current clinical practice [4]. On T1 MR Images acquired after administration of a contrast agent (gadolinium), blood vessels and parts of the tumour, where the contrast can pass the blood–brain barrier are observed as hyper intense areas. There are various attempts for brain tumour segmentation in the literature which use a single modality, combine multi modalities and use priors obtained from population atlases. Another method is active contour method which is suitable for finding edges of a region whose gray scale intensities are significantly different from the Surrounding region in the image. To segment homogenous regions, the semi automatic region growing methods first requires users to identify a seed point. In this paper we proposed a full automatic region-growing segmentation technique. First we found the seed automatically using textural features from Co-occurrence matrix (COM) and run length features. Then using gray scale, spatial information and Otsu thresholding method, region growing was applied to segment the region. Image processing is one of most growing research area these days and now it is very much integrated with the medical and biotechnology field[5]. Image Processing can be used to analyze different medical an MRI images to get the abnormality in the image.

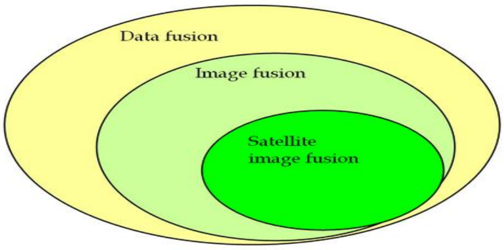


Figure.2:-Types of Fusion

1. Traditional multi-scale image fusion ways need more than 2 scales to get satisfactory fusion results. The key contribution of this paper is to gift a quick two-scale fusion technique that doesn't trust heavily on a specific image decomposition technique. An easy average filter is qualified for the planned fusion framework [6].
2. A completely unique weight construction technique is planned to combine component strikingness and spatial context for image fusion. Rather than victimization, optimization based mostly ways guided filtering is adopted as an area filtering technique for image fusion.
3. A vital observation of this paper is that the roles of two measures, i.e., component strikingness and spatial consistency are quite totally once fusing different layers. In this paper, the roles of component strikingness and spatial consistency are controlled through adjusting the parameters of the guided filter.

II. Literature Survey

Literature survey is the most important step in software development process. Before developing the tool it is necessary to determine the time factor, economy and company strength. Once these things are satisfied, then next step is to determine which operating system and language can be used for developing the tool. Once the programmers start building the tool the programmers need lot of external support. This support can be obtained from senior programmers, from book or from websites. Before building the system the above considerations are taken into account for developing the proposed system.

Survey-1.Multiresolution DCT decomposition for multifocus image fusion

Image fusion is gaining momentum in the research community with the aim of combining all the important information from multiple images such that the fused image contains more accurate and comprehensive information than that contained in the individual images. In this paper, it is proposed to fuse multifocus images in the multiresolution DCT domain instead of the wavelet domain to reduce the computational complexity. The performance of the fused image in the proposed domain is compared with that of the wavelet domain with four recently-proposed fusion rules. The proposed method is applied on several pairs of multifocus images and the performance compared visually and quantitatively with that of wavelets. It is found that the performance of the proposed method is superior/similar to that of wavelets in terms of visual quality and quantitative parameters with extra benefits of computational efficiency and simplicity of implementation.

Survey-2.Multi-focus image fusion for visual sensor networks in DCT domain

The objective of image fusion is to combine relevant information from multiple images into a single image. The discrete cosine transform (DCT) based methods of image fusion are more efficient and time-saving in real-time systems using DCT based standards of still image or video. Existing DCT based methods are suffering from some undesirable side effects like blurring or blocking artifacts which reduce the quality of the output image. Furthermore, some of these methods are rather complex and this contradicts the concept of the simplicity of DCT based algorithms. In this paper, an efficient approach for fusion of multi-focus images based on variance calculated in DCT domain is presented. Due to simplicity of our proposed method, it can be easily used in real-time applications. The experimental results verify the efficiency improvement of our method both in output quality and complexity reduction in comparison with several recent proposed techniques.

Survey-3.Discrete Cosine Transform based fusion of multi-focus images for visual sensor networks

This paper presents a simple and efficient multi-focus image fusion scheme explicitly designed for wireless visual sensor systems equipped with resource constrained, battery powered image sensors employed in surveillance, hazardous environment like battlefields etc. Here the fusion of multi-focus images is based on higher valued Alternating Current (AC) coefficients calculated in Discrete Cosine Transform (DCT) domain. The proposed method overcomes the computation and energy limitation of low power devices and is investigated in terms of image quality and computation energy. Simulations are performed using Atmel Atmega128 processor of Mica 2 mote to measure the resultant energy savings. The experimental results verify the significant efficiency improvement of the proposed method in output quality and energy consumption, when compared with other fusion techniques in DCT domain.

III. Proposed Method

Wavelet Transform:-

Wavelets are an extension Fourier analysis. The mathematics of Fourier analysis dates back to the nineteen century but it wasn't until the mid twentiethcentury,Wavelet analysis uses a similar approach but instead of sinusoids, waves of limited duration, termed basis function or mother wavelets, are used [Figure].

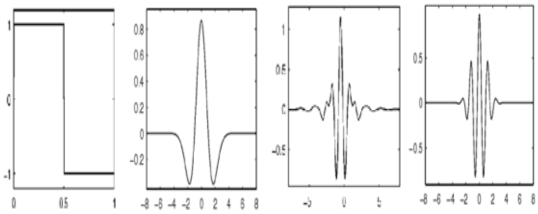


Figure.3:- Wavelet family examples, from left to right: Haar, Mexican Hat, Daubechies and Morlet

Unlike Fourier transformation, a number of different mother wavelet families exist. While Fourier transformation breaks a signal up into sin and cosine functions of various frequencies, wavelet transformation breaks a signal up into shifted and scaled versions of the mother wavelet [Figure].

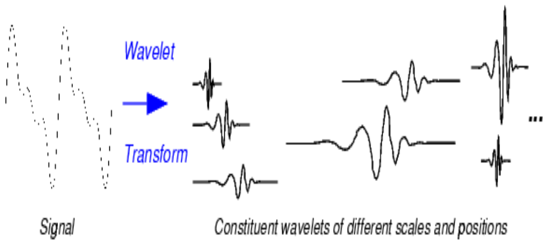


Figure.4:- Wavelet analysis represents the signal as combinations of scaled and shifted mother wavelets.

Project Implementation:

Image Preparation

Digital images of melanoma and benign nevi were collected in JPEG format from different sources totaling 72, half melanoma and half benign. MATLAB's Wavelet Toolbox only supports indexed images with linear monotonic color maps so the RGB images were converted to grayscale images. The next step in the process was to segment the lesion from the surrounding skin. Since a clear color distinction existed between lesion and skin, thresholding was very suitable for this task. A black and white image was produced and its size increased by six pixels all around in order to include the entire border region in the segmented image.

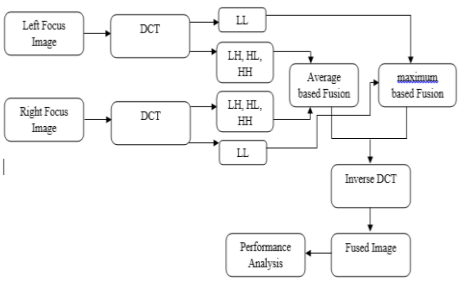


Figure.5:- Proposed Block diagram using DWT and DCT Methods

Multi-Level Discrete Wavelet Transform and Feature Extraction

Discrete Wavelet transform (DWT) is a mathematical tool for hierarchically decomposing an image. The DWT decomposes an input image into four components labeled as LL, HL, LH and HH [9]. The first letter corresponds to applying either a low pass frequency operation or high pass frequency operation to the rows, and the second letter refers to the filter applied to the columns. The lowest resolution level LL consists of the approximation part of the original image. The remaining three resolution levels consist of the detail parts and give the vertical high (LH), horizontal high (HL) and high (HH) frequencies. Figure 3 shows three-level wavelet decomposition of an image.

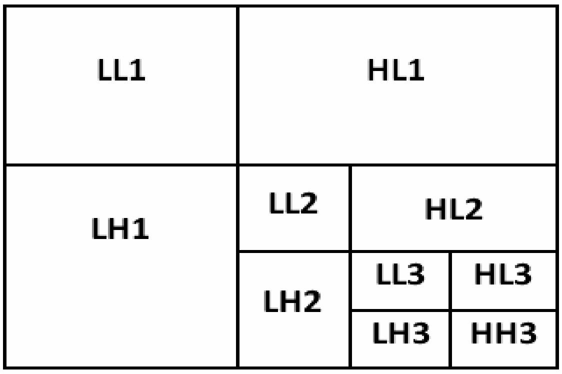


Figure.6:- Three-level Discrete Wavelet Transform.

The black and white mask from the segmentation step was used to determine which coefficient to select from the transformed image. Typically, discrete multi dimensional wavelet transforms produce a wavelet matrix half the size of the original image using a technique called down-sampling where only half the coefficients are preserved. In order to maintain the original image size, a discrete wavelet transformation was used which suppresses down-sampling, producing a wavelet matrix the same size as the input matrix. For both levels, the mean and variance of wavelet coefficients for approximations and details were calculated, resulting in a total of 8 features. Features were then normalized to range between 0 and 1.

Since the wavelet is of limited duration, it can be shifted down the signal at known intervals. At each step a coefficient is calculated representing how closely the wavelet resembles this section of signal. By scaling the wavelet, stretching or compressing it, information about the overall signal trend to small details can be obtained.

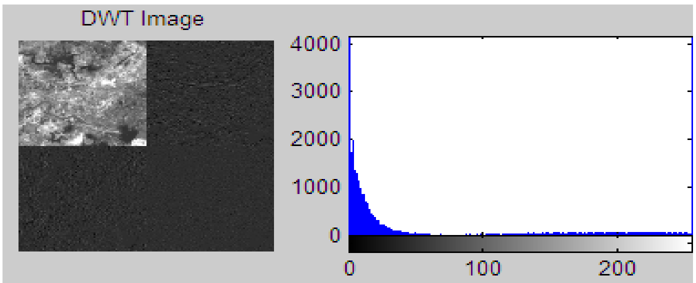


Figure.7:-Example of DWT Image and Histogram Image

1.2 NSCT-based Fusion Algorithm:

Principle of NSCT:

In the foremost contourlet transform [6] downsamplers and upsamplers are presented in both the laplacian pyramid and the DFB. Thus, it is not shift-invariant, which causes pseudo-Gibbs phenomena around singularities. NSCT is an improved form of contourlet transform. It is motivated to be employed in some applications, in which redundancy is not a major issue, i.e. image fusion. In contrast with contourlet transform, nonsubsampled pyramid structure and nonsubsampled directional filter banks are employed in NSCT. The nonsubsampled pyramid structure is achieved by using two-channel nonsubsampled 2-D filter banks. The DFB is achieved by switching off the downsamplers/upsamplers in each two-channel filter bank in the DFB tree structure and upsampling the filters accordingly. As a result, NSCT is shift-invariant and leads to better frequency selectivity and regularity $(C_1^K(x+m,y+n))$ than contourlet transform.Fig.8 shows the decomposition framework of contourlet transform and NSCT.

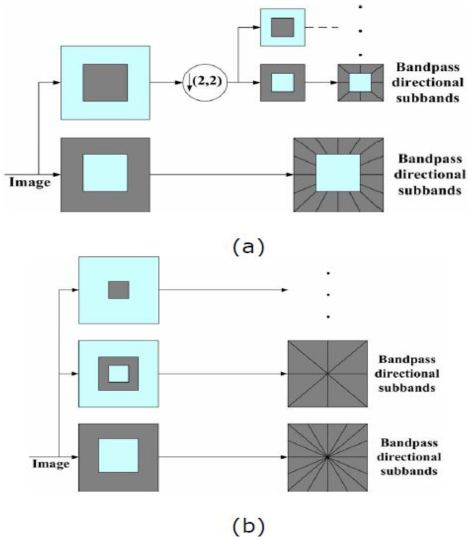


Figure.8: Decomposition framework of contourlet transform and NSCT.

In this paper, image decomposition is performed by the NSCT. We hope that predominance of NSCT, which are shift-invariant, multi resolution, localization, directionality, and anisotropy, will be more suitable for image fusion and other image processing, i.e. target recognition, object detection, etc. In the fusion process, both neighborhood coefficients and cousin coefficients information are utilized in the salience measure.

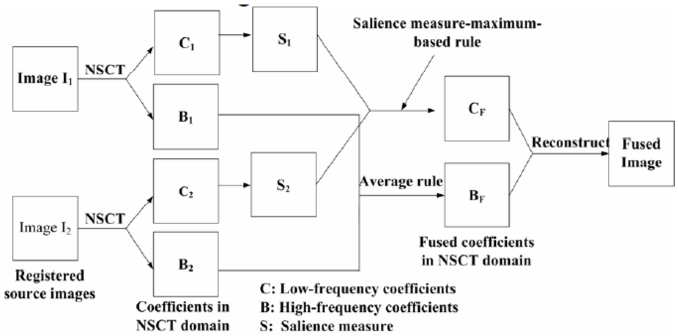


Figure.9: Framework of the NSCT-based fusion algorithm

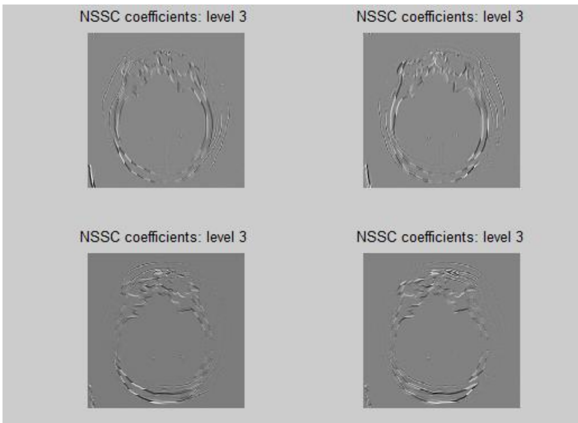


Figure.10: NSCT coefficients for different levels

DCT(Discrete curvelet transform):

We used the second generation of curve let transform, discrete curve let transform (DCT), and modified the DCT coefficients by a suitable nonlinear function. One way to increase the image contrast is to enhance the image ridges, which play an important role in enhancing image contrast. In order to simultaneously enhance the weak edges and eliminate the noise, the modifying function parameters are defined based on some statistic features of DCT (DCT) coefficients.

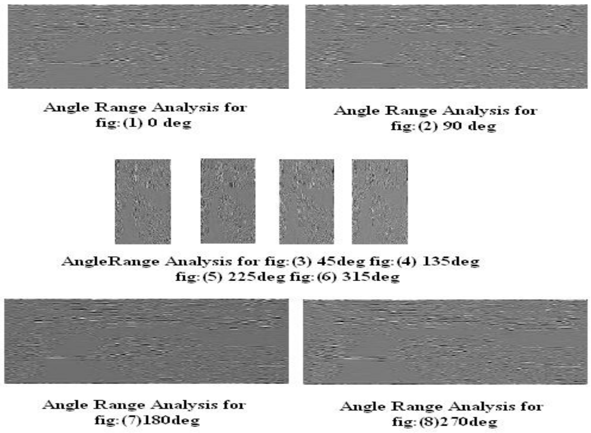


Figure.11: Discrete Curve let Transform Process

IV. Image Fusion

Image Fusion is the process of combining relevant information from two or more images into a single image. The fused image should have more complete information which is more useful for human or machine perception.

Fusion of low-frequency coefficients

Considering the images' approximate information is constructed by the low-frequency coefficients, average rule is adopted for low-frequency coefficients. Suppose $B_F(x, y)$ is the fused low-frequency coefficients, then

$$\frac{B_1(\mathrm{x,y})+B_2(\mathrm{x,y})}{2} = B_F(x,y) \qquad (1)$$

where$B_1(x, y)$ and 2 $B_2(x, y)$denote the low-frequency coefficients of source images.

Fusion of high-frequency coefficients

High-frequency coefficients always contain edge and texture features. In order to make full use of information in the neighborhood and cousin coefficients in the DWT domain, a salience measure, as a combination of region energy of DWT coefficients and correlation of the cousin coefficients, is proposed for the first time. We define region energy by computing the sum of the coefficients' square in the local window. Suppose C_l^k (x y) is the high-frequency DWT coefficients, whose location is (x,y) in the subband of k-th direction at l-th decomposition scale. The region energy is defined as follows:

$$E^K_{1(x,y)} = \sum_{m,n \in SM+N} (C^K_1(x+m, y+n))^2 \qquad (2)$$

where $S_{M\times N}$ denotes the regional window and its size is M × N (typically 3×3).Region energy, rather than single pixel value, will be more reasonable to extract features of source images by utilizing neighbors' information.

Contrast enhancement:

In spite of increasing demand for enhancing remote sensing images, existing histogram-based contrast enhancement methods cannot preserve edge details and exhibit saturation artefacts in low- and high-intensity regions. In this section, we present a novel contrast enhancement algorithm for remote sensing images using dominant brightness level-based adaptive intensity transformation. If we do not consider spatially varying intensity distributions, the correspondingly contrast-enhanced images may have intensity distortion and lose image details in some regions. For overcoming these problems, we decompose the input image into multiple layers of single dominant brightness levels. To use the low-frequency luminance components, we perform the DWT + NSCT on the input remote sensing image and then estimate the dominant brightness level using the log-average luminance in the LL sub band. Since high-intensity values are dominant in the bright region, and vice versa.

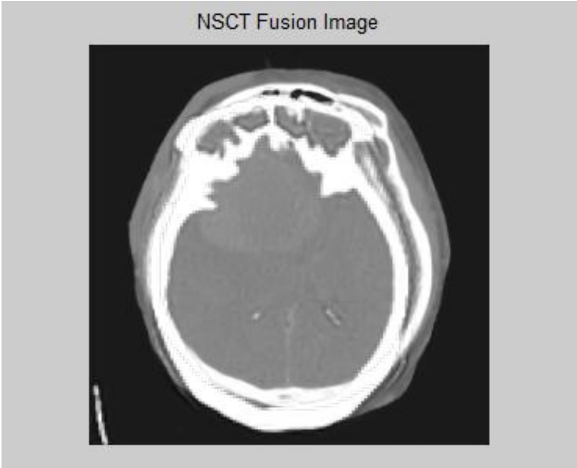


Figure.12:- Fusion Image

V. Result Analysis

Here we report some experimental results that illustrate the performance of the proposed approach. The experiments were performed under windows and matlab running on a desktop machine.

Quality Measurement:-

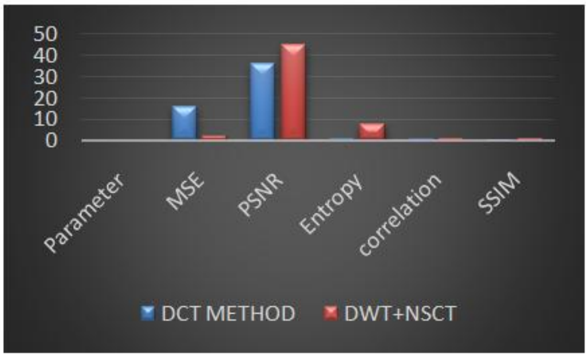
The Quality of the reconstructed image is measured in-terms of mean square error (MSE) and peak signal to noise ratio (PSNR) ratio. The MSE is often called reconstruction error variance σ_q^2. The MSE between the original image f and the reconstructed image g at decoder is defined as:

$$\textbf{MSE} = \frac{1}{MXN} \sum_{j,k} (f[j,k] - g[j,k]) \quad \textbf{(3)}$$

Where the sum over j, k denotes the sum over all pixels in the image and N is the number of pixels in each image.

Method	**DCT METHOD**	**DWT+NSCT**
Parameter		
MSE	**15.7486**	**2.0719**
PSNR	**36.1584**	**44.9672**
Entropy	**0.885451**	**7.5912**
correlation	**0.6999693**	**0.9837**
SSIM	**0.00429584**	**0.963**

Table.1:-Performance of DCT and DWT+NSCT Methods



Bargraph of various parameters for existing and proposed methods.

From that the peak signal-to-noise ratio is defined as the ratio between signal variance and reconstruction error variance. The PSNR between two images having 8 bits per pixel in terms of decibels (dB) is given by:

$$\textbf{PSNR} = 10 \log_{10}\left(\frac{255^2}{MSE}\right) \quad (4)$$

Generally when PSNR is 20 dB or greater, then the original and the reconstructed images are virtually in-distinguishable by human eyes.

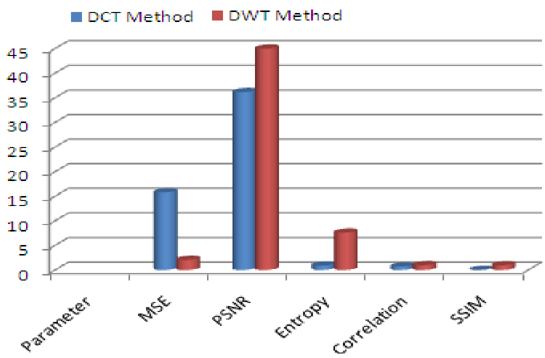


Figure.13:-Comparison graph for DCT and DWT Methods

VI. Conclusion

In this letter, a new approach based on spatial frequency for fusion of multi-focus images has been proposed in the DWT domain instead of the spatial domain. We evaluate the performance of the proposed method with various evaluation metrics and it is found that the performance of fusion in the DCT domain is superior to that of conventional approaches based on DWT and the state-of-the-art methods including Curve let, and NSCT, in terms of visual quality and quantitative parameters. Moreover, the proposed method is simple to implement and computationally efficient when the source images are coded in JPEG format, especially in wireless visual sensor networks.

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