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Different Levels of Image Fusion Techniques in Remote Sensing Applications and Image Classification

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Abstract: The present study documents the various different image fusion techniques. The main application of image fusion in multi-focus cameras to combine information from multiple images of the same scene in order to deliver only the multi focused image. The discrete cosine transforms (DCT) based methods of image fusion are more suitable and time-saving in real-time systems using DCT based standards of still image or video. Such an increase makes the application of image fusion techniques in remote sensing important. The present study aims to show where image fusion paradigm, to present some other applications of image fusion in remote sensing, and to highlight the advantages that image fusion can provide.

Index Terms—image fusion, data fusion, remote sensing, image processing, signal processing. Visual Sensor, DCT.

I. INTRODUCTION

In all sensor networks, every sensor can receive, produce and transfer data. Visual Sensor Networks (VSN) refers to a system with a large number of cameras that are used to geographically spread resources and monitoring of many points. In VSN, sensors are cameras which can record either video sequences or still images. Therefore, the processing of output information is related to machine vision subjects and image processing. A distinguished feature of visual sensor is to generate great amount of data. These characteristics of visual sensor

Image fusion is the process of to combine relevant information from two or more images into a single image. The resulting image will contain all the important information as compare to input images. The new image will extracts all the information from source images. Image fusion is a useful technique for merging single sensor and multi-sensor images to enhance the information. The objective of image fusion is to combine information from multiple images in order to produce an image that deliver only the useful information. The discrete cosine transformation (DCT) based methods of image fusion are more suitable and time-saving in real-time systems. In this paper an efficient approach for fusion of multifocal images is presented which is based on variance calculated in dct domain. Image fusion takes place at three different levels i.e. pixel, feature and decision. Pixel level is a low level of fusion which is used to analyze and combine data from different sources before original information is estimated and recognised. Feature level is a middle level of fusion which extract important features from an image like shape, length, edges, segments and direction. Decision level is a high level of fusion which points to actual target. Remote sensing is the "non-contact recording of information from the ultraviolet, visible, infra-red, and microwave regions of the electromagnetic spectrum by means of instruments such as cameras, scanners, lasers, linear arrays, and/or area arrays located on platforms such as aircraft or spacecraft, and the analysis of acquired information by means of visual and digital image processing" (Jensen, 2000). As the definition suggests, the field of remote sensing is associated with substantial amounts of visual data originating from a broad range of sensors which vary in their spectral, spatial, and temporal characteristics. Examples of such sensors are Panchromatic sensor (PAN), Multi-Spectral sensor (MS) (coastal blue, blue, green, yellow, red, near infrared), hyper-spectral sensor (100s of bands), Light Detection and Ranging (LIDAR), and Synthetic Aperture Radar (SAR). With such diverse and huge amounts of data, image fusion techniques can play a vital role in remote sensing deliver only the useful information which is represented at a conceptualized level Principal Component Analysis (PCA), based methods are special domain methods. But special domain methods.

II. IMAGE FUSION TECHNIQUES

In the Image Fusion method the good information from each of the given images is fused together to form a resultant image whose quality is superior to any of the input images. Image fusion method can be broadly classified into two group's i.e.

- Spatial domain fusion method
- Transform domain fusion

In spatial domain techniques, we directly deal with the pixel value of an image. The pixel values are manipulated to achieve desired result. In frequency domain methods the pixel value is first transferred in to domain methods by applying dct and dft based fusion methods and further image is enhanced by altering frequency component of an image. Image Fusion applied in every field where images are ought to be analyzed. For example, medical image analysis, microscopic imaging, analysis of images from satellite, remote sensing application, computer vision and battlefield monitoring. The fusion methods such as averaging, Brovey method, principal component analysis (PCA) and IHS based methods fall under spatial domain approaches. Another important spatial domain fusion method is the high pass filtering based technique.

The multi resolution analysis has become a very useful tool for analyzing remote sensing images. The discrete wavelet transform has become a very useful tool for fusion. Some other fusion methods are also there such as Laplacian pyramid based, Curvelet transform based etc. These methods show a better performance in spatial and spectral quality of the fused image compared to other spatial methods of fusion of fusion.

A showing the Left blurred Image
B showing the right blurred image.
C showing the fused image as it is clearly showing the entire object in the given image.

III. PRINCIPAL COMPONENT ANALYSES (PCA)

PCA is a mathematical tool which transforms a number of correlated variables into a number of uncorrelated variables. The PCA is used extensively in image classification and image compression. The PCA involves a mathematical formula that transforms a number of correlated variables into a number of uncorrelated variables called principal components. It computes a compact and optimal description of the data set. The first principal component accounts for as much of the variance in the data as possible and each succeeding component accounts for as much of the remaining variance as possible. First principal component is taken to be along the direction with the maximum variance. The second principal component is constrained to lie in the subspace perpendicular of the first. Within this Subspace, this component points the direction of maximum variance. The third principal component is taken in the maximum variance direction in the subspace perpendicular to the first two and so on.

IV. DISCRETE COSINE TRANSFORM

It is most of the spatial domain image fusion methods are complex and time consuming which are hard to be performed on real-time applications. Moreover, when the source images are coded in Joint Photographic Experts Group (JPEG) standard or when the fused image will be saved or transmitted in JPEG format, the fusion approaches which are applied in DCT domain will be very efficient. To perform the JPEG coding, an image (in color or grey scales) is first subdivided into blocks of 8x8 pixels. The Discrete Cosine Transform (DCT) is then performed on each block. This generates 64 coefficients which are then quantized to reduce their magnitude. The coefficients are then reordered into a one-dimensional array in a zigzag manner before further entropy encoding. The compression is achieved in two stages: the first is during quantization and the second during the entropy coding process. JPEG decoding is the reverse process of coding. We denote A and B as the output images of two cameras that have been compressed in JPEG coding standard in the sensor agent and further transmitted to fusion agent of VSN. In the case of using spatial domain method these images must be decoded and transferred to spatial domain. Then after applying fusion procedure, the fused image must be coded again in order to be stored or transmitted to an upper node. Tang , (1997) has considered the above mention issue of complexity reduction and proposed two image fusion techniques in DCT domain, namely, DCT + Average and DCT+ Contrast. DCT +Average is calculated by simply taking the average of all the DCT coefficients of all the input images. This simple method of averaging leads to undesirable side effects including blurring.

For the second technique called DCT + Contrast, fusion criterion or activity level is based on a contrast measure which is calculated for every 63 AC coefficients of the blocks from source images. Then the contrast measures of each coefficient in source images are compared. Then the coefficient with the highest contrast value is selected .The DCT Block of the output image is made up of AC coefficients with the highest contrast in comparing procedure, and DC coefficient of each block in the output image is the average of DC coefficients of the corresponding blocks in the input images. This algorithm is also complex in calculating the contrast measure for each coefficient. Furthermore, it suffers from side effects including blocking artifacts due to the manipulation in the diverse selection of DCT coefficients.

In order to reduce the complication for the real-time applications and also enhance the quality of the output image, an image fusion technique in DCT domain. Here, the variance of 8×8 blocks calculated from DCT coefficients is used as a contrast criterion for the activity measure. Then, a consistency verification (CV) stage increases the quality of output image. Simulation results and comparisons show the considerable improvement in the quality of the output image and reduction of computation complexity.

V. THE DIFFERENT LEVELS OF FUSION

In the context of fusing images, there are three abstrac-tion levels at which the combination mechanism can take place, (Zheng, 2007): pixel (signal), feature, and symbol levels as shown in

Fig. 1. Fusion levels can be distinguished by several attributes which are the output format, the representation of sensory information, the required degree of registration accuracy, and the methodologies used for fusion (Luo and Kay, 1994). The choice of the appropriate level depends on the characteristics of sensory data, fusion application, and availability of tools (Luo and Kay, 1994). In what follows, levels of fusion are discussed in further detail.

A. Pixel-level Fusion

The input of pixel-level fusion is the set of images. The fusion process is a local operation where each pixel in the

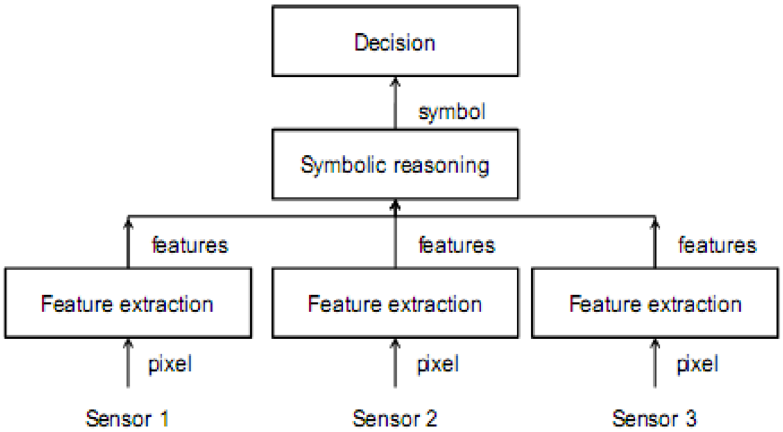


Fig. 3. A schematic diagram of fusing images at feature-level.

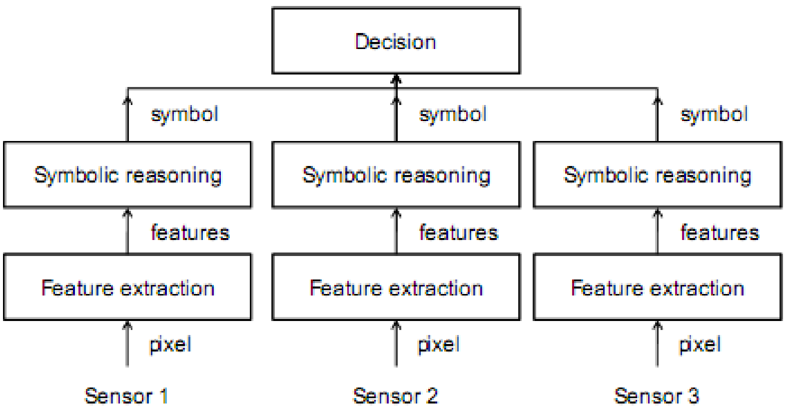


Fig. 4. A schematic diagram of fusing images at symbol-level.

fused image is determined by considering a single pixel value or a small region of pixels in input images (Lewis, 2007). The process can be applied in spatial or transform domains. The output is another image with an increased information content (Luo and Kay, 1994).. This is to say that the fused image would allow new information to be inferred that would not be possible considering each input separately. A schematic diagram of fusing images at pixel-level is presented in Fig.2.

B. Fusing multi-modal images

Multi-modal images are those capturing different physi-cal attributes using different imaging principles (Nikolov, 1999). Multi-modal image fusion helps enhancing temporal coverage and extending the range of operation to different environmental conditions (Waltz Llinas, 1990). Also, multi-modal image fusion can be used to sharpen images which allows better detection of features. Pan-sharpening falls under this subcategory. Pan-sharpening is a vital application in remote sensing since satellites usually have two complementary sensors,

1) the panchromatic sensor which has high spatial resolution and low spectral resolution and 2) the multi-spectral sensor which has low spatial resolu-sensors (e.g., exposure and focus) cannot be changed after tworks, and fuzzy logic (Zeng et al., 2006).

C. Fusing multi-temporal images

Multi-temporal fusion is the fusion of two or more images of the same scene captured at different times. Multi-temporal fusion can be used to construct cloud-free images . (Liew and Kwoh, 2004). Multi-temporal fusion can be also used in detecting and monitoring changes over a period of time (Pohl and Van Genderen, 1998)

Another example is the process of constructing cloud-free images. It is common with remote sensing images to be obstructed by clouds and their shadows. Images from different

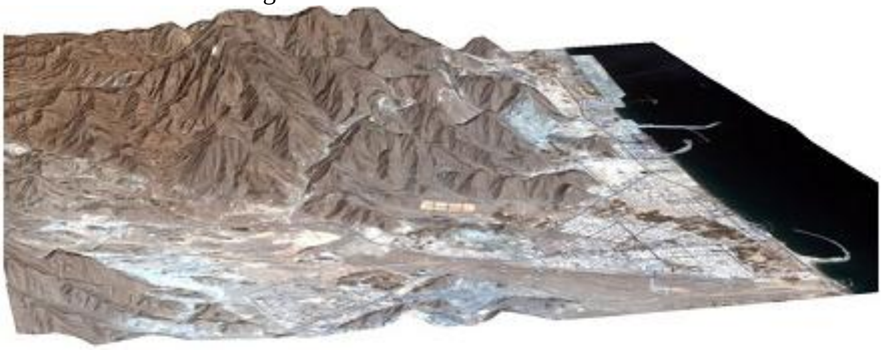


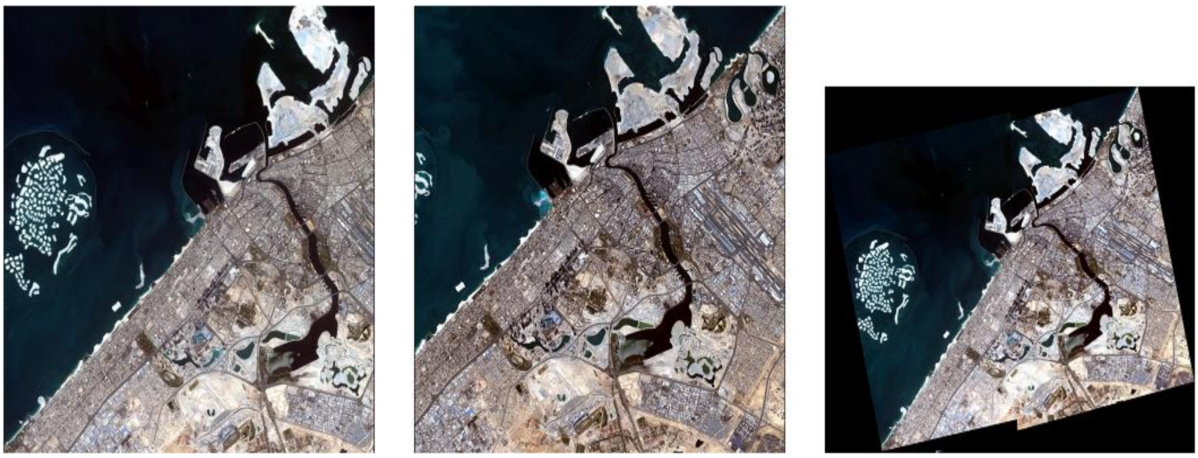
Fig. 8. A 3D image of Fujairah City.

are areas that are depicted in both input images but some are exclusively present in one image. For example, the world islands (i.e., the group of islands at the centre left of Fig. 5(a)) are visible in the first image but not in the second. In the fused image, complimentary data are combined and redundant data are reduced as seen in Fig. 5(c). Mosaicing is used in creating large highly-detailed images of cities and countries.

Another application of multi-view image fusion is stereo-imaging. Stereo-imaging aims to extract depth information of the scene. The process mimics a similar one that occurs inhuman. From two images taken from different perspectives, a 3D model of the scene can be constructed as shown in Fig. 8. Based on 3D models, further studies can be carried out such as mineral/oil/gas explorations and urbanism (Baillard and Matre, 1999).

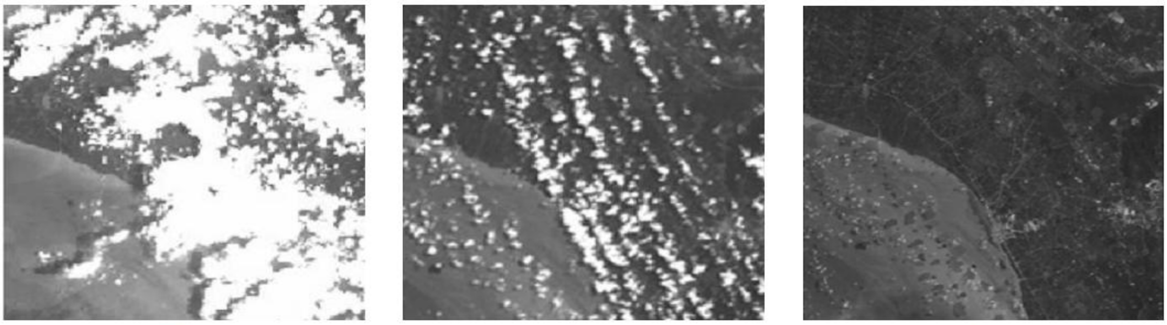
D. Advantages of pixel-level image fusion

Pixel-level image fusion can help extending the spatial range, temporal range, and operational conditions of sen- sors (Waltz and Llinas, 1990). Moreover, using image fusion increases the overall robustness of the system as it does not have a single point-of- failure. In other words, a failure in one sensor does not lead to a failure of the whole system (Waltz and Llinas, 1990).. Pixel-level image fusion allows also for a better, more accurate, and more confident de- tection of features as a result of multiple sensor reporting (Toet *et al.,* 1997).



(a) (b) (c)

Fig. 5. Constructing an image with a wider field-of-view of the scene through mosaicing.



(a) (b) (c)

Fig. 6. Constructing a cloud-free image of the scene (obtained from [17]).

(a) (b) (c)

Fig. 7. Monitoring construction progress in Meydan City through fusion.

Fusion, nowadays, is found useful in number of applications such as mapping (Pohl, 1996) hazard assessment (Huggel et al., 2002), environmental studies (Deeudomchan et al., 2006) urbanism, damage assessment, site surveillance, mineral and oil/gas explorations, land-use analysis, and planning search-and-rescue operations.

Image Classification

The intent of the classification process is to categorize all pixels in a digital image into one of several land cover classes, or *"themes"*. This categorized data may then be used to produce thematic maps of the land cover present in an image. Normally, multispectral data are used to perform the classification and, indeed, the spectral pattern present within the data for each pixel is used as the numerical basis for categorization (Lillesand and Kiefer, 1994). The objective of image classification is to identify and portray, as a unique gray level (or color), the features occurring in an image in terms of the object or type of land cover these features actually represent on the ground.

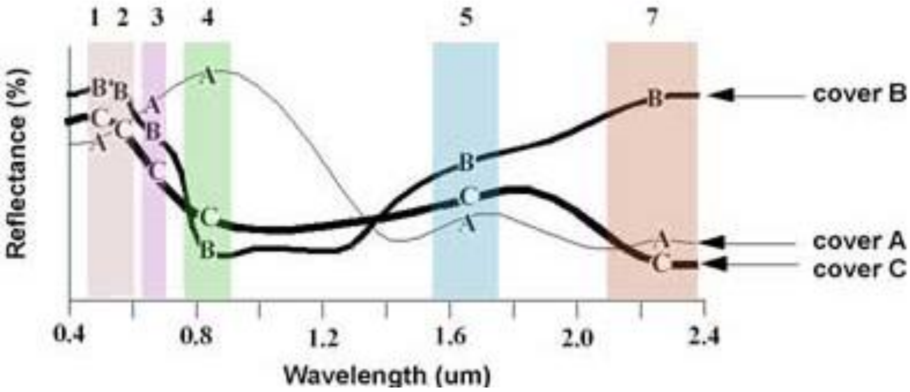


Figure :24-Spectral Reflectance curve of 3 land covers

Image classification is perhaps the most important part of digital image analysis. It is very nice to have a *"pretty picture"* or an image, showing a magnitude of colors illustrating various features of the underlying terrain, but it is quite useless unless to know what the colors mean. Two main classification methods are *Supervised Classification* and *Unsupervised Classification.*

Maximum likelihood Classification

Maximum likelihood Classification is a statistical decision criterion to assist in the classification of overlapping signatures; pixels are assigned to the class of highest probability.

The maximum likelihood classifier is considered to give more accurate results than parallelepiped classification however it is much slower due to extra computations. We put the word *`accurate'* in quotes because this assumes that classes in the input data have a Gaussian distribution and that signatures were well selected; this is not always a safe assumption.

Minimum distance Classification

Minimum distance classifies image data on a database file using a set of 256 possible class signature segments as specified by signature parameter. Each segment specified in signature, for example, stores signature data pertaining to a particular class. Only the mean vector in each class signature segment is used. Other data, such as standard deviations and covariance matrices, are ignored (though the maximum likelihood classifier uses this).

The result of the classification is a theme map directed to a specified database image channel. A theme map encodes each class with a unique gray level. The gray-level value used to encode a class is specified when the class signature is created. If the theme map is later transferred to the display, then a pseudo-color table should be loaded so that each class is represented by a different color.

Parallelepiped Classification

The parallelepiped classifier uses the class limits and stored in each class signature to determine if a given pixel falls within the class or not. The class limits specify the dimensions (in standard deviation units) of each side of a parallelepiped surrounding the mean of the class in feature space.

If the pixel falls inside the parallelepiped, it is assigned to the class. However, if the pixel falls within more than one class, it is put in the overlap class (code 255). If the pixel does not fall inside any class, it is assigned to the null class (code 0).

The parallelepiped classifier is typically used when speed is required. The draw back is (in many cases) poor accuracy and a large number of pixels classified as ties (or overlap, class 255).

Supervised Classification

With supervised classification, we identify examples of the Information classes (i.e., land cover type) of interest in the image. These are called *"training sites"*. The image processing software system is then used to develop a statistical characterization of the reflectance for each information class. This stage is often called "*signature analysis*" and may involve developing a characterization as simple as the mean or the rage of reflectance on each bands, or as complex as detailed analyses of the mean, variances and covariance over all bands. Once a statistical characterization has been achieved for each information class, the image is then classified by examining the reflectance for each pixel and making a decision about which of the signatures it resembles most.

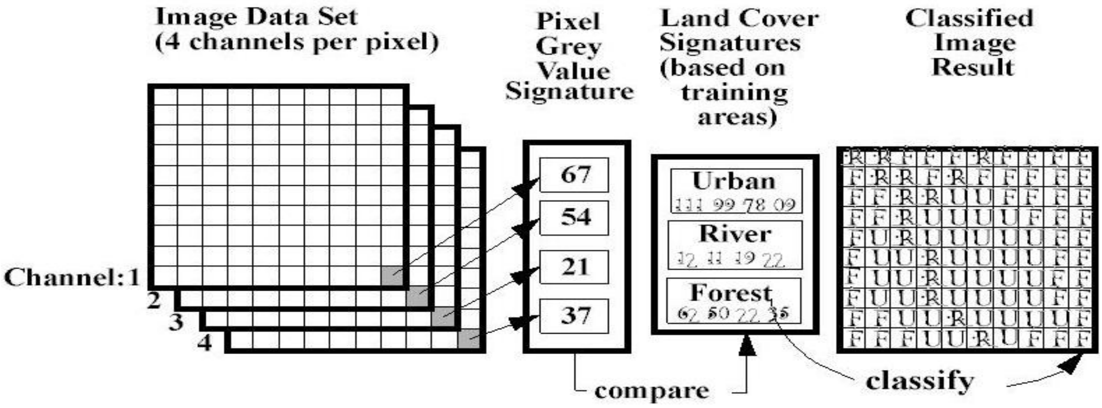


Figure:25- Steps in Supervised classification

Unsupervised Classification

Unsupervised classification is a method which examines a large number of unknown pixels and divides into a number of classed based on natural groupings present in the image values. Unlike supervised classification, unsupervised classification does not require analyst-specified training data. The basic premise is that values within a given cover type should be close together in the measurement space (i.e. have similar gray levels), whereas data in different classes should be comparatively well separated (i.e. have very different gray levels)

Unsupervised classification is becoming increasingly popular in agencies involved in long term GIS database maintenance. The reason is that there are now systems that use clustering procedures that are extremely fast and require little in the nature of operational parameters. Thus it is becoming possible to train GIS analysis with only a general familiarity with remote sensing to undertake classifications that meet typical map accuracy standards. With suitable ground truth accuracy assessment procedures, this tool can provide a remarkably rapid means of producing quality land cover data on a continuing basis

VI. CONCLUSION

This paper has presented a related work on the different image fusion techniques ,classification and remote sensing application. The main goal of image fusion in multi-focus cameras to integrate the information from several pictures of the identical scene in order to deliver only the multi focused image, classification of images and application. Classifications are maximum likely wood, minimum distance, super wised, Unsupervised, Parallelepiped .The DCT based methods of image fusion are proved to be more suitable and time-saving in real-time systems for still images or videos. Pixel-level image fusion has many applications in the field of remote sensing not limited to pan-sharpening. The list includes image mosaicing, stereo-imaging, construction of cloud-free images, change detection, and live coverage of areas. These applications can serve different purposes in civil-ian and military domains. In this paper an efficient approach for fusion of multi-focus images based on variance calculated in DCT domain and classification of application remote sensing has been presented. By understanding the capabilities of image fusion and its connection with remote sensing, processing remote sensing image can be further developed.

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