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# An Efficient CBIR of Brain MR Images Using Histogram of Oriented Gradients and Local Binary Pattern

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**Abstract**— Retrieval of similar images from large dataset of brain images across patients would help the experts in the decision diagnosis process of diseases. Generally used feature extraction methods are color texture and shape. In medical images texture and shape features are most efficient. A combination of low level features will get better result. The real MR images contain brain and non-brain voxels (especially the skull). The presence of the skull degrades the performance of the system. So in this paper we perform a preprocessing step, called skull stripping. Then the methods are applied to the preprocessed image. Here we propose a combined method of HOG (Histogram of Oriented Gradients) and LBP (Local Binary Pattern). HOG is a shape feature extraction method and it results HOG histogram. LBP is a texture feature extraction method and its output is LBP histogram. Then combine these methods by adjusting appropriate weights. The results shows that the combined feature outperforms the individual feature and preprocessed image is outperform the original image for image retrieval.

**Index Terms**— CBIR, Histogram of Oriented Gradients, Local Binary Pattern and Skull Stripping

## I. INTRODUCTION

INTEREST in the potential of digital images has increased enormously over the last few years, fuelled at least in part by the rapid growth of imaging on the World-Wide Web. The enormous increase of digital information available locally or on the Internet makes it almost impossible to annotate the digital objects manually. Efficient image searching, browsing and retrieval tools are required by users from various domains, including remote sensing, fashion, crime prevention, publishing, medicine, architecture, etc. For this purpose, many general-purpose image retrieval systems have been developed.

There are two frameworks: text-based and content-based. The text-based approach can be traced back to 1970s. In such systems, the images are manually annotated by text descriptors, which are then used by a database management system (DBMS) to perform image retrieval. There are two disadvantages with this approach. The first is that a considerable level of human labour is required for manual annotation. The second is the annotation inaccuracy due to the subjectivity of human perception.

To overcome the above disadvantages in text-based retrieval system, content-based image retrieval (CBIR) was introduced in the early 1980s. Content-Based Image Retrieval (CBIR) systems aim to recognize and retrieve information based on content of images instead of looking at metadata provided with the images. The major content in images used consists of color, shape and texture features.

### A. Color [1]

In Image Retrieval, color is an important feature which is commonly applicable in stock photography (large, varied databases for being used by artists, advertisers and journalists). It is relatively robust to background noise, image size and orientation but can be altered by surface texture, lighting, shading effects and viewing conditions. These colour distortions are extremely difficult to handle for computers, because they extract the colour information from an image without context information. Additionally, in different contexts, people use various levels of colour specificity. Color Histogram is the commonly used method for color feature extraction in digital images. Color histograms have the advantages of speed and low memory space. Color histogram method is invariant to rotation but it is not invariant to scaling.

### B. Texture [1]

Texture is an intuitive concept which allows us to distinguish regions of the same color. Together with color, texture is a powerful discriminating feature, present nearly everywhere in nature. Textures can be described according to their spatial frequency or perceptual properties (e.g., periodicity, coarseness, preferred direction, or degree of complexity). In particular, textures emphasize orientation and spatial depth between overlapping objects. In contrast to color, textures describe repeating visual patterns in homogeneous regions, i.e., texture is a region instead of a pixel property.

### C. Shape [1]

Shape is an important feature for Content Based Image Retrieval, because it is invariant to translation, rotation and scaling. Unlike texture, shape is a fairly well-defined concept

and there is considerable evidence that natural objects are primarily recognized by their shape. There are two types of shape representations: contour based and region based. Contour based uses only outer boundary of the shape while the region based is uses the entire region.

In medical domain application especially for brain MR Images CBIR becomes more challenging. In this paper, we use HOG for feature extraction. HOG features are first proposed by Navneet Dalal and Bill Triggs [2]. The main idea behind the HOG descriptors is based on edge information. But HOG performs poorly when the background is cluttered with noisy edges. Local Binary Pattern [3], [4] is complementary in this aspect which gives a textural information of the images. In this paper, an attempt has been made to evaluate the performance of the shape descriptor and texture descriptor with respect to the retrieval of similar brain MR images.

## II. STATE OF ART

### A. Shape Matching Techniques

There are mainly two types of shape matching techniques. They are:

#### 1) Geometry Based Shape Matching

Geometry based Shape matching is a mathematical approach of matching the geometrical properties like points, lines, curve, circle etc. This geometric features are usually enough to represent any given shape of an image. So with the help of the geometric features, shape matching is performed to improve the accuracy.

##### *Point Based Shape Matching [5],[6],[7]:*

Here, image matching is performed based on a single point or tuples of point matching. In a set of single point matching, it considers a point from the source image to match a point in the target images and these points could be an edge or a corner. Image matching done in this way may sometimes fail, if the images hold similar local appearances. So to improve the matching accuracy, a better solution is to include some additional constraints like distances, angles between the points, which has lead to the development of tuples of point matching techniques. Tuples of point matching may refer to point pair matching, triple point matching or higher point matching. In point pair matching, two points separated by a fixed distance and in triple point matching, a triangle of three points, having same total angle value or same distance value is used to compute image matching. Thus the accuracy is increased with the additional burden of computational cost.

##### *Line, Curve, Polygon Based Matching [8],[9],[10]:*

Line, curve, polygon are the categories of geometrical properties. Lines calculated from the images can be used as a feature for image matching. Curve includes circle, ellipse, semi-circle etc which are helpful for extracting needed features for matching. Similarly different polygon shapes (like triangle) are also considered for image matching. Each method has its own strength and based on the requirement, a particular method can be chosen.

##### *Blob and Graph Based Matching [11],[12]:*

A blob is a region of a digital image in which some properties are constant or vary within a prescribed range of values. All the points in a blob can be considered in some sense to be similar to each other. Blob detection is used to obtain regions of interest for further processing which may not be possible with other edge or corner detectors. These regions could signal the presence of objects or parts of objects in the image domain which finds application in object recognition and/or object tracking.

Graphs are a flexible and powerful representation mechanism for complex scenes that have been successfully applied in computer vision, pattern recognition and related areas. When graphs are used to represent objects of a particular domain, the recognition problem turns into the task of graph matching. It can be formulated as an attributed graph matching problem, where the nodes of the graphs correspond to local features of the image and edges correspond to relational aspects between features. Graph matching then used to match the correspondence between nodes of the two graphs such that they look most similar.

#### 2) Structural based Shape Matching [13],[14]

The Structural shape matching includes features that are based on structures which may be parts of an object or symmetric resemblance of an object with various transformations. It provides a higher level of compositional shape description which could discriminate a level higher than the geometrical shape description by updating its similarity measure. Normally, human recognizes a shape not only by its local and global geometrical variations, but also by a high-level understanding of the shape structure. So to improve the retrieval accuracy of semantically related images, a combination of structural and geometrical features have been adopted.

### B. Texture Matching Techniques

There are many methods for texture feature extraction. Based on the domain from which the texture feature is extracted, these methods are broadly classified in to two categories. They are Spacial texture feature extraction method and Spectral texture feature extraction methods.

In spatial approach, texture features are extracted by computing the pixel statistics or finding the local pixel structures in original image domain. The spatial texture feature extraction techniques can be further classified as structural, statistical and model based. In spectral texture feature extraction techniques, an image is transformed into frequency domain and then feature is calculated from the transformed image.

#### 1) GCLM

Haralick [15] suggested the use of grey level co-occurrence matrices (GLCM) to extract second order statistics from an image. Statistical features of grey levels were one of the earliest methods used to classify textures. GLCMs have been used very successfully for texture classification in evaluations. Haralick defined the GLCM as a matrix of frequencies at which two pixels, separated by a certain vector, occur in the image. The distribution in the matrix will depend

on the angular and distance relationship between pixels. Varying the vector used allows the capturing of different texture characteristics. Once the GLCM has been created, various features can be computed from it. These have been classified into four groups: visual texture characteristics, statistics, information theory and information measures of correlation.

### 2) Tamura

Tamura et al. [16] have proposed a texture features corresponding to human visual perception. It is very useful for optimum feature selection and texture analyzer design. Here they approximated in computational form six basic textural features, namely, coarseness, contrast, directionality, line-likeness, regularity, and roughness. Computational measures have been developed and improved in order that they may correspond to the psychological measurements. With respect to coarseness, contrast, and directionality, we have attained very successful results. These three features are so significant in global descriptions of textures that they can be expected to be useful separately in cases where the texture differs only in one of them or in combinations for image classification and segmentation problems. Especially, coarseness is a highly essential factor in texture. In order to improve the other features, its results should be utilized.

### 3) FD

The FD method [17] is based on the theory of fractal geometry which characterizes shapes or patterns of self-similarity. It attempts to find the smallest structure which replicates the whole pattern. In practice, FD method models a grey level image as a 3D terrain surface, and a differential box counting is conducted under the surface to measure how rough the surface is. As the logarithmic number of boxes and the logarithmic box size have a linear relationship, FD can be estimated from the least-square fit of the two variables. As FD only models the roughness feature, other features like directionality and contrast are missed from FD. Therefore, in Chaudhuri and Sarkar, six FDs have to be computed from a number of modified images. Furthermore, FD is not rotation invariant.

### 3) Gabor

One of the most popular signal processing based approaches for texture feature extraction has been the use of Gabor filters [18]. These enable filtering in the frequency and spatial domain. It has been proposed that Gabor filters can be used to model the responses of the human visual system. Turner first implemented this by using a bank of Gabor filters to analyse texture. A bank of filters at different scales and orientations allows multichannel filtering of an image to extract frequency and orientation information. This can then be used to decompose the image into texture features.

### 4) FT/DCT

FT method is used in Hervé and Boujemaa [19]. Two histograms are computed from the FT spectra, one with the circular partition and the other with the wedged partition. Although FT is a powerful image analysis tool, it can only

capture global features which are not sufficient for texture analysis. Ngo et al. arrange the low order DCT [20] coefficients into Mandala space which represents the partial derivatives of the original image. Texture features are computed from the variance of each of the derivative images. DCT method is also used by Lu et al., but they use mean and standard deviation as the texture features instead. Similar to FT, DCT method can only capture the global features.

### 5) Local Binary Pattern

The basic local binary pattern operator, introduced by Ojala et al. [3], was based on the assumption that texture has locally two complementary aspects, a pattern and its strength. In that work, the LBP was proposed as a two-level version of the texture unit to describe the local textural patterns. The original version of the local binary pattern operator works in a  $3 \times 3$  pixel block of an image. The pixels in this block are thresholded by its center pixel value, multiplied by powers of two and then summed to obtain a label for the center pixel. As the neighborhood consists of 8 pixels, a total of  $2^8 = 256$  different labels can be obtained depending on the relative gray values of the center and the pixels in the neighborhood.

## III. METHODOLOGY

Here we have done a combination of two methods HOG and LBP.

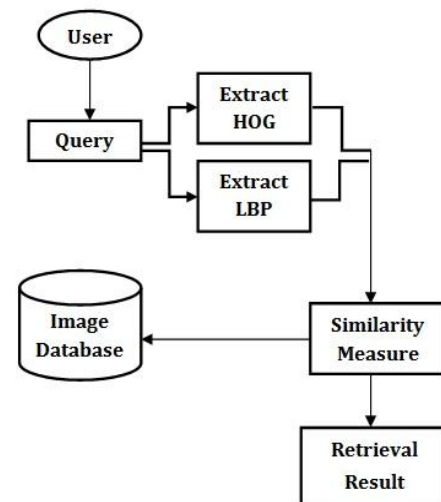


Fig. 1: CBIR System

### A. Pre-processing step

Most brain quantitative MRI study methods use skull stripping as a first step to eliminate non-brain tissue. To perform this first compute the histogram of the original grey scale image. Then according to the histogram value the binary image is generated. There gives threshold to create the binary image. After create the binary image seal off the bottom of the head to make the last row white. Then fill the holes inside the white portion. This gives a cleaned binary image. After that erode away 15 layers of pixels, which will

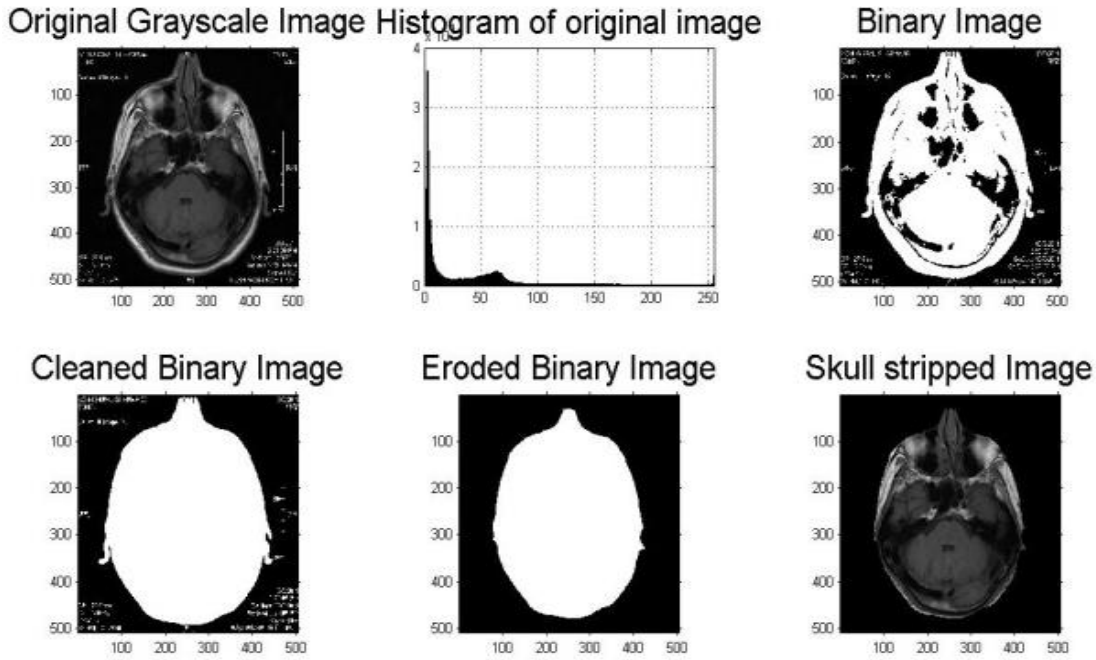


Fig. 2: Skull stripping process steps

results eroded binary image. Then the last step is mask the gray image with the eroded binary image. The outcome of this process is the skull stripped image. The entire process and its outcome is shown in the Fig. 2.

**B. Histogram of Oriented Gradient (HoG)**

Histogram of oriented gradient (HoG) feature descriptors was proposed by Dalal and Triggs [2]. The idea behind HoG descriptor is based on edge information. The HoG descriptor technique counts occurrences of gradient orientation in localized portions of an image - detection window, or region of interest (ROI).

The first step is divide the image into small connected regions called cells, and for each cell computes a histogram of gradient directions or edge orientations for the pixels within the cell. Then discretize each cell into angular bins according to the gradient orientation. Gradient value is computed by apply the 1dimensional centered point discrete derivative mask in both the horizontal and vertical directions. Each cell's pixel contributes weighted gradient to its corresponding angular bin. Groups of adjacent cells are considered as spatial regions called blocks. The grouping of cells into a block is the basis for grouping and normalization of histograms. Normalized group of histograms represents the block

histogram. The set of these block histograms represents the descriptor. An example input image and its corresponding Histogram of Oriented Gradients shown in Fig. 4.

**C. Local Binary Patterns**

Local binary patterns were introduced by Ojala et al. [3] as a fine scale texture descriptor. Local Binary Pattern (LBP) [4] is a simple yet very efficient texture operator which labels the pixels of an image by thresholding the neighborhood of each pixel and considers the result as a binary number. Due to its discriminative power and computational simplicity, LBP texture operator has become a popular approach in various applications. It can be seen as a unifying approach to the traditionally divergent statistical and structural models of texture analysis. Perhaps the most important property of the LBP operator in real-world applications is its robustness to monotonic gray-scale changes caused, for example, by illumination variations. Another important property is its computational simplicity, which makes it possible to analyze images in challenging real-time settings.

LBP description of a pixel is created by thresholding. The values of the 3X3 neighborhood of the pixel against the central pixel and interpreting the result as a binary number. The process is illustrated in Fig. 6.



Fig. 3: Block diagram of Histogram of Oriented Gradients

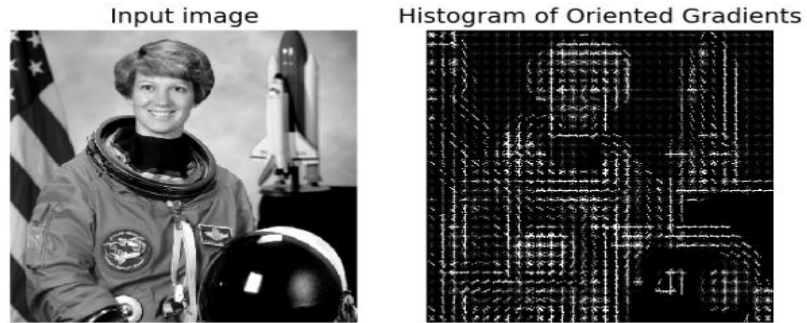


Fig. 4: Input image and Histogram of Oriented Gradients

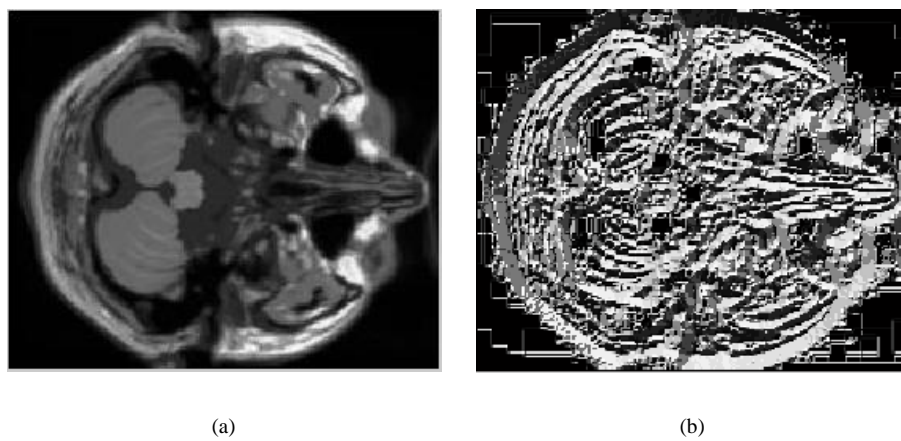


Fig. 5: Query image and its corresponding LBP pattern

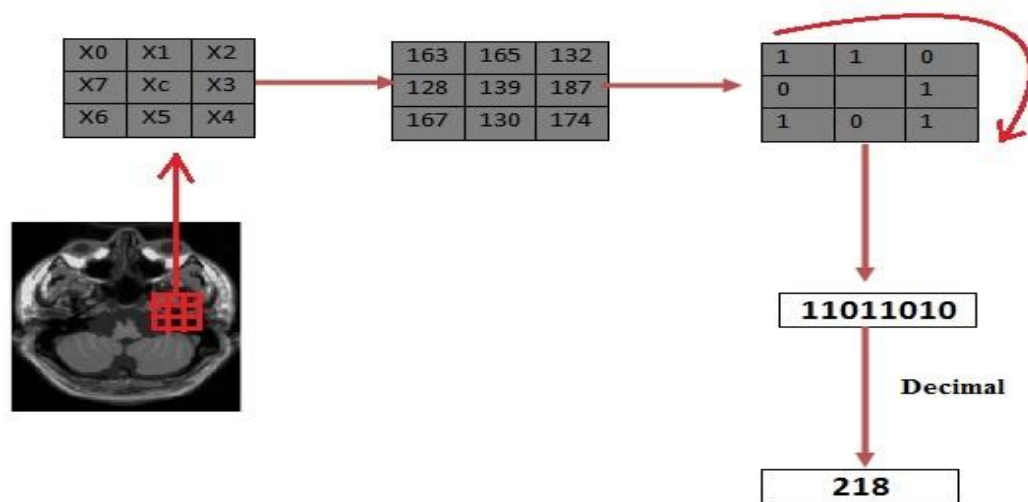


Fig. 6: The standard LBP calculation principle

#### D. Similarity Measure

For comparing the similarity of two metric we use Euclidean distance. In Cartesian coordinates, if  $p = (p_1, p_2, \dots, p_n)$  and  $q = (q_1, q_2, \dots, q_n)$  are two points in Euclidean  $n$ -space, then the distance ( $d$ ) from  $p$  to  $q$ , or from  $q$  to  $p$  is given by the Pythagorean formula:

$$d(p, q) = \sqrt{\sum_{i=1}^n (p_i - q_i)^2} \quad (1)$$

#### IV. PERFORMANCE EVALUATION

##### A. Average Rank

Average rank is calculated using the images retrieved based on a set of random number of query images. In perfect case its value is 1 i.e., relevant images are in a succeeding order

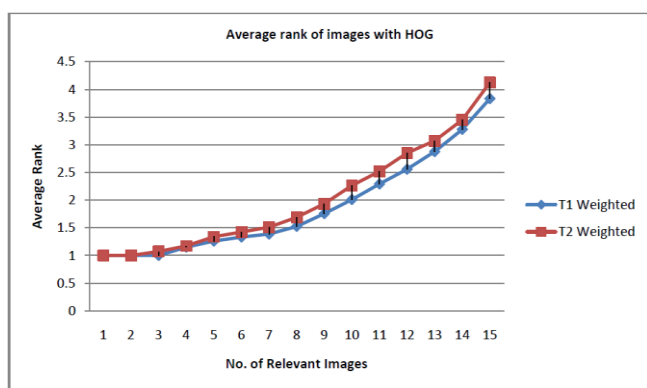
without the presence of irrelevant images in between them. Average rank is calculated using the formula:

$$\text{Average rank} = \frac{1}{N_R} \left( \sum_{i=1}^n R_i - \frac{N_R(N_R-1)}{2} \right) \quad (2)$$

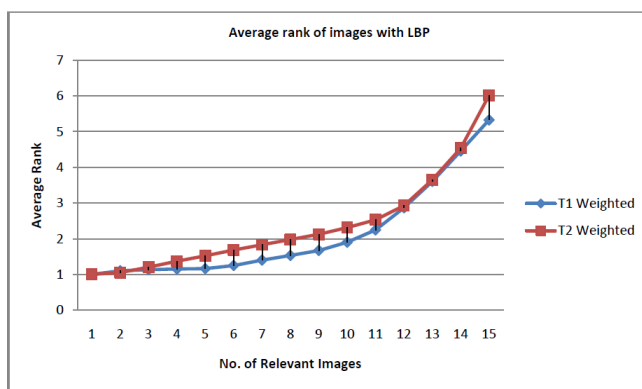
#### V. RESULTS

Our experiment is done with real dataset brain images of T1 weighted and T2 weighted. Each dataset contains 220 images. In Fig. 7, the average rank verses number of images retrieved is shown.

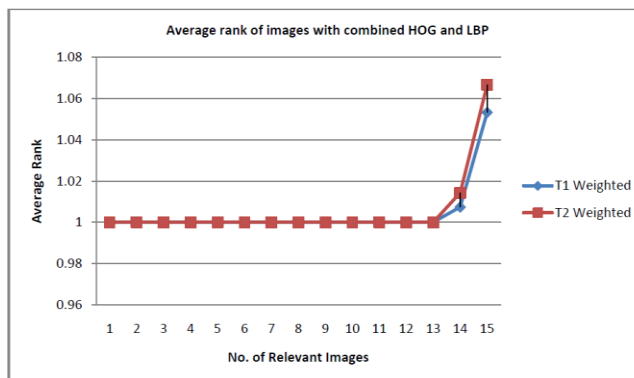
The results shows that HOG gives better performance than LBP and the combined HOG and LBP gives much better performance. Combined feature results perfect performance for about 12 to 13 images.



(a)



(b)



(c)

Fig. 7: Average Rank verses the number of relevant images retrieved.

#### VI. CONCLUSION

Medical imaging technologies, such as Magnetic Resonance Imaging (MRI), provide important insights for understanding the disease pathology and are essential for biomedical research and health care. However, the increasingly large medical collections pose great challenges in medical data management and retrieval. In this paper, a combined HOG and LBP feature extraction method is used.

Histogram of Orient Gradients (HOGs) is a shape feature extraction method and Local Binary pattern is a texture feature extraction method. Histograms of Oriented Gradients (HOGs) have proven to be an effective descriptor for object recognition in general. Local binary pattern (LBP) has been recently proved useful in describing medical images, which has a low computational complexity and a low sensitivity to changes in illumination. But the result shows that in this

application HOG outperforms LBP. And the combined result gives much accurate performance.

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