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Image Set Compression Based on Undirected Weighted Graph

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Abstract. *With the development of imaging capturing technology, a huge number of pictures have been created. Most of the pictures are of high resolution and large size. Traditional compression schemes like JPEG compress pictures individually. Since many pictures may be taken in the same or similar scene, they can be compressed as an image set to improve the compression ratio. This paper proposes an image set compression scheme based on the undirected weighted graph. We first down sample the Y-component of all images in the image set and use correlation coefficient as the parameter of edge weight function to construct an undirected weighted graph. Then we calculate the Minimum Spanning Tree (MST) of the graph using Kruskal's algorithm and rearrange the images based on the depth of the leaf vertex and Breadth First Search (BFS). At last, the rearranged images are coded by the latest video coding technique High Efficiency Video Coding (HEVC). Experimental results show that our method performs better than both JPEG and JPEG2000.*
Keywords: image set compression; undirected weighted graph; correlation coefficient; minimum spanning tree; video coding

1. **Introduction.** The fast development of image technology and digital cameras brings a big challenge for image storage and transmission.Usually, images taken by cameras have already compressed by traditional compression methods like JPEG. Although JPEG method has achieved a large compression ratio in image compression, it compresses images individually and ignores the redundancy among the images. Many images may be taken in the same or similar scene, so they can be compressed as an image set to further improve the compression ratio. The redundancies in digital images are the coding redundancy, the interpixel (or spatial) redundancy and the psychovisual redundancy. There is also another kind of redundancy called set redundancy [1] that exists in a set of similar images.

Several Set Redundancy Compression (SRC) methods have been proposed such as Min-Max Differential (MMD) method [2], Min-Max Prediction (MMP) method [2], centroid method [3], multilevel centroid method [4], MMP MED (MMPM) method [5] and Low Frequency Template (LFT) method [6]. These methods all need to generate one or two images which represent the common information of the image set and then calculate the difference between every original image and the generated images. Both the generated images and the differences are compressed by Huffman or Arithmetic coding method. The key to these methods is to find the images which can well represent the common information of the image set.

Another type of image set compression method is based on the graph theory. Chia-ping et al. [7] proposed a new scheme to compress an image set by building its minimal-cost prediction structure. Nielsen et al. [8] proposed an algorithm using a minimum spanning tree to conduct the image set and both the root image and the differences between the image and its father image are coded by traditional compression method JPEG2000. In [9] and [10], directed weighted graph is used to conduct the image set. The method proposed in [10] combined graph theory with video coding methods HEVC to compress personal album. Tree depth is constrained in [10] to reduce the time of accessing an image. More sophisticated image set compression techniques which are based on local features have also proposed in [11, 12, 13].

Most of the image set compression methods proposed previously have achieved nice compression results, but image set compression methods are time consuming compared with single image compression methods because of the preprocessing of the image set. So its meaningful to reduce the preprocessing time in image set compression. For this reason, undirected weighted graph instead of directed weighted graph is used to conduct the image set in this paper. The Y-component of the images are also down sampled to further reduce the time of graph construction.

2. Compression scheme.

Our compression scheme is illustrated in Figure. 1. We preprocess the original image set and then get the rearranged image set. Since the rearranged image set is like a video sequence, video coding method is used to compress it.

In order to reduce the time of graph construction, the images in image set is first down sampled. Then the graph is constructed based on the down sampling images. After the graph construction, MST is generated and the new order of the images is obtained. Finally, the images are rearranged based on the new order. This is all preprocessing of the image set before coding.

After preprocessing of the image set, video coding method is used to compress the rearranged images. As shown in Figure. 1, compressed image set is got at last.

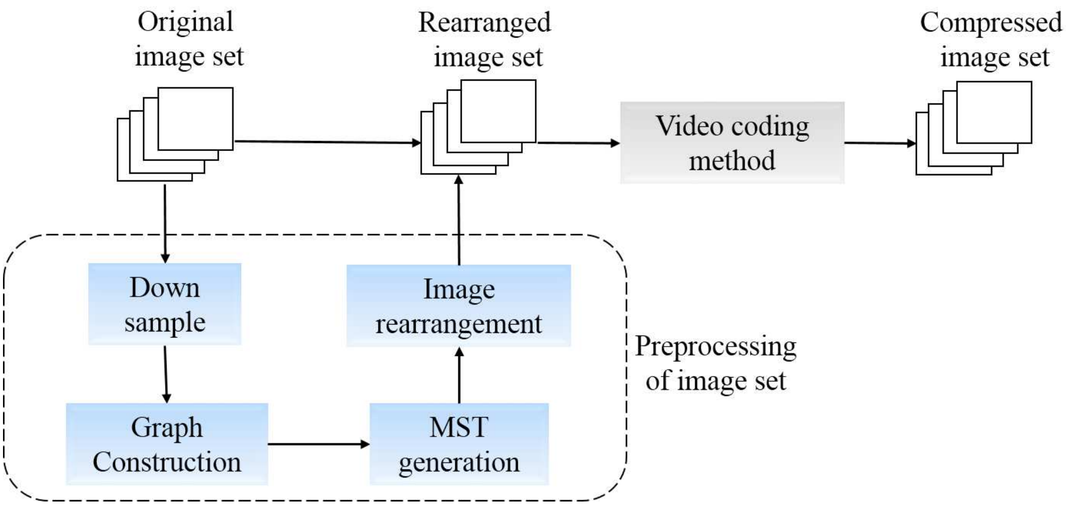

FIGURE 1. Compression scheme

3. Image set preprocessing.

3.1. **Graph construction.** Assuming that there is an image set S which contains n images and these images are of same dimension, an undirected weighted graph $G = (V, E)$ is used to represent the image set S. $V = \{v_1, v_2, \cdots, v_n\}$ is the vertex set which represents the images in S and $E = \{e_{ij} | i = 1, 2, \cdots, n, j = 1, 2, \cdots, n\}$ is the edge set of graph G. Each edge of the graph has a weight function $w(v_i, v_j)$ that represents the correlation between vertex v_i and v_j.

For two datasets $X = (x_1, x_2, \cdots, x_N)$ and $Y = (y_1, y_2, \cdots, y_N)$, the mean value of X and Y are x_m and y_m. The liner correlation coefficient is defined as [1]:

$$r(X,Y) = \frac{\sum_{i=1}^{N} (x_i - x_m)(y_i - y_m)}{\sqrt{\sum_{i=1}^{N} (x_i - x_m)^2}\sqrt{\sum_{i=1}^{N} (y_i - y_m)^2}} \tag{1}$$

For avoiding negative values, r^2 is often used instead of r. The range of r^2 is from 0 to 1. If $r^2 = 1$, the dataset X and Y are much correlated while if $r^2 = 0$ they have no correlation. In this paper, weight function in which v_i and v_j represent the different images in image set is defined as:

$$w(v_i, v_j) = 1 - r^2(v_i, v_j) \tag{2}$$

YUV color space is used in this paper, so Y-component of image v_i and v_j is used to calculate the edge weight. In order to further reduce the complexity, the Y-component is down sampled to 1/16 of the original image. For example, if the image dimension is 2560×1920, it will be down sampled to 640×480. Note that the images used in this paper is high definition and there is few objects in an area less than 4×4. So there is few objects that will be removed while down sampling. This processing reduces the complexity and has little influence to the value of the edge weight.

As shown in Figure. 2(a), a graph containing 4 images is constructed as an example. If an image set contains n images, the number of edges in the undirected weighted graph is:

$$N_u = n(n-1)/2 \tag{3}$$

While the number of edges in the directed weighted graph is:

$$N_d = n(n-1) \tag{4}$$

The equation (3) and equation (4) show that when the number of images is equal, the number of undirected edges is half than that of directed edges. Therefore, it is with lower complexity to construct an undirected weighted graph compared with directed graph.

3.2. **MST generation.** According to the equation (2) it is obvious that when the correlation coefficient r^2 is larger, the value of the weight function will be smaller. So if we want to get the maximum correlation of the image set, we need to find the minimum total weight of graph G. Therefore, the Minimum Spanning Tree (MST) of the graph is needed.

The MST of a graph is a spanning tree of a weighted graph with the smallest total weight. Algorithms to find a MST of a graph have been well studied. When the edges of a graph are directed, Chu/Liu and Edmond algorithm [14] can be used to find the MST of a directed graph effectively. The complexity of Chu/Liu and Edmond algorithm is $O(nN_d)$. However, when the weight of a graph is undirected, both Kruskal's algorithm and PRIM algorithm [15] can be used to calculate the MST. The complexity of Kruskal's algorithm is $O(N_u logn)$. So the complexity of Kruskal's algorithm is lower than that of Chu/Liu and Edmond algorithm. Since the graph constructed in this paper is undirected,

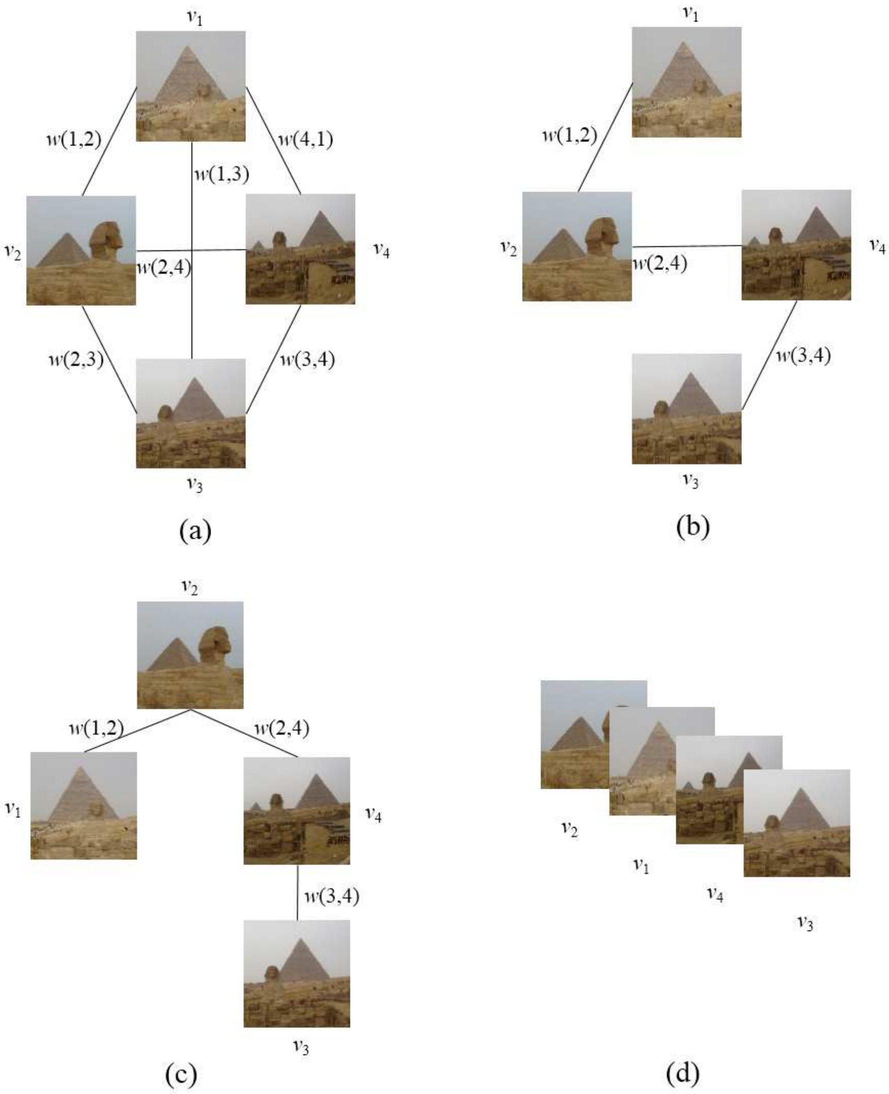

FIGURE 2. An example of the graph framework
(a)Graph constructed for an image set; (b)MST of the graph; (c)A new MST; (d)Rearranged image set

Kruskal's algorithm is used to calculate the MST that is illustrated in Figure. 2(b).

After the MST generation, the root vertex has to be selected and the branches of the MST have to be arranged. For the vertex set $V = v_1, v_2, \cdots, v_n$, the number of edges from each vertex is $M_V = \{m_1, m_2, \cdots, m_n\}$. Since the root vertex will be the I-slice in video coding, the vertex v_i which has the largest m_i is chosen as the root vertex. If $m_i = m_j$, the total weight of all of the edges from v_i and v_j will be calculated and the vertex that has the less total weight will be chosen as the root vertex. As shown in Figure. 2(c), v_2 and v_4 both have two edges, so the total weight of v_2 and v_4 have to be calculated. Since $w(1,2) + w(2,4) < w(2,4) + w(3,4)$, v_2 is selected as the root vertex.

Each branch of the MST has a Leaf Vertex (LV) and different leaf vertex has different depth. Assuming that there are m leaf vertexes $LV = \{lv_1, lv_2, \cdots, lv_m\}$ and the depth of them are $D_{LV} = \{d_1, d_2, \cdots, d_m\}$, the branches are arranged as:

$$d_i \le d_j \le \cdots \le d_k \tag{5}$$

in which:$d_i, d_j, \cdots, d_k \in D_{LV}, i, j, \cdots, k \leq m$

After the root vertex is selected and the branches are arranged, the new MST called MST$_N$ which is shown in Figure. 2(c) is generated.

3.3. **Image rearrangement.** Generally, a frame is more similar to its adjacent frames in video sequence. Different from video sequence, the images in image set are arranged in chronological order and the correlation between adjacent images is unknown. So in order to apply video coding method to compress image set, the images in image set are needed to be rearranged.

In MST, a vertex is more similar to its parent vertex or child vertexes. So it should be arranged closer to its parent vertex and child vertexes as far as possible. In this paper, Breadth First Search (BFS) of the MST$_N$ is used to rearrange the images in image set. BFS is a graph search algorithm in graph theory. It begins at the root vertex and explores all of the neighboring vertexes. The deepest vertex is assumed to be the vertex that we want to find in our method. As shown in Figure. 2(c), v_3 is assumed to be the vertex that we want to find and the search path of v_3 using BFS is v_2, v_1, v_4, and v_3. Then the images is rearranged based on the search path of the deepest vertex.

The rearranged image set is illustrated in Figure. 2(d), the more similar the images are, the closer they will be arranged. Then video coding methods can be used to compress the rearranged image set.

4. **Compression using video coding method.** After preprocessing, the image set is more suitable to be compressed by video coding method. Since most of the images are high-resolution images, HEVC is adopted to compress the rearranged image set.

Different from video sequence which is decoded sequentially, images in image set have to be access randomly and the less time it costs to reach an image the better. So the low delay scheme containing “IPP$\cdots$P” GOP structure in HEVC is not used in this paper. As shown in Figure. 3, the random access scheme which contains “IBB$\cdots$B” GOP structure in HEVC is used instead. When the B-slice is used instead of the P-slice, the compression ratio will also be improved.

Note that not only HEVC but also other video coding methods like H.264/AVC can be used in our scheme.

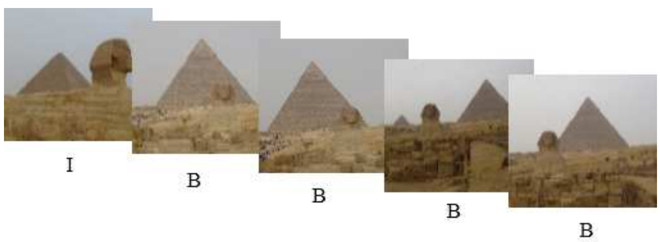

FIGURE 3. Video coding scheme

5. **Experimental results.** Experiments have been conducted on four image sets which contains different number of images respectively. The basic information of the four image sets are shown in Table 1. Note that the image set is not very large. In fact, if the image set is very large, it can be divided into several image subsets so that they can be compressed in parallel. Each image set contains images of the same dimension. As shown in Figure. 4, the pictures in different image set are taken in daily life and different scenes. The encoding/decoding software used in our scheme is HEVC test model HM 11.0. The

configure file of random access is default so that the HEVC test model can be directly used in our scheme without changing.

TABLE 1. Image set information

Image set name	Number of images	Resolution	Camera
Sphinx	6	2560×1920	Olympus Digital Camera X-2
Coral Reef	7	2048×1536	Canon PowerShot S1 IS
Fruits	10	2816×2112	Canon PowerShot A540
Mountains	12	2560×1920	Olympus Digital Camera X-2

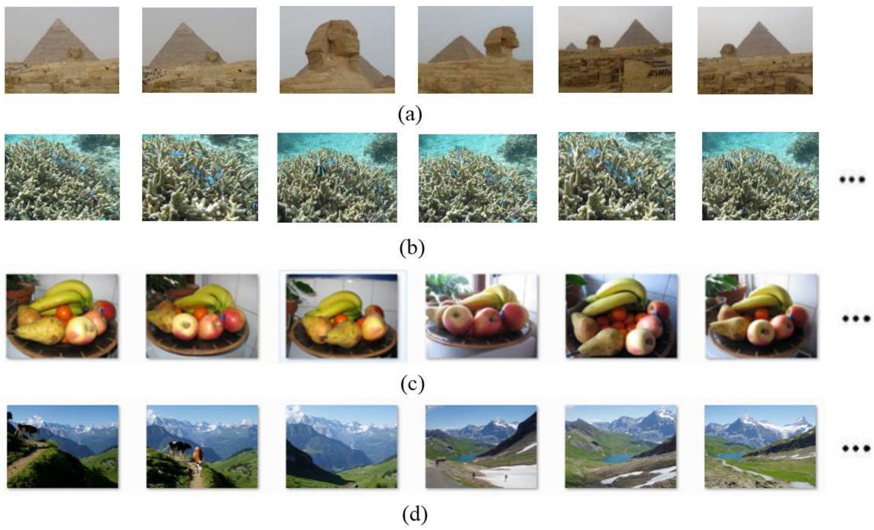

FIGURE 4. Examples of image set
(a) Sphinx set; (b) CoralReef set; (c) Fruits set; (d) Mountains set

5.1. **Overall performance.** The experimental results are shown in Figure 5. As denoted in Figure 5, the method proposed in this paper performs better than both JPEG and JPEG2000. The PSNR achieved an average gain of about 1.5dB and 3.0dB compared with JPEG2000 and JPEG respectively.

In order to show the effectiveness of image set preprocessing, HEVC is used to compress both the Unarranged Image Set (UIS) and Rearranged Image Set (RIS). The improvement percentage is also calculated. As shown in Table 2, the total bits of the compressed image set is reduced after preprocessing of the image set.

TABLE 2. Performance of preprocessing

Image set name	Total Bits(in MB)		Improvement Percentage (in %)
	UIS	RIS	
Sphinx	0.12	0.11	8.33
Coral Reef	0.43	0.41	4.65
Fruits	0.21	0.19	9.52
Mountains	0.69	0.65	5.80

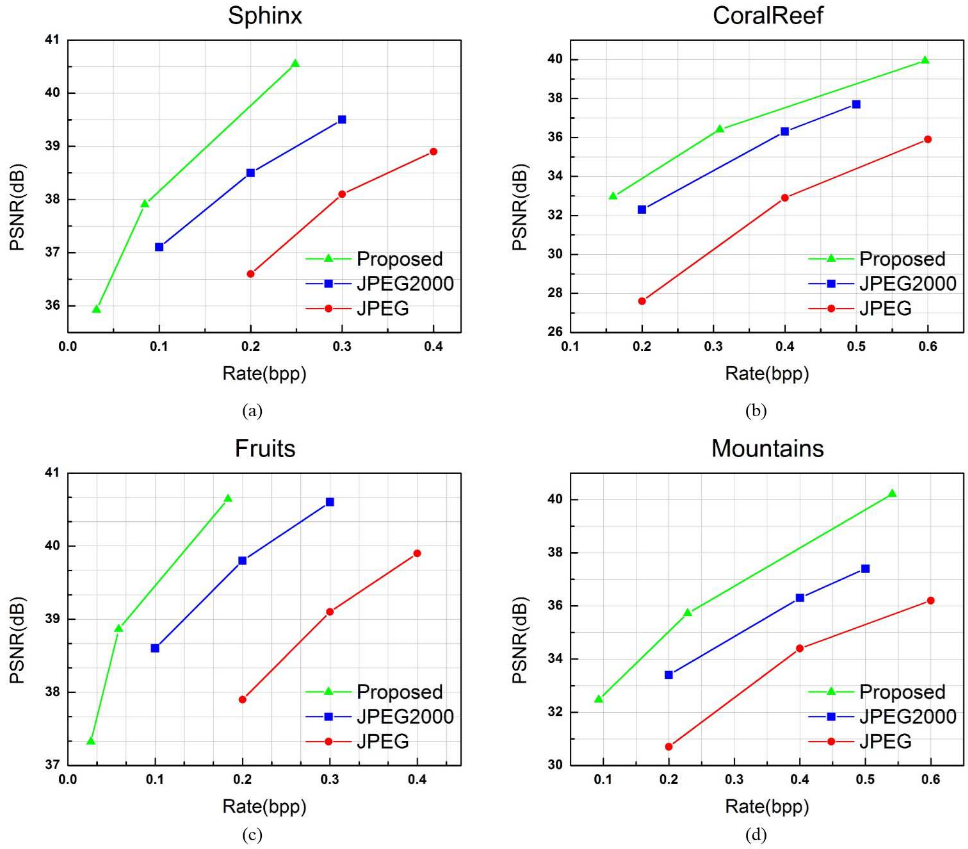

FIGURE 5. The overall performance of proposed method
(a) Sphinx set; (b) CoralReef set; (c) Fruits set; (d) Mountains set

5.2. **Complexity.** The compression scheme proposed in this paper is much more complex than JPEG as video coding method is used in our compression scheme. It is also more complex than HEVC because of the preprocessing module. Since it is possible to adopt HEVC to compress the image set directly, the image set is compressed by both HEVC and our proposed scheme to compare the complexity of them.

Figure 6 shows the average time of encoding one image of the image set. All of the four image sets are encoded by both HEVC and our scheme. As denoted in Figure 6, the encoding time of our scheme contains two parts: the preprocessing time and the HEVC encoding time.

As shown in Figure 6, the HEVC encoding time after preprocessing is a little less than that of directly encoding the image using HEVC. However, the time of our scheme is more than that of directly using HEVC to encode the image. But the incremental time is quite limited. The encoding time of our scheme is almost the same to that of HEVC, which is much less than 9.2% in [10]. In other words, the complexity of our scheme that applies undirected weighted graph is lower than that of directed weighted graph.

6. **Conclusions.** In this paper, we propose an image set compression scheme based on undirected weighted graph. The method proposed first down samples Y-component of the images in image set and use correlation coefficient between the down sampling images as the parameter of edge weight function to construct an undirected weighted graph. Then Kruskal's algorithm is used to calculate the MST of the constructed graph. After the MST generation, a new MST is formed and BFS is used to rearrange the images based on the

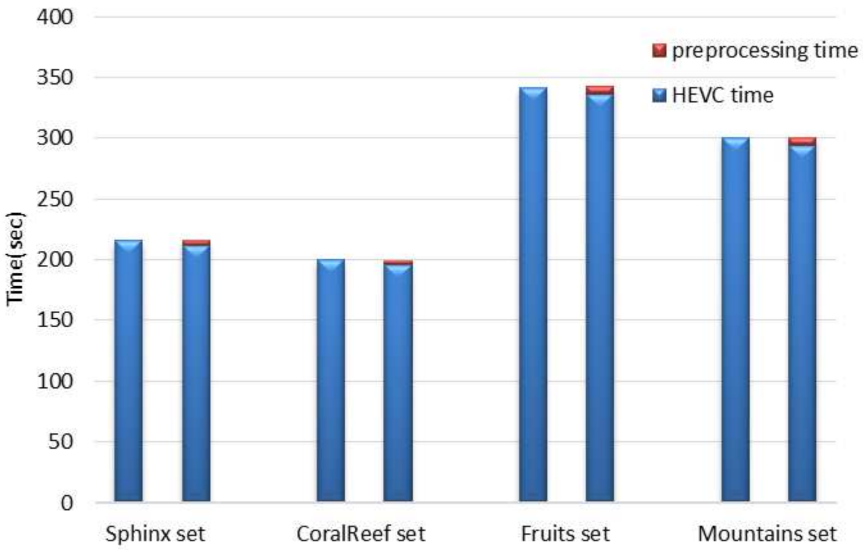

FIGURE 6. Average time of encoding one image of the image set

MST_N. At last, random access scheme in HEVC is applied to compress the rearranged images. Experimental results show that our method achieves considerable improvement than both JPEG and JPEG2000 format. Our preprocessing scheme using undirected weighted graph is also with lower complexity than that of directed weighted graph.

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