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Extraction of Potential Sunny Region for Background Subtraction under Sudden Illumination Changes

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Abstract

This paper proposes a novel background subtraction method robust for sudden illumination changes that often happen in outdoor scenes. The method first estimates regions where are sunny regions or would become sunny regions when the sun is not behind clouds, which we call "potential sunny regions." For the estimation, spatio-temporal analysis is applied to image sequences of the recent days of a target day considering the periodicity of the sun's movement. Once the potential sunny regions are obtained, they are used for judging if the sudden illumination change happens in the target scene. When it happens, then the illumination changes within the sunny regions are suppressed to obtain better subtraction results. Experimental results in several outdoor scenes show effectiveness of the proposed method.

Keywords: Background subtraction, long-term observation, spatio-temporal analysis

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1. Introduction

Background subtraction is one of the fundamental techniques for many scene understanding application, especially for video surveillance. It is useful because it can provide foreground segmentation without any prior about the foreground, and so there are still so many studies about the background subtraction [1].

Among the studies, pixel-wise background modeling is the most popular approach. In this approach, distribution of pixel value is modeled by such as an average or median of the recent pixel value history [2, 3, 4], Gaussian mixture model (GMM) [5], kernel density estimation [6], Parzen density estimation [7], and so on. Liu *et al.* proposes another model named Effect Components Description (ECD) [8]. These pixel-wise methods have an advantage that the subtraction results do not loose resolution of their input images; they output the results with the same resolution as their input. On the other hand, however, they have an essential problem that they cannot discriminate between pixel value changes by foregrounds and illumination changes, since each model knows only history of the corresponding pixel. Indeed such illumination change is learnt in the model after a certain period, but it is theoretically impossible to adapt to the change immediately. To overcome the problem, other studies adopt region-based background modeling [9, 10, 11]. In these methods, not each pixel but relationship among neighboring pixels is modeled, and they are more robust for the illumination change. The resolution of their output is, however, usually decreased compared with their input.

In this paper, therefore, we proposed a novel background subtraction method that solve this trade-off; the proposed method gives as high resolution output images

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as the input but is robust for sudden illumination changes. The key idea for the method is to exploit long-term observation. Considering the background subtraction is for a fixed camera, which should have been observing the scene for a long time, we may be able to extract useful information from the observation. This idea has already been proposed in several studies [12, 13, 14]. Motivated by these studies, we propose the background subtraction method robust for sudden illumination changes utilizing long-term observation. Indeed the motion of the sun, which is the main cause of the illumination change, is periodical, and this periodicity can be analyzed by the long-term observation.

The proposed method first estimates regions where are sunny regions or would become sunny regions when the sun is not behind clouds, which we call "potential sunny regions." For this estimation, we perform spatio-temporal analysis [15, 16] of image sequences of the recent days of a target day utilizing the periodicity. Once the potential sunny regions are obtained, they are used for judging if the sudden illumination change happens. When it happens, then the illumination changes within the sunny regions are suppressed to obtain better subtraction results.

2. Potential Sunny Region

In outdoor scenes, when the sun is not hidden by clouds, some regions on the ground receive the sunlight directly. In this paper, we call these regions "sunny regions." The other regions, which do not receive the direct sunlight, appear darker than the other regions, and are observed as shadows. When the sun gets behind clouds, however, the sunny regions become as dark as the shadow regions, so that the shadows disappear. It is notable that such changes happen suddenly without any prior notice, and it is impossible to expect the changes only from observation of the scenes. Existing background subtraction methods, which estimate a background image by images in the past, suffer from this characteristics; once the change happens, not only foreground regions but also the sunny regions would be detected mistakenly.

Figure 1 shows time series of some pixels on captured images. We find that while the time series of P is almost constant, those of the points Q and R have some sudden changes caused by the appearing and disappearing of the sun. These sudden changes are indeed hard to expect from the recent pixel value history, and so they cause the failure of the background subtraction. These graphs, however, also show another important property. Comparing the graphs (ii) and (iii), we find the series look very similar to each other. It means that brightness change at every location on the sunny regions is affected only by the sun, pixels on the sunny regions should show the same tendency in their value series. If we know where are the sunny regions before the sunny regions appear in fact, therefore, we would be able to achieve more robust background sub-

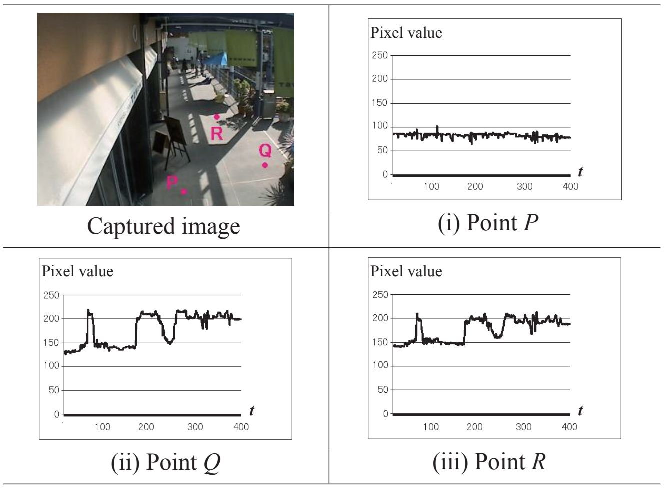


Figure 1: Time series of pixel values in outdoor scenes.

traction by canceling the brightness change on the sunny regions.

Motivated by this consideration, we define as "potential sunny regions" regions that would become the sunny regions when the sun comes out of clouds. This paper proposes a method to obtain the potential sunny regions from long-term observation, and a robust background subtraction method utilizing it.

3. Proposed Method

The proposed method consists of the following two steps:

- Estimation of the potential sunny regions.
- Background subtraction considering the potential sunny regions.

Note that the proposed method is for a fixed camera, and we assume that we can refer the past images corresponding with one or a few weeks.

3.1. Extraction of Potential Sunny Regions

As the first step, we estimate the potential sunny regions at a certain time. Only from an image at the time, it is impossible to know where are the sunny regions. It is apparently impossible when it is cloudy because we cannot observe the shadow and sunny regions. Even when it is sunny, it is still impossible; although we can observe the shadow and sunny regions, we do not know whether they are indeed the shadow and sunny regions or they are just patterns on the ground in cloudy time. In other words, to know where are the sunny regions, we need observation of a certain length of period. By the above consideration, therefore, the proposed method estimates the potential sunny regions from the image sequences in the past.

Figure 2 shows outline of the potential sunny region estimation. We first collect the past images to generate

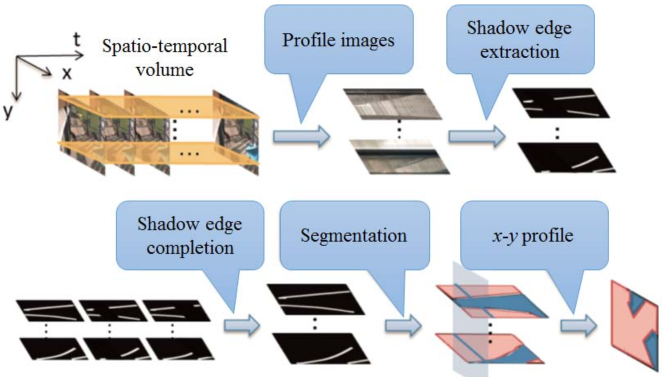


Figure 2: Outline of the potential sunny region estimation.

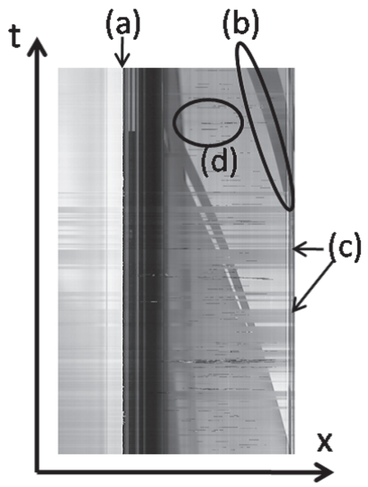


Figure 3: Profile image of the spatio-temporal volume.

spatio-temporal volume for each day in the past. For each profile image of the volume, we extract edges corresponding with boundaries between the shadow and sunny regions, which we call "shadow edges." Then the edges of multiple days are integrated to obtain complete edges. Once we obtain the complete edges, we segment the profile image into the shadow and sunny regions, so that we finally obtain the potential sunny region as a x-y profile image. The followings are details of this procedure.

3.1.1. Generation of spatio-temporal volume

To generate the spatio-temporal volume, we pick up images with a certain interval (30 seconds, in this paper) and pile up the images in order of time.

3.1.2. Profile images

Figure 3 is an example of a profile image of the spatio-temporal volume along the time axis. It includes several kinds of edges. Lines parallel to the time axis, (a) in this figure, correspond with fixed edges in the scene. Other

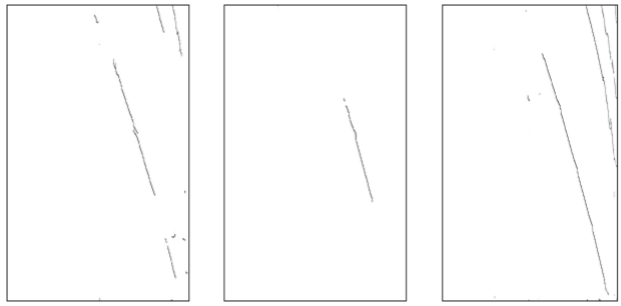


Figure 4: Discontinuous edges obtained from 1-day observation.

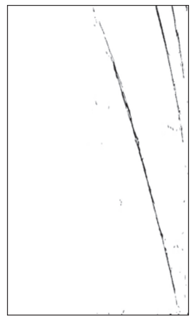


Figure 5: Complete shadow edges by integrating multiple edge images.

curved lines like (b) correspond with the shadow edges; they moves gradually in a day, and often disappear when the sun is behind clouds. Indeed the horizontal lines like (c) correspond with the cloudy periods. We also find other short lines like (d). They correspond with foregrounds including people, each of who appear only in a short period.

3.1.3. Shadow edge extraction

Considering the above discussion, we extract the shadow edges from each profile image. First, the canny edge detector is applies to the profile to extract all kinds of edges. Then the Hough transformation [17, 18, 19] is then applied to extract all the straight lines, and vertical and horizontal lines like (a), (c), (d) are eliminated from the edge images. We finally obtain the image that includes only the edges corresponding with the shadow edges.

3.1.4. Shadow edge completion

It is hard to obtain the complete shadow edges only from the spatio-temporal volume of a day, since it might be a cloudy day. Even if it is a sunny day, it is very rare that the sun is never behind clouds. As a result, the obtained shadow edges for each day are discontinuous as shown in Figure 4. We thus use observations of multiple days to obtain the complete edges. Since the position of the sun at the same moment in neighboring days are almost the same, the positions of the shadow edges are also almost

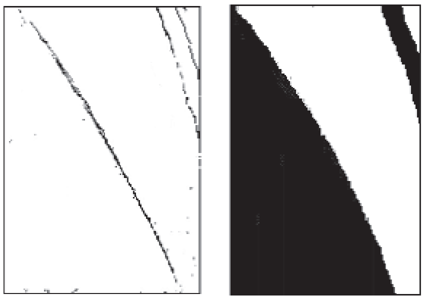


Figure 6: Binary image where only the sunny regions have non-zero value.

the same in the neighboring days. Considering this property, we collect the edge images of the neighboring days and integrate them to obtain the complete edges. Strictly speaking, however, the positions of the shadow edges are slightly and gradually moved as days go by. We, therefore, have to consider it for this integration. In the proposed method, assuming the positions of the shadow edges moves approximately linearly in the profile images, we use an edge image of the recent day as a reference image, and align edge images of the former days to the reference image so as to maximize the number of the edge pixels. An example of the integrated edge image is shown in Figure 5.

3.1.5. Segmentation of sunny regions

Once we obtain the complete shadow edges, we can obtain binary images where pixels on the sunny regions have non-zero values while the other pixel values are zero, as shown in Figure 6.

3.1.6. Mapping the sunny regions on images

Piling up the binary profile images, we reconstruct the spatio-temporal volume. By picking up a x-y profile of the volume at a certain time, we obtain a binary image describing the sunny regions at the time. Since the obtained sunny regions are estimated not from a target frame but from its former frames, the sunny regions are obtained even when the sunny regions are in fact observed on the target frame. They are, therefore, called the “potential” sunny regions.

3.2. Robust Background Subtraction

The outline of the background subtraction step is shown in Figure 7. It is based on existing pixel-wise background modeling using recent pixel value sequence, such as Gaussian Mixuture Model (GMM). Indeed such methods work well as long as illumination condition of the scene changes gradually. The key process of the proposed method is cancellation of sudden illumination change by using the potential sunny regions.

We first apply the GMM-based background subtraction for each frame. Each output of the background subtraction is then compared with the potential sunny region of

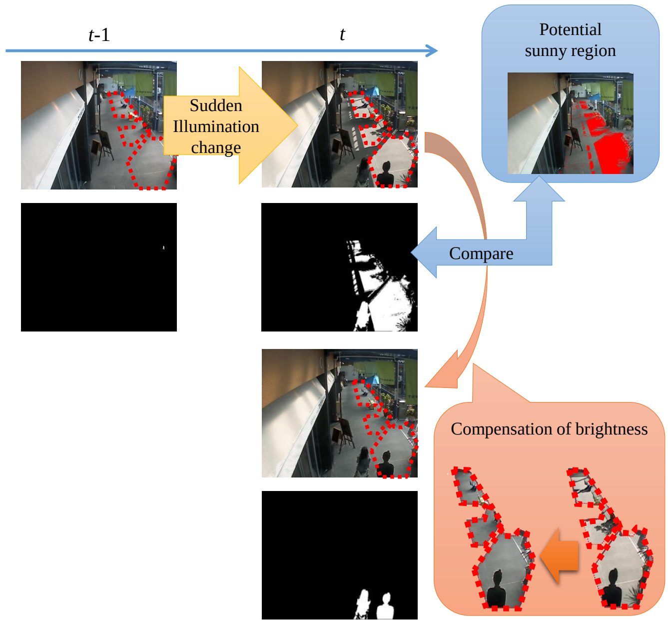


Figure 7: Outline of the proposed method.

the time by their correlation. When the correlation is below a certain threshold (0.7 in this paper), which means there is no sudden illumination change, the output is used as that of the proposed method. When the correlation is above the threshold, on the other hand, it is regarded as a moment when the sudden illumination change happens. In this case, pixel values included in the potential sunny regions are controlled so as to get similar to those in the previous frame, where no sudden illumination change happens. This control is performed by multiplying each pixel value with a constant. To determine the constant, we pick up multiple points randomly in the potential sunny regions, and for each point we calculate a rate of pixel values between the current and previous frame. If there is no foreground object, the rates of all the points would be similar. But if there is some foreground objects, points on them would give different rate. Considering this, we choose the median rate among them. By this operation, the rate is robustly estimated against existence of foregrounds.

Note that this linear control of pixel values is not theoretically correct. But we experimentally confirmed that this approximation works well in most outdoor scenes.

4. Experiments

4.1. Experimental Settings

To evaluate effectiveness of the proposed method, we apply the method to two real outdoor scenes (I) and (II) as shown in Figure 8. As shown in the table, the resolution of images is 640×480, and the potential sunny regions are generated for every 30 seconds. The interval for constructing the spatio-temporal volume is also 30 seconds. The

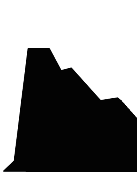
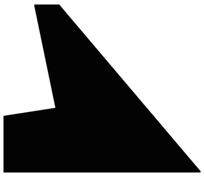
	(I)	(II)
Resolution	640 x 480	640 x 480
Frame interval	30 seconds	30 seconds
Period	12:00 - 15:00	12:00 - 15:00
Number of days	7 days	5 days
Captured image		
Mask image		

Figure 8: Two outdoor scenes.

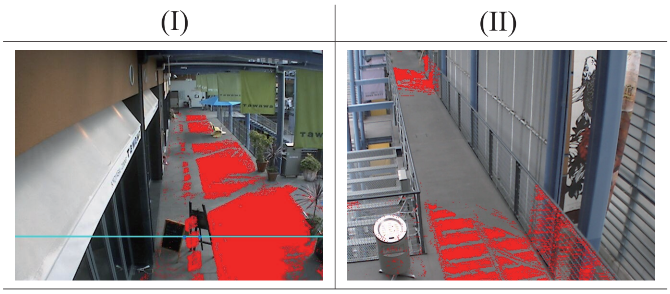


Figure 9: Estimated potential sunny regions.

potential sunny regions are estimated from about a week observation.

In this experiment, we prepare mask images that correspond with corridors for these scenes, because the proposed method is for detecting people, who appear only within the corridor regions.

4.2. Potential Sunny Regions

Estimated potential sunny regions for the scenes at a certain moment is shown in Figure 9, where the estimated potential sunny regions are colored red.

To evaluate accuracy of the estimation, we then picked up sunny moments, so that in these images the shadow and sunny regions appear clearly. The results is shown in Figure 10. By comparing the real sunny regions and the estimated potential sunny regions, we subjectively confirmed the proposed method works so well. In addition, for quantitative evaluation, we calculated recall and precision rate of these results, as shown in Table 1.

Estimation errors mainly appear around the shadow edges. The main reason is considered to be the shadow edge completion. In the integration of multiple edge images, the edges tend to get more thick. The approximation of the linear translation may be another reason. In addition, the fact that the shadow edges in fact move continuously is also a cause of the errors. In spite of the continuity, the estimation is performed just for discrete moments.

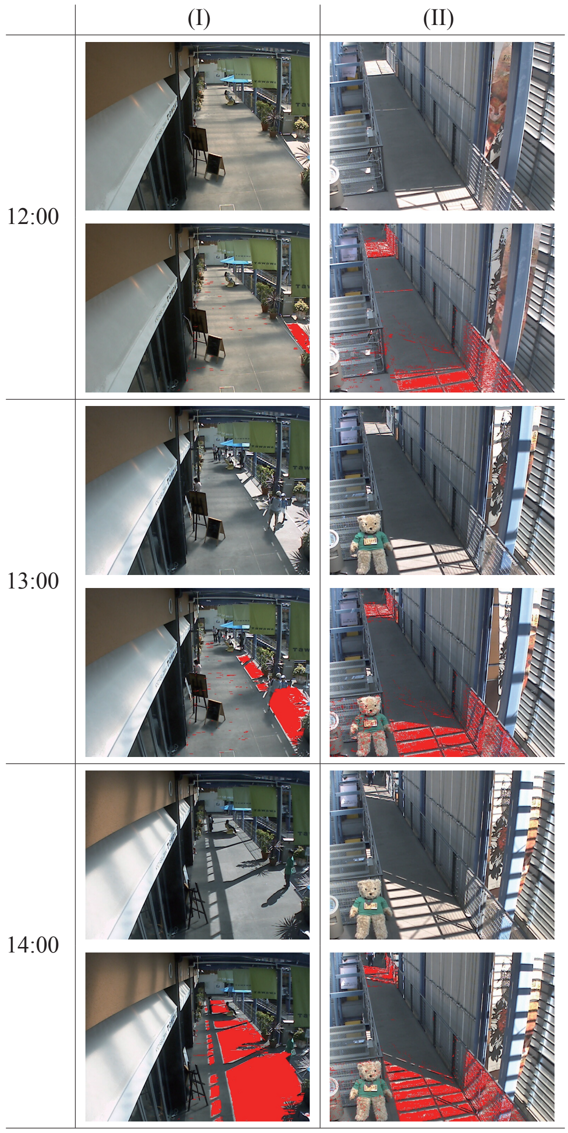


Figure 10: Comparison between the estimated potential sunny regions and the real sunny regions. It is confirmed that the proposed method works well.

Table 1: Quantitative evaluation of accuracy of the potential sunny region estimation.

	(I)		(II)	
	Precision	Recall	Precision	Recall
12:00	93.9%	97.5%	85.8%	83.0%
13:00	98.4%	94.1%	88.4%	84.6%
14:00	99.2%	97.8%	96.0%	89.7%

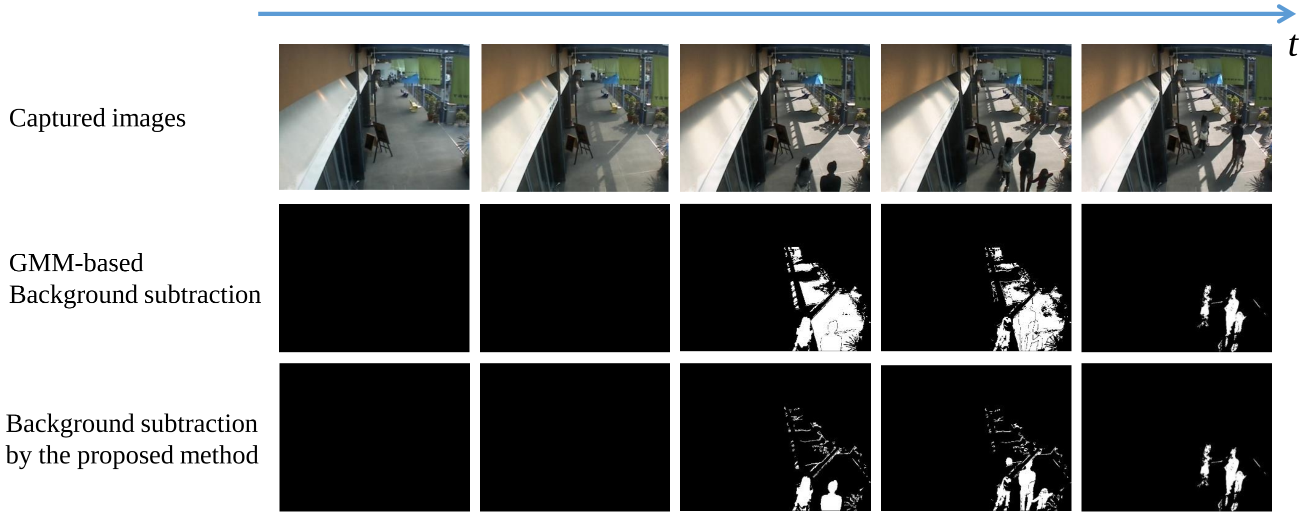


Figure 11: Results of the background subtraction of our method. In the case of the simple GMM-based background subtraction method, although it finally adapted to the change in the fifth frame, it mistakenly extracted not only people but also the sunny regions. On the other hand, the proposed method gave much better results. even for the frames of the sudden illumination change. Since it well canceled the change by using knowledge of the potential sunny regions, most sunny regions are not contained in the subtraction results.

4.3. Background Subtraction

We then applied the background subtraction step using the estimated potential sunny regions. Figure 11 shows a captured image sequence where sudden illumination change happened at the third frame.

As discussed in Section 3.2, as long as illumination condition is constant or gradually changed, The simple GMM-based background subtraction is fine. We found, however, that it fails when the sudden illumination change occurred: In the case of the simple GMM-based method, although it finally adapted to the change in the fifth frame, it mistakenly extracted not only people but also the sunny regions. The period length of this adaptation may be changed by controlling parameters of the background model. It is, however, impossible to completely eliminate the period.

On the other hand, the proposed method gave much better results even for the frames of the sudden illumination change. Since it well canceled the change by using knowledge of the potential sunny regions, most sunny regions are not contained in the subtraction results.

The results in fact contain errors around edges of the sunny regions. It is because of the error of the potential sunny region estimation discussed in Section 4.2. Although it is difficult to eliminate all these errors, they are actually not a serious problem; since they are just thin line-shaped regions, we should just apply morphological operations (erosion and dilation) as a post-processing.

5. Conclusion

This paper proposes a novel background subtraction method robust for sudden illumination changes that often happen in outdoor scenes. The method first estimates regions where are sunny regions or would become sunny regions when the sun is not behind clouds, which we call the “potential sunny regions.” For this estimation, spatio-temporal analysis is applied to image sequences of recent days considering the periodicity of the sun’s movement. Once the potential sunny regions are obtained, they are used for judging if the sudden illumination change happens. When it happens, then the illumination changes within the sunny regions are suppressed to obtain better subtraction results. The experimental results in several outdoor scenes show effectiveness of the proposed method.

Future work contains a more sophisticated way for the bright compensation. As described in Section 3.2, in the proposed method, when the sudden illumination change is detected, the pixel values in the potential sunny regions are simply controlled by multiplying a constant. It might be possible to control more intelligently using the observation history. Consideration about the number of days that are required for the proposed method is also a important topic.

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