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# Development of Wire Breakage Detection Method Using Image Processing

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***Abstract*— Most wire rope inspection work for construction machinery is performed manually at construction sites. Therefore, there are restrictions on the work environment, such as the equipment that can be used for inspection and the working time, and as a result, inspection results depend on the skill of the inspector. The purpose of this research is to develop a wire rope inspection system that is not affected by the work environment or worker skill. In this paper, we discuss a detection method using image processing technology for detecting wire breakage, which is one of the most serious damages to wire ropes.**

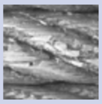
## I. Introduction

Wire ropes are widely used in the main structures of machinery and equipment used in construction sites for loading, unloading, and transporting. Examples are cranes and elevators, which are very large. Therefore, if a wire rope breakage, it can lead to a serious and large-scale accident, such as the collapse of a machine or the fall of a suspended load. When using such machinery and equipment, it is necessary to have the correct knowledge of wire ropes and to manage them correctly by regularly inspection them [1].

In the case of wire rope inspection work on cranes, in Japan, the wire rope is checked visually by field operators in accordance with the wire rope disposal standard and inspection manual provided by the Japan Crane Association. Table I. shows examples of inspection checklist. It is important to conduct daily inspections based on the standard to keep track of the presence or absence of damage and the state of deterioration. However, since most of these inspections are conducted manually and visually at construction sites, there are various restrictions on the work, and as a result, the inspection results depend on the skill of the operator. There is therefore a strong demand for automation of wire rope inspection.

There are several non-destructive approaches to inspection of wire ropes [2]. The most populer method is the electromagnetic method. In this method, a magnetic field is generated by placing a magnetic sensor around the wire rope. At this time, at the point where the wire rope has a break, leakage magnetic flux is measured, and this feature is utilized to detect the break. Furthermore, by measuring the total magnetic flux passing through the wire rope, cross-sectional defects caused by corrosion can be evaluated. Li et al. extract feature vectors from magnetic and infrared images and propose a method to solve broken wires classification problems using a kernel-based extreme learning machine network [3]. Xu et al. developed a sensor unit for wire rope inspection of cable-stayed bridges and verified its effectiveness in laboratory experiments [4]. A fundamental problem with this method is that the detected signal strength depends on the separation and relative speed between the wire rope and sensor. This is a major issue in terms of reproducibility of damage detection, and as a result, the accuracy of damage detection varies greatly depending on the operation of the wire rope during the inspection. Signal noise reduction is also an issue in all research. In addition, it is inherently difficult to completely link high signal strength to the presence of damage, so even if an abnormal signal is confirmed, the actual damage must ultimately be confirmed in the field. Other methods include the acoustic emission method, ultrasonic guided wave testing method, and radiography testing method. Li et al. conducted fatigue experiments using AE techniques on corroded bridge cables and showed AE characteristic parameters for fatigue damage [5]. Xu et al. have proposed a method to detect multiple breakage in the same wire of a prestressing wire using guided waves [6]. By using both low and high frequencies, they

TABLE I. Checklist And Disposal Standard

| Checklist | Disposal Standard |
|---|---|
|  Break | The number of wire breaks:<br>• ≧10% from 1 pitch<br>• ≧20% from 5 pitches |
|  Abrasion | Diameter decrease exceeding 7% of nominal diamete |
|  Corrosion | Pitting on the surface of strands<br>Loose strands due to internal corrosion |
|  Deformation | Kinking, Waviness, Flattening<br>Protrusion of core steel,<br>Large bending, etc. |

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were able to determine whether two single breakage in different positions are in the same wire or in different wires.

Recently, image sensor and image processing techniques have been developed as an alternative to visual inspection. Approaches based on image processing techniques are the most appealing due to their ease of installation onto existing machinery. The study in [7], a wear detection method based on template matching is proposed for images of elevator traction wire ropes. The study in [8] employed a model-based approach with visual sensing by where a model of the inspected wire rope was matched against the captured image. Such an approach is conditioned by the adequacy of the wire rope model. A more general and common approach is to use object detection methods to recognize defects by posing the problem as one of classification [9]. However, the performance of such a classification model is conditioned by the quality of its training data and obtaining training data for defect classes is difficult since in practice defects do not occur often [10]. Zhou et al. proposed a wire rope damage detection method based on texture features [11]. The damage detection procedure consists of image filtering, scanning with the LBP operator, and dimensionality reduction with PDC in the preprocessing stage, followed by classification with multiple classification methods. As a result, the influence of each preprocessing and classification method on the diagnostic accuracy is mentioned. While the experiments are very detailed, the data set prepared seems to be limited. The actual damage is variable, and the methods that focus on damage characteristics are optimized for the training data, which is still a problem. Additionally, most of these methods are aimed at elevators and indoor overhead cranes. On the other hand, construction sites are a cluttered and varied environment. Therefore, each wire rope operates in an environment that can be considered unique, further compounding the challenges of an object detection approach to this issue.

The purpose of this development is to develop a wire rope inspection system that is not affected by the work environment or the skill of the operator. In particular, we focus on image sensor/image processing technologies that are easy to handle, inexpensive, and enable easy understanding of inspection results. This paper on a detection method using image sensor and image processing technology for detecting wire breakage, which is one of the most serious damages to wire ropes.

## II. Problem Settlement

The following are the main issues to be addressed when applying the image sensor/image processing technology focused on in this research to wire rope inspection work at construction sites.

### *A. Environment*

As mentioned above, most of the wire rope inspection work of construction machinery is performed in the field environment, so when selecting a measurement method, it is necessary to consider the harsh measurement environment, such as vibration of the machine itself caused when the construction machinery is in operation and blurring when the wire rope is in operation, especially when the measurement equipment is permanently installed. This is even more so when the measurement equipment is permanently installed. Slesarev et al. [12] shows an example of a wire rope condition monitoring system using magnetic sensors installed on drilling rigs. The authors point out the mechanical influence of the sensor on the rope, and state that the gap between the sensor and the wire rope should be reduced to increase the sensitivity to wire rope breakage, but that this reduces the robustness of the machine. As a result, the sensor is not able to be attached to the wire rope. As a result, the sensor is not permanently installed in the wire rope, but can be installed at each daily wire rope inspection. This indicates the limited installation locations of sensors and the low maintainability of the sensors, which may hinder their widespread use in general machines. Although there are still examples where sensor units are installed at each periodic inspection to replace visual inspections, this results in an increase in the cost of a single inspection. From this point of view, the image sensor focused on in this development is a non-contact sensor, so the mechanical influence pointed out by Slesarev et al. is expected to be small. Figure 1 shows the envisioned image sensor installation situation.

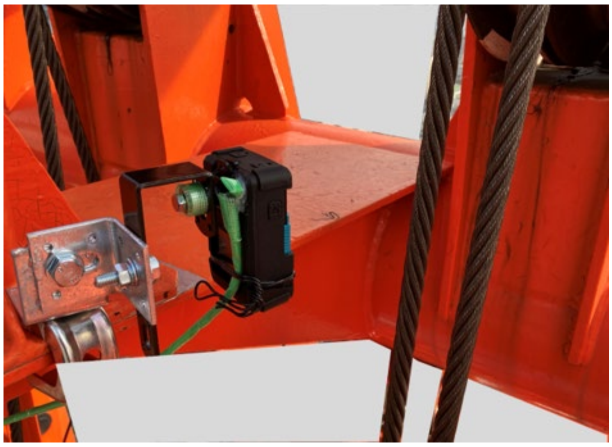

Fig. 1 Image sensor installation situation

### *B. Features of wire breakage*

Damage to wire ropes is not limited to wire breakage, which is the subject of this paper, but varies in type and degree, and it is difficult to extract and represent image features for such damage. Furthermore, it is difficult to collect many samples because wire breakage rarely occur in wire ropes in use (early replacement is performed based on daily maintenance and operating hours). Therefore, it is difficult to detect unknown damage that will occur in the future using, for example, a matching method that uses known wire breakage images as templates or an image classification method based on supervised learning. Therefore, the concept of the proposed method in this paper is to consider the features of the normal state of wire rope, and to define the abnormal state as the one with different features from the normal state. This eliminates the need to define the characteristics of the damage, and the proposed method is robust to detecting unknown damage. Given these features, this development aims to develop a method that can detect a wide range of damage states, with wire breakage as the primary target.

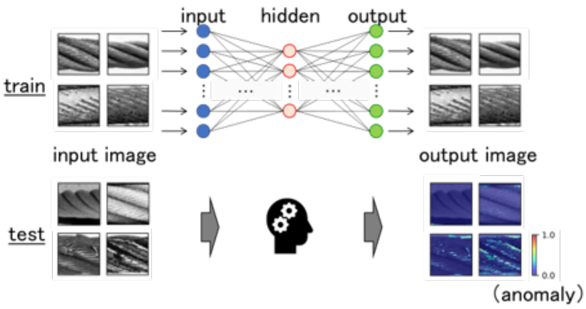


Fig. 2  Detection by autoencoder method

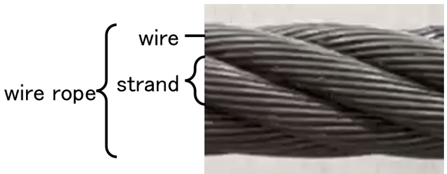


Fig. 3  Wire rope structure

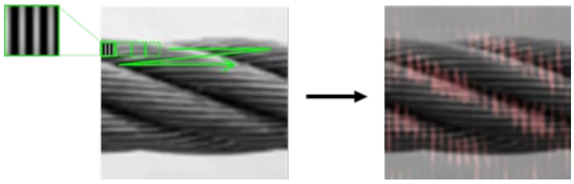

Fig. 4  Feature extraction by Gabor filter
(left) Convolution using Gabor filter
(right) Red shows the boundary of the strand

TABLE II.  CALCULATION CONDITIONS

| | |
|---|---|
| Train data | 3,870 |
| Activation function | Encoder : ReLu<br>Decoder : Softmax |
| Error function | MSE |
| Optimizer | Adam |
| Epochs | 100 |

## III. METHOD

### A. Autoencoder

To solve the problem described in the previous section, we examine a method for detecting broken wire using autoencoder.

Autoencoder is a type of unsupervised deep learning, which is a convolutional neural network that learns to make the input and output layers identical. The network structure consists of an encoder part that compresses the input data once and a decoder part that reconstructs the output data to be the same as the input data.

Figure 2 shows the concept of the method for detecting broken wire. First, in the learning phase, only normal (undamaged) wire rope images are used as input to learn features in the normal state. Next, in the prediction phase, an unknown wire rope image is input to the learned network, and reconstruction of the input image is attempted in the same way as in the learning phase. The reconstruction of the original image is possible when the input image is normal, and difficult when the input image is abnormal (damaged).

In Fig. 2, the difference in luminance values for the same pixel in the input and output images is represented as a reconstruction error (value: 0~1), and the abnormal areas are visualized by the color map in the lower right of the figure. The green to red areas indicate a larger error (i.e., a higher degree of anomaly).

### B. Gabor filter

As another method for detecting wire breakage, a method using local frequency features with a Gabor filter is considered.

The wire rope structure is decomposed into wire rope, strand, and wire (the smallest unit) as shown in Fig. 3. The combination of wire and strand twisting can be classified into four wire types, and the wire of all wire ropes flows in a constant direction as shown in the figure. In the “right hand ordinary lay (sZ)” type wire shown in the figure, the wires are almost parallel to the rope axis (horizontal direction). If we focus on a wire region in the image, the spatial frequency intensity in the direction parallel to the wires in that region is low. Conversely, if the wire of interest has a break, there will be a discontinuous sequence of brightness, where the spatial frequency intensity will be higher than that of a normal wire. Figure 4 shows the result of calculating the spatial frequency intensity in the direction parallel to the wire in a normal image by convolving a Gabor filter (green square) orthogonal to the strand. The size of the wire rope image is 64 * 64 [pixel] and the Gabor filter to be convolved is 11 * 11 [pixel]. The red areas on the right side of the figure indicate the higher intensity. Here, high spatial frequency intensity is observed at the strand boundaries, but not in the area where the wires are continuous. From the above, it is considered that when a local frequency feature is found in the wire region by the Gabor filter, it is judged that there is some kind of an anomaly.

## IV. EXPERIMENT

### A. Autoencoder

The training conditions for detecting wire breakage using the autoencoder method are shown below (Fig. 5, TABLE II.). A total of 3,870 images were used for training, consisting of normal wire rope images obtained in the field and in the laboratory, as well as images obtained by color transformation (brightness, contrast, saturation, and hue), rotation, and left/right/up flipping. When input to the network, the images were resized to 64 * 64 pixels, converted to grayscale, and converted to a 1D tensor. The encoder layer performs dimensionality reduction in the order of 4096, 2048, and 1024, and the decoder layer reconstructs the images in the reverse order, resulting in a 64 * 64 pixels image as the

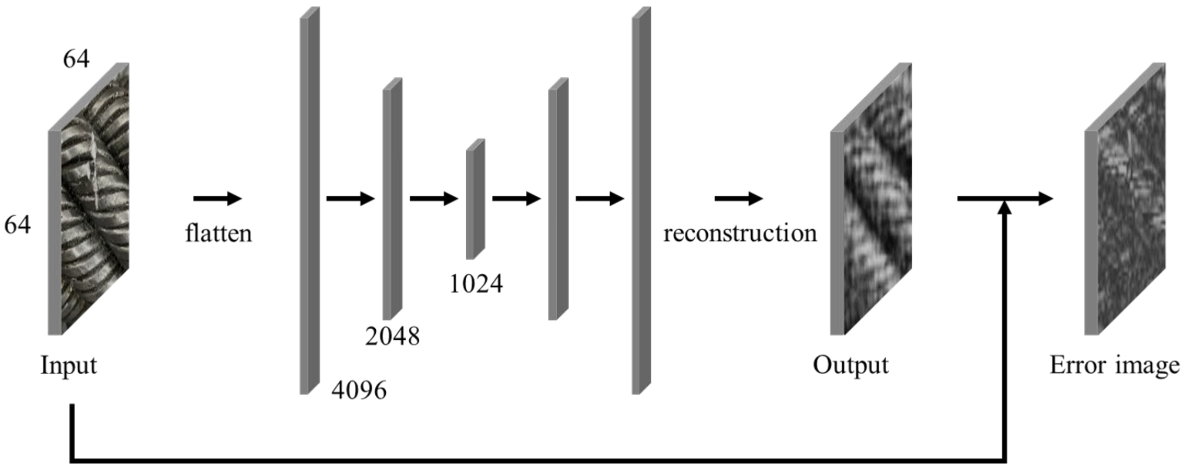


Fig. 5 Autoencoder network structure

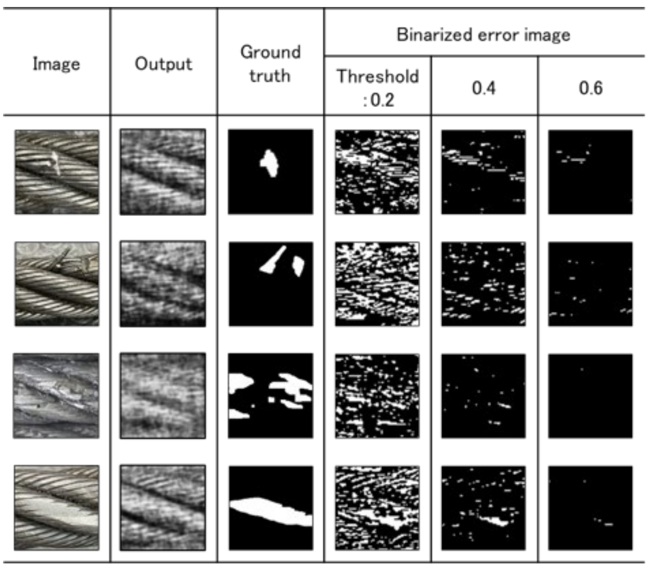


Fig. 6 Anomaly detection result by Autoencoder
(White : anomaly region)

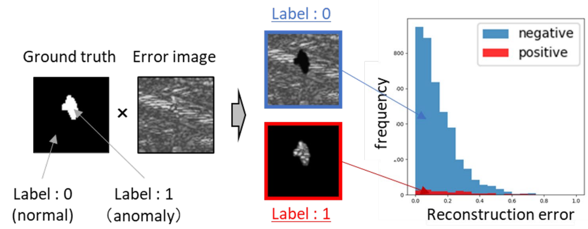


Fig.7 Pixel-level classification performance

final output. The activation function is a ReLU function for the encoder layer, a sigmoid function for the decoder layer, the error function is the mean squared error (MSE), and Adam was used as the optimization method. The training was performed for 100 epochs.

Figure 6 shows the validation results. From the left column, the input image, damage labels, and binarized error images (with threshold values of 0.2, 0.4, and 0.6, respectively) are shown. As representative examples, the top three disconnection images and the bottom wear image are shown. The ideal result is that the ground truth image and the error image coincide at any of the threshold values, and the threshold value at that time is the reference for inspection.

However, in this verification, only wire breakage could not be detected with high accuracy at any of the threshold values. Here, we evaluate the binary classification performance of our method. Figure 7 shows the pixel-level classification performance evaluation using ground truth and reconstruction error in the input image in the top row of Fig. 6. The histogram on the right shows reconstruction error on the horizontal axis and frequency on the vertical axis. Blue indicates the frequency of reconstruction error values in normal areas (label:0) of the ground truth image, and red indicates the frequency of reconstructions error values in anomaly areas (label:1). In general, when the binary classification performance is high, the blue and red histograms have separate peaks. However, this is not the case in the present results, and no matter what threshold is set for the reconstruction error, the binary classification performance is low. The same results were obtained for all input images in Fig. 6.

These may be due to the fact that the network structure of the autoencoder is very simple, so reconstruction was not elaborate, and the reconstruction error of the input/output images was used as an indicator of normality/abnormality. As a whole, the results did not reveal only damage features that appeared only locally in the images. In addition, it may be difficult to separate the damage from noise (false detection points) in the error image because the wire breakage focused on in this paper are very minute in themselves.

For comparison purposes, anomaly detection was performed using a Convolutional Autoencoder (CAE). The CAE extends the conventional autoencoder framework by incorporating convolutional layers into its architecture, enabling it to effectively capture spatial hierarchies and local patterns in the data. The training conditions were as follows: the input images were the same as those used earlier. The encoder consisted of three layers, which progressively reduced the dimensions of the input from 1 * 64 * 64 to 16 * 32 * 32, and finally to 32 * 16 * 16. The decoder mirrored this structure, upsampling the dimensions in reverse order.

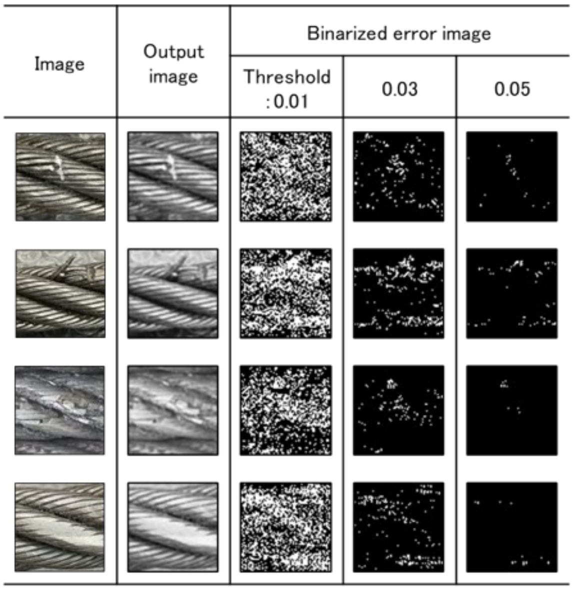


Fig. 8 Anomaly detection result by CAE
(White : anomaly region)

The activation functions are ReLU for the each encoder layers and the first two layers of the decoder, while a Sigmoid function was used in the final layer of the decoder. The error function employed was MSE, and Adam was used as the optimization method. The training was performed for 100 epochs.

The comparative results are shown in Fig. 8. Similar to the previously mentioned Autoencoder, the CAE failed to precisely detect only the anomaly regions, making it difficult to determine which approach was superior. Moreover, at a threshold of approximately 0.05, the anomaly regions (label:1) nearly disappeared, and the anomaly scores were approximately one order of magnitude smaller compared to the results obtained using the proposed method. This indicates that, despite not being trained on anomaly images, the CAE reconstructed the input data with relatively high precision. However, this also meant that the damaged regions, which were intended to be detected, were reconstructed too accurately, thus failing to achieve the primary objective of damage detection.

However, when the error image for the bottom wear image is focused on, not only scattered anomaly (white) but also a coherent area of anomalies in the center of the image can be confirmed, which appears to match the area of wear scars that exist areal to areal in the input image. As an additional verification, we focused on connectivity in the image. Connectivity is a concept that defines a region in a binary image as a set of regions, which is a set of regions when there are identical pixel values around the pixel of interest. In this study, we focus on the 4-linkage component, which defines the linkage of the pixels above, below, left, right, and right of the pixel of interest. Figure 9 shows the results of the additional verification. After calculating the reconstruction error as described above, a binary error image was obtained by Otsu's binarization [13], and of the four connected components in the image, the one with the largest area was extracted (green rectangle). As a result, the extraction of areas close to the wear was generally successful. Additionally, the potential for detecting damage of a certain size, such as wear, was confirmed in the images.

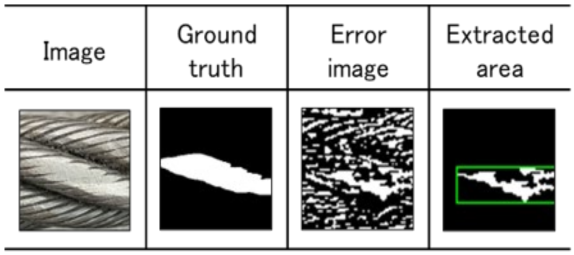


Fig. 9 Anomaly detection result by connectivity

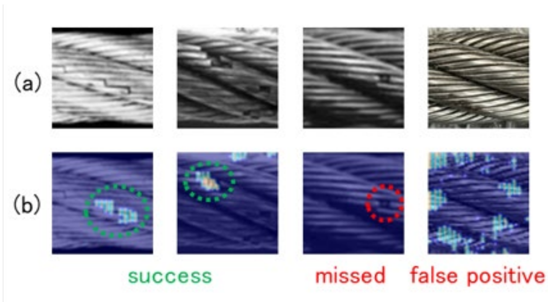


Fig. 10 Anomaly detection by Gabor filter
(a) Input image, (b) Detection result

## B. Gabor filter

Verification was conducted to confirm the effectiveness of the method. The wire rope image was adjusted so that the rope axis was horizontal, and the Gabor filter shown in Fig. 4 was used. Figure 10 shows the verification results. The two images on the left show the results of successfully detecting wire breakage in the area indicated by the green circle. The two images on the right show the results of missed and false detections, respectively. As a result, the autoencoder method succeeded in detecting a small number of wire breakage, which was difficult to detect with the previous autoencoder method. On the other hand, the missed and false positive results are considered to be caused by lighting conditions, oil and grease adhesion, and other factors. Future work is needed to minimize the effects of these factors. In this method, the direction of the strand and the direction of the Gabor filter must be orthogonal to each other. Since the purpose of this paper is to verify the effectiveness of the method for detecting wire breakage using a Gabor filter, the orientation of the input image was adjusted manually for verification. In order to perform continuous inspection of a large number of wire rope images in operation in the future, it is necessary to automatically perform the pre-processing for this purpose. The position adjustment method proposed by Zhou et al. [14] that combines segmentation and boundary recognition is effective for this purpose.

# V. Conclusion

This paper describes a detection method using image processing technology for detecting broken wire in wire rope inspections of construction machinery. Since there are a variety of broken wire and it is difficult to define their image features, two detection methods using the features of normal wire rope images were investigated: detection by autoencoder and detection by Gabor filter. The former did not give good results in efficiently detecting only wire breakage. However, by considering the connectivity in the error image, good results were obtained for the detection of wear. The latter succeeded in detecting the very fine wire breakage that attracted our attention. This shows that it is possible to detect minute damage such as broken strands by using a simple image filter such as the Gabor filter used in this study alone, without much preprocessing of the input image. And, this paper also shows the possibility of detecting abrasion, which is one of the types of wire rope damage, by using the connectivity.

In this research, the detection of wire breakage, which is the most critical damage for wire rope as described in this paper, is the most important issue, and we will continue to improve the detection method further in the future. In addition, we are investigating detection methods for other types of damage, with the aim of developing a robust inspection system that can be used even in a messy and varied environment such as a construction site.

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