# Analysis of Sensor Photo Response Non-Uniformity in RAW Images

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**Abstract.** The focus of this paper is a review of a digital camera identification technique proposed by Lukas et al [1], and a modification of the denoising filter, allowing it to be used for raw sensor data. The approach of using raw sensor data allows analysis of the noise pattern separate from any artefacts introduced by on-board camera processing. We use this extension for investigating the reliability of the technique when using different lenses between the same camera and between cameras of the same manufacturer.

**Keywords:** digital forensic, source identification, sensor noise, reference noise pattern.

## 1 Introduction

The recent growth of digital devices used among society today has led to the expansion of forensics into the digital domain. In particular, digital cameras are a source for forensic applications which include; camera identification, proving a photograph came from a camera or a type of camera, grouping photographs from a large database by their processing history, providing baseline evidence to prove or disprove image tampering and fast-tracking the physical evidence retrieval process.

In this study we review a method for camera identification, [1] using JPEG and extend the technique for raw images. We apply the extension in both a controlled laboratory and outdoor environment using different lenses between cameras of the same manufacturer. The aim is to verify the significance of the image sensor for camera identification by eliminating artefacts introduced by on-board processing.

The EXIF [5] format can be used to embed information such as timestamps and camera details inside an image file. However this can be easily edited using a text editor or software packages such as ExifTool [6], making it unreliable for camera identification in a forensic context. This provides a motivation for studying the technique proposed in [1] in further detail.

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# 2 Background

## 2.1 Technique Overview

The approach begins with an implementation of the digital camera identification technique proposed by Lukas et al [1] [2] [3]. These papers make the assumption that the high-medium frequency component (HMFC) of the sensor noise pattern is an equivalent bullet scratch for the camera, and thus can be used for camera identification.

Their proposed method involves calculating the reference noise pattern (RNP) for a camera by averaging the noise components of multiple images. This process is implemented using the denoising filter explained in [1, Appendix A]. The RNP is unique to a digital camera and its presence can be found in an image using correlation detection.

In related work, Lukas et al [3] and in [1], found that the HMFC of the noise pattern for both CCD and CMOS sensors are stable over the life of the camera. This supports its suitability for use in camera identification.

## 2.2 Noise Model

The classification of noise outlined in [1] is based on noise in a digital image a component of both the shot noise or photonic noise (random) and the pattern noise (deterministic). The process of averaging multiple images suppresses the random shot/photonic components and enhances the pattern noise, which remains constant across all images. This allows use of the pattern noise for camera identification and is the focus of the noise breakdown.

As stated in [1], the pattern noise is both a component of the fixed noise pattern (FPN) and the photo-responsive non-uniformity (PRNU). The FPN is due to dark currents, and increases with exposure duration and temperature. The FPN can be removed by subtracting a dark frame from an image and is performed by a number of middle to high-end cameras.

The PRNU is the more dominant component due to pixel non-uniformity (PNU). PNU is the variation of sensitivity between pixels for a uniform level of light intensity, and occurs from differences and imperfections in the silicon wafer used to manufacture the imaging sensor. These physical differences provide the unique sensor fingerprint on which the identification technique is based.

Lower frequency components such as light refraction on dust and camera lenses also contribute to the PRNU, but are independent of the sensor. For this reason, [1] establish that these lower frequency components should not be used for sensor identification and that only the sensor dependent PNU component should be used.

## 2.3 Camera Identification

Using the techniques described in [1] for JPEG-compressed images as both the reference and test data, we successfully identified one camera from seven different camera reference patterns. Each reference pattern was generated using a data set

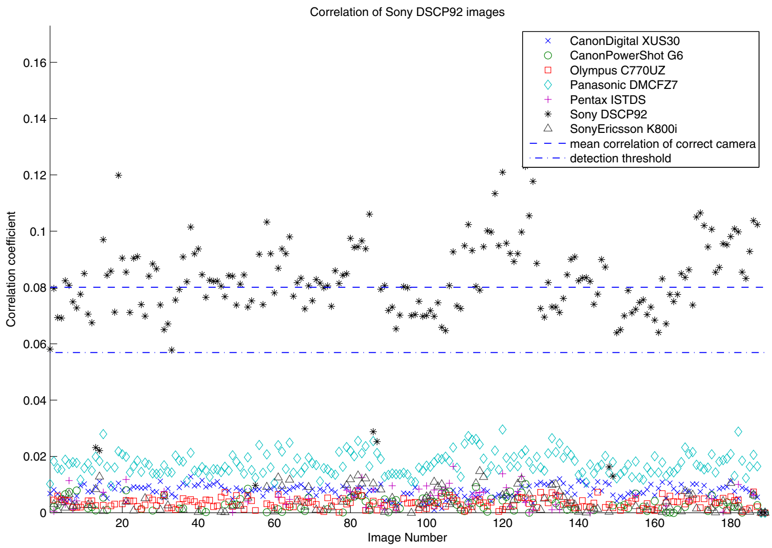


**Fig. 1.** Camera Identification by RNP correlation

of approximately 50 JPEG images for each camera. A further 190 JPEG images from one test camera (a Sony DSC-P92) were used to test the identification technique. It was found that the correlation coefficient of just six of those images were too low to conclude a match, and that none of the other noise patterns matched the test images, corresponding to a detection rate of 97% and a false match rate of 0. Hence we conclude from our experimental results that the technique is effective. The results can be seen in Figure 1.

### 2.4 Identification After Resampling

The performance of the technique for different resolution images was verified. The Sony DSC-P92 reference pattern was generated using images taken at 3 Megapixel (MP) resolution.

A set of images were taken using the same Sony DSC-P92 at 5MP, and correlated against the 3MP reference pattern. The results can be seen as the first set of 50 data points in Figure 2, where the images taken at 5MP are not successfully identified. To address this, the 5MP images were downsampled to 3MP using bicubic interpolation and an anti aliasing filter, and then correlated against the 3MP reference pattern. The results of this can be seen as the second set of 50 data points in Figure 2, where identification is now successful after the images were downsampled to the same resolution as the RNP. This is an important result as digital photos are commonly taken across a range of resolution settings.

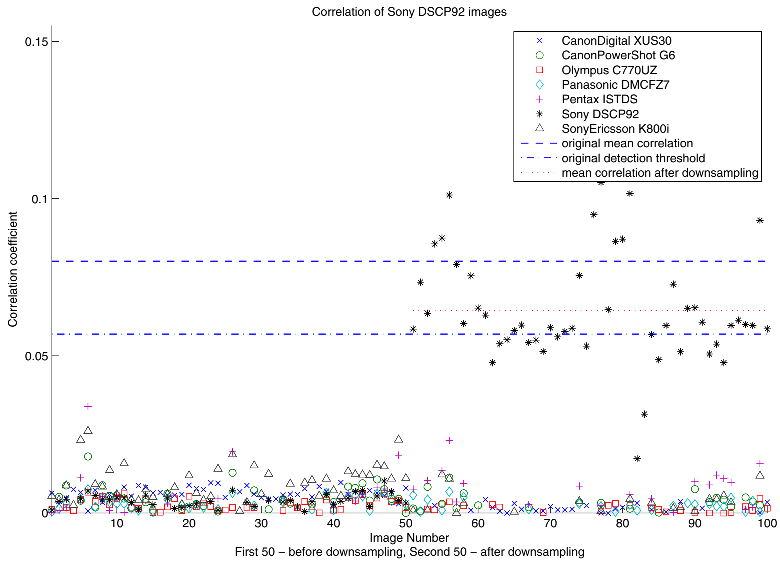


**Fig. 2.** Before and After Downsampling

# 3 Extension Using RAW Sensor Data

## 3.1 Original Image Format (JPEG)

The images used for camera identification were taken in the JPEG format. This is the most common image format, but involves post sensor processing including colour interpolation, white balance and gamma correction. This processing may be unique to a manufacturer's implementation and often will add additional noise components to the image. These noise components may be unique to a manufacturer or camera model, but could not be used reliably to differentiate between two identical model cameras. Additionally the camera firmware can often be upgraded, potentially changing the noise characteristics over time.

The technique proposed in [1], outlines that the identifier for a camera is due to its pixel non uniformity (PNU) unique to the sensor. This is separate from any on-board processing. In order to establish the sensor alone as a fingerprint for the camera, we investigated the denoising filter using the raw sensor output.

## 3.2 Bayer Matrix and Conversion of Raw Sensor Data

Digital camera image sensors measure only light intensity, and are unable to distinguish between different colours. In order to measure colours, most digital cameras use colour filters before the sensors. The most common arrangement is known as a Bayer matrix, where the colour pattern in a 2 by 2 block alternates between Red (R), Green (G) and Blue (B) filters.

The RAW image format stores the sensor readings directly, before the on-board processing and compression stages in the camera. This is suitable for our investigation of the camera sensor alone. There is no industry standard for RAW formats. The Pentax *ist DS and DL cameras discussed in this paper save their sensor data using the proprietary Pentax *.PEF* format.

The Bayer Matrix was extracted in Matlab by reverse engineering the binary structure of a saved .PEF RAW image. The data was extracted as a 12-bit number and up shifted to 16-bit, allowing the image to be saved in the 16-bit lossless TIFF format. Upon close inspection of the extracted image, the Bayer pattern of the image was visible, confirming the technique.

An alternative method to extract the RAW image is a tool such as the open source software package *dcraw* [7]. This software is designed to process a RAW format file into a final image, but can also be used to extract only the sensor readings using the command:

```
dcraw -D -T -4 -W Image.PEF
```

A 4 bit upshift was performed on the extracted 12 bit image to remain consistent with the Matlab extraction approach. This resulted in the same image as using the Matlab approach. The use of a software package such as *dcraw* would allow our RAW technique to be extended to the majority of digital cameras without requiring the camera's RAW format reverse engineered.

### 3.3 Modified Denoising Filter for RAW Images

The technique proposed in [1] could not be directly applied to converted RAW Bayer pattern images. The large differences in pixel intensity between red, green and blue pixels meant that each surrounding pixel contained edge effects. These high frequency components were extarcted by the denoising filter, and were present with the PNU in the resulting RNP.

The approach taken was to decimate the Bayer matrix into four planes; red, green1, green2 and blue, each of which should share the same pixel sensitivity. Each plane is then a quarter of the size of the original extracted Bayer matrix, and is denoised using the filter described in [1, Appendix A]. Once each plane has been denoised, the Bayer matrix is reassembled from the four planes and subtracted from the original image. This gives the noise pattern for the RAW image. This decimated approach avoids introducing additional noise, which techniques such as interpolation would do.

When decimating the Bayer matrix into the four different planes the starting sequence for the Bayer matrix does not need to be known. The requirement is that every second pixel in both the horizontal and vertical directions belongs to the same colour level (red, green or blue) and should share the same sensitivity. This allows the implementation to be used for different manufacturers which may vary the arrangement of the Bayer matrix pattern.

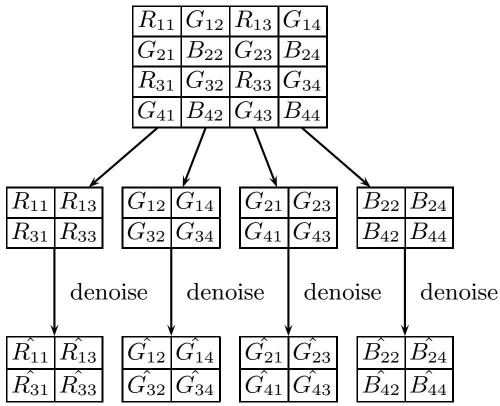


**Fig. 3.** Bayer matrix decimation method for an 8x8 image

| | | | |
|---|---|---|---|
| $\hat{R}_{11}$ | $\hat{G}_{12}$ | $\hat{R}_{13}$ | $\hat{G}_{14}$ |
| $\hat{G}_{21}$ | $\hat{B}_{22}$ | $\hat{G}_{23}$ | $\hat{B}_{24}$ |
| $\hat{R}_{31}$ | $\hat{G}_{32}$ | $\hat{R}_{33}$ | $\hat{G}_{34}$ |
| $\hat{G}_{41}$ | $\hat{B}_{42}$ | $\hat{G}_{43}$ | $\hat{B}_{44}$ |

**Fig. 4.** Reconstructed denoised Bayer Matrix

# 4 Camera Lenses

## 4.1 Overview of Optical Effects

This section discusses the motivation for the lens study.

Imperfections in lenses contribute to distortions in the final image, and can be categorised as either high (affecting a small image section) or low frequency components (affecting the whole image).

Modern consumer digital cameras are either compact (point and shoot) cameras which have an inbuilt lens or Digital SLR cameras which have interchangeable lenses. If the lenses had an impact on the RNP, interchangeable lenses would reduce the reliability of the camera identification process. The fixed micro lens which serves to focus incoming light onto each sensor is not studied in this paper, as it is fixed to the camera. [9]

Commonly observed optical aberrations include radial distortion (barrel or pincushion effects), vignetting (darker sections towards edge of image) and chromatic aberration (colour fringing). These distortion effects are typically low frequency [10], and should not be extracted by the denoising filter. Research into the forensics properties of these effects has been conducted in [11], and [12].

Noise sources such as scratches, dust [13] and imperfections in the materials also contribute noise to an image. If they affect a small region of the image, they would be categorised as high frequency noise and be extracted by the denoising filter.

These imperfections are unique to an individual lens and may hold forensic utility in lens identification. Importantly they may be present in methods to extract the sensor pattern noise such as the filter outlined in this paper, which would impact the reliability of the identification technique.

The aim of our lens study was to determine the significance of these lens effects on each RNP found using the technique outlined above.

### 4.2 Approach

Two similar Pentax camera models, the *ist DS and *ist DL, were used to study the effect of lenses on the noise pattern. These cameras were selected as they allowed the PENTAX-F (small) and Tamron (large) lenses to be used interchangeably between both cameras. All images were taken in the RAW format and processed using the modified RAW denoising filter described earlier. A *baseline* and *merged* RNP set were generated for correlation analysis.

The *baseline* set contained RNPs for each camera and lens combination, consisting of RNPs: DL Large, DL Small, DS Large and DL Small. This set was used to study the correlation result for a camera with the lens used to take the photo versus an alternative lens.

The *merged* set was generated by merging the images unique to each camera and each lens, consisting of RNPs: DL Camera, DS Camera, Small Lens and Large Lens. This allowed the study of the significance of the image sensor versus the significance of the lens, based on the correlation results.

### 4.3 Data Sets

Both *baseline* and *merged* RNP sets were generated in both controlled laboratory and outdoor environments.

**Indoor Controlled Laboratory.** An indoor imaging laboratory was used as a controlled environment, in which images were taken of a suspended blank sheet of white paper. A low fan setting was used to vary the image content between images, ensuring any effects of the image content would be averaged out of the resulting RNP. Light and temperature were maintained at a constant level and the cameras were powered using either a constant voltage power supply, or freshly charged batteries. These environmental conditions may affect the noise present in an image, so it is important their effect is minimsed.

The zoom was varied between 18mm, 35mm and 50mm for each camera and lens combination. This reduced the effect of the secondary (zoom) lens. The following table shows the data set taken for the laboratory environment.

| **PENTAX-F Lens** | *18mm* | *35mm* | *50mm* |
|---|---|---|---|
| DL Camera | Subset A | Subset B | Subset C |
| DS Camera | Subset D | Subset E | Subset F |
| **Tamron Lens** | *18mm* | *35mm* | *50mm* |
| DL Camera | Subset G | Subset H | Subset I |
| DS Camera | Subset J | Subset K | Subset L |

Each *baseline* RNP was generated using 75 images for each zoom setting. The *merged* RNPs used 20 images from each zoom setting for a total of 120 images used. For example, to generate a *merged* RNP unique to just the DL camera, 20 images from subset A, B, C, G, H, I would be used. For a *merged* RNP unique to the Tamron lens, 20 images from subset G, H, I, J, K and L would be used.

**Outdoors.** The outdoors data set was taken around the university campus, to provide a level of randomness and variability of image content typical of real world images. The zoom setting was also varied arbitrarily. The following table shows the data set captured for outdoors.

| | **PENTAX-F Lens** | **Tamron Lens** |
|---|---|---|
| DL Camera | Subset M | Subset N |
| DS Camera | Subset O | Subset P |

Each *baseline* RNP was generated using 75 images for each subset and the *merged* RNPs where generated by combining two subsets common to either the camera or lens for a total of 150 images used. For example, to generate a *merged* RNP unique to just the DS camera subsets O and P would be combined. A *merged* RNP unique to the PENTAX-F lens would combine subsets M and O.

## 5 Results

### 5.1 Indoor Controlled Laboratory

The baseline results in Figure 5 show a clear correlation with the correct camera. The mean correlation is stable which is expected for images with uniform image

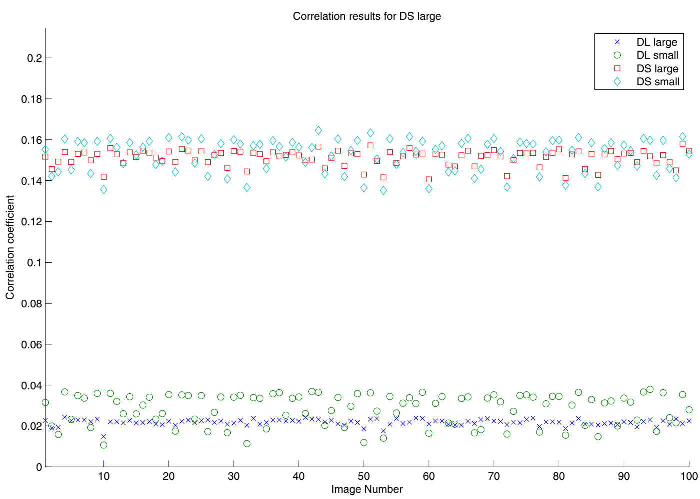


**Fig. 5.** Scatterplot for Indoor DS Large Lens Baseline

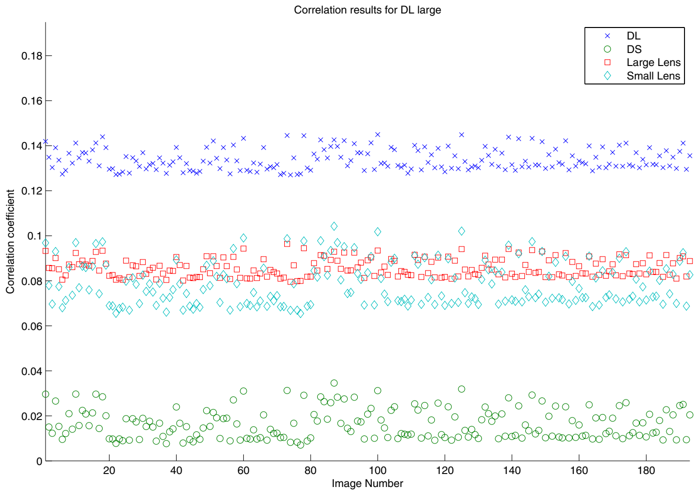


**Fig. 6.** Scatterplot for Indoor DL Large Lens Merged

content (controlled). Determining the lens however is inconclusive. The small lens has greater variance than the large lens, but both have a similar mean.

The merged set was used to compare the significance of the sensor against the lens, by averaging a common component (camera or lens). The results in Figure 6 show clearly a result for the correct camera. Under controlled lab conditions this shows that the sensor has a greater significance on the noise pattern than the lens. In the common middle tier there is a slight bias for the correct lens.

### 5.2 Outdoors

Baseline and merged results were also considered for the outdoor data set. Again for the baseline results in Figure 7 there is strong correlation for the correct camera but with greater variance than observed for the indoor set. This is likely due to the image content varying between images. The temperature and battery level of the cameras also varied over the outdoor data, which may have contributed to greater variance in correlation.

The merged results in Figure 8 again confirm that the sensor is more dominant for identification than the lens. This is followed by the correct lens, the incorrect lens and then the incorrect camera giving the lowest correlation. This was also confirmed by the outdoor CDF shown in Figure 9.

In both indoor and outdoor sample sets we have established that camera sensor is more dominant than lens although within the middle tier it may be also be possible to identify the correct lens. Note that some of our results did not have clear speration between lenses for merged sets which could be due to a number of reasons such as random image content for outdoors.

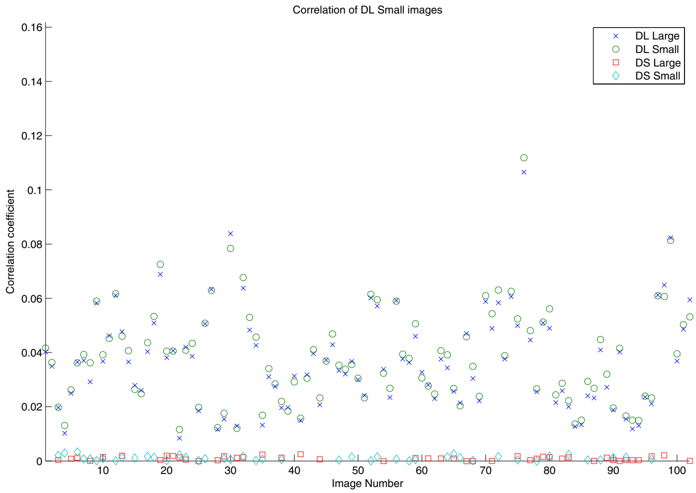


**Fig. 7.** Scatterplot for Outdoor DL Small Lens Baseline

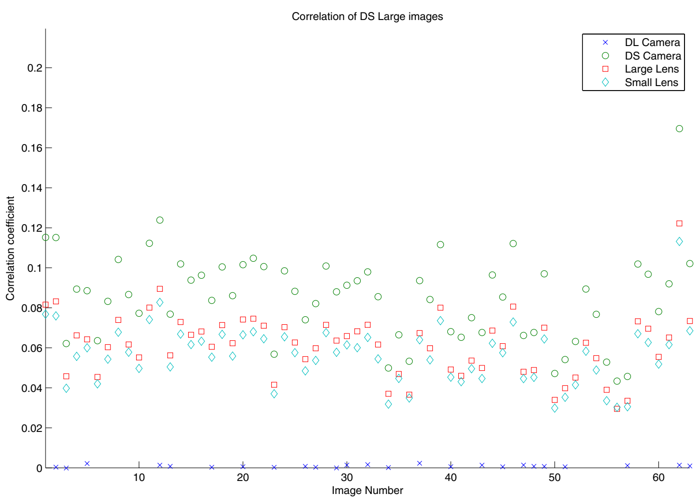


**Fig. 8.** Scatterplot for Outdoor DS Large Lens Merged

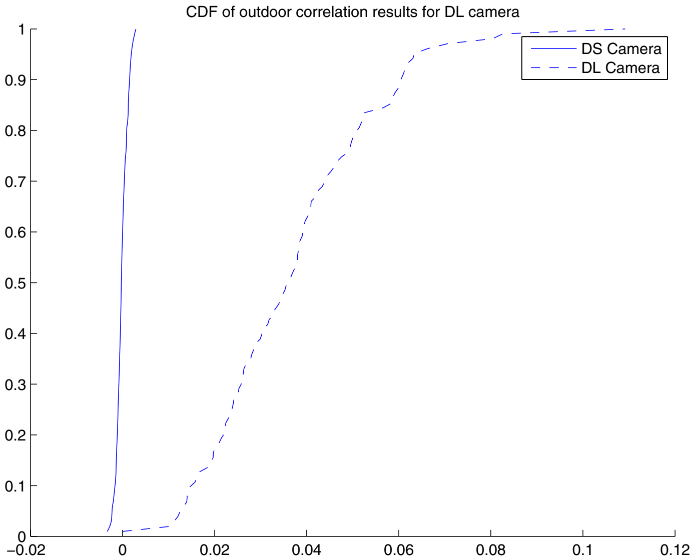


**Fig. 9.** CDF of outdoor DL Small Lens dataset

## 6 Conclusion

In this paper we have reviewed a technique for digital camera identification [1] using the JPEG format. We have also tested the robustness of the technique for images at different resolutions. The technique is extended for raw sensor data by modifying the denoising filer. The purpose of this is to eliminate post sensor processing artefacts and focus on the noise pattern unique to the sensor.

For both controlled indoor and outdoor data sets, the correlation results show clear correlation with the correct camera. Further, the merged results show that the camera sensor is more dominant than the lens for identification. This is strong evidence to support the assumption that the reference noise pattern found for a camera is unique to that camera's sensor.

Other applications of the developed extension for RAW images may include measuring the noise pattern of images in different temperature environments or for cameras with different battery levels. This may allow for more information associated with an image to be determined. In the case of temperature, the time of day or typical environment could be determined and in the case of battery, images could be ordered chronologically to determine a sequence of events.

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