Secure and Efficient Transmission of Hyperspectral Images for Geosciences Applications

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Abstract. Hyperspectral images are acquired through air-borne or space-borne special cameras (sensors) that collect information coming from the electromagnetic spectrum of the observed terrains. Hyperspectral remote sensing and hyperspectral images are used for a wide range of purposes: originally, they were developed for mining applications and for geology because of the capability of this kind of images to correctly identify various types of underground minerals by analysing the reflected spectrums, but their usage has spread in other application fields, such as ecology, military and surveillance, historical research and even archaeology. The large amount of data obtained by the hyperspectral sensors, the fact that these images are acquired at a high cost by air-borne sensors and that they are generally transmitted to a base, makes it necessary to provide an efficient and secure transmission protocol. In this paper, we propose a novel framework that allows secure and efficient transmission of hyperspectral images, by combining a reversible invisible watermarking scheme, used in conjunction with digital signature techniques, and a state-of-art predictive-based lossless compression algorithm.

1. Introduction
The fact that an object reflects, absorbs and emits electromagnetic radiation according to its chemical composition, is exploited by the remote sensing [9] through which we can acquire information on distant objects without coming into physical contact with them. It is possible to obtain a spectral signature of an object by analysing its reflected radiations as a function of the wavelengths. A spectral signature is a sort of unambiguous fingerprint, which can be involved in the unique characterization of any given material. Several organizations (e.g., NASA, etc.) have outlined a catalogue of the various spectral signatures of minerals, which simplify the identification of the mapped materials.

The information obtained by means of hyperspectral remote sensing are generally organized as hyperspectral images and they are involved in several real-life scenarios and applications, such as earth imaging, environmental sciences, surveillance, historical research, archaeology, monitoring of environmental hazards, assessment of food quality, biomedical imaging, forensics, skin health, etc.

Hyperspectral sensors acquire information by the observation of the electromagnetic spectrum, they analyze the frequencies from 400-760 nanometres (visible part) to about 2400 nanometers (near-infrared). A hyperspectral image is composed by a sequence of narrow and contiguous spectral bands, which compose a three-dimensional data structure (datacube).

For example, the NASA AVIRIS (Airborne Visible/Infrared Imaging Spectrometer) sensors acquire information from the frequencies of ultraviolet and infrared rays at wavelengths varying from 400 to 2500 nm (nanometres), they produce hyperspectral images composed by 224 bands [10].
Generally, hyperspectral images are shared and exchanged among several entities (for example different research centres, etc.) to effectively and efficiently carry out conjunct tasks. Many of the application scenarios in which these data are involved are sensitive and it is therefore important to ensure the protection of the information. In addition, these images are generally transmitted to a base as soon as they are acquired and it is necessary to provide an efficient and secure transmission protocol between the airplane (or satellite) and the base where they will be analyzed.

In this paper, we address the problem of the secure and efficient transmission of hyperspectral data by proposing a novel framework: a lossless compression algorithm based on linear prediction coupled with a reversible, invisible, watermarking scheme. The watermarking scheme is also able to embed hidden information into the hyperspectral image.

In Section 3.1, we review the reversible invisible watermarking scheme. By means of this approach it is possible to embed an invisible watermark into hyperspectral images. One of the main characteristics of this scheme is its reversibility, therefore data can be exactly restored after the extraction of the watermark. In our scheme, the watermarked hyperspectral image is transmitted on an insecure channel and the receiver can extract the watermark and recover the original data. Furthermore, by using this watermarking scheme, in conjunction with digital signature techniques it is possible to guarantee the inalterability of the hyperspectral image. We remark that the watermarked hyperspectral image can be potentially used for purposes in which an acceptable distortion level is allowed (as for instance, browsing of images, etc.), since the embedded watermark is not human perceivable (invisible).

Subsequently, in Section 3.2, we review the Lossless MultiBand compression for Hyperspectral Images (LMBHI) algorithm, described in [10], which permits the efficient and lossless compression of hyperspectral images. The LMBHI algorithm is based on the predictive-based model.

Therefore, we present our secure and efficient transmission framework, that relies on the combination of these schemes, and we experimentally prove its efficiency.

This paper is organized as follows: Section 2 shortly describes related works, Section 3 highlights the proposed framework, Section 4 outlines our experimental results and Section 4 draws our conclusions.

2. Related works
The lossless compression of hyperspectral images is generally based on the predictive coding model. The main advantage of the predictive-based approaches is the usage of limited resources in terms of computational power and memory. These approaches achieve good compression performances and they are often suitable for on board implementations.

Spectral-oriented Least SQuares (SLSQ) [11], Fast Lossless (FL) [15], CALIC-3D [16] and M-CALIC [16] are some state-of-art predictive-based lossless coding techniques.

In literature, there are several schemes designed for offline compression. These approaches are not suitable for an on-board implementation since they use more sophisticated techniques and/or they require the complete availability of the hyperspectral image. Of course, these approaches achieve better compression performances. In [17], Mielikainen proposes an approach for the compression of hyperspectral image using a Look-Up Table (LUT). The LUT is used to predict each pixel by considering all the pixels in the current and in the previous band. In detail, the prediction is performed by searching the nearest neighbor in the previous band which has the same pixel value as the pixel located in the correspondent spatial coordinates as the current pixel. This approach needs significant resources in terms of memory and CPU usage, but it achieves a high compression performance.

Other lossless compression algorithms are based on dimensionality reduction by means of principal component transform (e.g., the one addressed in [18]).

The lossless compression algorithms for hyperspectral images are generally based on the 3D frequency transforms, namely, the 3-D Discrete Wavelet Transform (3D-DWT) [19] or the 3-D Discrete Cosine Transform (3D-DCT) [20] or the Karhunen–Loève transform (KLT) [21], etc. These
approaches are easily scalable, but they require to maintain in memory the entire hyperspectral image, and this is not generally possible in an on-board implementation.

Digital watermarking techniques are an efficient approach for ensuring security, content authentication and copyright protection [1, 2, 6]. By means of such techniques, the input data (i.e., hyperspectral images) might become a sort of information carrier which can be used for delivering important data [7, 8].

3. The Proposed Framework

3.1. Reversible Invisible Watermarking Scheme for Hyperspectral Images

In this section, we review the reversible invisible watermarking scheme. We proposed in [14] a preliminary scheme which relies on the approaches outlined in [4] and [5]. This is an additive scheme: the watermark string \( w \) is directly added to the input pixels of the hyperspectral image \( HI \). Thus, the watermarked hyperspectral image, \( HI^w \) contains both \( HI \) and \( w \). The embedding phase is performed by using a secret key \( K \).

It is important to highlight that our scheme is fragile. This means that a simple modification of \( HI^w \) may cause the disappearance of the embedded watermark \( w \). We remark that our scheme is reversible: it is therefore possible to extract the watermark \( w \) and restore the original \( HI \).

Basically, the objective of our scheme is to spread the bits of \( w \) among all the bands of \( HI \). More precisely, each bit of \( w \), referred to as \( b_w \), will be embedded into a set of four pixels \( S_p = \{x(0), x(0), x(2), x(3)\} \). These pixels are pseudo-randomly selected by means of a Pseudo-Random Number Generator (PRNG) based on the secret key \( K \).

Not all the sets \( S_p \) can be used to carry \( b_w \) since the extraction algorithm might be unable to extract the hidden bit. Thus, we classify (as in [5]) the sets into:

- **Carrier set**;
- **Non-carrier set**.

The difference between the two is that a carrier set is a set in which a bit \( b_w \) can be embedded, and a non-carrier set is a set in which a bit \( b_w \) cannot be embedded.

**Algorithm 1.** The embedWatermarkBit procedure (pseudo-code from [14]).

```
procedure embedWatermarkBit\( (S_p, b_w) \)
1. if \( b_w == 1 \) then
2. \( x^w(0) = x(0) + 1; \)
3. \( x^w(1) = x(1) - 1; \)
4. \( x^w(2) = x(2) - 1; \)
5. \( x^w(3) = x(3) + 1; \)
6. else
7. \( x^w(0) = x(0) - 1; \)
8. \( x^w(1) = x(1) + 1; \)
9. \( x^w(2) = x(2) + 1; \)
10. \( x^w(3) = x(3) - 1; \)
11. endif
12. \( S_p^w = \{x^w(0), x^w(1), x^w(2), x^w(3)\}; \)
13. return \( S_p^w \);
end procedure
```
Once a carrier set $S_p$ is identified, a bit $b_w$ can be embedded by means of the embedWatermarkBit procedure, reported in Algorithm 1. We referred to the output of such a procedure as $S_p^w$, which represents the set $S_p$ in which $b_w$ is embedded.

Algorithm 2. The estimate procedure (pseudo-code from [14]).

```
procedure estimate($S_p$)
    1. $x_i^E(0) = \frac{2 \times x(0) + x(1) + x(2)}{4}$;
    2. $x_i^E(1) = \frac{2 \times x(2) + x(0) + x(2)}{4}$;
    3. $x_i^E(2) = \frac{2 \times x(3) + x(0) + x(3)}{4}$;
    4. $x_i^E(3) = \frac{2 \times x(1) + x(1) + x(2)}{4}$;
    5. $S_p^E = \{x_i^E(0), x_i^E(1), x_i^E(2), x_i^E(3)\}$;
    6. return $S_p^E$;
end procedure
```

Algorithm 3. The embed procedure (pseudo-code from [14]).

```
procedure embed($H1, w, K$)
    1. Let $G$ be a PRNG;
    2. $N = lengthOf(w)$;
    3. Subdivide $w$ into $\{w_1, w_2, ..., w_M\}$;
    4. for $i = 1$ to $M$ do
        5. $idx = 1$;
        6. $N_i = lengthOf(w_i)$
        7. repeat
            8. $b_w = w_i[idx]$;
            9. By using $G$ along with $K$, selects $x(0), x(1), x(2), x(3)$ from $H1(i)$;
            10. $S_p = \{x(0), x(1), x(2), x(3)\}$;
            11. $S_p^E = estimate(S_p)$;
            12. $D = |x(0) - x_i^E|$;
            13. if $D < 1$ then
                14. $S_p^w = embedWatermarkBit(S_p, b_w)$;
                15. $idx + +$;
            16. else
                17. Modifying of $S_p$, by using $S_p = embedWatermarkBit(S_p, 0)$ or $S_p = embedWatermarkBit(S_p, 1)$, in order to increase the value of $D$;
                18. endif
            19. Setting of the coordinates of $x(0), x(1), x(2)$ and $x(3)$ no longer selectable;
        20. until $idx \leq N_i$;
    21. end for
    22. Copying of all modified and unmodified pixels to $HI^w$;
    23. return $HI^w$;
end procedure
It is possible to identify if a set $S_P$ is a carrier set or not by considering the relationship between $S_P$ and its estimation $S_E^P$. This estimation is computed by means of a linear combination of the pixels of $S_P$, as outlined in the estimate procedure (Algorithm 2).

Through the estimation, the extraction algorithm is able to determinate, in two steps, if a set $S_P$ is a carrier set or not. In addition, starting from a watermarked carrier set, the extraction algorithm can restore the original pixel values of the carrier set. In this manner, the reversibility property is obtained. In Algorithm 3, we report the pseudo-code of the embed procedure, which embeds the watermark string $w$ into the input hyperspectral image $HI$ by using $K$ as the secret key for the embedding.

First the PRNG, denoted as $G$, is initialized by using $K$ as a seed and $w$ is subdivided into $M$ substrings, where $M$ is the number of bands of $HI$. The $i$-th substring, $w_i$, will be embedded into the $i$-th band of $HI$ (we referred to as $HI_{0(i)}$) and each band will carry at least $\lceil N/M \rceil$ bits (where $N$ denotes the length of $w$).

For each substring $w_i$, the following steps are performed until all the bits of $w_i$ are embedded.

In order to try the embedding of the current bit of $w_i$ (denoted to as $b_w$) into a set $S_P$, four pixels are selected by means of the PRNG $G$. We refer to such pixels as $x_{(0)}$, $x_{(1)}$, $x_{(2)}$, and $x_{(3)}$, respectively. These pixels are stored into the set $S_P$. Subsequently, the estimation $S_E^P$ of $S_P$ is computed. $S_E^P$ is composed by the estimated pixels, denoted as $x_{(0)}^E$, $x_{(1)}^E$, $x_{(2)}^E$, and $x_{(3)}^E$. Then the difference $D_i$ in absolute value between $x_{(0)}$ and $x_{(0)}^E$ is computed to identify if $S_P$ is a carrier set.

If $D < 1$, the set $S_P$ is a carrier set. Therefore, the embedWatermarkBit procedure (Algorithm 1) is performed to embed $b_w$ into $S_P$ and the processing of bit $b_w$ is complete. The coordinates of the pixels $x_{(0)}$, $x_{(1)}$, $x_{(2)}$, and $x_{(3)}$ will be no longer selectable and the algorithm proceeds by the next bit of $w_i$.

Otherwise, if $S_P$ is a non-carrier set, the value of the pixels of $S_P$ are modified to increase the difference $D$. In this way, the extraction algorithm can identify the fact that $S_P$ is a non-carrier set. Consequently, the bit $b_w$ is not embedded into the set $S_P$ and other four pixels (different from the ones already selected) will be identified and stored into the new set $S_P$, in order to try again the embedding.

3.2. Multi-Band Lossless Compression of Hyperspectral Images

In this section, we revisit the predictive-based Lossless MultiBand compression for Hyperspectral Images (LMBHI) algorithm [10] that exploits both the inter-band correlation (the correlation among contiguous bands) and the intra-band correlations (the correlation within the same band), by using a predictive coding model.

Each pixel of the input hyperspectral image $HI$, is linearly predicted by using a predictive structure. The pixels that belong to the first band are predicted by using the 2-D Linearized Median Predictor (2-D LMP) [10], which exploits only the intra-band correlation (since the first band has no previous reference bands).

All the other pixels are predicted by using the 3-D MultiBand Linear Predictor (3D-MBLP), that will be explained in Section 3.2.1. All the other pixels are predicted by using the 3-D MultiBand Linear Predictor (3D-MBLP), that will be explained in Section 3.2.1. The 3D-MBLP predictor uses a three-dimensional prediction context, composed by the adjacent pixels (retrieved from the current band and from the previous ones) of the pixel that is undergoing processed.

After the prediction step the prediction error $e$ is modelled and coded. The prediction error $e$ is obtained by subtracting the value of its prediction from the value of current the pixel.

3.3. 3-D MultiBand Linear Predictor (3D-MBLP)

The MultiBand Linear Predictor uses a three-dimensional prediction context, obtained by considering two parameters: $B$ and $N$. The $B$ parameter indicates the number of the previous reference bands. The $N$ parameter, indicates the number of pixels that will be included in the prediction context in the current band and the previous $B$ reference bands.

In order to allow the relative indexing of the pixels, with respect to the current pixel (i.e., the pixel that is currently under analysis) an enumeration $E$ is defined. In the following, we use the notations $I_{i,j}$
to indicate the $i$-th pixel (according to the enumeration $E$) of the $j$-th band, and we suppose that the current band is the $k$-th band. It is important to note that the $I_{0,j}$ indicates the pixel with the same spatial coordinates of the current pixel $I_{0,k}$, of the $j$-th band.

The 3D-MBLP predictor is based on the least squares optimization technique. In Equation (1), we report how the prediction is computed.

$$I_{0,k} = \sum_{i=1}^{B} a_i \cdot I_{0,k-i}$$  \hspace{1cm} (1)

We remark that the coefficients $\alpha_0 = [\alpha_1, ..., \alpha_B]^T$ are chosen to minimize the energy of the prediction error, as reported by Equation (2).

$$P = \sum_{i=1}^{N} (I_{i,k} - \overline{I}_{i,j})^2$$  \hspace{1cm} (2)

Equation (2) can be rewritten by using the matrix notation, as outlined in the following equation:

$$P = (C\alpha - X)^T \cdot (C\alpha - X), \text{where } C = \begin{bmatrix} I_{1,k-1} & \cdots & I_{1,k-B} \\ \vdots & \ddots & \vdots \\ I_{N,k-1} & \cdots & I_{N,k-B} \end{bmatrix} \text{ and } X = [I_{1,k}, ..., I_{N,k}]^T.$$

Afterward, by computing the derivate of $P$ and by setting it to zero, the optimal coefficients can be obtained:

$$(C^T C)\alpha_0 = (C^T X)$$  \hspace{1cm} (3)

By obtaining the coefficients $\alpha_0$, which solve the linear system of Equation (3), the prediction $\overline{I}_{0,k}$, of the current pixel $I_{0,k}$, can be obtained.

### 3.4. Secure and Efficient Transmission Framework

In figure 1, we show the architecture of the proposed transmission framework. $HI$ and $K$ denote the input hyperspectral image and the secret key. In the first phase a digital signature provided by a cryptographic hash function $h(.)$ (e.g., SHA-3 Keccak [3], etc.), is invoked to compute the digest $h(HI)$. Subsequently, the obtained digest $h(HI)$ is embedded into $HI$ (i.e., the watermark string is $h(HI)$), by the reversible invisible watermarking scheme described in Section 3.1. Finally, the watermarked hyperspectral image $HI^w$ is then compressed by the LMBHI algorithm. The results of the compression (denoted as $HICW$) can now be efficiently transmitted.

In the following, we denote as $HI'$, the hyperspectral image, which is reconstructed from $HI^w$ (where $HI^w$ is obtained as the output of the decompression of $HICW$), and as $w'$ the watermark string which is extracted from $HI^w$.

It is possible to verify the integrity of $HI$ since if there are no alterations of $HI^w$, the value of $h(HI')$ will be equal to the value of $h(HI)$. Consequently, it is satisfied that $w = h(HI) = h(HI') = w'$ and $HI'$ is exactly equal to $HI$.

### 4. Results and discussions

#### 4.1. Dataset Description

The test dataset is composed by five AVIRIS hyperspectral images that were provided by the JPL (Jet Propulsion Laboratory) of NASA [13].
Each one of the hyperspectral images is subdivided into sub-images denoted as scenes. A scene is composed by 614 columns, 512 lines (except for the last scene, which might have a lower number of lines) and 224 spectral bands. A pixel is stored by using 16 bits (signed integers). Table 1 shows the number of scenes for each of the hyperspectral images in our test set.

Table 1. Number of scenes for each tested hyperspectral image.

| Hyperspectral Image | Number of scenes |
|---------------------|------------------|
| Cuprite             | 5                |
| Jasper Ridge        | 6                |
| Low Altitude        | 8                |
| Lunar Lake          | 3                |
| Moffett Field       | 4                |

4.2. Reversible Invisible Watermarking Scheme Results and Discussion

The watermark we used in our experiments is pseudo-randomly generated and composed by 1120 bits. The value of $K$ (i.e., the secret key) is 4567.

We consider the Peak-Signal-to-Noise-Ratio (PSNR) metric (outlined in Equation (4)), to evaluate the distortion between the original hyperspectral image $HI$ and the watermarked hyperspectral image $HI^W$. In Equation (4), the notation $HI(i)$ is used to indicate the $i$-th band of $HI$.

$$PSNR(HI, HI^W) = \frac{1}{M} \sum_{i=1}^{M} 10 \log_{10} \left( \frac{2^{16} - 1}{\text{MSE}(HI(i), HI^W(i))} \right)$$  \hspace{1cm} (4)$$

The Mean Squared Error (MSE) is defined in Equation (5), in which the notation $HI(i)(x,y)$ is referred to the pixel at the coordinates $(x,y)$ of the $i$-th band.

$$\text{MSE}(HI(i), HI^W(i)) = \frac{1}{WH} \sum_{x=1}^{H} \sum_{y=1}^{W} \left( HI(i)(x,y) - HI^W(i)(x,y) \right)^2$$  \hspace{1cm} (5)$$

Tables 2 reports the experimental results achieved, in terms of PSNR, for each scene (first column) of the “Cuprite” (second column), “Jasper Ridge” (third column), “Low Altitude” (fourth column), “Lunar Lake” (fifth column) and “Moffett Field” (sixth column) images. We also graphically show the trend of the PSNR (on the y-axis), for all the scenes (on the x-axis) of each image, in figure 2.
Table 2. Experimental results by the reversible invisible watermarking scheme for each hyperspectral image (the results are reported in term of PSNR).

| Scenes         | Cuprite | Jasper Ridge | Low Altitude | Lunar Lake | Moffett Field |
|----------------|---------|--------------|--------------|------------|--------------|
| Scene 01       | 124.45  | 123.21       | 123.40       | 125.21     | 123.34       |
| Scene 02       | 123.03  | 123.28       | 122.89       | 125.13     | 125.32       |
| Scene 03       | 124.36  | 122.45       | 124.11       | 124.27     | 127.09       |
| Scene 04       | 124.58  | 122.41       | 123.75       | -          | 123.28       |
| Scene 05       | 124.83  | 122.81       | 123.72       | -          | -            |
| Scene 06       | -       | 122.60       | 123.96       | -          | -            |
| Scene 07       | -       | -            | 123.67       | -          | -            |
| Scene 08       | -       | -            | 123.09       | -          | -            |

Average: 124.25 122.79 123.57 124.87 124.76

Figure 2. The PSNR trend achieved for the hyperspectral images of the test dataset: (a) “Cuprite”, (b) “Jasper Ridge”, (c) “Low Altitude”, (d) “Lunar Lake” and (e) “Moffett Field”.

As it is possible to observe from Table 3, which synthetizes the average PSNR values we achieved in our experiments, the average PSNR is high in all the tested images. In fact, the watermark results to be invisible (i.e., not human perceivable).

Table 3. Average PSNR values.

| Hyperspectral Image | Average PSNR |
|---------------------|--------------|
| Cuprite             | 124.25       |
| Jasper Ridge        | 122.79       |
| Low Altitude        | 123.57       |
| Lunar Lake          | 124.87       |
| Moffett Field       | 124.76       |
4.3. Lossless Compression Results and Discussions

In Tables 4 and 5 we report, in terms of Bits Per Pixels (BPP), the experimental results for the LMBHI compression algorithm. Table 4 reports the experimental results achieved for each hyperspectral image (rows from the second to the sixth), by setting the $N$ parameter equal to 8 and by using the following values for the $B$ parameter: $B=1$ (second column), $B=2$ (third column) and $B=3$ (fourth column). Table 5 reports other experimental results, as in Table 3 but by setting the $N$ parameter to 16.

As outlined in [10], the LBMHI algorithm achieves results that are comparable with the other state-of-the-art approaches. In addition, it provides an interesting trade-off between compression performance and computational complexity.

Table 4. Experimental results by the LMBHI algorithm for each hyperspectral image, with the $N$ parameter equals to 8 (the results are reported in term of PSNR).

| Hyperspectral Image | Average BPP $N = 8$, $B = 1$ | Average BPP $N = 8$, $B = 2$ | Average BPP $N = 8$, $B = 3$ |
|---------------------|-------------------------------|-------------------------------|-------------------------------|
| Cuprite             | 5.0165                        | 4.9886                        | 5.3947                        |
| Jasper Ridge        | 5.0722                        | 5.0271                        | 5.0870                        |
| Low Altitude        | 5.3442                        | 5.2995                        | 5.3947                        |
| Lunar Lake          | 5.0207                        | 4.9796                        | 5.1117                        |
| Moffett Field       | 5.1012                        | 5.0313                        | 5.1173                        |

Table 5. Experimental results by the LMBHI algorithm for each hyperspectral image, with the $N$ parameter equals to 16 (the results are reported in term of PSNR).

| Hyperspectral Image | Average BPP $N = 16$, $B = 1$ | Average BPP $N = 16$, $B = 2$ | Average BPP $N = 16$, $B = 3$ |
|---------------------|-------------------------------|-------------------------------|-------------------------------|
| Cuprite             | 4.9835                        | 4.8958                        | 4.9091                        |
| Jasper Ridge        | 5.0682                        | 4.9535                        | 4.9552                        |
| Low Altitude        | 5.3293                        | 5.2166                        | 5.2239                        |
| Lunar Lake          | 4.9875                        | 4.8850                        | 4.8923                        |
| Moffett Field       | 5.0997                        | 4.9594                        | 4.9522                        |

5. Conclusions

Hyperspectral images are often used for sensitive applications (e.g., geoscience or military applications) and their acquisition is onerous and expensive. Therefore, it is important to ensure their protection and to guarantee the inalterability of these data.

In this paper, we have proposed a novel framework for the secure and efficient transmission of hyperspectral images. Our approach combines the reversible invisible watermarking scheme (outlined in Section 3.1) and the Lossless MultiBand compression for Hyperspectral Images algorithm (outlined in Section 3.2).

Future works will consider the possible design of a hybrid approach which provides protection and compression at the same time, and the extension of the proposed framework to other typologies of 3-D data: e.g., 3-D medical images (see [12]), etc.

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