Survey on Hyperspectral Image Denoising

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Abstract: *In image processing noisy images cause harmful effect on subsequent application and degrade visual quality of their particular views. The term denoising refers to method of estimating the unknown (original) signal from available noisy data. Hyperspectral imaging has been proved that it has many applications in agriculture, diagnostic medicine, and military surveillance. However, in these applications, the presence of the noise decreases significantly the classification accuracy by blurring the boundaries of objects of interest and affects the accurate determination of irregularly occurring end members. HSI denoising is very important preprocessing step before these images/data are analyzed. This paper is analyzing some techniques of hyperspectral image denoising and shows their performance in reducing noise. This paper describes various approaches to achieve better hyperspectral image denoising in some depth.*

Keywords: Hyperspectral image (HSI) denoising, low rank, sparse representation, total variation.

1. Introduction

One of the most important problems of image processing is denoising, the reconstruction of the original image from a noisy image. In our day to day life applications digital images plays an important role such as satellite television, magnetic resonance imaging, computer tomography as well as in areas of research and technology such as geographical information systems and astronomy. It also useful in many applications such as environmental modeling and assessment for Earth-based and atmospheric studies, risk/hazard prevention and response including wild land fire tracking, biological threat detection, monitoring of oil spills and other types of chemical contamination, target detection for military and defense/security purposes, urban planning and management studies, etc.. In these application data sets collected by image sensors are generally contaminated by noise. For this, sometimes imperfect instruments are responsible. Imperfect instruments, problems with the data acquisition process, and interfering natural phenomena can all degrade the data of interest and noise can be entered in images. Furthermore, noise can be introduced by transmission errors and compression. Thus, denoising is often a necessary and the first step to be taken before the images data is analyzed. Due to large amount of raw data generated by these sensors there should be some techniques is necessary to minimize human workload and achieve optimal result. It is necessary to apply an efficient denoising technique to compensate for such data corruption.

Hyperspectral imaging also know as image spectrometry, this is now familiar concept in remote sensing world. These images are spectrally over determined, they provide ample spectral information to identify and distinguish between spectrally similar (but unique) materials. Consequently, hyperspectral imagery provides the potential for more accurate and detailed information extraction than is possible with other types of remotely sensed data. This hyperspectral data provides normally contiguous or noncontiguous 10-nm bands throughout the 400-2500-nm region of the electromagnetic spectrum. These images look like a being stacked on top of each other, creating as an image cube. This creates a pixel vector; the vector can be used to distinguish one material from another. A Hyperspectral image contains wealth of data which essential should acquired accurate as possible. But interpreting them requires an understanding of exactly what properties of ground materials we are trying to measure, and how they relate to the measurements actually made by the hyperspectral sensor. So a hyperspectral image denoising is an important problem.

Hyperspectral remote sensing is use for measurement, analysis and interpretation of spectral information provided by specific object or scenes from remote distance by an airborne or satellite sensor or hyperspectral imaging instruments.

To achieve hyperspectral image denoising some techniques are employed to get better and improved image denoising as close to as original image. These techniques are for example: an HSI was treated as a hypercube in order to take into account the correlation among different bands [13]; tensor-algebra was brought to jointly analyze the 3D HSI, PCA (principle component analysis) for inter-band correlation and dimensionally reduction [14] , a combination of spatial and spectral wavelet shrinkage used to catch dissimilarity of signal nature in spatial and spectral dimensions [9]. Some methods achieve denoising with transforming each band HRSI into curvelet domain [15]. A noise reduced HSI can obtain by[16] combining the rank-1 tensors using an eigenvalue intensity sorting and reconstruction technique and some methods focus on spatial and spectral correlation and sparse approximation[2]-[3] etc.

In recent few years, different denoising methods have been proposed. This paper study and presents a review of some significant work in the area of hyperspectral image denoising. Insights and potential future trends in the area of hyperspectral image denoising are also discussed.

2. Literature Survey

The simplest way of HSI denoising is to utilize traditional 2-D or 1-D denoising methods to reduce noise in HSI band by band or pixel by pixel. But this method does not give accurate result (close to actual images) it only removes spatial or spectral domain noise. Thus artifacts and distortion can introduce in other domain and these kinds of methods destroy the correlation in spatial or spectral domain.

In paper[1] it proposed a spectral and spatial adaptive total variation (TV)denoising method, it suggest that noise intensity is different in band by band or can say variation in noise intensity band by band, so there should be different technique or the denoising strength should be adjust with variation in noise intensity in different bands. But as we know in HSI there exists different spatial property with respect to color, edge and texture forms. So to remove these type of variation in noise here a hyperspectral image denoising algorithm employing a spectral–spatial adaptive total variation (TV) model is used, it deals with the spectral noise differences and spatial information differences in process on reducing noise. Thus it enforces the spatial smoothness and spatial discontinuity.

A hyperspectral image is usually viewed from the front, which is the spatial view. However, a hyperspectral image, if viewed from the side direction, will also have a spectral view. For a hyperspectral image, noise not only exists in the spatial view but also in the spectral view. In most hyperspectral image denoising methods, the hyperspectral image is just denoised from the spatial view, ignoring the role of the spectral view so result is that some noise remains present in those denoising methods. Therefore, in [2] paper, it proposes a spatial–spectral view fusion algorithm for hyperspectral image denoising. A noisy hyperspectral image is first denoised using the hyperspectral total variation (TV) [1] approach proposed in previous work, from both the spatial and spectral views, and then the denoising results of the two views are fused using a metric *Q*-weighting strategy.

In paper [3], author proposes an HSI denoising algorithm by utilizing the local and global RAC in spatial and spectral domains jointly to reduce noise. After studying the characteristics of HSI it represented data representation scheme to capture local and global RAC in spatial and spectral domain in sparse representation framework. Sparse coding called for modeling data vectors as a linear combination of a few elements from a dictionary. A critical component in this approach is how to sparsely encode a signal given the dictionary. Taking image patches from continuous spectral bands it then approximated by dictionary learned from the noisy HSI. Global RAC in the spectral domain is utilized by the regularization of low rank. It suggest reasons for incorporating low rank constraint as an additional regularization term as sometimes spectral distortion will introduced in global RAC to reduce this proper regularization of low rank which make ill-posed denoising problem solvable. The low rank of HSI is in is helpful to reduce error by enforcing low rank on the denoised data, which is introduced in the process of sparse coding and dictionary learning.

With considering hyperspectral image cube as whole integrity a cubic total variation (CTV) model [4], it considers both features of 2-D total variation model for spatial domain with the 1-D total variation model for spectral domain. For improving image denoising augmented lagrangian method is utilized to get the desired result.

Although state-of-the-art denoising methods are numerically impressive and approach theoretical limits, they suffer from visible artifacts. While they produce acceptable results for natural images, human eyes are less forgiving when viewing synthetic images. At the same time, current methods are becoming more complex, making analysis and implementation difficult. In [5] propose image denoising as a simple physical process, which progressively reduces noise by deterministic annealing. The results of implementation are numerically and visually excellent. It further demonstrates that our method is particularly suited for synthetic images. Finally, offer a new perspective on image denoising using robust estimators. This method produces high-quality results, void of artifacts typical to patch based methods. It performs not only well for natural images, but also for synthetic images where artifacts are more apparent. It is also of practical interest that algorithm is unusually short, fitting into a column of this paper.

To maintain image details in low-noise-level case, where noise intensity is low , the noise in the spectral domain was increased by using spectral derivative, and then, wavelet-based spatial and spectral denoising was implemented [9].In this method it also focuses on correlation among spatial and spectral dimensions.

Some denoising methods rearrange the HSI data 3-D to 2-D data and ignores the spectral relationship in different bands of images. A hyperspectral image (HSI) is always modeled as a three-dimensional tensor, with the first two dimensions indicating the spatial domain and the third dimension indicating the spectral domain. The tensor decomposition method has been adopted to denoise hyperspectral image, for instance Tucker3 called three-mode factor analysis model. This type of model has problem with uniqueness of decomposition and in multiple ranks estimation. To overcome this problem [8] introduces a powerful multi-linear algebra model, named parallel factor analysis (PARAFAC), and thus number of estimated rank is reduced to one.

3. Comparative Study/Analysis

Hyperspectral Denoising Model can be can be written as

$$f = u + n \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \text{(1)}$$

where $u = [u_1, u_2, \ldots, u_j, \ldots, u_B]$ is the clear/noise-free hyperspectral image, with the size $M \times N \times B$, in which M represents the samples of each band in the whole image, N stands for the lines of the image, and B is the number of bands. $f = [f_1, f_2, \ldots, f_j, \ldots, f_B]$ is the noise degradation image, which is also of size $M \times N \times B$, and $n = [n_1, n_2, \ldots, n_j, \ldots, n_B]$ is the additive noise with the same size as u and f.

This model represented as the regularization-based problem as

$$\hat{u} = \arg\min\{\sum_{j=1}^{B}\|u_j - f_j\|_2^2 + \lambda R(u)\} \quad \ldots\ldots\ldots\text{(2)}$$

$\sum_{j=1}^{B}\|u_j - f_j\|_2^2$ is the data fidelity term which stands for the fidelity between the observed noisy image and the original clear image, and $R(u)$ is the regularization item, which gives a prior model of the original clear hyperspectral image u, λ is the regularization parameter, which controls the relative contribution between the data fidelity and the regularization item. Below are some methods which are explained in some details.

A) A spectral–spatial adaptive total variation (TV) model

For a gray-level image u, the TV model is defined as follows:

$$R(u) = TV(u) = \sum_i \sqrt{(\nabla^h_i u)^2 + (\nabla^v_i u)^2} \; \ldots\ldots (3)$$

where ∇^h_i and ∇^v_i are linear operators corresponding to the horizontal and vertical first-order differences, respectively, at pixel i. $\nabla^h_i u = u_i - u_{r(i)}$ and $\nabla^v_i u = u_i - u_{b(i)}$, where $r(i)$ and $b(i)$ represent the nearest neighbors to the right of and below the pixel.

$$HTV_1(u) = \sum^{MN}_{i=1} \sqrt{\sum^{B}_{j=1} (\nabla_{ij} u)^2} \ldots\ldots\ldots\ldots\ldots\ldots (4)$$
$$SSAHTV_2(u) = \sum^{MN}_{i=1} W_i \sqrt{\sum^{B}_{j=1} (\nabla_{ij} u)^2} \ldots\ldots\ldots (5)$$
$$G = \sqrt{\sum^{B}_{j=1} (\nabla u_j)^2} \;\; ; \tau_i = 1/(1 + \mu G_i)$$
$$W_i = \tau_i / \check{\tau} \;\; ; \check{\tau} = (\sum^{MN}_{i=1} \tau_i)/MN \ldots\ldots\ldots\ldots\ldots (6)$$

Here MN is the total number of pixels in one hyperspectral band, and B is the total number of bands. ∇_{ij} is linear operators corresponding to the first-order differences at the i^{th} pixel in the j^{th} band, respectively. ∇u_j is the gradient map of the j^{th} band. G means the gradient information of every band is added together and the square root is taken of each element of the sum. W_i is a weighting parameter to control the regularization strength in the different pixels. The first model in (4) is called the spectral adaptive hyperspectral TV model, which can shows a consideration to the noise distribution characteristic of the hyperspectral image and automatically adjust/or adopt the denoising strength in different spectral bands with the noise intensity. Noise intensity differs band by band as variation in intensity. So in higher noise intensity bands, a strong denoising strength will be used, while in low noise intensity bands a weak strength will be used. The second model in (5) is called the spectral–spatial adaptive TV model, which can not only adaptively adjust the denoising strength in the different spectral bands, in the same way as the spectral adaptive model, but it can also constrain the denoising strength in different pixels, with the help of the spatial information parameter Wi. For the pixels in flat regions, strong regularization strength is enforced to suppress noise and, conversely, weak regularization strength is enforced on the edge pixels to preserve them. With SSAHTV model, final denoising model is written as

$$\hat{u} = \arg\min \{ \sum^{B}_{j=1} \|u_j - f_j\|^2_2 + \lambda \sum^{MN}_{i=1} W_i \sqrt{(\sum^{B}_{j=1} (\nabla_{ij} u))^2} \} \ldots (7)$$

B) Spatial–Spectral View Fusion Strategy

Denoising model for Spatial Spectral View denoising *as*

Spatial view denoising

$$\hat{u}^{spa} = \arg\min \{ \sum^{B}_{j=1} \|u^{spa}_j - f^{spa}_j\|^2_2 + \lambda \sum^{MN}_{i=1} W_i \sqrt{(\sum^{B}_{j=1} (\nabla_{ij} u^{spa}))^2} \} \ldots (8)$$

Spectral view denoising

$$\hat{u}^{spe} = \arg\min \{ \sum^{B}_{j=1} \|u^{spe}_j - f^{spe}_j\|^2_2 + \lambda \sum^{MN}_{i=1} W_i \sqrt{(\sum^{B}_{j=1} (\nabla_{ij} u^{spe}))^2} \} \ldots (9)$$

In the above two equations, u^{spa} and f^{spa} are the clear and noisy images in the spatial views, u^{spe} and f^{spe} are the clear and noisy images in the spectral views, B is the band number, and j means the j^{th} band. The two models are both optimized with the split Bregman method in this.

Analysis of the complementary nature of spatial and spectral view, it is difficult to make fusion of these two views with each other for denoising . So this technique uses a blind image quality matrix Q as

$$Q = s1((s1 - s2)/(s1 + s2)) \ldots\ldots (10)$$

Where s1 and s2, respectively singular values of the gradient matrix G over N × N window (w_i) and G as

$$G = \begin{bmatrix} \vdots & \vdots \\ p_x(k) & p_y(k) \\ \vdots & \vdots \end{bmatrix} \quad k \in w_i$$

where k denotes the k^{th} pixel in the window w_i .The denoised result from spatial view $\hat{u}^{spa} = [\hat{u}^{spa}_1, \hat{u}^{spa}_2, \hat{u}^{spa}_3, \ldots, \hat{u}^{spa}_B]$ as and denoised result from spectral view

$\hat{u}^{spe} = [\hat{u}^{spe}_1, \hat{u}^{spe}_2, \hat{u}^{spe}_3, \ldots, \hat{u}^{spe}_B]$ It compute value of Q as

$$Q^{spa} = [Q^{spa}_1, Q^{spa}_2, Q^{spa}_3, \ldots, Q^{spa}_B] \ldots\ldots\ldots (11)$$

$$Q^{spe} = [Q^{spe}_1, Q^{spe}_2, Q^{spe}_3, \ldots, Q^{spe}_B] \ldots\ldots\ldots (12)$$

The final denoising result is then obtained by applying the metric Q weighted fusion strategy to the two denoising results of the different views can be expressed as

$$\hat{u}_j = (Q^{spa} \hat{u}^{spa}_j + Q^{spe} \hat{u}^{spe}_j)/(Q^{spa} + Q^{spe}) \ldots\ldots\ldots (13)$$

C) Sparse representation and low rank constraint method

Many researchers suggested that sparsity of wavelet coefficient can gives good result in image denoising. In sparse representation technique signal can be represented by some atoms but noise cannot be represented by atoms and with the help of dictionary learning noise can be remove in some limits. In sparse representation images can be represented by using fixed bases, such as discrete cosine transform or wavelet bases or using atoms of dictionary learning. Sparse coding called for modeling data vectors as a linear combination of a few elements from a dictionary. A critical component in this approach is how to sparsely encode a signal given the dictionary. So this focuses on sparse representation it mentioned $X \approx D\alpha$, X as noise free image, D as dictionary, α as coefficient close to 0, D can be estimated as from noisy image Y by L_0 minimization problem

$$\{D, \hat{\alpha}\} = \arg\min_{D,\alpha} \|Y - D\alpha\|^2_2 + \eta\|\alpha\|_0 \ldots\ldots\ldots (14)$$

Parameter η controls the tradeoff between data fitting term and sparsity term, it obtain D and $\hat{\alpha}$, X can be $X = D\hat{\alpha}$.

L_0-minimization is an NP hard combinatorial search problem, and it is usually solved by greedy algorithms. The L_1-minimization, as the closest convex function to $L0$-minimization, is then widely used as an alternative approach to solving the $L0$-minimization problem

$$\{D, \hat{\alpha}\} = \arg\min_{D,\alpha} \|Y - D\alpha\|^2_2 + \eta\|\alpha\|_1 \ldots\ldots\ldots (15)$$

L1 norm defines the sum of elements absolute value and it is convex function. With the replacement of L_0 to L_1 norm uniqueness of solution generated.

In this method rank analysis also analyzed with clean and noisy images, here HSI follows the linear mixture model such as

$$X = AS \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (16)$$

Where $X \in \mathbb{R}^{MN \times L}$ is the HSI. $S \in \mathbb{R}^{P \times L}$ is the end member matrix $S = [s_1, s_2, \ldots, s_P]T$, $s_i \in \mathbb{R}^L$. $A \in \mathbb{R}^{MN \times P}$ is the abundance matrix, and element $a_{i,j}$ denotes the fractional abundance of the j^{th} end member for spectral response in the i^{th} pixel.

Rank of Y satisfies ;

$$rank(Y) \geq rank(W) - rank(X) \approx rank(W) >> rank(X) \ldots. (17)$$

Here rank of noise component W is

$$rank(W) = \min(MN, L) >> (rank(X))$$

It stated that rank of noisy signal is too small than the size of HSI and it suggest that low rank is reasonable point for noise free HSI.

The denoising objective function for HSI in sparse representation framework can be represented as given as:

$$\{X, D, \alpha_i\} = \arg\min_{D,X,\alpha_i} \gamma\|X - Y\|^2_2 + \sum_i \|R_i X - D\alpha_i\|^2_2 + \sum_i \eta_i \|\alpha_i\|_0 \ldots\ldots (18)$$

Where X *is* noise-free, $Y \in \mathbb{R}^{M \times N \times L}$ is noisy HSIs, respectively. R_i is the operator that extracts i^{th} overlapping patch $R_i X$ from X. The first term in (18) is the data fidelity term, of which weight γ depends on the variance of noise. This term helps to remove visible artifacts on patch boundaries. The second and third terms indicate that every patch of HSI could be represented linearly with small error using few atoms in dictionary *D*. It stated that denoising performance can be increases if global RAC is used and rank of noise-free HSI expected to be low. By considering global restriction in the spectral domain, (18) can be modified as

$\{X,D, \alpha i\} = \arg\min_{D,X,\alpha i} \gamma\|X - Y\|_2^2 + \sum_i \|R_i X - D\alpha_i\|_2^2 + \sum_i \eta\|\alpha_i\|_0 + \mu \mathrm{Rank}(X)$ ……(19)

Thus objective function can be written as

$\{X,D, \alpha i\} = \arg\min_{D,X,\alpha i} \gamma\|X - Y\|_2^2 + \sum_i \|R_i X - D\alpha_i\|_2^2 + \sum_i \eta\|\alpha_i\|_0 + \mu\|X\|_*$……………(20)

where $\|.\|_*$ denotes the nuclear norm. The solution *X* in (20) is the result of recovered noise-free HSI.

D) Cubic Total Variation (CTV) Model

The standard TV model for gray-level image looks like

$$R(v)=\sum_{m=1}^{M} \sqrt{(\nabla_x v_m)^2+(\nabla_y v_m)^2} \quad \ldots(21)$$

where ∇x and ∇y represent the gradient operators of the horizontal and vertical directions, and *M* is the total number of pixels in gray-level image *v*.

$$R(u_{b,:})=\sum_{m=1}^{M} \sqrt{(\nabla_x u_{b,m})^2+(\nabla_y u_{bm})^2} \quad \ldots(22)$$

where *b*,: ***u*** represents the b^{th} band of hyperspectral image ***u*** , *B* is the number of bands of hyperspectral image,
and M Represents total no. of pixels in band b, $R(u_{b,:})$ represents the standard TV model for the b^{th} band of hyperspectral image:

The 1-D TV model for the m^{th} pixel of the hyperspectral image can be written as:

$$R(u_{:,m})=\sum_{b=1}^{B} |\nabla_z u_{b,m}| \quad \ldots(23)$$

Cubic total variation model for

$$R_c(u)=\sum_{b=1}^{B} R_c(u_{b,:})$$

$$R_c(u_{b,:})=\sum_{m=1}^{M} \sqrt{(\nabla_x u_{b,m})^2+(\nabla_y u_{bm})^2+\beta(\nabla_z u_{b,m})^2} \ldots(24)$$

Here β represents the weight of spectral dimension relative spatial domain and based on the MAP estimation theory, the denoising model for a hyperspectral image can be represented as the following constrained least squares problem as

$\hat{u} = \arg\min_u \|g-u\|_2^2 + \lambda R(u)$

by (24) cost function will get as

$\hat{u} = \arg\min_u \|g-u\|_2^2 + \lambda \sum_{b=1}^{B} R_c(u_{b,:})$………(25)

The desired hyperspectral image can be solved by optimizing the cost function with Lagrangian method to improve speed of the method.

4. Discussion

Performance of HSI denoising is measured in quantative assessing indexes**.** The assessing indexes normally used are peak signal-to-noise ratio (PSNR), signal to noise ratio (SNR), structural similarity index measurement (SSIM) and feature similarity index measurement (FSIM), in term to visual or analytical quality of images to measure performance of denoising methods using quantitative performance measures. In ideal case of denoising priori knowledge of the noise should know and in practical situation variance of noise information not known. It is critical to reduce the noise in hyperspectral image and improve its quality.

In the [1] SSAHTV model, PSNR and SSIM indices use for performance evaluation, these values are calculated between each clear band and denoised band then averaged them .This methods gives the better result in the edge information are well preserved and shows the noise robustness, but it has computational time slightly longer than other previous methods.

In fusion [2] model it uses merging of spatial and spectral views denoising . Here same for hyperspectral image, compute the PSNR and SSIM values between each clear band and denoised band, and then average them. For calculating spectral fidelity of denoising result, the mean spectral angle (MSA) index is also used. Regularization parameter λ adjusted until better result is arrived. This shows that it gives better result than single-view denoising. This method gives better result than SSAHTV model in terms of PSNR values.

The Spa+Lr(sparse representation and low rank constraint) [3] method stated that if sparsly representation data can minimize noise and it focuses on spectral and spatial correlation among different domain. This scheme uses image patches of few continues spectral band for dictionary learning from noisy data. It uses SVM as classifier and overall accuracy as utilization index. Then low rank used for eliminating distortion from global RAC (redundancy and correlation), proper utilization made for improving performance. The analysis of method shows the overall complexity $O(MNL^2 + MNL + L)$. Assessing indices MPSNR, MSSIM, MFSIM calculated for images on different spectral bands. This method show that it reduces noise than individual sparse representation and low rank method and the experiment result shows that it achieves competitive performance than other state of art methods. But in heavy noise situation denoising performance may decrease so some improvement in this section it will be its future work.

CTV model [4] combines advantage of the 2-D total variation model for spatial domain with the 1-D total variation model for spectral domain to achieve HSI denoising. It considers HSI image as whole integrity as a hyperspectral image cube for implementation of HSI denoising. CTV model gives better result in the HSI denoising method with the traditional band-by-band TV model.

5. Conclusion

The paper presents the analysis of some hyperspectral image denoising techniques and shows their performances in reducing noise.

In SSAHTV[1] model spectral and spatial noise distribution between different bands are considered and with focusing on spatial information difference between different pixels are considered, this control denoising strength between different band and different spatial properties and adjust the strength across the bands. In this model if consider the gradient aspect in spectral dimension it can use 3d segmentation or clustering result to constraint the denoising problem in particular patch region perceptive.

The spatial-spectral fusion model [2] uses a TV model for spatial and spectral views and then both are fused together with Q-weighting method, this gives better result when individual spatial and spectral views are denoised. This method can further improved for signal dependent noise type.

The method of denoising[3] via sparse representation and low rank constraint suggest that if images can be sparsely represented then it can easily suppress noise with images .to avoid large spectral distortion global RAC in spectral dimension low rank constraint has been added as regularization in this model. The rank of noise-free HSI data is should be low to because there is high RAC among different bands, while rank should be full if there is more noise in HSI data. This technique is not suitable for higher noisy data, whenever noise increases its performance decreases.

CTV[4] model consider HSI image as whole integrity as a hyperspectral image cube, considering its 3-D dimension image denoising performed in spatial and spectral view. The augmented Lagrangian method is utilized to improve the speed of this model to get desired hyperspectral image.

Thus this paper gives review of some significant work in the area of hyperspectral image denoising. Insights and potential future trends in the area of hyperspectral denoising are also discussed.

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