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Dictionary Learning Based Image Deblurring Using Sparse Domain

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Abstract: *Image Restoration Involves Extraction Of A High Quality Image Out Of Degraded Version Of The Same Image. Nowadays, The Image Restoration Is Being Done On A Domain Which Is Completely Different Domain, Which Is Not Either Spatial Or Frequency. The Domain Involves The Similarity Measure Of The Input Degraded Image With A Set Of Image Patches. These Image Patches Can Be Thought Of As The Atoms Of Particle Constituting A Complete Physical Object. This Domain Is Referred To As Sparse Representation. In This Paper, The Sparse Domain Scheme Is Used To Perform Image Deblurring. In Addition To The Proposal Of Sparse Domain, A Method To Select Adaptively, One Set Of Bases To Characterize The Local Sparse Domain. Two Kinds Of Blurs Are Considered, Uniform And Gaussian. Psnr And Ssim Values Calculated Show That The Proposed Scheme Performs Well Compared To Many Existing Methods.*

Keywords*-Dictionary Learning, Image Deblurring, Image Restoration, Sparse Representation.*

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I. INTRODUCTION

The Objective Of Image Restoration Is To Retrieve A Quality Image $\boldsymbol{X}$ From Its Degraded Version $\boldsymbol{Y}$. Image Restoration Is Typically An Ill-Posed Inverse Problem And It Is Modeled As

$$\boldsymbol{Y}=\boldsymbol{Dhx} + V, \quad (1)$$

Here $\boldsymbol{X}$ Is The Image To Be Estimated, $\boldsymbol{H}$ And $\boldsymbol{D}$ Are Degrading Operators And V Is Additive Noise. When $\boldsymbol{H}$ And $\boldsymbol{D}$ Are Identities, The Restoration Problem Becomes Denoising; When $\boldsymbol{D}$ Is Identity And $\boldsymbol{H}$ Is A Blurring Operator, The Restoration Becomes Deblurring; When $\boldsymbol{D}$ Is Identity And $\boldsymbol{H}$ Is A Set Of Random Projections, Restoration Becomes Compressed Sensing [1-3]; When $\boldsymbol{D}$ Is A Down-Sampling Operator And $\boldsymbol{H}$ Is A Blurring Operator, The Restoration Becomes Super-Resolution. As The Restoration Is A Fundamental Problem In Image Processing, It Has Been Extensively Studied In The Past Three And Half Decades [3-8]. This Paper Focus On Deblurring Which Is Crucial In Many Practical Applications. Due To The Ill-Posed Nature Of Restoration, The Solution To Eq. (1) With An L_2-Norm Fidelity Constraint, I.E.,

$$\hat{x} = \underset{x}{\arg\min} \|y - DHx\|_2^2$$

Is Generally Not Unique. To Find A Better Solution, Prior Knowledge Of Natural Images Can Be Used To Regularize The Restoration Problem. One Of The Most Commonly Used Regularization Models Is The Total Variation (Tv) Model [9]:

$$\hat{x} = \underset{x}{\arg\min} \left\{ \|y - DHx\|_2^2 + \lambda . |\nabla x|_1 \right\},$$

Where $|\nabla \boldsymbol{X}|_1$ Is The L_1-Norm Of The First Order Derivative Of $\boldsymbol{X}$ And Λ Is A Constant. Since The Tv Model Favors The Piecewise Constant Image Structures, It Tends To Smooth Out The Fine Details Of An Image. To Better Preserve The Image Edges, Many Algorithms Have Been Later Developed To Improve The Tv Models [10-14]. The Success Of Tv Regularization Validates The Importance Of Good Image Prior Models In Solving The Restoration Problems. In Wavelet Based Image Denoising [15], Researchers Have Found That The Sparsity Of Wavelet Coefficients Can Serve As Good Prior. This Reveals The Fact That Many Types Of Signals, E.G., Natural Images, Can Be Sparsely Represented (Or Coded) Using A Dictionary Of Atoms, Such As Dct Or Wavelet Bases. That Is, Denote By Φ The Dictionary, We Have $\boldsymbol{X} \approx \Phi\alpha$ And Most Of The Coefficients In A Are Close To Zero. A Critical Issue In Sparse Representation Modeling Is The Determination Of Dictionary Φ.

Analytically Designed Dictionaries, Such As Dct, Wavelet, Curvelet And Contourlets, Share The Advantages Of Fast Implementation; However, They Lack The Adaptivity To Image Local Structures. Recently, There Has Been Much Effort In Learning Dictionaries From Example Image Patches [16-17], Leading To State-

Of-The-Art Results In Image Denoising And Reconstruction. Many Dictionary Learning (Dl) Methods Aim At Learning A Universal And Over-Complete Dictionary To Represent Various Image Structures. However, Sparse Decomposition Over A Highly Redundant Dictionary Is Potentially Unstable And Tends To Generate Visual Artifacts [18-19].

In This Paper We Propose An Adaptive Sparse Domain Selection (Asds) Scheme For Sparse Representation. By Learning A Set Of Compact Sub-Dictionaries From High Quality Example Image Patches. The Example Image Patches Are Clustered Into Many Clusters. Since Each Cluster Consists Of Many Patches With Similar Patterns, A Compact Sub-Dictionary Can Be Learned For Each Cluster. Particularly, For Simplicity We Use The Principal Component Analysis (Pca) Technique To Learn The Sub-Dictionaries. For An Image Patch To Be Coded, The Best Sub-Dictionary That Is Most Relevant To The Given Patch Is Selected. Since The Given Patch Can Be Better Represented By The Adaptively Selected Sub-Dictionary, The Whole Image Can Be More Accurately Reconstructed Than Using A Universal Dictionary, Which Will Be Validated By Our Experiments.

II. Sparse Representation With Adaptive Sparse Domain Selection

In This Section We Propose An Adaptive Sparse Domain Selection (Asds) Scheme, Which Learns A Series Of Compact Sub-Dictionaries And Assigns Adaptively Each Local Patch A Sub-Dictionary As The Sparse Domain. With Asds, A Weighted L_1-Norm Sparse Representation Model Will Be Proposed For Restoration Tasks. Suppose That $\{\Phi_k\}$, K=1, 2… K, Is A Set Of K Orthonormal Sub-Dictionaries. Let $\boldsymbol{X}$ Be An Image Vector, And $\boldsymbol{X}_i=\boldsymbol{R}_i\boldsymbol{x}$, I = 1, 2… N, Be The I^{th} Patch (Size: Root (N) × Root (N)) Vector Of $\boldsymbol{X}$, Where $\boldsymbol{R}_i$is A Matrix Extracting Patch $\boldsymbol{X}_i$from $\boldsymbol{X}$. For Patch $\boldsymbol{X}_i$, Suppose That A Sub-Dictionary, Φ_k Is Selected For It. Then, $\boldsymbol{X}_i$can Be Approximated As $\hat{x}_i = \Phi_{k_i}\alpha_i, \|\alpha_i\|_1 \le T$, Via Sparse Coding. The Whole Image $\boldsymbol{X}$ Can Be Reconstructed By Averaging All The Reconstructed Patches $\hat{x}_i$, Which Can Be Mathematically Written As [20]

$$\hat{x} = \left(\sum_{i=1}^{N} R_i^T R_i\right)^{-1} \sum_{i=1}^{N} R^T{}_i \Phi_{k_i}\alpha_i \tag{2}$$

In Eq. (2), The Matrix To Be Inverted Is A Diagonal Matrix, And Hence The Calculation Of Eq. (2) Can Be Done In A Pixel-By-Pixel Manner [20]. Obviously, The Image Patches Can Be Overlapped To Better Suppress Noise [20, 21] And Block Artifacts. For The Convenience Of Expression, We Define The Following Operator "O":

$$\hat{x} = \Phi\ o\ \alpha \equiv \left(\sum_{i=1}^{N} R_i^T R_i\right)^{-1} \sum_{i=1}^{N} R^T{}_i \Phi_{k_i}\alpha_i \tag{3}$$

Where Φ Is The Concatenation Of All Sub-Dictionaries $\{\Phi_k\}$ And Α Is The Concatenation Of All $Α_i$. Let $\boldsymbol{Y} = \boldsymbol{Dhx} + \boldsymbol{V}$ Be The Observed Degraded Image, Our Goal Is To Recover The Original Image $\boldsymbol{X}$ From $\boldsymbol{Y}$. With Asds And The Definition In Eq. (3), The Ir Problem Can Be Formulated As Follows:

$$\hat{\alpha} = \underset{\alpha}{\arg\min} \left\{ \|y - DH\Phi\ o\ \alpha\|_2^2 + \lambda\|\alpha\|_1 \right\} \tag{4}$$

Clearly, One Key Procedure In The Proposed Asds Scheme Is The Determination Of Φ_k, For Each Local Patch.To Facilitate The Sparsity-Based Ir, We Propose To Learn Offline The Sub-Dictionaries $\{\Phi_k\}$, And Select Online From $\{\Phi_k\}$ The Best Fitted Sub-Dictionary To Each Patch $\boldsymbol{X}_i$.In Order To Learn A Series Of Sub-Dictionaries To Code The Various Local Image Structures, We Need To First Construct A Dataset Of Local Image Patches For Training. To This End, We Collected A Set Of High-Quality Natural Images, And Cropped From Them A Rich Amount Of Image Patches With Size Root(N) × Root(N) . A Cropped Image Patch, Denoted By $\boldsymbol{S}i$, Will Be Involved In Dl If Its Intensity Variance $Var(\boldsymbol{S}_i)$ Is Greater Than A Threshold Δ, I.E., $Var(\boldsymbol{S}_i) > \Delta$. This Patch Selection Criterion Is To Exclude The Smooth Patches From Training And Guarantee That Only The Meaningful Patches With A Certain Amount Of Edge Structures Are Involved In Dl. Suppose That M Image Patches $\boldsymbol{S}=[\boldsymbol{S}_1, \boldsymbol{S}_2, \ldots, \boldsymbol{S}_m]$ Are Selected.

We Aim To Learn K Compact Sub-Dictionaries $\{\Phi_k\}$ From $\boldsymbol{S}$ So That For Each Given Local Image Patch, The Most Suitable Sub-Dictionary Can Be Selected. To This End, We Cluster The Dataset $\boldsymbol{S}$ Into K Clusters, And Learn A Sub-Dictionary From Each Of The K Clusters.Apparently, The K Clusters Are Expected To Represent The K Distinctive Patterns In $\boldsymbol{S}$. To Generate Perceptually Meaningful Clusters, We Perform The Clustering In A Feature Space. In The Hundreds Of Thousands Patches Cropped From The Training Images, Many Patches Are Approximately The Rotated Version Of The Others. Hence We Do Not Need To Explicitly Make The Training Dataset Invariant To Rotation Because It Is Naturally (Nearly) Rotation Invariant. Considering The Fact That Human Visual System Is Sensitive To Image Edges, Which Convey Most Of The

Semantic Information Of An Image, We Use The High-Pass Filtering Output Of Each Patch As The Feature For Clustering. It Allows Us To Focus On The Edges And Structures Of Image Patches, And Helps To Increase The Accuracy Of Clustering. The High-Pass Filtering Is Often Used In Low-Level Statistical Learning Tasks To Enhance The Meaningful Features [22].

Denote By $S_h = \left[s_1^h, s_2^h, ..., s_M^h\right]$ The High-Pass Filtered Dataset Of ***S***. We Adopt The *K*-Means Algorithm To Partition $\boldsymbol{S}_h$into *K* Clusters $\{C_1, C_2, C_3, \dots, C_k\}$ And Denote By *K* The Centroid Of Cluster $\boldsymbol{C}_k$. Once $\boldsymbol{S}_h$is Partitioned, Dataset ***S*** Can Then Be Clustered Into *K* Subsets $\boldsymbol{S}_k$, *K*=1, 2… *K*, And $\boldsymbol{S}_k$is A Matrix Of Dimension $N\times M_k$, Where $M_k$denotes The Number Of Samples In $\boldsymbol{S}_k$. Now The Remaining Problem Is How To Learn A Sub-Dictionary *K* From The Cluster $\boldsymbol{S}_k$such That All The Elements In $\boldsymbol{S}_k$can Be Faithfully Represented By Φ_k. Meanwhile, We Hope That The Representation Of $\boldsymbol{S}_k$over $\Phi_k$is As Sparse As Possible. The Design Of $\Phi_k$can Be Intuitively Formulated By The Following Objective Function:

$$\left(\hat{\Phi}_k, \hat{\Lambda}_k\right) = \underset{\Phi_k, \Lambda_k}{\arg\min} \left\{ \left\| S_k - \Phi_k \Lambda_k \right\|_F^2 + \lambda \left\| \Lambda_k \right\|_1 \right\} \tag{5}$$

Where $\Lambda_k$is The Representation Coefficient Matrix Of $\boldsymbol{S}_k$over Φ_k. Eq. (5) Is A Joint Optimization Problem Of $\Phi_k$and Λ_k, And It Can Be Solved By Alternatively Optimizing $\Phi_k$and Λ_k, Like In The K-Svd Algorithm [23].

However, We Do Not Directly Use Eq. (5) To Learn The Sub-Dictionary $\Phi_k$based On The Following Considerations. First, The L_2-L_1 Joint Minimization In Eq. (5) Requires Much Computational Cost. Second And More Importantly, By Using The Objective Function In Eq. (5) We Often Assume That The Dictionary $\Phi_k$is Over-Complete. Nonetheless, Here $\boldsymbol{S}_k$is A Sub-Dataset After *K*-Means Clustering, Which Implies That Not Only The Number Of Elements In $\boldsymbol{S}_k$is Limited, But Also These Elements Tend To Have Similar Patterns. Therefore, It Is Not Necessary To Learn An Over-Complete Dictionary $\Phi_k$from $\boldsymbol{S}_k$. In Addition, A Compact Dictionary Will Decrease Much The Computational Cost Of The Sparse Coding Of A Given Image Patch. With The Above Considerations, We Propose To Learn A Compact Dictionary While Trying To Approximate Eq. (5). The Principal Component Analysis (Pca) Is A Good Solution To This End.

Pca Is A Classical Signal De-Correlation And Dimensionality Reduction Technique That Is Widely Used In Pattern Recognition And Statistical Signal Processing [24]. In [25], Pca Has Been Successfully Used In Spatially Adaptive Image Denoising By Computing The Local Pca Transform Of Each Image Patch. In This Paper We Apply Pca To Each Sub-Dataset $\boldsymbol{S}_k$to Compute The Principal Components, From Which The Dictionary $\Phi_k$is Constructed. Denote By $\Omega_k$the Co-Variance Matrix Of Dataset $\boldsymbol{S}_k$. By Applying Pca To Ω_k, An Orthogonal Transformation Matrix $\boldsymbol{P}_k$can Be Obtained. If We Set $\boldsymbol{P}_k$as The Dictionary And Let $\boldsymbol{Z}_k = \boldsymbol{P}_k^t \boldsymbol{s}_k$, We Will Then Have $\left\| S_k - P_k Z_k \right\|_F^2 = \left\| S_k - P_k P_k^T S_k \right\|_F^2 = 0$. In Other Words, The Approximation Term In Eq. (5) Will Be Exactly Zero, Yet The Corresponding Sparsity Regularization Term $\|\boldsymbol{Z}_k\|_1$ Will Have A Certain Amount Because All The Representation Coefficients In $\boldsymbol{Z}_k$are Preserved. To Make A Better Balance Between The L_1-Norm Regularization Term And L_2-Norm Approximation Term In Eq. (5), We Only Extract The First *R* Most Important Eigenvectors In $\boldsymbol{P}_k$to Form A Dictionary Φr, I.E. $\boldsymbol{\Phi r} = [\,\boldsymbol{P}1, \boldsymbol{P}2, ..., \boldsymbol{Pr}\,]$. Let $\boldsymbol{\Lambda_r} = \boldsymbol{\Phi_r}^t \boldsymbol{S_k}$.

Applying The Above Procedures To All The *K* Sub-Datasets $\boldsymbol{S}_k$, We Could Get *K* Sub-Dictionaries Φ_k, Which Will Be Used In The Adaptive Sparse Domain Selection Process Of Each Given Image Patch. In Fig. 1, We Show Some Example Sub-Dictionaries Learned From A Training Dataset. The Left Column Shows The Centroids Of Some Sub-Datasets After *K*-Means Clustering, And The Right Eight Columns Show The First Eight Atoms In The Sub-Dictionaries Learned From The Corresponding Sub-Datasets.

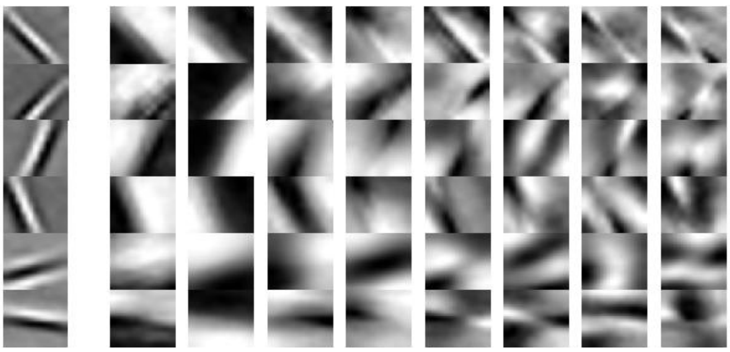

Fig. 1. Examples Of Learned Sub-Dictionaries. The Left Column Shows The Centriods Of Some Sub-Datasets After *K*-Means Clustering, And The Right Eight Columns Show The First Eight Atoms Of The Learned Sub-Dictionaries From The Corresponding Sub-Datasets.

So Far, We Have Learned A Dictionary $\Phi_k$for Each Subset $\boldsymbol{S}_k$. Meanwhile, We Have Computed The Centroid $M_k$of Each Cluster $\boldsymbol{C}_k$associated With $\boldsymbol{S}_k$. Therefore, We Have K Pairs $\{\Phi_k, M_k\}$, With Which The Asds Of Each Given Image Patch Can Be Accomplished. In The Proposed Sparsity-Based Ir Scheme, We Assign Adaptively A Sub-Dictionary To Each Local Patch Of $\boldsymbol{X}$, Spanning The Adaptive Sparse Domain. Since $\boldsymbol{X}$ Is Unknown Beforehand, We Need To Have An Initial Estimation Of It. The Initial Estimation Of $\boldsymbol{X}$ Can Be Accomplished By Taking Wavelet Bases As The Dictionary. Denote By $\hat{x}$ The Estimate Of $\boldsymbol{X}$, And Denote By $\hat{x}_i$ A Local Patch Of $\hat{x}$. Recall That We Have The Centroid $M_k$of Each Cluster Available, And Hence We Could Select The Best Fitted Sub-Dictionary To $\hat{x}_i$ By Comparing The High-Pass Filtered Patch Of $\hat{x}_i$, Denoted By $\hat{x}_i^h$, To The Centroid M_k.

III. DICTIONARIES

Although Image Contents Can Vary A Lot From Image To Image, It Has Been Found That The Micro-Structures Of Images Can Be Represented By A Small Number Of Structural Primitives (E.G., Edges, Line Segments And Other Elementary Features), And These Primitives Are Qualitatively Similar In Form To Simple Cell Receptive Fields [27-27]. The Human Visual System Employs A Sparse Coding Strategy To Represent Images, I.E., Coding A Natural Image Using A Small Number Of Basis Functions Chosen Out Of An Over-Complete Code Set. Therefore, Using The Many Patches Extracted From Several Training Images Which Are Rich In Edges And Textures, We Are Able To Train The Dictionaries Which Can Represent Well The Natural Images. To Illustrate The Robustness Of The Proposed Method To The Training Dataset, We Use Two Different Sets Of Training Images In The Experiments, Each Set Having 5 High Quality Images As Shown In Fig. 2.

Fig. 2. The Two Sets Of High Quality Images Used For Training Sub-Dictionaries And Ar Models. The Images In The First Row Consist Of The Training Dataset 1 And Those In The Second Row Consist Of The Training Dataset 2.

IV. SIMULATION RESULTS

In This Section, The Simulation Results Of Image Deblurring Using The Proposed Representation Are Presented. Two Types Of Blurs Are Considered; Gaussian And Uniform. Gaussian Blur With Standard Deviation Of 1 And 3 Are Considered. Uniform Blur With Kernel Size 3x3 And 9x9 Are Considered. As The Proposed Scheme Involves Iterative Operation, The Number Of Iterations Are Limited To 1000. The Ssim Values Are Calculated Between The Blurred Image And The Image Obtained At Last Iteration. These Values Are Given In Table 1. The Psnr Values Obtained In Uniform Blur Case And Gaussian Blur Case Are Given In Tables 2 And 3 Respectively.

Table 1. Ssim Values Obtained In Different Cases Of Blurs

Ssim		
Uniform Blur, Kernel Size 9x9	D1	0.89974
	D2	0.89984
Uniform Blur, Kernel Size 3x3	D1	0.96534
	D2	0.96543
Gaussian Blur, Standard Deviation 1	D1	0.96517
	D2	0.96464
Gaussian Blur, Standard Deviation 3	D1	0.86318
	D2	0.86227

Table 2. Psnr Values Obtained In Uniform Blur Case

	Uniform Blur, Kernel Size 9x9		Uniform Blur, Kernel Size 3x3	
Iteration	Dictionary - 1	Dictionary – 2	Dictionary – 1	Dictionary - 2
0	23.87	23.87	30.71	30.71
40	27.92	27.91	35.76	35.75
80	28.63	28.62	35.38	35.38
120	29.01	29.00	35.18	35.19
160	29.32	29.31	35.12	35.13
200	29.62	29.61	35.08	35.10
240	29.84	29.83	35.04	35.06
280	30.01	30.00	35.01	35.03
320	30.15	30.14	35.00	35.02
360	30.27	30.26	34.99	35.01
400	30.36	30.35	34.98	35.00
440	30.44	30.43	34.97	34.99
480	30.51	30.50	34.97	34.98
520	30.56	30.56	34.96	34.98
560	30.61	30.60	34.96	34.97
600	30.65	30.64	34.95	34.96
640	30.68	30.68	34.95	34.96
680	30.71	30.71	34.95	34.96
720	30.74	30.73	34.95	34.96
760	31.02	31.01	36.20	36.22
800	31.12	31.11	37.09	37.10
840	31.20	31.18	37.21	37.21
880	31.26	31.24	37.23	37.23
920	31.23	31.19	37.99	37.98
960	31.24	31.20	38.04	38.04
1000	31.27	31.23	38.03	38.04

Table 2. Psnr Values Obtained In Gaussian Blur Case

	Gaussian Blur, Standard Deviation 1		Gaussian Blur, Standard Deviation 3	
Iteration	Dictionary – 1	Dictionary - 2	Dictionary - 1	Dictionary - 2
0	30.16	30.16	24.07	24.07
40	36.11	36.10	26.52	26.51
80	36.06	36.04	26.84	26.84
120	36.03	36.01	27.02	27.01
160	36.05	36.03	27.15	27.15
200	36.07	36.05	27.26	27.26
240	36.07	36.06	27.35	27.34
280	36.07	36.06	27.42	27.41
320	36.03	36.02	27.48	27.47
360	35.99	35.98	27.53	27.52
400	35.97	35.97	27.58	27.57
440	35.96	35.96	27.62	27.60
480	35.95	35.95	27.65	27.64
520	35.95	35.95	27.68	27.67
560	35.94	35.95	27.70	27.69
600	35.94	35.95	27.72	27.71
640	35.94	35.94	27.74	27.73
680	35.93	35.94	27.76	27.75
720	35.93	35.94	27.77	27.77
760	36.99	36.97	27.79	27.78
800	37.52	37.47	27.80	27.78
840	37.58	37.52	27.81	27.79
880	37.59	37.53	27.82	27.80
920	37.87	37.80	27.83	27.80
960	37.89	37.83	27.83	27.80
1000	37.89	37.83	27.84	27.81

V. CONCLUSION

In This Paper, A Sparse Representation Has Been Proposed To Be Used In Image Restoration Problems. In Addition To The Proposal Of Sparse Representation, An Adaptive Selection Scheme To Select Sub-Dictionaries Is Presented. The Choice Of Sub-Dictionaries Is So Central To The Whole Sparse Representation. Two Dictionaries Are Formed By Considering A Set Of Five Images Containing Different Kinds Of Edges, Line Segments And Other Elementary Features. The Proposed Sparse Representation Has Been Used On The Restoration Problem Image Deblurring. Gaussian And Uniform Blurs With Different Quantities Are Considered. Psnr And Ssim Are Calculated And These Metrics Highlight The Significance Of

The Proposed Sparse Representation.

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