IMAGE INPAINTING VIA WEIGHTED SPARSE NON-NEGATIVE MATRIX FACTORIZATION

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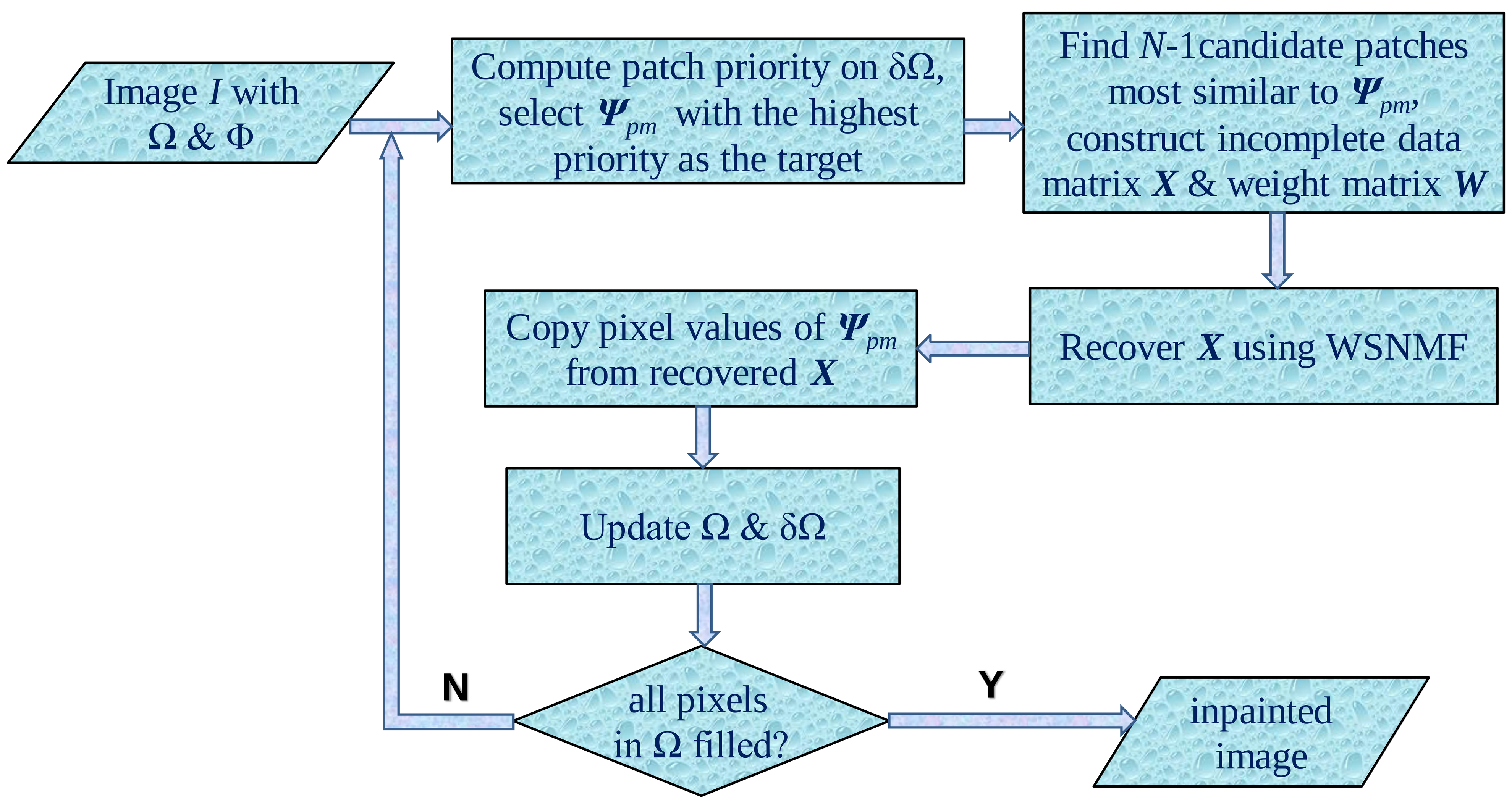
MOTIVATION

- **Drawback** of exemplar-based inpainting approaches
  - single exemplar-based (SE) (Criminisi et al.) — most similar candidate patch → dominant role
  - sparse representation based (SR) (Shen et al.) — less similar candidate patches → little effect

  Greedy & Information Lost
- **Reformulate** inpainting task
  - sequential low-rank matrix recovery and completion
  - analogous to **Collaborative Filtering**
- **Higher** level incomplete signal
  - single target patch → target patch + several similar intact candidate patches

  Simultaneously Fitting & Information from candidate patches **all combined**
- **Assumption**
  - low-dimensional additive sparse linear model
- **Domain** change
  - image patch bases → **self-adaptively** constructed basis set
  - original image domain → **transformed** domain

FRAMEWORK



★ target region Ω | source region Φ | boundary $\delta\Omega$ | patch vector Ψ_p

APPROACH

Construction of data matrix

- target patch Ψ_{pm} (**incomplete**)
- N-1 patches $\Psi_{qj,\, j=2,\dots,N}$ in Φ most similar to Ψ_{pm} (**intact**)

$$\Psi_{qj}=\arg\min_{\Psi_q\in\Phi\setminus\Psi_{qk,k=2,\dots,j-1}} d(\Psi_{pm},\Psi_q)$$

distance $d(.)$ is SSD defined in the already filled parts of both patches

- data matrix X

$$X=[\Psi_{pm},\Psi_{q2},\dots,\Psi_{qj},\dots\Psi_{qN}]=[X_1,X_2,\dots,X_N]\in\mathbb{R}_{\geq 0}^{M\times N}$$

Construction of weight matrix

- W_1 → binary weights

$$W_{i1}=\begin{cases}1 & \text{if } X_{i1} \text{ is in the source region}\\ 0 & \text{if } X_{i1} \text{ is in the target region}\end{cases}$$

- W_2~W_N → decreasing function reflecting decay in the confidence from Ψ_{q2} to Ψ_{qN},

$$W_{ij}=\frac{\min(d(\Psi_{pm},\Psi_{qj}))}{d(\Psi_{pm},\Psi_{qj})}=\frac{d(\Psi_{pm},\Psi_{q2})}{d(\Psi_{pm},\Psi_{qj})},\ \text{for } i=1,\dots,M,\ j=2,\dots,N$$

EM procedure based WSNMF

- Weighted NMF → matrix completion
- sparseness constraint on coefficient matrix V → enforce sharp inpainting results
- objective function to be minimized

$$J_{WSNMF}(X,UV)=\frac{1}{2}\sum_{ij}W_{ij}(X_{ij}-[UV]_{ij})^2+\lambda\sum_{ij}V_{ij}$$

- WSNMF → maximum-likelihood problem
- **Expectation step**: compute filled-in matrix Y from the current model estimation

$$Y\leftarrow W\otimes X+(1_{M\times N}-W)\otimes(UV)$$

- **Maximization step**: utilize unweighted Sparse NMF algorithm(SENSC) on Y to reestimate the decomposition model

EXPERIMENTAL RESULTS

- structure and texture inpainting

- composite texture inpainting

- unwanted artifact prevention

★ From left to right are original image, target region marked in green, inpainting results by SE, SR, and proposed algorithm

CONCLUSIONS

- more **adequate exploitation** of available information from multiple exemplars
- capable of inferring **both structure and composite textures** of large missing region
- **less greedy** to prevent unwanted artifacts
- **sharp** inpainting results due to the introduction of **sparseness** prior on the combination coefficients