**MOTIVATION**

- **Drawback** of exemplar-based inpainting approaches
  - single exemplar-based (SE) (Criminisi et al.) most similar candidate patch \( \rightarrow \) dominant role
  - sparse representation based (SR) (Shen et al.) less similar candidate patches \( \rightarrow \) 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 \( \rightarrow \) 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 \( \rightarrow \) self-adaptively constructed basis set
  - original image domain \( \rightarrow \) transformed domain

**FRAMEWORK**

- **Inpainting**
  - **Compute patch priority on** \( \delta \Omega \), select \( \Psi_{pm} \) with the highest priority as the target
  - **Copy pixel values of** \( \Psi_{pm} \) from recovered \( \Psi \)
  - **Update** \( \Omega \) & \( \delta \Omega \)

- **Find** \( N \)-1-candidate patches most similar to \( \Psi_{pm} \)
  - construct incomplete data matrix \( X \) & weight matrix \( W \)

- **Recover** \( X \) using WSNMF

- **Update** \( \Omega \) & \( \delta \Omega \)

- **all pixels** in \( \Omega \) filled?

**APPROACH**

- **Construction of data matrix**
  - target patch \( \Psi_{pm} \) (incomplete)
  - \( N \)-1 patches \( \Psi_{q_j, j=2,...,N} \) in \( \Phi \) most similar to \( \Psi_{pm} \) (intact)

\[
\Psi_{q_j} = \arg \min_{\Psi_{q_j}, \Psi_{q_k}, j=2,...,N} d(\Psi_{pm}, \Psi_{q_j})
\]

- distance \( d(,.) \) is SSD defined in the already filled parts of both patches
- data matrix \( X \)

\[
X = [\Psi_{pm}, \Psi_{q_2}, ..., \Psi_{q_j}, ..., \Psi_{q_N}] = [X_1, X_2, ..., X_N] \in \mathbb{R}^{M \times N}
\]

- **Construction of weight matrix**
  - \( W_1 \rightarrow \) binary weights

\[
W_{ij} = \begin{cases} 
1 & \text{if } X_{ji} \text{ is in the source region} \\
0 & \text{if } X_{ji} \text{ is in the target region}
\end{cases}
\]

- \( W_2 \sim W_N \rightarrow \) decreasing function reflecting decay in the confidence from \( \Psi_{q_j} \) to \( \Psi_{q_k} \)

\[
W_q = \frac{\min(d(\Psi_{pm, \Psi_{q_j}}))}{d(\Psi_{pm, \Psi_{q_j}})} = \frac{d(\Psi_{pm, \Psi_{q_j}})}{d(\Psi_{pm, \Psi_{q_k}})}, \text{ for } i = 1, ..., M; j = 2, ..., N
\]

- **WSNMF** \( J_{WSNMF}(X,UV) = \frac{1}{2} \sum_{q} W_q (X_q - [UV]_q)^2 + \lambda \sum_{q} V_q \)

**EXPERIMENTAL RESULTS**

- **EM procedure based WSNMF**
  - Weighted NMF \( \rightarrow \) matrix completion
  - sparseness constraint on coefficient matrix \( V \) \( \rightarrow \) enforce sharp inpainting results
  - objective function to be minimized

\[
J_{WSNMF}(X,UV) = \frac{1}{2} \sum_{q} W_q (X_q - [UV]_q)^2 + \lambda \sum_{q} V_q
\]

- **WSNMF** \( \rightarrow \) maximum-likelihood problem
- **Expectation step**: compute filled-in matrix \( Y \) from the current model estimation

\[
Y \leftarrow W \odot X + (I_{M \times N} - W) \odot (UV)
\]

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

- **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