

INTRODUCTION

- Example-based style transfer: transform an image to **mimic the style** of a given example
- Style as a combination of global **color** and local **texture** transfer
- Previous patch-based texture transfer methods assume regular grid

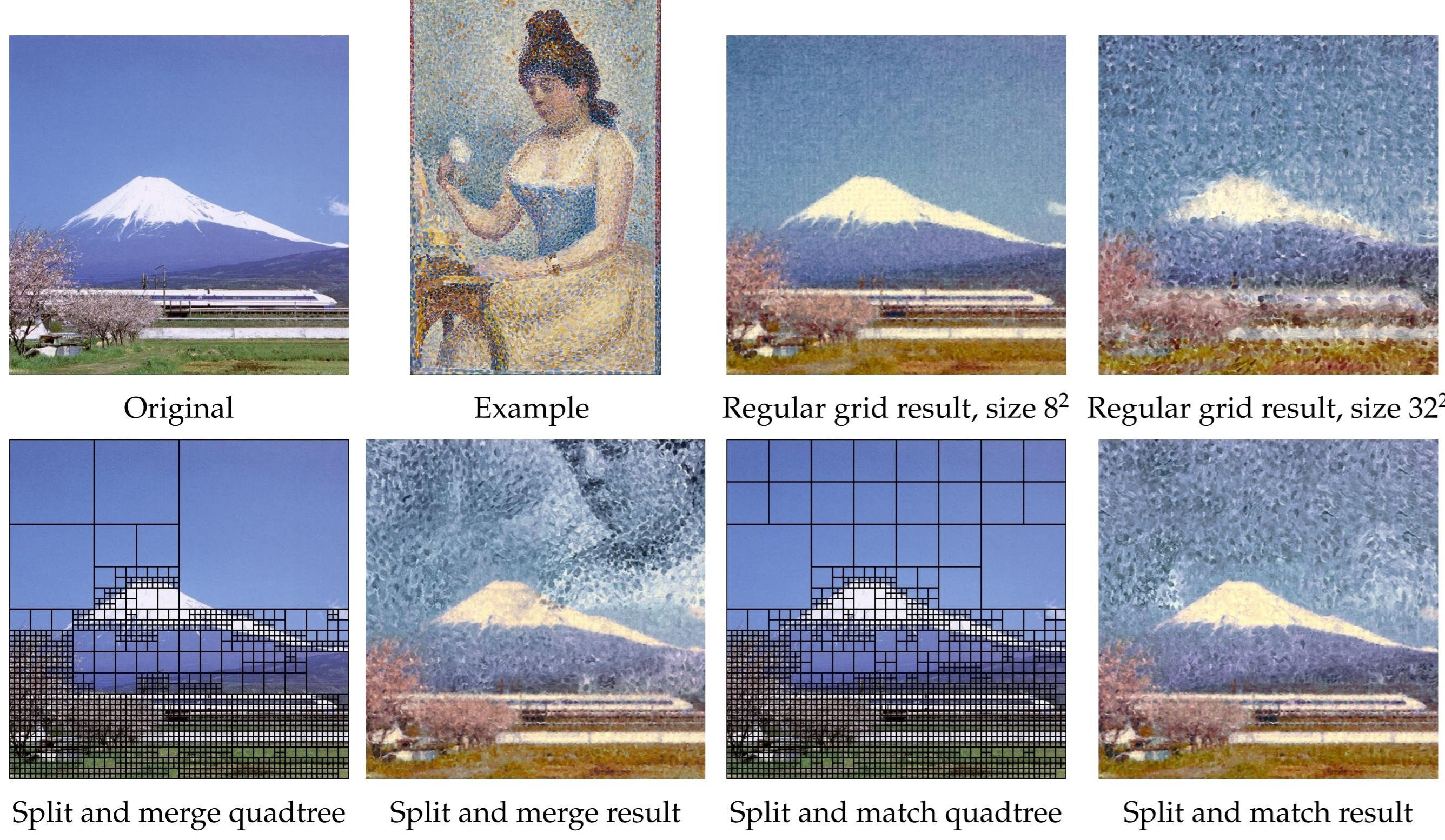
OUR APPROACH

- Let $u : \Omega_u \rightarrow \mathbb{R}^3$ be an input image and $v : \Omega_v \rightarrow \mathbb{R}^3$ an example style image
- Search for correspondence map $\varphi : \Omega_u \rightarrow \Omega_v$, with texture transfer defined as $\hat{u} = v(\varphi)$
- We follow the steps below to achieve style transfer:
 - Split and match:** compute an adaptive partition R of Ω_u ;
 - Optimization:** Search for the optimal map φ ;
 - Bilinear **blending** between neighbor regions and reconstruction of \hat{u} ;
 - Global **color transfer** [2] and **contrast matching**.

ADAPTIVE PATCH PARTITION

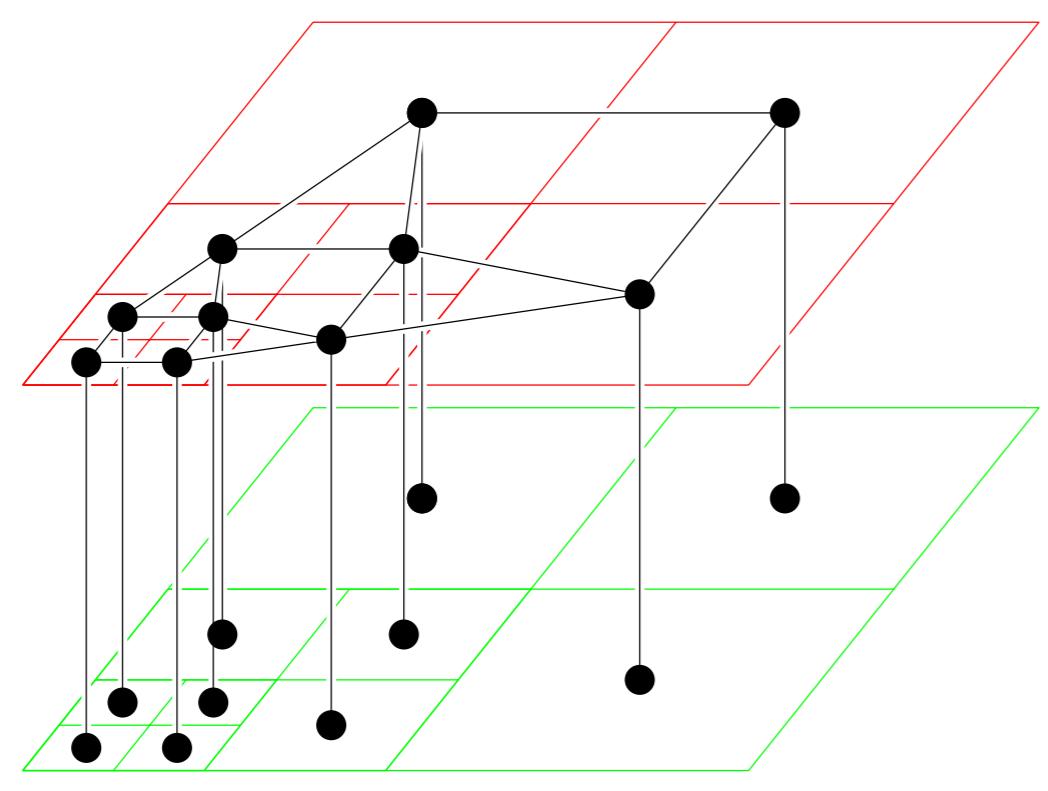
- Quadtree partition inspired by classic **Split and Merge**
- Region R_i is split in four regions only if

$$(\sigma_i + d[p_{x_i}^u, p_{y_i}^v] > \omega \text{ and } \tau_i > \gamma_0) \text{ or } \tau_i > \gamma_1$$
- y_i is the best match of $p_{x_i}^u$ in v , σ_i is the standard deviation of $p_{x_i}^u$
- Distance between patches $p_{x_i}^u$ and p_y^v of size τ_i^2 given by $d[p_{x_i}^u, p_y^v] = \frac{\|p_{x_i}^u - p_y^v\|^2}{\tau_i^2}$



OPTIMAL CANDIDATE SELECTION

- Patch correspondences as a **labeling problem**
- Label assignments given by MAP inference from joint probability distribution on $L = \{L_i\}_{i=1}^n$
- MRF model over **non-regular grid**



- For quadtree patch $p_{x_i}^u$, K candidates $L_i = \{l_{ik}\}_{k=1}^K$ are computed by k -nearest neighbors
- Then we search for label assignments $\hat{L} = \{\hat{l}_i\}_{i=1}^n$ maximizing

$$P(L) = \frac{1}{Z} \prod_i \phi(l_i) \prod_{(i,j) \in \mathcal{N}} \psi(l_i, l_j),$$

where $\phi(l_i) = \exp(-d[p_{x_i}^u, p_{l_i}^v]\lambda_d)$

$\psi(l_i, l_j) = \exp(-d[\bar{p}_{l_i}^v, \bar{p}_{l_j}^v]\lambda_s + |l_i - l_j|^2\lambda_r)$

Approximate inference by **loopy belief propagation** [4]

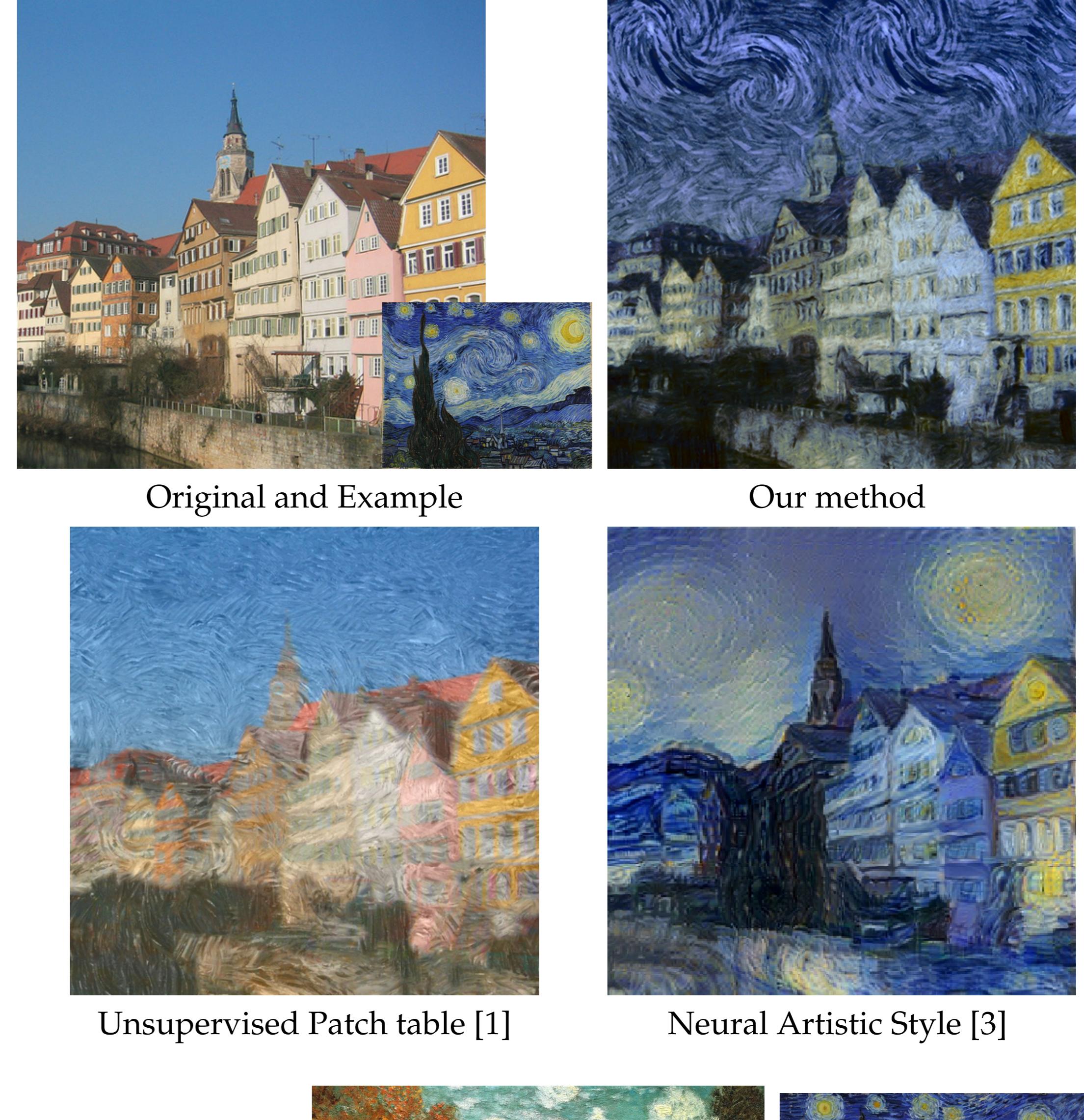
BLENDING

- Given a set of overlapping patches P of arbitrary sizes
- Blending as a weighted sum of all overlapping intensities:

$$\hat{u}(x) = \sum_{s=1}^S \alpha_s(x) \tilde{p}_{x_s}^u(x), \text{ where } \alpha_s(x) = \frac{\delta(x, \partial \tilde{p}_{x_s}^u)}{\sum_{s=1}^S \delta(x, \partial \tilde{p}_{x_s}^u)} \text{ and } \delta(x, \partial \tilde{p}_{x_s}^u) = \frac{|x - \partial \tilde{p}_{x_s}^u|^2}{\tau_s^2}$$

$\alpha_s(x)$ is a weight and $\delta(x, \partial \tilde{p}_{x_s}^u)$ is the distance between pixel x and patch border $\partial \tilde{p}_{x_s}^u$

RESULTS AND DISCUSSION



Unsupervised Patch table [1] Neural Artistic Style [3]

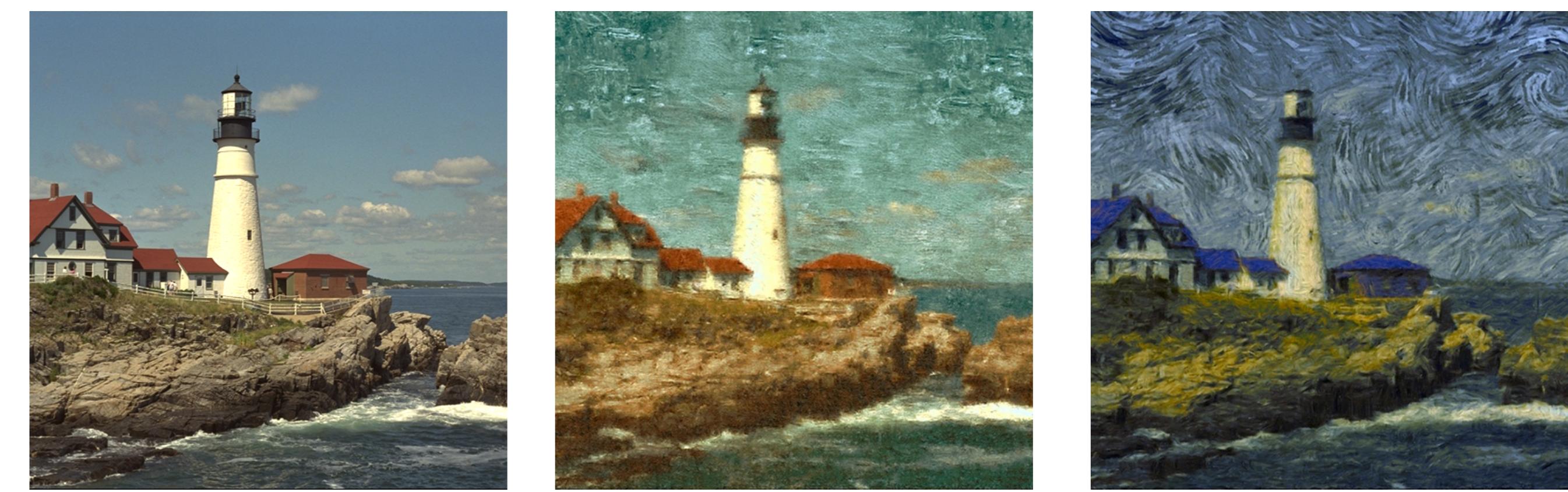


Figure: Results of our method with Monet's and Van Gogh's paintings as examples.

CONCLUSION

- Style transfer synthesizing **textures of different scales**
- Local texture modeling and global color transfer leads to **structure-preserving stylization**
- Future work will **extend our method to videos**

REFERENCES

- [1] C. Barnes, F.-L. Zhang, L. Liu, X. Wu, and S.-M. Hu. Patchable: Efficient patch queries for large datasets and applications. In SIGGRAPH, Aug. 2015.
- [2] O. Frigo, N. Sabater, V. Demoulin, and P. Hellier. Optimal transportation for example-guided color transfer. In ACCV, pages 655–670, 2014.
- [3] L. A. Gatys, A. S. Ecker, and M. Bethge. A neural algorithm of artistic style. CoRR, abs/1508.06576, 2015.
- [4] Y. Weiss. Belief propagation and revision in networks with loops. Technical report, Cambridge, MA, USA, 1997.