EXAMPLAR-BASED INPAINTING BASED ON LOCAL GEOMETRY

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Abstract: In this paper, we propose a novel inpainting algorithm combining the advantages of PDE-based schemes and examplar-based approaches. The proposed algorithm relies on the use of structure tensors to define the filling order priority and template matching. The structure tensors are computed in a hierarchic manner whereas the template matching is based on a K-nearest neighbor algorithm. The value K is adaptively set in function of the local texture information. Compared to two state of the art approaches, the proposed method provides more coherent results.

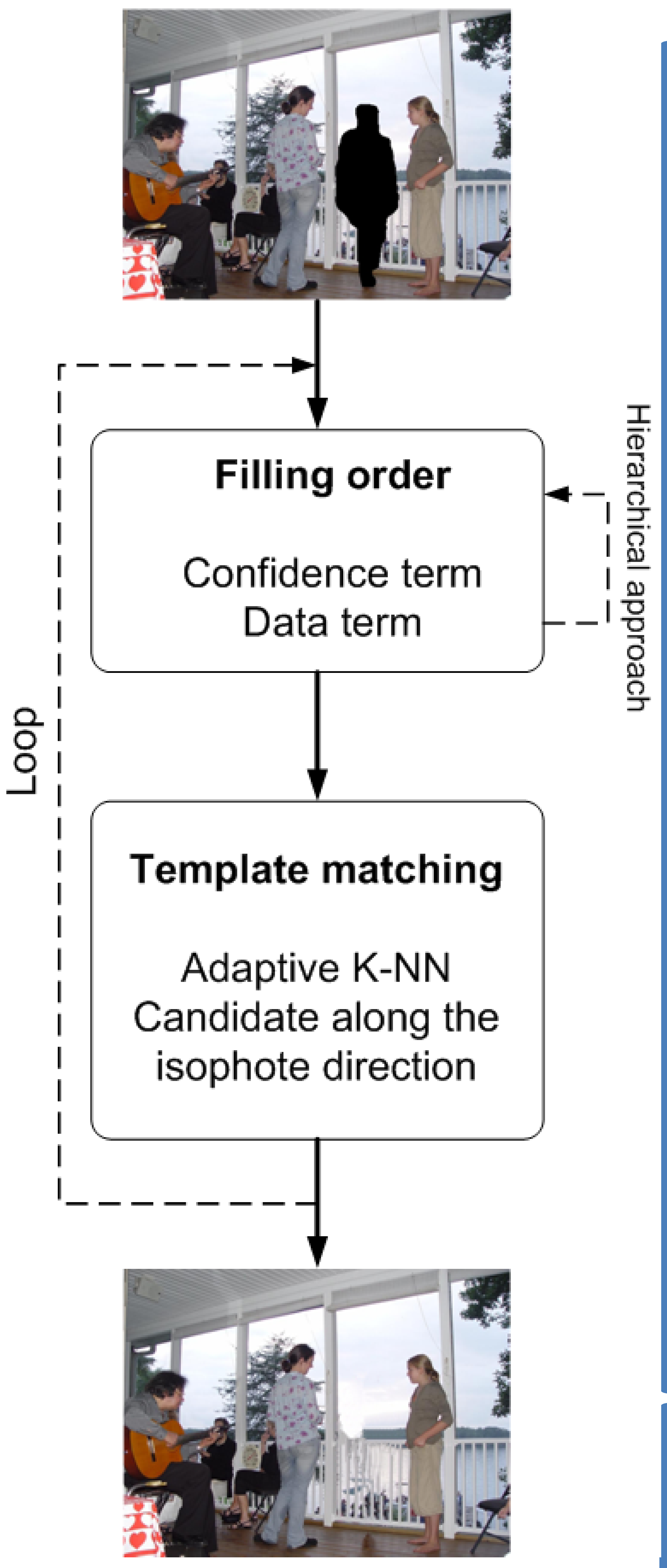
Objective

To design a new examplar-based inpainting method based on the local geometry of the scene

Contributions compared to the state-of-the art methods

- Structure tensors used to define the filling order
- Hierarchical approach to estimate the dominant orientation
- Constrained template matching
- Adaptive K-Nearest Neighbors

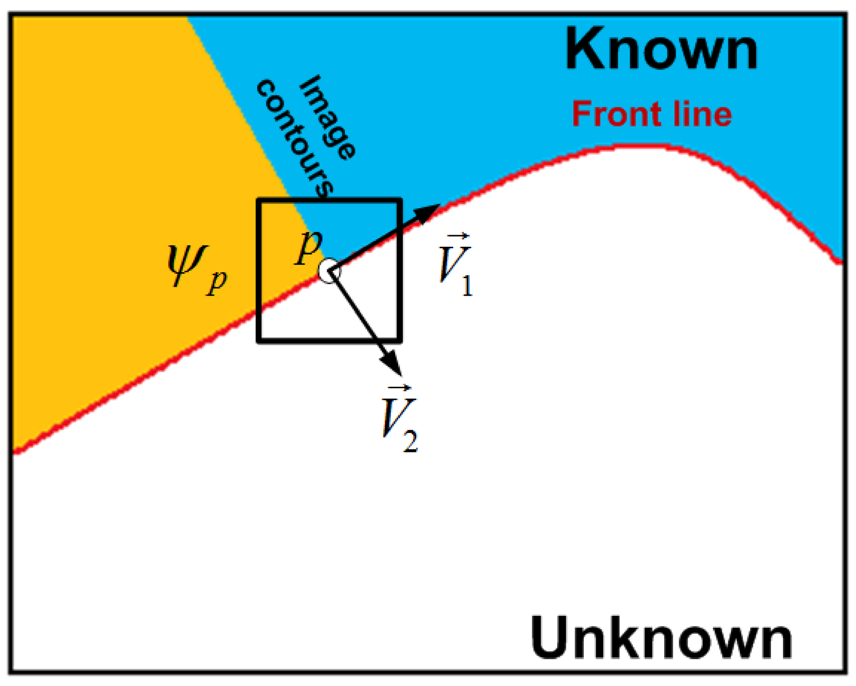
Proposed method based on Criminisi's framework [1]



Filling order computation:

- a filling order P is defined to favor the propagation of structure in the isophote direction

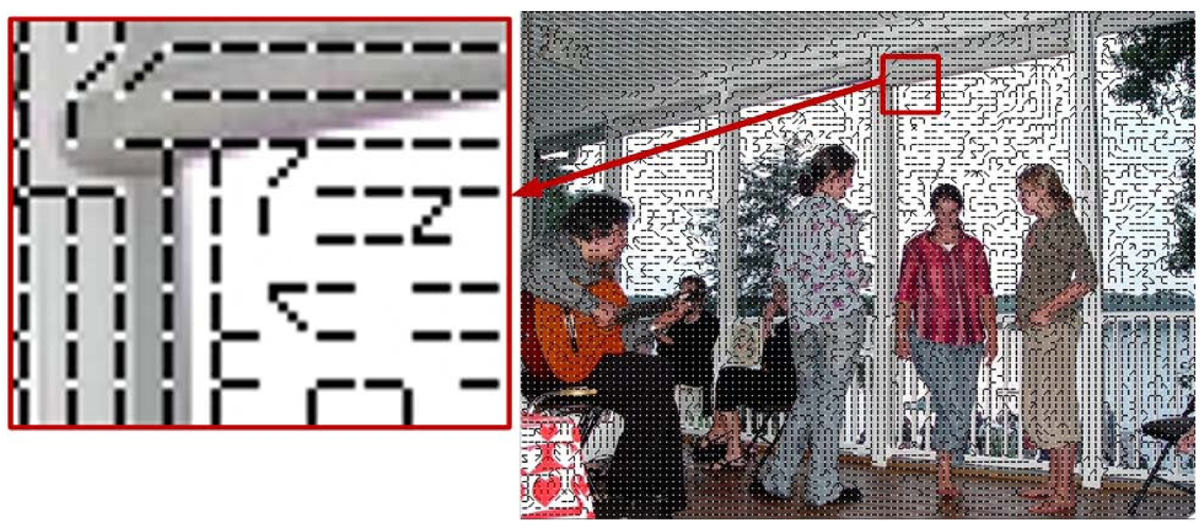
$P(\mathbf{p}) = C(\mathbf{p}) \times D(\mathbf{p})$ with C(p) a confidence term [1] and D(p) a data term described below:



1. Gradient computation $\nabla I_l = \left[\partial I_l / \partial x \quad \partial I_l / \partial y\right]^T$
2. Di Zenzo structure tensor $J(\mathbf{p}) = \sum_{l=R,G,B} \nabla I_l \nabla I_l^T$
3. Eigen values computation $\lambda_1 \approx \lambda_2$ indicates homogeneous regions; $\lambda_1 >> \lambda_2$ indicates the presence of structure
4. Data term D(p) based on the coherence norm [2]:

$$D(\mathbf{p}) = \alpha + (1-\alpha)\exp\left(-\frac{C}{(\lambda_1 - \lambda_2)^2}\right)$$

Estimation of the isophote directions



coherence norm: black areas correspond to areas for which there is no dominant direction

Template matching:

- a template matching is performed in order to find the best candidates to fill in the hole

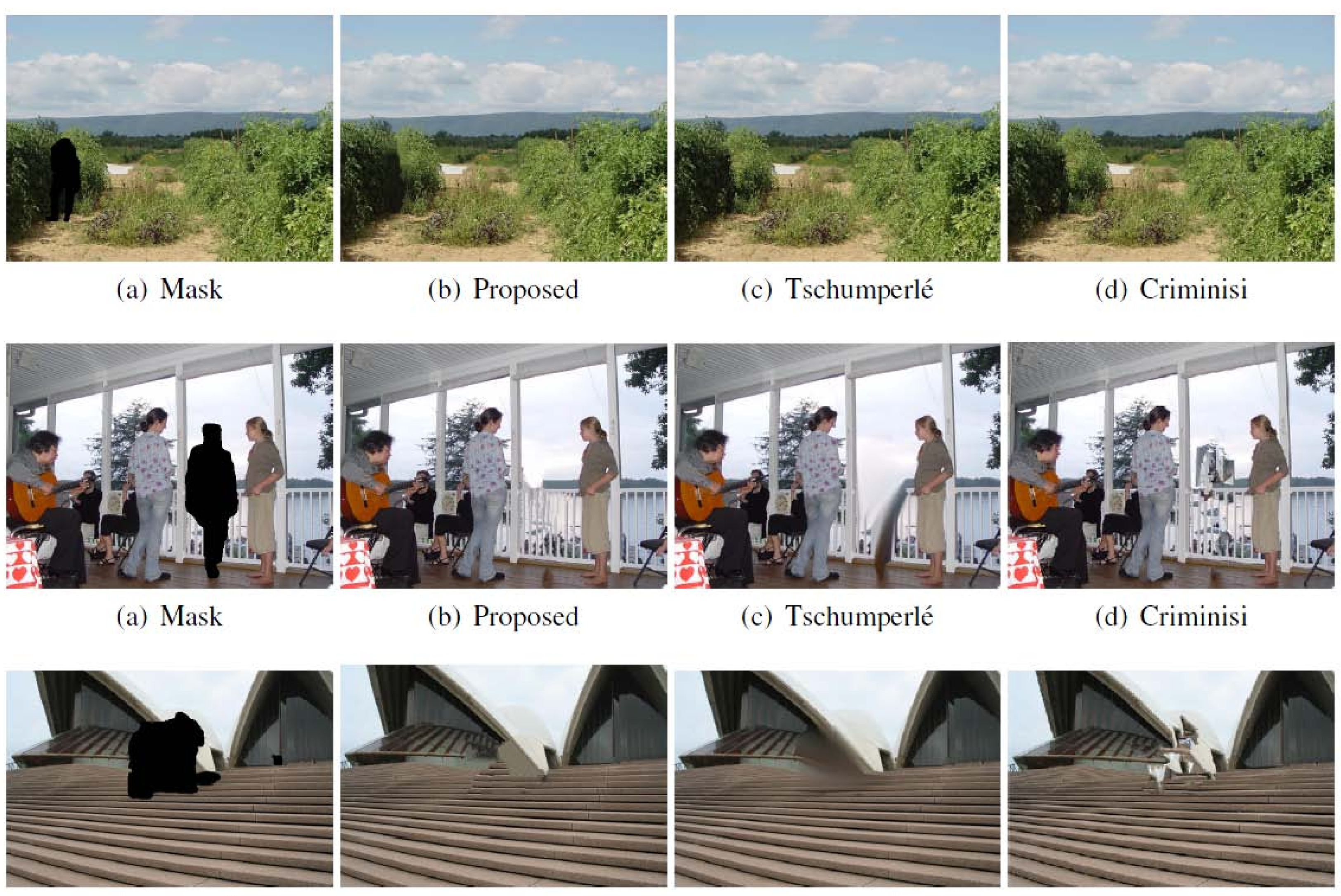
$$\psi_{\hat{q}} = \arg\min_{\psi_q \in W}\left[d(\psi_p, \psi_q) + \left(\frac{\lambda_1 - \lambda_2}{\lambda_1 + \lambda_2}\right)^2 \times f(\mathbf{p},\mathbf{q})\right] \quad \text{with} \quad f(\mathbf{p},\mathbf{q}) = \frac{1}{\varepsilon + \frac{|\vec{v}_2 \cdot \vec{v}_{pq}|}{\|\vec{v}_{pq}\|}}$$

$d(\psi_p, \psi_q)$: Distance between the known parts of the current patch and a candidate (SSD)

$\left(\frac{\lambda_1 - \lambda_2}{\lambda_1 + \lambda_2}\right)^2 \times f(\mathbf{p},\mathbf{q})$: Term to favor candidates in the isophote direction

The final patch is a linear combination of the K best candidates. The weights depend on the distance between the patch and the candidates.

Benefit of the use of the hierarchical approach



(a) Mask (b) Proposed (c) Tschumperlé (d) Criminisi

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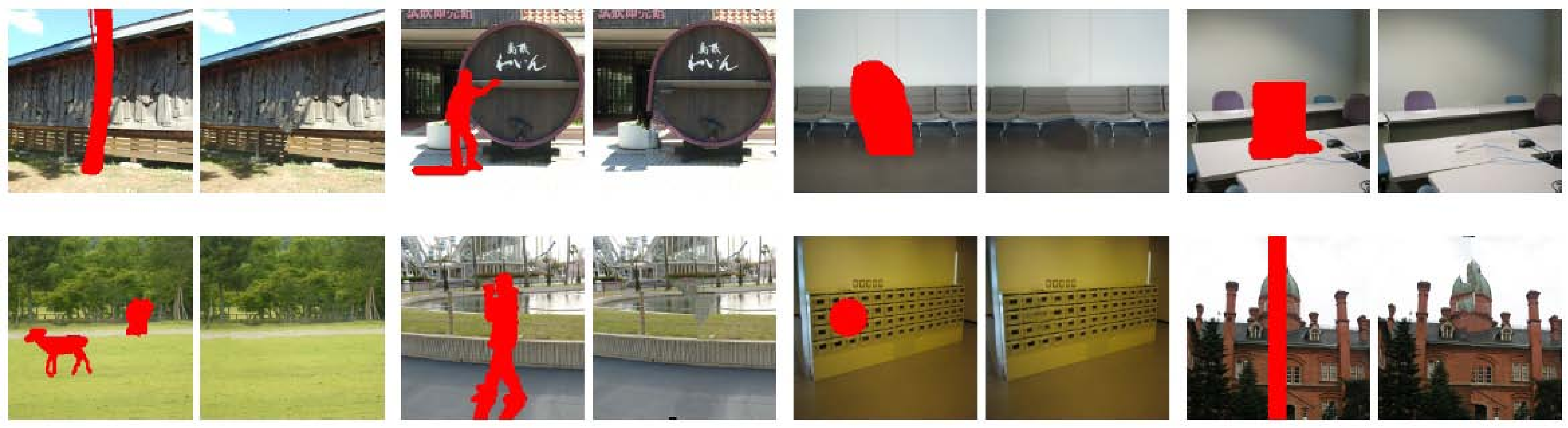

Conclusion: In this paper, a novel examplar-based inpainting approach is proposed. Structure tensors are computed in a hierarchic manner providing coherent information of local orientation as well as robustness to local orientation singularities. The filling process is based on a K-nearest neighbor approach for which the number of candidates used to fill in the hole is adaptively chosen in function of the local context.

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[1] A. Criminisi, P. Pérez, and K. Toyama, "Region filling and object removal by examplar(based image inpainting," IEEE Trans. On Image Processing, vol. 13, pp. 1200–1212, 2004.
[2] J. Weickert, "Coherence-enhancing diffusion filtering," International Journal of Computer Vision, vol. 32, pp. 111–127, 1999.