Simultaneous Inpainting and Super-resolution Using Self-learning

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Introduction

In applications like creating immersive walk-through systems or digital reconstruction of invaluable artwork, both inpainting and super-resolution of the given images are the preliminary steps in order to provide better visual experience. The usual practice is to solve these problems independently in a pipelined manner. In this paper we propose a unified framework to perform simultaneous inpainting and super-resolution (SR). The main focus of this paper is inpainting, i.e. to remove objects in photographs and replace them with visually plausible backgrounds. The super-resolved version is obtained as a by-product in the process of using an additional constraint that helps in finding a better source for inpainting.

Key Idea

- We search for the inpainting exemplars by comparing patch details at finer resolution.
- The finer resolution details are self-learnt using the constructed dictionaries of image-representative low and high resolution patch pairs from the known regions in the test image and its coarser resolution.

Advantages

- Additional constraint in the form of finer resolution matching results in better inpainting.
- The obtained finer resolution patches represent the super-resolved patches in the missing regions. As a result, inpainting is obtained not only in the given spatial resolution but also at higher resolution leading to super-resolution inpainting.

Conclusion

An additional constraint of matching patches at both original and higher resolution not only provides better source patches for inpainting but also results in super-resolution inpainting.

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References

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Proposed method

Constructing LR-HR pair dictionaries:

- Find matches for LR in the coarser resolution and obtain the corresponding HR.
- Many LR patches may be mapped to one HR patch.
- Create dictionaries D_{HR} and D_{LR} using the highly mapped HR patches and corresponding LR patches, respectively.

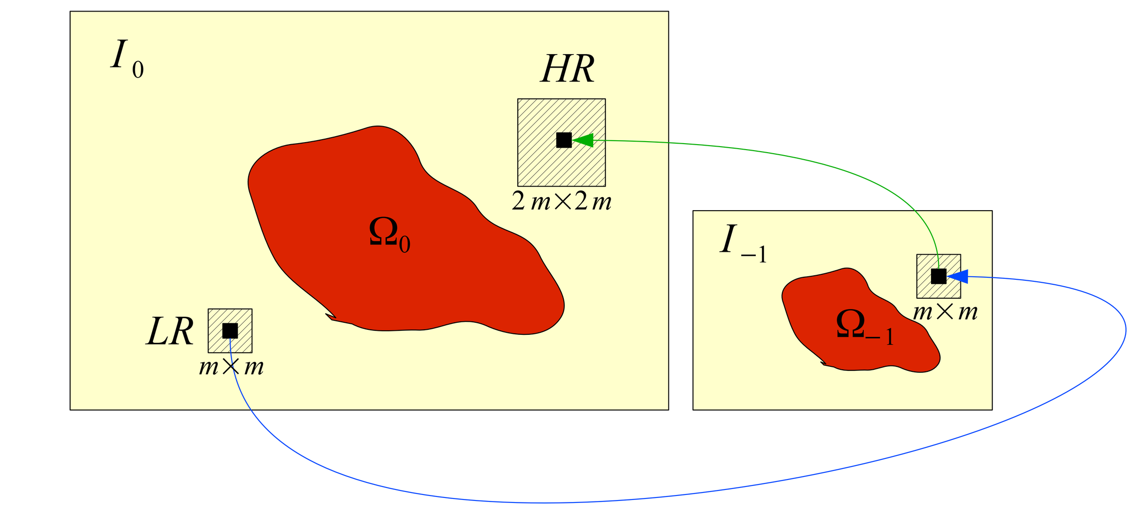


Figure 1: Finding LR-HR patch pairs using the given image I_0 and its coarser resolution I_{-1}.

Selecting highest priority patch and finding candidate exemplars:

- A patch $y_p = y_p^k \cup y_p^u$ on the boundary of the inpainting region Ω_0 is selected for inpainting based on presence of structure and proportion of known pixels y_p^k [1].
- Candidate exemplars $y_{q_1}, \ldots, y_{q_K}$ are found by comparing y_p with every $m \times m$ sized patch in $I_0 - \Omega_o$.

Estimating HR using constructed dictionaries:

The HR patch Y corresponding to an LR patch y is self-learnt [2] using the LR-HR patch pair dictionaries as $\boxed{Y = D_{HR} * \alpha}$, where, α is the sparse representation obtained by optimizing

$$\boxed{\min ||\alpha||_{l_1}, \quad \text{subject to} \quad y = D_{LR} * \alpha}.$$

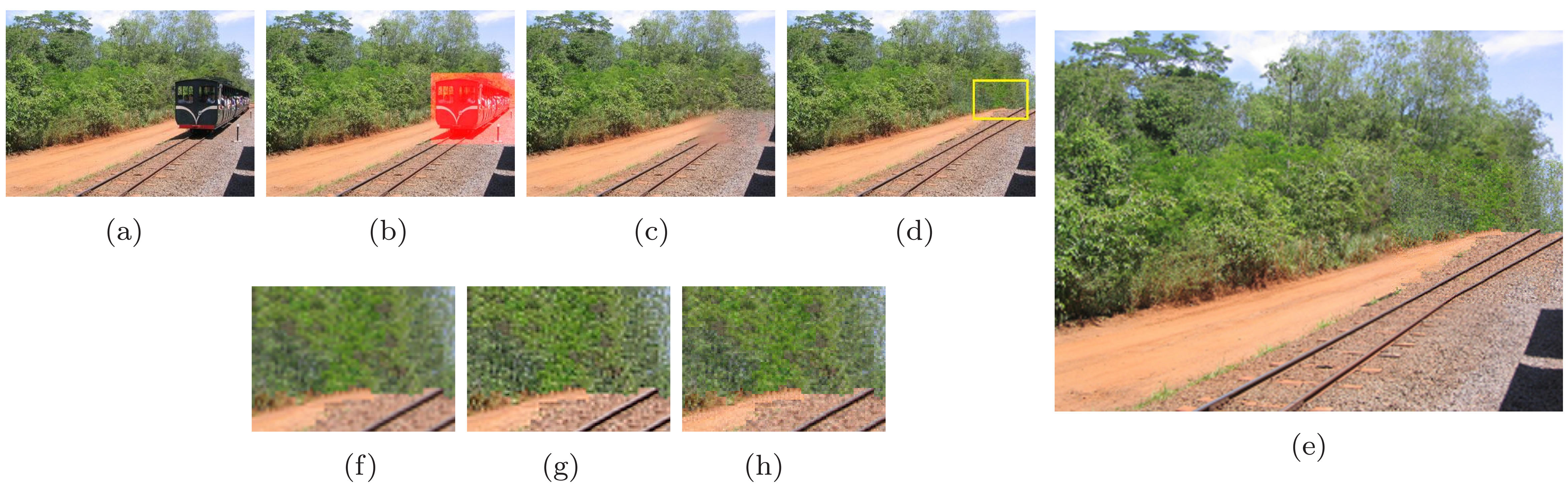
This is used to estimate $Y_{q_1}, \ldots, Y_{q_K}$ from $y_{q_1}, \ldots, y_{q_K}$, respectively. Similarly Y_p corresponding to y_p is estimated by considering the known pixels y_p^k and corresponding rows in the LR dictionary D_{LR}.

Inpainting:

- Compare HR patches $Y_{q_1}, \ldots, Y_{q_K}$ with Y_p and choose the one having minimum sum of squared distance as Y_q.
- Inpainted HR patch: $H_p = Y_p$ followed by $H_p^u = Y_q^u$.
- Inpainted LR patch: Obtain L_p from H_p using the same transformation that was used to obtain I_{-1} from I_0.
- Update Ω_0.
- Repeat till all patches in Ω_0 are inpainted.

Results

Result 1:



Result 2:

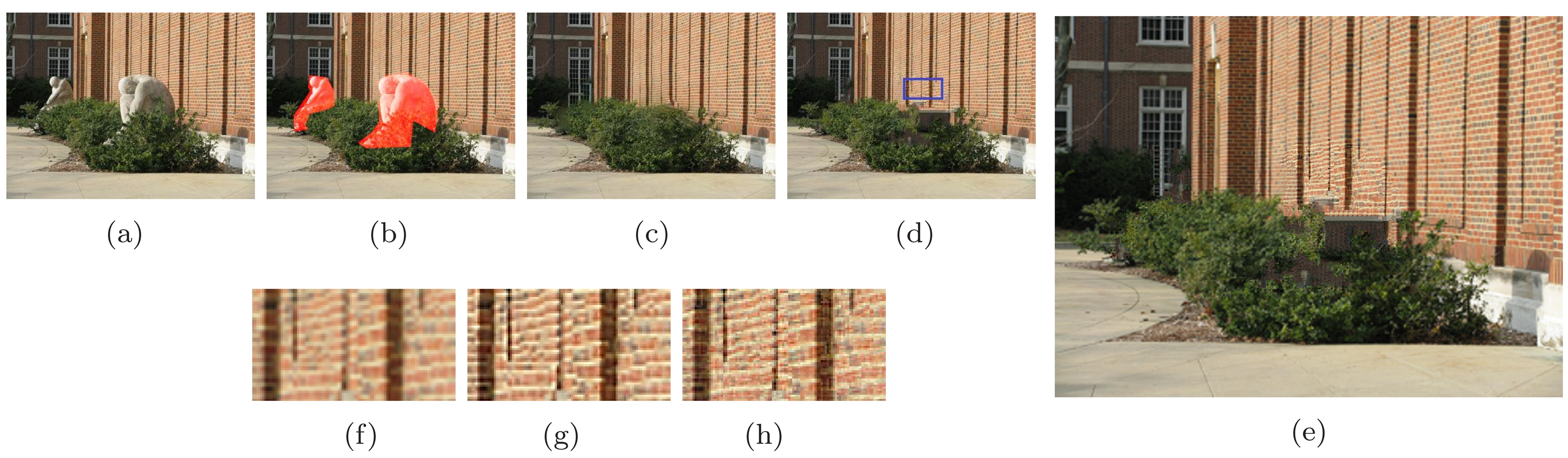


Figure 2: Simultaneous inpainting and super-resolution: (a) input; (b) region to be inpainted; (c) inpainting using planar structure guidance [3]; (d) inpainting using proposed method showing a box inside the inpainted region; (e) simultaneously inpainted and super-resolved image (by a factor of 2) using the proposed method with known regions upsampled using bicubic interpolation; (f)–(h) expanded versions after upsampling (the region marked by the box in (d)) using various approaches viz. (f) bicubic interpolation, (g) Glasner *et al.*'s method [4] and (h) proposed method for super-resolution.