Image Super Resolution

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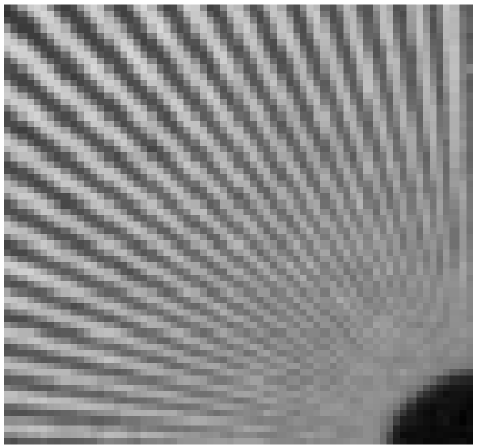
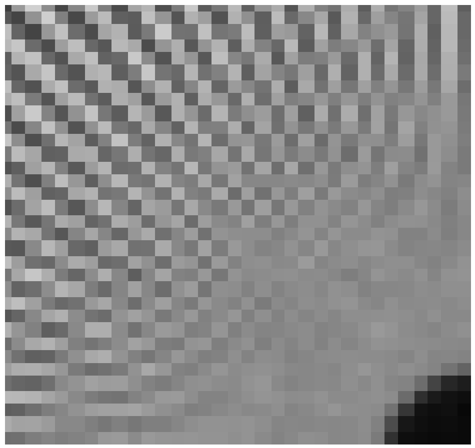
Super Resolution

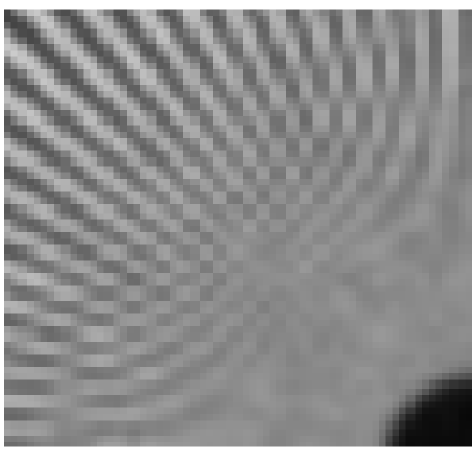
High-res (GT)



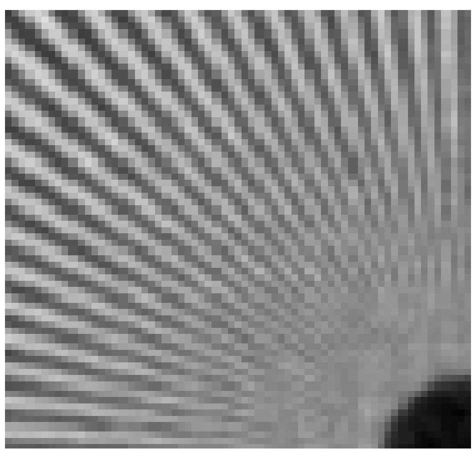
Low-res (input)



Traditional res-enhance



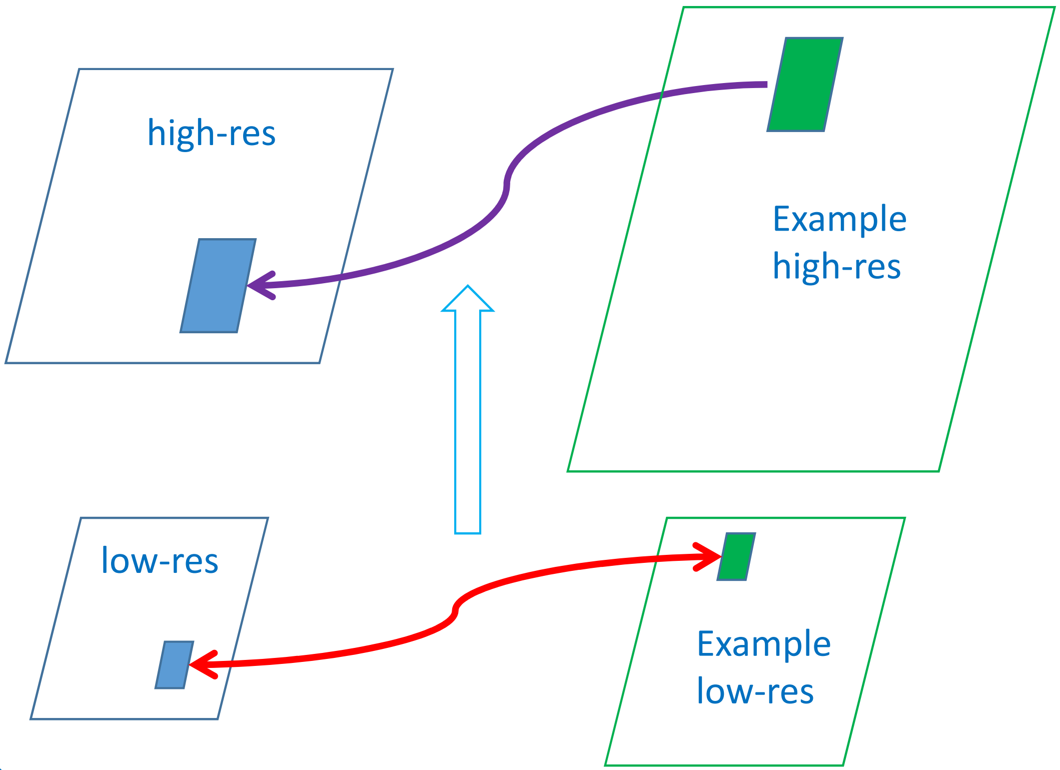
New super-res (output)



- Super-resolution:
  - Low-res image to high-res image
  - “Beats Nyquist limit” by using constraints and training data
  - The constraints: cross-res correlation
- Potential benefits to security:
  - Better quality images from less expensive scanners
  - Better image quality without hardware upgrades
  - Better ATR performance
- Conditions for super-res to work:
  - The constraints have to be valid and the high-res image to be recovered has to be similar to those in the training data

How super resolution work: basic idea

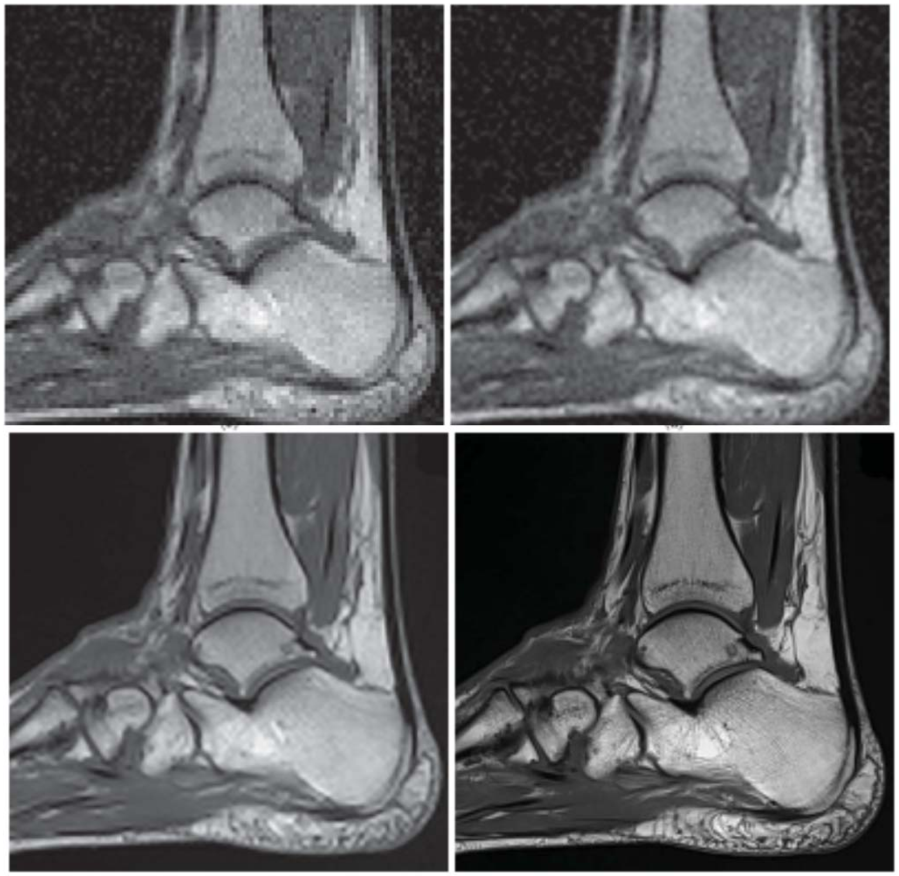
- Start with a low-res image
- Also a database of high-res example images (and their low-res versions)
- Apply this constraint/assumption: if a patch in the low-res image is similar to an example low-res patch, the corresponding high-res example patch can be used to recover a high-res patch
- In other words: low-res similarity implies high-res similarity
- “Beat Nyquist limit” by using extra information in training data
- Many ways to implement the basic idea



One implementation: using sparse representation

- Trinh et al (2014, IEEE Trans. IP) applied to MRI images
- Use example images to construct two dictionaries, D_l (low-res) and D_h (high-res)
- For each input low-res patch, p_l , find its representation under D_l, with $p_l = D_l a_l$, where a_l is coefficient vector
- Use a_l to reconstruct the high-res patch, with $p_h = D_h a_l$
- How was the constraint applied? a_l is used for high-res representation
- Sparse representation: a_l is found through l_1 minimization

Their results



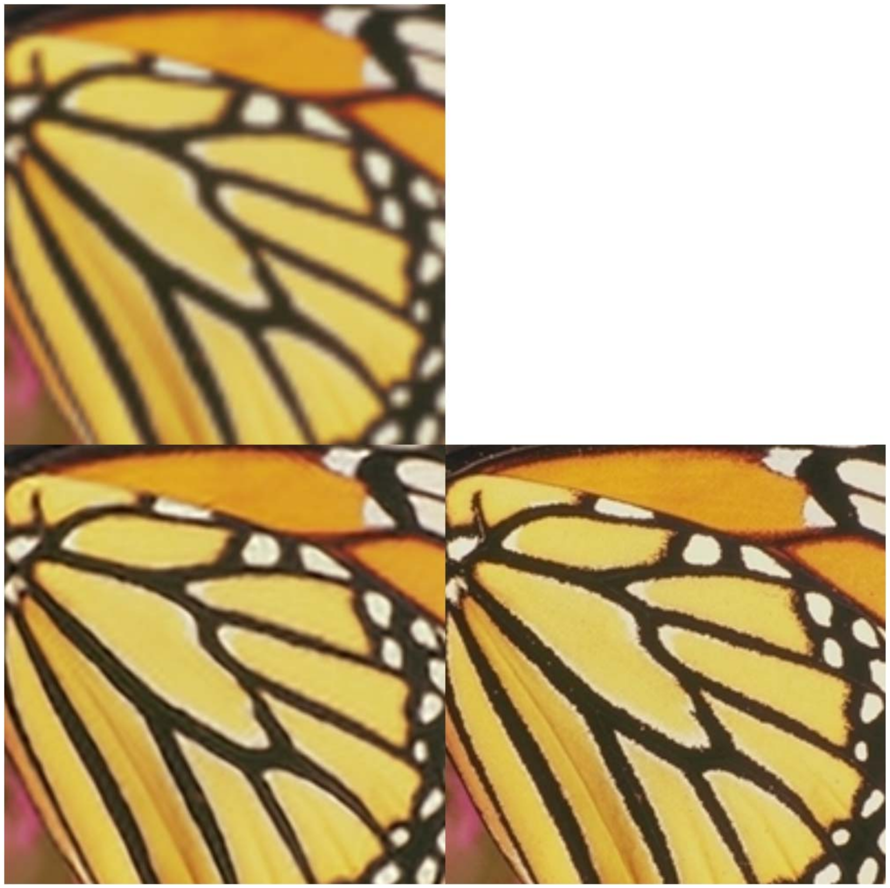
(e) (f)

- 1st row: low-res and interpolation result
- 2nd row: super-res and ground truth
- From Trinh 2014
- Images in example database are similar to the high-res ground truth

Another implementation

- Peleg and Elad (2014, IEEE Trans IP), applied to natural images
- Use example images to construct two dictionaries, D_l (low-res) and D_h (high-res)
- For each input low-res patch, p_l , find its representation under D_l, with $p_l = D_l a_l$, where a_l is coefficient vector
- Use a_l to predict high-res representation, with a_h=$F(a_l)$, where $F(\cdot)$ is a trained prediction function/network
- Reconstruct the high-res patch, with $p_h = D_h a_h$
- Other innovations: cluster-based predictions, multi-level reconstruction, and overlapping patches, etc.

Their Results



- From: Peleg and Elad (2014 IEEE Trans. IP)
- 1^{st} row: interpolation of low-res and super resolution
- 2^{nd} row: Peleg and Elad and ground truth

Advantages/Disadvantages of Using a Dictionary

- Advantages:
  - More adapted to the signals/images of interest
  - More sparse representations
- Disadvantage:
  - more computations need to obtain representation coefficients (compared with using an orthonormal basis)

Summary and Future Work

- Super resolution can “beat Nyquist limit” using training examples
- For this to work: the examples need to be similar to the images to be recovered/enhanced
- Future work
  - Apply to security images for ATR
    - Perform super resolution on images obtained with fewer views
    - See if this improves PD and PFA
  - A major problem for ATR: image artifacts; does super resolution help?
    - Test to see if super resolution help to reduce artifacts and improves PD and PFA