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MOTION BLUR REMOVAL VIA COUPLED AUTOENCODER

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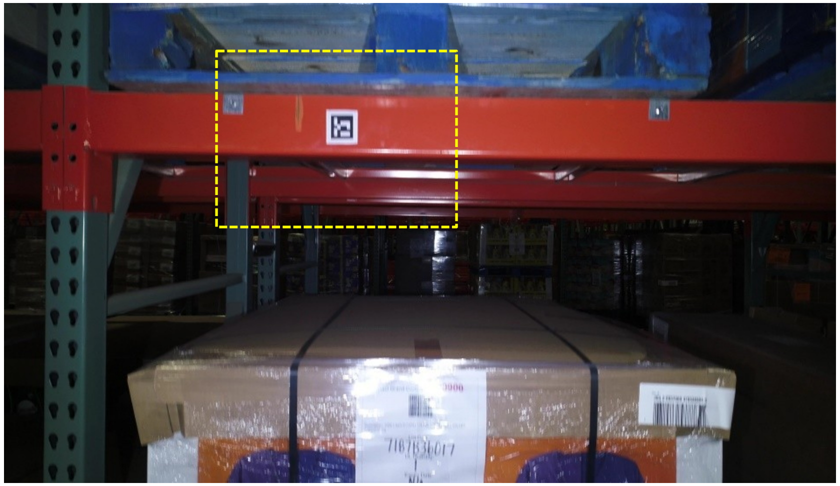
Motivation

- Motion blur - a common source of image corruption.
- Occurs while acquiring images and videos :
  - cameras fitted to the high speed motion drones
  - even when drone is hovering.
- Distorted images intervene with the mapping of the visual points.
- Need for real time Deblurring techniques:
  - Optical flow
  - scene understanding
  - SLAM
  - visual odometry etc.



Contribution

- Existing deblurring algorithms fail due to :
  - non-generalized kernel based approaches
  - computational complexity.

- Usual deblurring techniques solve an iterative inverse problem :
  - good quality images
  - *precludes* itself from real-time applications.

- Propose deblurring as a *transfer learning problem.*

- We solve it via learning framework : Coupled Autoencoder

- Proposed technique is :
  - Generic.
  - Used for any inverse problem in imaging, e.g. denoising, inpainting, super-resolution etc.
  - operate on-the-fly.
  - does not require solving any costly inverse problem.

State of the Art

- Image deblurring techniques categorized in two types :
  - blind
  - non-blind

- *Non-blind* : require priors about the blur kernel and it's parameters.

- *Blind* : assume that the kernel is unknown.

- Estimation of accurate kernels is detrimental especially for space variant blurs.

- Few Single image deblurring techniques:
  - jointly estimate the motion kernels and sharp image.
  - use sparsity priors to retreive latent sharp image for better kernel estimations.(*Krishnan et al. CVPR 2011 , Pan et al. CVPR 2014, Xu et al. CVPR 2013*)
  - estimated in the camera motion space itself.(*Whyte et al. IJCV 2014*)

State of the Art

- Recent development on devising learning based techniques - *learning the degradation models.*
- Plethora of studies on neural networks and CNNs frameworks for solving computer vision tasks (*Xu et al. NIPS 2014 , Dong et al. PAMI 2016*)
- *Xu et al. NIPS 2014*, proposed an image deconvolution neural network for non-blind deconvolution which focuses on removal of uniform blur.
- *Ren et al. AAAI 2015*, VCNN showed improvement on various high and low level vision tasks.
- Sun et al. CVPR 2015 paper predicted the motion kernel at patch level using a CNN and focused on Non-Uniform motion blur.

Coupled Representation Learning

- Coupled dictionary learning has a rich literature.(*Wang et al. CVPR 2012 , Yang et al. TIP 2012)*

- Used for solving a variety of problems in image synthesis:
  - single image super-resolution
  - photo-sketch synthesis
  - cross spectral (RGB-NIR) face recognition
  - RGB depth classification etc.

- *Main idea* : learning of dictionaries for the two domains - source and target, linear mapping the coefficients.

- The concept of coupled autoencoder is new; it follows from dictionary learning.

- *Main idea* : learn an autoencoder for the source and another for the target along with a mapping from the source to the target (*semi-coupled*) and vice versa (*fully coupled*).

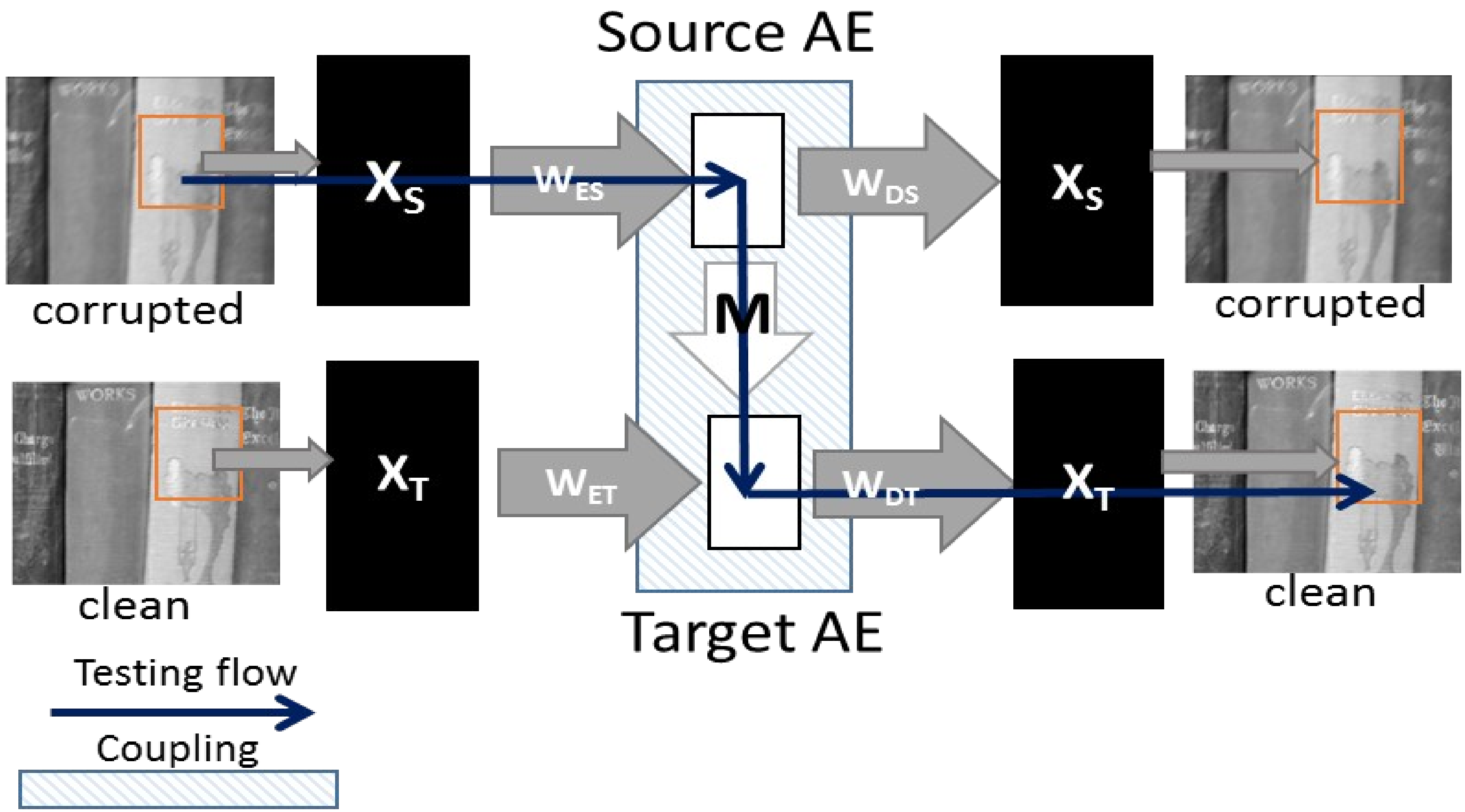
Coupled Autoencoder

- Handful of studies on Coupled Autoencoders.
- In Zeng et al., two deep stacked autoencoders for two domains - are learnt separately. Once learnt a mapping from the deepest layer of the source autoencoder is learnt to the target autoencoder - *piecemeal and sub-optimal.*
- In Wang et al., it learns coupled shallow autoencoders and stacks them up to form a deep architecture greedily.
- The only prior work by Wang et al. , optimally learns the mapping during training process is using a MDAs, which is much simpler to solve compared to the full autoencoder.

Proposed Method

- Introduces an *optimal formulation* for Coupled autoencoder.
- Autoencoders for source and target are learnt simultaneously with the linear mapping between the two.
- Optimal in the sense that all the variables influence each other in the learning process - *missing in prior works.*
- Source autoencoder uses the blurred samples and the target autoencoder uses the corresponding clean samples.
- Coupling learns to map the representation from the source (blurred) to the target (clean).

Proposed Method



Schematic Diagram of Coupled Autoencoder

Formulation

Mathematically this is expressed as,

$$\underset{W_{DS},W_{ES},W_{DT},W_{ET},M}{\arg\min} \underbrace{\left\| X_S - W_{DS}\varphi(W_{ES}X_S) \right\|_F^2}_{\text{Source AE}} + \underbrace{\left\| X_T - W_{DT}\varphi(W_{ET}X_T) \right\|_F^2}_{\text{Target AE}} + \underbrace{\lambda \left\| \varphi(W_{ET}X_T) - M\varphi(W_{ES}X_S) \right\|_F^2}_{\text{Coupling}}$$

- Solve via Variable Splitting and Split Bregman Technique.
- Reduce the formulation to multiple sub problems.
- Simple least squares problems having an analytic solution in the form of pseudo inverse.
- Update the Bregman relaxation variables.

Dataset

- Standard image blur dataset - CERTH dataset.
  - Training set :
    - 630 undistorted
    - 220 naturally-blurred
    - 150 artificially-blurred
  - Testing set :
    - 619 undistorted
    - 411 naturally-blurred
    - 450 artificially-blurred
- Small subset of the dataset - 50 images for training, 20 images for testing
- Two scenarios Uniform blur and Non-Uniform Blur.
- Patchwise Deblurring of overlapping patches
- No pre-processing on the images.

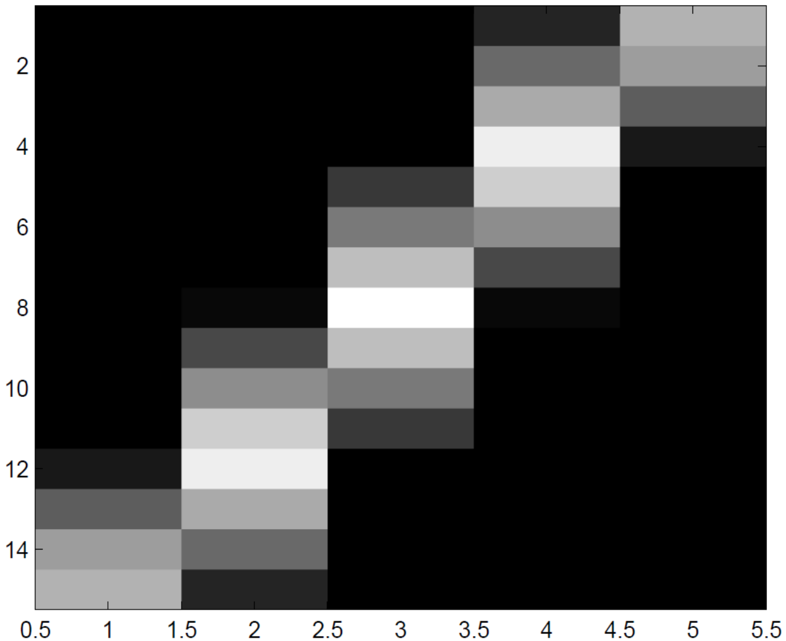
Results

Blur Type	Krishnan et al.[1]	Whyte et al.[2]	Pan et al.[3]	Xu et al.[4]	Xu et al.[5]	Ren et al.[6]	Proposed
Uniform (PSNR)	23.7679	23.5257	23.6927	22.9265	25.6540	20.9342	**30.8893**
(SSIM)	0.6929	0.6899	0.7015	0.6620	0.7708	0.7312	**0.8787**
Non- Uniform (PSNR)	20.3013	20.4161	19.6594	20.5548	19.9718	20.8226	**29.6364**
(SSIM)	0.5402	0.5361	0.5345	0.5812	0.5692	0.7328	**0.8711**

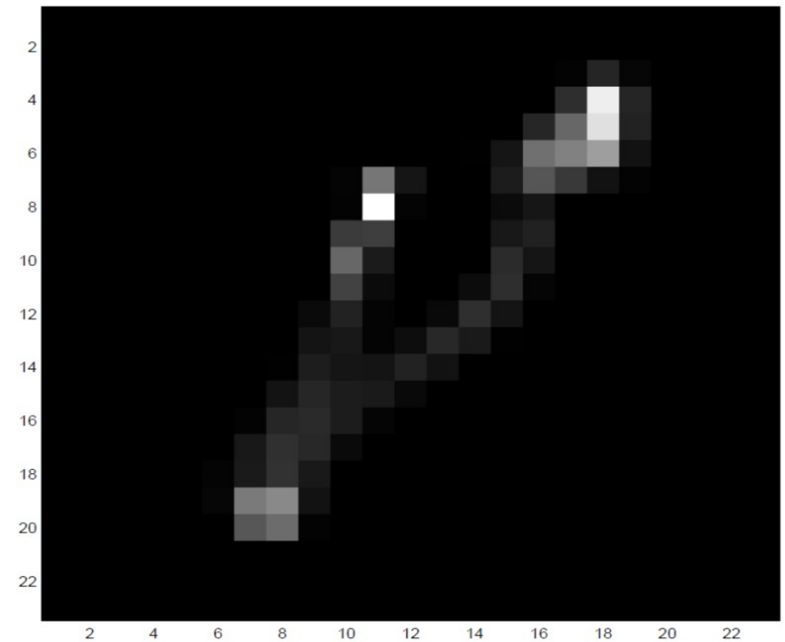
1. D. Krishnan, T. Tay, and R. Fergus, “Blind deconvolution using a normalized sparsity measure,” in Computer Vision and Pattern Recognition (CVPR), 2011 IEEE Conference on. IEEE, 2011, pp. 233–240.
2. O. Whyte, J. Sivic, and A. Zisserman, “Deblurring shaken and partially saturated images,” International journal of computer vision, vol. 110, no. 2, pp. 185–201, 2014.
3. J. Pan, Z. Hu, Z. Su, and M. Yang, “Deblurring text images via l0-regularized intensity and gradient prior,” in Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, 2014, pp. 2901–2908.
4. L. Xu, S. Zheng, and J. Jia, “Unnatural l0 sparse representation for natural image deblurring,” in Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, 2013, pp. 1107–1114.
5. L. Xu and J. Jia, “Two-phase kernel estimation for robust motion deblurring,” in European Conference on Computer Vision. Springer, 2010, pp. 157–170.
6. J. S. Ren and L. Xu, “On vectorization of deep convolutional neural networks for vision tasks,” arXiv preprint arXiv:1501.07338, 2015.

Results

Blur Kernels used for experimentation.



Uniform Blur Kernel



Non Uniform Blur Kernel*

**A. Levin, Y.Weiss, F. Durand, andW. T Freeman, "Understanding and evaluating blind deconvolution algorithms," in Computer Vision and Pattern Recognition, 2009. CVPR 2009. IEEE Conference on. IEEE, 2009, pp. 1964–1971.*

Results (Uniform)

Clean

Corrupt

Output of Ren et al. AAAI 2015

Proposed

Results (Non Uniform)

Clean

Corrupt

Output of Ren et al. AAAI 2015

Proposed

Conclusion

- Proposed optimal formulation of learning coupled autoencoders simultaneously learning mapping between source and target autoencoders.
- Our method is generalized and can be applied to any transfer learning problem.
- Through experimental evaluation we showed success of our proposed method on motion blurred images.
- Our method is computationally inexpensive and deblur images in seconds.

Future Work

- Testing on real datasets i.e. videos captured from the moving drones.
- Extensive testing for other inverse problems such as super-resolution , denoising and reconstruction.
- Adding constraints and priors to the formulation.

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