A . Brömme, C. Busch, A. Dantcheva, C. Rathgeb and A. Uhl (Eds.): BIOSIG 2017,
Lecture Notes in Informatics (LNI), Gesellschaft für Informatik, Bonn 2017

Exploring Texture Transfer Learning via Convolutional Neural Networks for Iris Super Resolution

Eduardo Ribeiro [1,2], Andreas Uhl [2]

Abstract: Increasingly, iris recognition towards more relaxed conditions has issued a new super-resolution field direction. In this work we evaluate the use of deep learning and transfer learning for single image super resolution applied to iris recognition. For this purpose, we explore if the nature of the images as well as if the pattern from the iris can influence the CNN transfer learning and, consequently, the results in the recognition process. The good results obtained by the texture transfer learning using a deep architecture suggest that features learned by Convolutional Neural Networks used for image super-resolution can be highly relevant to increase iris recognition rate.

Keywords: Single-Image Super Resolution, Iris Recognition, Transfer Learning, Convolutional Neural Networks.

1 Introduction

Iris recognition is one of the most accurate biometric modality for human identification mainly because of the intrinsic randomic and stable nature of the iris texture besides its high degree of freedom and noninvasive acquisition [Hs16]. In an effort to solve the problems related to the resolution of images mainly due to the iris capture distance and the inclusion of mobile devices in this field, researchers have focused on improving the image resolution that may allow the iris recognition of low resolution images since there is a substantial performance decrease directly related to the lack of pixel resolution. [Ka10]

One of the most relevant areas related to this problem is the Single-Image Super Resolution, which aim to recover a high-resolution image from a low resolution one. Examples are the use of internal patch recurrence [HSA15], regression functions [Li15] [TDV15] and sparse dictionary methods [Ya12]. However, the use of SR techniques for biometric systems especially for iris recognition is still limited including methods based on PCA eigen-patch transformation [AFFB15] and non-parametric Bayesian dictionary learning [Al15].

Over recent years, new techniques applying deep learning have been widely explored to map models from low resolution to high resolution patches primarily based in previous models applied to image denoising. Some examples are the use of Convolutional Neural Networks and Autoencoders [JAL16], [Le16], [Sh16]. Among these several successful examples, two approaches have become very popular: first the Super-Resolution Convolutional Neural Network (SRCNN) presented by [Do16] that became to be a good alternative in the first experiments for an end-to-end approach in super-resolution using Convolutional Neural Networks and then the Very Deep Convolutional Networks for Super-Resolution

This research was partially supported by CNPq-Brazil for Eduardo Ribeiro under grant No. 00736/2014-0.
[1] Federal University of Tocantins, Department of Computer Sciences, Tocantins, Brazil, uft.eduardo@uft.edu.br
[2] University of Salzburg, Department of Computer Sciences Salzburg, Austria, uhl@cosy.sbg.ac.at

(VDCNN) proposed by [KLL16] inspired by the VGG-net used for the ImageNet classification [SZ14] increasing the network depth to achieve better accuracy.

Some studies show that the use of transfer learning (approach used to improve the performance of machine learning by harnessing the knowledge acquired in another task) also can be used to assist in the task of single image super resolution as in [YZL17], [SZJ16] and [SH17]. The main problem is to know which database is more suitable to perform this transfer learning and to be able to learn the correct patterns that will be useful in the target database.

For this, in this work we aim to answer the following questions: is the similarity of the dataset used in the transfer learning important to a better mapping? Are different Iris Databases more feasible for transfer learning applied to Iris Super Resolution? In particular, do we get better results in applying the transfer learning for Super Resolution when the CNN is trained with natural image datasets, texture datasets or iris datasets? Another issue that we aim to test is if, in a practical application, we could use enrollment images in high definition already stored on the system to train a CNN and transfer the knowledge from this dataset to the entire database in order to increase accuracy of the results.

2 Methodology

2.1 Target/Test Database

To test the transfer learning with the different training databases, the chosen target database was the public iris dataset CASIAIrisV3-Interval that is the most widely use on biometrics experiments containing a total of 2.655 NIR images of size 280x320 pixels, from 249 subjects captured with a self-developed close-up camera, resulting in 396 different eyes.

In a pre-processing step, all images from this database are resized via bicubic interpolation to have the same sclera radius, then a square region of 231x231 around the pupil center is cropped. The images that do not fit in this cropping are discarded. After this procedure, 1872 images from 249 users are remained in the database. For the evaluation method, we divide this resulting database into two: one containing the first three images of each user (representing the registration images) and other containing the remaining images from each user (representing the authentication images). The registration database will be one of the used databases in the training of the CNN's and the other (authentication database) will be used for all transfer learning evaluation.

2.2 Origin/Training Databases

For the CNN training, besides the use of the registration images from the Test Database as mentioned before, we use 10 different databases including four texture databases, two natural image databases and four iris databases (from the public IRISSEG-EP [Ho14] dataset) described as follows.

- Texture Databases: The Amsterdam Library of Textures (**ALOT**) with 27500 rough texture images of size 384x256 divided into 250 classes [BG09]. The Describable Texture Dataset (**DTD**) with 5640 images of sizes range betwenn 300x300 and 640x640 categorized in 47 classes [Ci14]. The Flickr Material Database (**FMD**) containing 1000 images of size 512x384 divided into 10 categories [SRA09]. The

Textures under varying Illumination, Pose and Scale (**KTH-TIPS**) database with 10 different materials containing 81 cropped images of size 200x200 in each class [Da99].

- Natural Image Databases: The **CALTECH101** Database is a natural image dataset with a list of objects belonging to 101 categories [FFFP07]. The **COREL1000** database is a natural image database containing 1000 color photographs showing natural scenes of ten different categories [RBB08].
- Iris Databases: The IIT Delhi Iris Database (**IITD**) is an Iris Database consisting of data acquired in a real environment resulting in 2240 images of size 230x240 from a digital CMOS near-infrared camera. The CASIA-Iris-Lamp (**CASIAIL**) is an Iris database collected using a hand-held iris sensor and containing 16212 images of size 320x280 with nonlinear deformation due to variations of visible illumination. The **UBIRIS** v2 Iris database is a database containing 2250 images of size 400x300 captured on non-constrained conditions (at-a-distance, on-the-move and on the visible wavelength), attempting to simulate more realistic noise factors. The **NOTREDAME** Iris Database is a collection of close-up near-infrared Iris images containing 837 images of size 640x480 with off-angle, blur, interlacing, and occlusion factors.

2.3 CNN Architectures and Frameworks

In this work, for the comparison between different databases using transfer learning we use a classical Single-Image Super Resolution approach as base called SRCNN [KLL16]. The framework of this approach consists of three steps: patch extraction/representation, non-linear mapping and reconstruction. In this method, for the training step, patches of size 33x33 (also called High Resolution (HR) patches) are extracted from the training images and used as labels for the CNN, then those same patches are downscaled in a factor of 2 and re-upscaled to the original size using bicubic interpolation being used as inputs to the network (also called Low Resolution (LR) Patches). The SRCNN architecture is composed by three convolutional layers, where: the first layer consists of 64 filters of size 9x9x1 with stride 1 and padding 0, the second layer with 32 filters of size 1x1x64 with stride 1 and padding 0, and the last layer with 1 filter of size 5x5x32 with stride 1 and padding 0. The loss function used in this case is the Mean Squared Error (MSE) and loss minimization is done using stochastic gradient descent with the standard backpropagation method [Le01].

We also decided to use the deeper CNN VDSR [SZ14] that increases significantly the depth of the network to have a better clarification of the issues raised in this work. The framework of this approach is done by the following steps: for the training, HR patches are extracted and downscaled for the factor two, three and four (LR patches) that will serve as input of the network. In the case of this approach the labels will be the residual between the LR inputs and then HR patches. The residual-learning boost the convergence and consequently, the performance of the CNN. The VDSR architecture is composed of 20 layers and the information used for reconstruction have size of 1x41x41 (much larger than the SRCNN). The training is carried out also based on the gradient descend with backpropagation [Le01] using the MatConvNet framework [VL14].

In both frameworks, for the CNN training, a subset of 150000 patches are extracted from each database to pre-train each CNN from scratch (when the CNN weights are initialized randomly) using the pre-selected databases and use them in the target database to perform the Super-Resolution.

3 Experimental Setup

In the method evaluation, to generate the reconstructed image we use the target image database: images from CASIAIrisV3-Interval that were not used in the training for the same database (registration versus authentication images) as explained in the previous section. For each transfer learning procedure the images from the authentication database are downscaled to the desired factor : 2 (115x115), 4 (57x57), 8 (29x29) and 16 (15x15) and re-upscaled using the bicubic interpolation for factor 2, then the images pass through the deep learning CNN (SRCNN or VDCNN) to reconstruct the final super-resolved image database. Therefore, in this case, to achieve the factor 2 the image will be interpolate and pass through the trained CNN just one time. To achieve greater factors, images have to pass through the procedure $\log_2(n)$ times, where n is the desired factor.

To evaluate the performance of the transfer learning approach by quality assessment algorithms we use the the Peak Signal to Noise Ratio (PSNR) and the Structural Similarity Index Measure (SSIM). In these two metrics, a high metric score reflects a high quality. For the quality tests, all images from the database are used in high resolution as reference images.

Besides the quality assessment performance, we also conduct recognition experiments using the USIT - University of Salzburg Iris Toolkit v2 for Iris Recognition [Ra16] with two different iris segmentation and two feature extraction methods. In the first approach the iris is segmented and unwrapped to a normalized rectangle of 64x512 pixels using the weighted adaptive Hough and ellipsopolar transform (WAHET). Then, a complex Gabor filterbank with eight different filter size and wavelength is used to extract the iris features (CG) that will be compared using the normalized Hamming distance [Ra16]. In the second approach, the iris is segmented also using the weighted adaptive Hough and ellipsopolar transform (WAHET). Then, a classical wavelet-based feature extraction is done with a selection of spatial wavelets (QSW) that will also be compared using the normalized Hamming Distance [Ra16]. In both cases, with these procedures, using the CASIAIrisV3-Interval database with 249 users containing at least five or more images per user, we obtain 5087 genuine and 1746169 impostors scores.

We compare our method with bilinear and bicubic interpolation. We are aware that this comparison is very limited, however Super-Resolution in Iris Recognition research still is a very new field and the improvement of the comparison of transfer-learning techniques will lead to a more profound and comprehensive framework to future evaluation.

4 Results

Table 1 shows the quality assessment results for the transfer learning in different databases using the SRCNN architecture for different factors: 2, 4, 8 and 16. It can be seen that all transfer learning approaches outperform the bilinear and bicubic interpolations for all factors including bigger factors showing the resilience of the deep-learning method when image resolution decreases.

It also can be noticed that the transfer learning using texture databases perform better in terms of similarity to the original HR database than the transfer learning using iris databases. However, the results from the Casia Interval transfer learning present good results compared to the other iris databases. The best result in this case is when the CNN is trained with the DTD database especially for higher factors and the Caltech101 database for smaller factors.

				Texture Databases				Natural Image Databases			Iris Databases			
LR Size (SCALING)		Bilinear	Bicubic	ALOT	DTD	FMD	KTH TIPS	CALTECH 101	COREL 1000	IITD	CASIAIL	UBIRIS	NOTRE DAME	CASIA INTERVAL
115X115	PSNR	0.8855	0.8957	0.9481	**0.9595**	0.9509	0.9485	0.9492	0.9491	0.9483	0.9422	0.9414	0.9495	0.9502
(1/2)	SSIM	30.77	31.07	35.17	**35.87**	35.82	35.79	35.85	35.34	35.43	35.12	34.67	35.70	35.80
57X57	PSNR	0.7949	0.8089	0.8243	**0.8259**	0.8245	0.8232	0.8250	0.8255	0.8214	0.8129	0.8131	0.8216	0.8240
(1/4)	SSIM	27.99	28.67	29.20	**29.32**	29.29	29.23	29.24	28.97	29.18	29.01	28.86	29.24	29.29
29X29	PSNR	0.6956	0.7061	0.7198	0.7228	0.7157	0.7204	**0.7251**	0.7236	0.7127	0.7064	0.7085	0.7128	0.7174
(1/8)	SSIM	24.59	25.06	25.61	25.79	25.57	25.69	**25.80**	25.50	25.44	25.15	25.12	25.44	25.54
15X15	PSNR	0.6120	0.6160	0.6510	0.6544	0.6471	0.6503	**0.6557**	0.6553	0.6439	0.6406	0.6430	0.6447	0.6494
(1/16)	SSIM	20.78	20.93	23.09	**23.23**	23.07	23.04	23.21	23.05	23.01	22.67	22.69	22.97	22.95

Table 1: Results of quality assessment algorithms for different databases training with different downscaling factors (average values on the test dataset) using the SRCNN architecture comparing to the Bilinear and Bicubic approach.

In the iris recognition verification, it can be seen from Table 2 that the results present different best results among the databases as well as presents mismatch results between the quality experimental results from table 2 and the verification results. In the case of EER the best result for the factor 2 (115X115) is when the DTD database is used (accuracy of 6.07%) in accordance with the quality assessment results (PSNR and SSIM) presenting even better results than the original database (6.657% of accuracy). Nonetheless, for the factor 4 (57x57), the best result is from the bicubic interpolation even better than all the results from the factor 2 and from the original HR database results. Among the training databases, for the recognition experiments, the more consistently beneficial for the transfer learning is the KTHTIPS database especially for the factors 4 and 8. Using the enrollment images from the same target database (Casia Interval) does not lead to good recognition performances, which means that the CNN poorly memorize the patterns from the users focusing more in general patterns, mainly because the depth of the network that does not allow a high feature discrimination.

				Texture Databases				Natural Image Database			Iris Databases			
LR Size (SCALING)		Bilinear	Bicubic	ALOT	DTD	FMD	KTH TIPS	CALTECH 101	COREL 1000	IITD	CASIAIL	UBIRIS	NOTRE DAME	CASIA INTERVAL
115X115	WAHET + CG	6.32	6.39	6.50	**6.07**	6.66	7.16	6.74	6.39	6.68	6.61	6.37	6.64	6.83
(1/2)	WAHET+QSW	**3.26**	3.58	3.58	3.32	3.81	4.28	4.02	3.53	3.89	3.92	3.42	4.02	3.84
57X57	WAHET + CG	9.36	**5.81**	7.19	6.67	6.88	6.22	6.83	6.51	7.90	7.84	8.41	7.59	6.66
(1/4)	WAHET+QSW	6.10	**2.65**	4.58	3.78	4.09	3.62	3.95	3.74	5.11	5.22	5.75	4.66	3.93
29X29	WAHET + CG	36.11	42.22	32.97	32.19	36.86	**22.41**	32.88	33.81	38.19	39.88	39.75	39.15	33.89
(1/8)	WAHET+QSW	33.60	42.34	30.62	31.13	34.89	**21.75**	32.10	33.26	36.50	38.53	37.33	37.04	30.65
15X15	WAHET + CG	31.66	32.96	33.95	33.10	33.03	33.96	33.02	34.68	32.73	**28.52**	29.62	31.50	31.57
(1/16)	WAHET+QSW	30.68	32.18	32.57	32.06	31.60	33.06	31.66	33.18	31.84	**27.60**	28.02	31.25	30.17

Table 2: Verification results (EER) for different databases training for different downscaling factors using the SRCNN architecture comparing to the Bilinear and Bicubic approach. The accuracy result for the original database with no scaling is 6.65% for WAHET + CG and and 3.81% for WAHET + QSW.

With the two better databases transfer learning from both quality assessment algorithms and recognition experiments (KTHTIPS and DTD) we decide to explore the deeper network (VDCNN) comparing the results with the CASIA INTERVAL registration images transfer learning approach also using the Very deep Super Resolution CNN (VDCNN). It can be seen in the Table 3 that this architecture leads to superior results comparing to the SRCNN in the quality measures and mainly for greater factors (8 and 16) in the recognition experiments. It also can be noticed that with deeper layers, the CNN could be able to extract more specific texture patterns from the Iris boosting the performance using Casia Interval database showing much better and consistent performances with this database.

				CASIA INTERVAL		KTHTIPS		DTD	
LR Size (SCALING)		Bilinear	Bicubic	SRCNN	VDCNN	SRCNN	VDCNN	SRCNN	VDCNN
115x115 (1/2)	PSNR	0.8855	0.8957	0.9502	0.9555	0.9485	0.9493	**0.9595**	0.9540
	SSIM	30.77	31.07	35.80	**36.90**	35.79	36.17	35.87	36.56
	WAHET + CG	6.32	6.39	6.83	6.63	7.16	6.43	**6.07**	6.32
	WAHET + QSW	**3.26**	3.58	3.84	3.78	4.28	3.63	3.32	3.53
57x57 (1/4)	PSNR	0.7949	0.8089	0.8240	0.8347	0.8232	0.8256	0.8259	**0.8348**
	SSIM	27.99	28.67	29.29	29.60	29.23	29.42	29.32	**29.65**
	WAHET + CG	9.36	**5.81**	6.66	6.51	6.22	6.83	6.67	6.69
	WAHET + QSW	6.10	**2.65**	3.93	3.26	3.62	3.41	3.78	3.41
29x29 (1/8)	PSNR	0.6956	0.7061	0.7174	0.7332	0.7204	0.7252	0.7228	**0.7374**
	SSIM	24.59	25.06	25.54	26.04	25.69	25.92	25.79	**26.21**
	WAHET + CG	36.11	42.22	33.89	**17.88**	22.41	22.14	32.19	19.07
	WAHET + QSW	33.60	42.34	30.65	**16.72**	21.75	19.20	31.13	17.07
15x15 (1/16)	PSNR	0.6120	0.6160	0.6494	0.6563	0.6503	0.6494	0.6544	**0.6633**
	SSIM	20.78	20.93	22.95	23.30	23.04	22.95	23.23	**23.57**
	WAHET + CG	31.66	32.96	**31.57**	33.87	33.96	**31.57**	33.10	33.85
	WAHET + QSW	30.68	32.18	**30.17**	32.03	33.06	**30.17**	32.06	31.76

Table 3: Quality assessment (PSNR and SSIM) and verification results (WAHET + CG and WAHET + QSW) for different databases training and different downscaling factors using the SRCNN and VDCNN architectures. The accuracy result for the original database with no scaling is 6.65% for WAHET + CG and 3.81% for WAHET + QSW.

It also can be noticed with the two different architectures comparing it to the bicubic and bilinear interpolations that, specially in the SSIM measure, the biggest drop can be observed for small down sampling factors. The CassiaInterval-VDCNN and DTD-VDCNN database present in both measures (SSIM and PSNR) superior results especially for low resolution images. On the other hand, for the recognition experiments, despite the good performance for small factors there is a significant degradation when it comes to very low resolution using these two databases. It also can be seen that despite the disparity between quality and recognition results, the databases that present the best recognition results in average are the KTHTIPS-VDCNN database and the CasiaInterval-VDCNN database specially for the factors 2, 4 and 8 that the performance is not significantly degraded. We consider that a good recognition performance is better than a quality measure in this case, so it can lead to the allowance of using small size images in systems under low storage or data transmission potential for example.

5 Conclusions

Exploring deep learning for single-image super resolution to improve the performance of iris recognition still is a new research area. In this paper we explore the use of texture transfer learning for super resolution applied to low resolution images. This approach was evaluated in a subset of Casia Iris Database representing the authentication images to also verify if the transfer learning from the registration image subset is suitable for this application. We have shown how the features from completely different nature can be transferred in the feature domain, improving the recognition performance if applied to bigger reduction factors comparing to the classical interpolation approaches.

The experiments showed that the transfer learning was successful using all databases especially for the texture databases and using a deeper architecture in an uncontrolled scenario (when both the enrollment and the authentication images are in low resolution) despite the fact that there was not a best database to be used in all factors. In future work we intend to explore the fusion between the best databases with the enrollment images to see if the results can be even better for all cases. The direction of this research can become much more practical to many real scenarios specially in real-life applications when both the malleability of capturing devices and the recognition rate are important aspects for a successful iris recognition system.

References

[AFFB15] Alonso-Fernandez, F.; Farrugia, R. A.; Bigun, J.: Eigen-patch iris super-resolution for iris recognition improvement. In: 2015 23rd European Signal Processing Conference (EUSIPCO). Aug 2015.

[Al15] Aljadaany, R.; Luu, K.; Venugopalan, S.; Savvides, M.: IRIS super-resolution via nonparametric over-complete dictionary learning. In: 2015 IEEE International Conference on Image Processing (ICIP). pp. 3856–3860, Sept 2015.

[BG09] Burghouts, G.; Geusebroek, J.: Material-specific adaptation of color invariant features. Pattern Recognition Letters, 30(3):306 – 313, 2009.

[Ci14] Cimpoi, M.; Maji, S.; Kokkinos, I.; Mohamed, S.; ; Vedaldi, A.: Describing Textures in the Wild. In: Proceedings of the IEEE Conf. on Computer Vision and Pattern Recognition (CVPR). 2014.

[Da99] Dana, K.; van Ginneken, B.; Nayar, S.; Koenderink, J.: Reflectance and Texture of Realworld Surfaces. ACM Trans. Graph., 18(1):1–34, January 1999.

[Do16] Dong, C.; Loy, C. C.; He, K.; Tang, X.: Image Super-Resolution Using Deep Convolutional Networks. IEEE Transactions on Pattern Analysis and Machine Intelligence, 38(2):295–307, Feb 2016.

[FFFP07] Fei-Fei, L.; Fergus, R.; Perona, P.: Learning Generative Visual Models from Few Training Examples: An Incremental Bayesian Approach Tested on 101 Object Categories. Comput. Vis. Image Underst., 106(1):59–70, April 2007.

[Ho14] Hofbauer, H.; Alonso-Fernandez, F.; Wild, P.; Bigun, J.; Uhl, A.: A Ground Truth for Iris Segmentation. In: 2014 22nd International Conference on Pattern Recognition. pp. 527–532, Aug 2014.

[Hs16] Hsieh, S. H.; Li, Y. H.; Tien, C. H.; Chang, C. C.: Extending the Capture Volume of an Iris Recognition System Using Wavefront Coding and Super-Resolution. IEEE Transactions on Cybernetics, 46(12):3342–3350, Dec 2016.

[HSA15] Huang, J. B.; Singh, A.; Ahuja, N.: Single image super-resolution from transformed self-exemplars. In: 2015 IEEE Conference on Computer Vision and Pattern Recognition (CVPR). pp. 5197–5206, June 2015.

[JAL16] Johnson, J.; Alahi, A.; Li, Fei-Fei: Perceptual Losses for Real-Time Style Transfer and Super-Resolution. CoRR, abs/1603.08155, 2016.

[Ka10] Kalka, N. D.; Zuo, J.; Schmid, N. A.; Cukic, B.: Estimating and Fusing Quality Factors for Iris Biometric Images. IEEE Transactions on Systems, Man, and Cybernetics - Part A: Systems and Humans, 40(3):509–524, May 2010.

[KLL16] Kim, J.; Lee, J. K.; Lee, K. M.: Accurate Image Super-Resolution Using Very Deep Convolutional Networks. In: 2016 IEEE Conference on Computer Vision and Pattern Recognition (CVPR). pp. 1646–1654, June 2016.

[Le01] LeCun, Y.; Bottou, L.; Bengio, Y.; Haffner, P.: Gradient-Based Learning Applied to Document Recognition. In: Intelligent Signal Processing. IEEE Press, 2001.

[Le16] Ledig, C.; Theis, L.; Huszar, F.; Caballero, J.; Aitken, A. P.; Tejani, A.; Totz, J.; Wang, Z.; Shi, W.: Photo-Realistic Single Image Super-Resolution Using a Generative Adversarial Network. CoRR, abs/1609.04802, 2016.

[Li15] Li, J.; Qu, Y.; Li, C.; Xie, Y.; Wu, Y.; Fan, J.: Learning local Gaussian process regression for image super-resolution. Neurocomputing, 154, 2015.

[Ra16] Rathgeb, C.; Uhl, A.; Wild, P.; Hofbauer, H.: Design Decisions for an Iris Recognition SDK. In (Bowyer, Kevin; Burge, Mark J., eds): Handbook of Iris Recognition, Advances in Computer Vision and Pattern Recognition. Springer, second edition edition, 2016.

[RBB08] Ribeiro, E.; Barcelos, C.; Batista, M.: Image Characterization via Multilayer Neural Networks. In: 2008 20th IEEE International Conference on Tools with Artificial Intelligence. volume 1, pp. 325–332, Nov 2008.

[Sh16] Shi, W.; J.Caballero; Huszár, F.; Totz, J.; Aitken, A. P.; Bishop, R.; Rueckert, D.; Wang, Z.: Real-Time Single Image and Video Super-Resolution Using an Efficient Sub-Pixel Convolutional Neural Network. CoRR, abs/1609.05158, 2016.

[SH17] Sun, L.; Hays, J.: Super-resolution Using Constrained Deep Texture Synthesis. CoRR, abs/1701.07604, 2017.

[SRA09] Sharana, L.; R.Rosenholtz; Adelson, E.: Material perception: What can you see in a brief glance? Journal of Vision, 9:784, 2009.

[SZ14] Simonyan, K.; Zisserman, A.: Very Deep Convolutional Networks for Large-Scale Image Recognition. CoRR, abs/1409.1556, 2014.

[SZJ16] Su, M.; Zhong, S.; Jiang, J.: Transfer Learning Based on A+ for Image Super-Resolution. In (Lehner, F.; Fteimi, N., eds): Knowledge Science, Engineering and Management: 9th International Conference, KSEM 2016, Passau, Germany, October 5-7, 2016, Proceedings. Springer International Publishing, Cham, pp. 325–336, 2016.

[TDV15] Timofte, R.; DeSmet, V.; VanGool, L.: A+: Adjusted Anchored Neighborhood Regression for Fast Super-Resolution. In: 12th Asian Conference on Computer Vision. Springer International Publishing, Cham, 2015.

[VL14] Vedaldi, A.; Lenc, K.: MatConvNet - Convolutional Neural Networks for MATLAB. CoRR, abs/1412.4564, 2014.

[Ya12] Yang, J.; Wang, Z.; Lin, Z.; Cohen, S.; Huang, T.: Coupled Dictionary Training for Image Super-Resolution. IEEE Transactions on Image Processing, 21(8), Aug 2012.

[YZL17] Yuan, Y.; Zheng, X.; Lu, X.: Hyperspectral Image Superresolution by Transfer Learning. IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing, 10(5):1963–1974, May 2017.