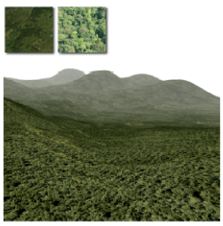
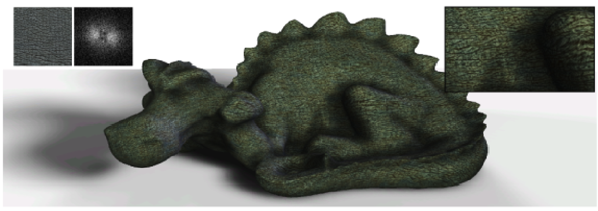
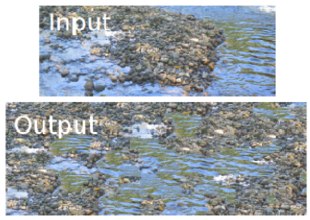
M2 Research internship – 2018

Deep learning cascade evaluation of texture synthesis methods

Host team: IGG (Computer Graphics and Geometry group) at ICube lab

Associated team: SDC (Data Science and Knowledge group) at ICube lab

Advisors: Rémi Allègre (allegre@unistra.fr), Basile Sauvage (sauvage@unistra.fr), Cédric Wemmert (wemmert@unistra.fr)

Starting date: From January 2018

Ending date: 6 months from the starting date

Funding: About 515 euros per month, net salary

Location: Strasbourg area, France

Background skills:

- Computer graphics or image processing, and/or data mining

- C++ programming

- Python programming is a plus

Possible continuation in Doctoral (PhD) thesis: excellent and motivated candidates will be invited to apply for a doctoral contract of the University of Strasbourg by June 2018

Context and problem statement

Textures contribute in a prominent way to the realism of 3D virtual environments. The goal of example-based texture synthesis is to automatically produce textures from input images, which facilitates the work of artists who have to cope with the increasing demand of highly detailed digital content in the computer graphics industry. There exists a vast variety of texture synthesis methods dedicated to this field of application [WLK+09, BZ17]. The IGG

group has developed original techniques for several years, trying to reconcile visual quality, scalability and control aspects [LSA+16, GSD+17]. Example-based texture synthesis also emerges as a promising approach to test and improve automated image analysis tools, e.g. in the medical field of histopathology [AFF+15].
Currently, there exists only few works providing evaluations of texture synthesis methods, especially for the visual quality of synthesis. Dai et al. [DRVG+14] define a set of properties on images in order to predict the visual quality of synthesis for various texture synthesis methods, but they do not provide any comparison of the methods. Kolar et al. [KDC+17] proposed a subjective experiment to evaluate the visual quality of synthesis for 21 properties, and also compare the performances of various methods. This study is not exhaustive in several ways: 1) it excludes some state-of-the-art methods, 2) it does not analyze the impact of the initialization, and 3) it does not consider parameter tuning. Many methods indeed incorporate a large set of user parameters that are often hard to tune manually, and that may greatly influence the visual quality of the synthesis results. Also, the authors' ranking is not representative for all applications. The subjective approach limits the ability to evaluate many methods on large collections of synthesized textures with varying initializations and values of the parameters.

Internship goal

Deep learning techniques such as Convolutional Neural Networks (CNNs) are a powerful and convenient way to perform image classification and recognition. A CNN consists of multiple convolution and pooling layers acting as feature extractors. Given an input image, the extracted features are then given as input to a classifier that outputs a probability distribution with respect to a pre-established set of classes. The weights of the convolution filters composing each convolution layer are learned in a training stage, which requires a large set of pre-classified images.
The goal of this internship is to develop a framework based on CNNs to evaluate and compare the visual quality of synthesized textures for different by-example texture synthesis methods, and help to guide parameter tuning. For each method, the training process will be achieved on patches of synthesized textures, so that it will be possible to get matching scores for patches of the input exemplar. This kind of methodology has been already investigated in the context of clustering algorithms evaluation [CTT+06] but has never been used in the context of texture synthesis.
The first stage of the internship will consist in a review of texture synthesis methods and familiarization with deep learning and CNNs. Then, the work will continue with the design, implementation and test of an appropriate CNN architecture. The texture synthesis methods available in the ASTex library [ASTex], developed by the IGG group, will be considered. The implementation will rely either on codes developed by the SDC group, or on publicly available high-level deep learning libraries supporting CNN, like e.g. Caffe or Keras.

References

[WLK+09] Li-Yi Wei, S. Lefebvre, V. Kwatra, and G. Turk. State of the Art in Example-based Texture Synthesis. Eurographics '09 State of the Art Reports (STARs), 2009.

[BZ17] C. Barnes and F.-L. Zhang. A survey of the state-of-the-art in patch-based synthesis. Computational Visual Media, 3(1):3-20, 2017.

[LSA+16] Y. D. Lockerman, B. Sauvage, R. Allègre, J.-M. Dischler, J. Dorsey, and H. Rushmeier. Multi-Scale Label-Map Extraction for Texture Synthesis. ACM Transactions on Graphics (SIGGRAPH'16 Tech. Papers) 35, 4, 140:1-140:12, 2016.

[GSD+17] G. Guingo, B. Sauvage, J.-M. Dischler, and M.-P. Cani. Bi-Layer Textures: A Model for Synthesis and Deformation of Composite Textures. Computer Graphics Forum, 36(4):111-122, 2017.

[AFF+15] G. Apou, F. Feuerhake, G. Forestier, B. Naegel, and C. Wemmert. Synthesizing whole slide images. International Symposium on Image and Signal Processing and Analysis (ISPA), pages 154-159, 2015.

[DRVG+14] D. Dai, H. Riemenschneider, and L. Van Gool. The Synthesizability of Texture Examples. IEEE Conference on Computer Vision and Pattern Recognition (CVPR), pages 3027-3034, 2014.

[KDC+17] M. Kolar, K. Debattista, and A. Chalmers. A Subjective Evaluation of Texture Synthesis Methods. Comput. Graph. Forum, 36(2):189-198, 2017.

[CTT+06] L. Candillier, I. Tellier, F. Torre, O. Bousquet. Cascade evaluation of clustering algorithm. Springer Verlag. 17th European conference on machine learning, Sep 2006, Berlin, Germany. Springer Verlag, 4212, pages 574-581, 2006, LNCS.

[ASTex] Analysis and Synthesis of Textures library, IGG group. https://astex-icube.github.io