Entropy Based Surface Quality Assessment of 3D Prints

Jarosław Fastowicz(✉) and Krzysztof Okarma

Department of Signal Processing and Multimedia Engineering,
Faculty of Electrical Engineering, West Pomeranian University of Technology,
Szczecin, 26 Kwietnia 10, 71-126 Szczecin, Poland
{jfastowicz,okarma}@zut.edu.pl

Abstract. In the paper the automatic method of visual quality assessment of surfaces of 3D prints is presented. The proposed approach is based on the use of entropy and may be applied for on-line inspection of 3D printing progress during the printing process. In case of observed decrease of the printed surface quality the emergency stop may be used allowing saving the filament, as well as possible correction of the printed object. The verification of the validity of the proposed method has been made using several prints made from different colors of the PLA filaments. Since the entropy of the image is related to the presence of structural information, the color to grayscale conversion of the test images has been applied in order to simplify further calculations. The analysis of the impact of the chosen color to grayscale conversion method on the obtained results is presented as well.

Keywords: 3D prints · Entropy · Image quality assessment · Image analysis

1 Introduction

One of the directions of development of image quality assessment methods is related to their applications in the world of 3D. Typically, such extension of metrics used for digital images is considered in view of the 3D graphics and several methods and specialized databases containing 3D images have been proposed during recent years. Most of them are intended for stereopairs [10,13,22] which can also be obtained as synthesized views [1] using Depth-Image-Based-Rendering (DIBR) techniques which are essential for the free-viewpoint television [18].

In order to verify the proposed image quality metrics useful for 3D images some databases containing subjective quality scores have been derived as well, e.g. IVP Anaglyph Image Database, IRCCyN/IVC NAMA3DS - COSPAD1 3D Video Quality Database, IRCCyN/IVC 3D Image Quality Database [2], LIVE 3D Image Quality Database [4,5] or MMSP 3D Video Quality Assessment Database [9], often together with the ideas of some new quality metrics. A short review of some of them can be found in the paper [15].

R. Silhavy et al. (eds.), *Artificial Intelligence Trends in Intelligent Systems*,
Advances in Intelligent Systems and Computing 573, DOI 10.1007/978-3-319-57261-1_40

Nevertheless, according to our best knowledge, currently there are no available databases and metrics which are specific for the images of the 3D prints. Although the 3D printing technology becomes more and more popular and the price of available devices still decreases, there are almost no attempts to automatic quality assessment of the 3D prints.

Analyzing the use of machine vision for monitoring of the 3D printing process some interesting attempts can be noticed e.g. relatively old on-line defect detection for fused deposition of ceramics proposed by Fang [7] or method of monitoring the top surface of the print [6]. The first idea is based on the comparison of so called process signatures determined for the images captured by a camera and the reference images. The second approach utilizes the fuzzy model applied for the comparison of adjacent layers allowing identification of over- and underfilling during printing.

Another recent direction of research is the application of neural networks [21] for the quality assessment of 3D printed electronic products. Nevertheless, in many situations, the use of neural networks is considered as the "last choice" due to the necessity of learning process which is often hard to control and therefore the final results are not always predictable and satisfactory. Such a system applied to a 3D inkjet printer is based mainly on the resistivity measurement together with comparison of shape and geometrical properties so its further combination with more advanced machine vision approach seems to be promising direction of research. Description of some other similar applications can be found in the Szkilnyk's [20] and Chauhan's [3] papers.

The most promising paper related to automatic correction of detected errors in desktop 3D printers has been published by Straub [19]. Nevertheless, the system presented in the paper, based on Raspberry Pi modules and five cameras, has been implemented only at a very initial stage and requires many interruptions of the printing process. Although it allows the detection of lack of filament (leading to so called "dry printing"), it is very sensitive to distortions caused by camera motion, dynamic lighting conditions etc. Due to the requirement of precise calibration, it is rather hard for practical implementation, especially for home use 3D printers.

In our earlier papers some attempts to the automatic quality assessment of 3D prints based on texture analysis and local similarity have been presented. The idea based on the analysis of the Gray Level Co-occurrence Matrix (GLCM) allows obtaining the no-reference metrics [8,14] but unfortunately is quite slow due to high amount of computations. Nevertheless, the application of Feature Similarity [16] and Structural Similarity based metrics [17] allows relatively fast and usually proper classification of 3D prints into lower and higher quality groups mainly for scanned images of 3D printed surfaces. Since the scanned images are characterized by more uniform lighting conditions, such an approach has also been used in this paper in order to verify the usefulness of proposed entropy based metric.

Considering the fact that most image quality metrics, including the Structural Similarity and Feature Similarity applied in both papers, can be computed for grayscale images, the necessity of color to grayscale conversion influences the obtained results as well. Similar verification for the entropy based metric is presented in further part of the paper as well.

2 The Idea of Entropy Based Metric

The idea of the application of entropy for the quality assessment of 3D prints originates from the assumption that the ideal surface of the 3D print observed by the side view camera can be characterized by regular linear patterns representing consecutive layers of the filament. In the presence of distortions this structure becomes corrupted and the observed pattern is more complicated. In such case the amount of information visible on the image plane increases and therefore the entropy of such image should be higher. For highly distorted surfaces of 3D prints the values of entropy should be much higher allowing the classification of the 3D prints.

From theoretical point of view image entropy is the statistical measure of randomness defined as:

$$E = -\sum_{i=1}^{N} p_i \cdot log_2(p_i) \tag{1}$$

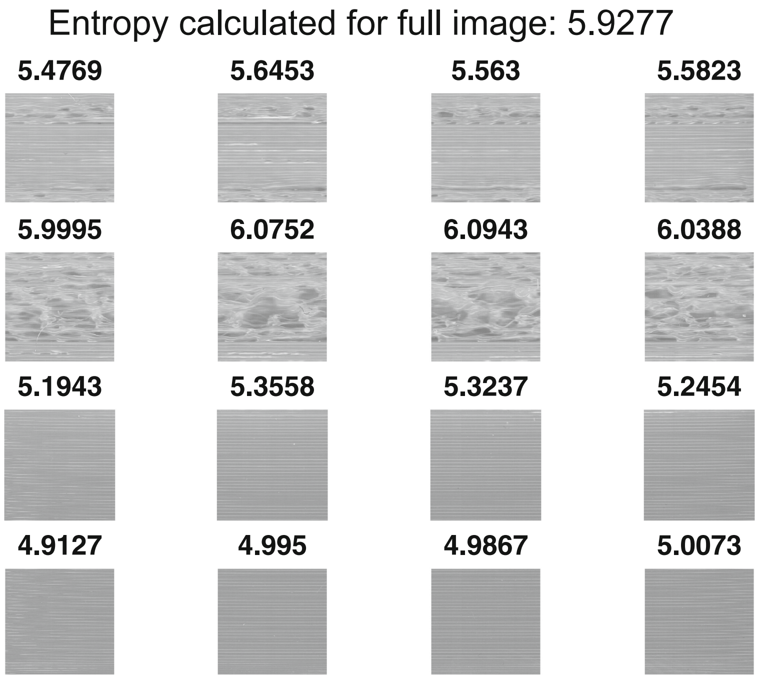

Fig. 1. Local entropy values for exemplary orange sample converted to greyscale with varying quality.

where the vector p contains the histogram counts calculated assuming N=256 bins for grayscale images.

Since the entropy values can be considered as the measure of amount of distortions, one may expect its high correlation with the perceived quality of the 3D printed surfaces. The additional advantage of the proposed use of entropy as the quality measure is the possibility of its local calculation for the specified fragment of the printed surface. Such an approach allows its utilization for the on-line monitoring of the 3D print quality during the printing process. In the case of increase of the local entropy in comparison to the values calculated for previously printed bottom parts of the object, some problems may be detected and the specified action may be taken. The illustration of the local entropy values for an exemplary sample of the 3D print with varying quality is presented in Fig. 1 where high entropy values are characteristic for the samples containing noticeable distortions.

3 Details of Experiments

Verification of the usefulness of the proposed approach for the automatic visual quality assessment of 3D prints has been made using several flat sample prints obtained using two 3D printers based on Fused Deposition Modeling (FDM) technology, namely RepRap Pro Ormerod 2 and Prusa i3. Several different colors sample plates made from bio-degradable polylactic acid (PLA) filaments have been obtained with forced local decrease of print quality. The lower quality samples have been obtained by hanging the temperature and modifications of speed of the filament's delivery speed. Some of them are presented in Fig. 2.

Such plates have been scanned from both sides with 1200 dpi resolution and additionally divided into parts in order to compute the local quality indicators as shown in Fig. 1. Captured images have been converted into grayscale using four commonly used methods based on popular color models and the luminance has been calculated as the maximum of RGB channels, the average of the RGB channels and as the weighted average according to the ITU recommendations:

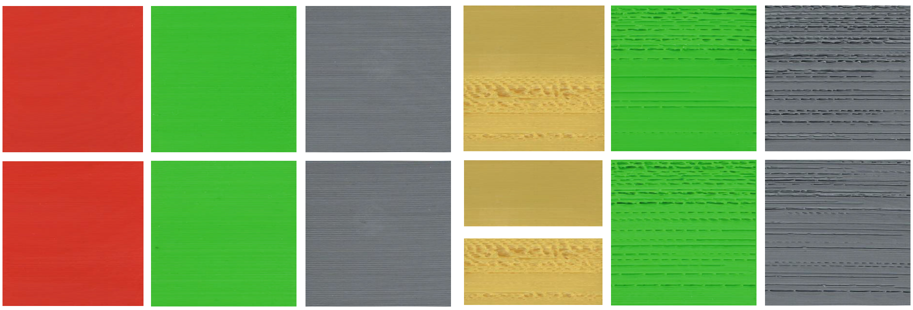

Fig. 2. Exemplary scans of the high and low quality 3D prints used in experiments.

BT.601-7 [11] used e.g. in MATLAB *rgb2gray* function and BT.709-6 [12] used mainly in HDTV.

For all scanned samples the global entropy values have been calculated as well as the local values obtained dividing the images for 4 and 16 parts. All the scans have been made in two ways scanning the samples perpendicularly to the filament's layers and in parallel to them. The results of the calculations assuming different color to grayscale conversion methods are illustrated in Figs. 3, 4, 5 and 6. The samples have been numbered such that the numbers 1–18 indicate the samples scanned perpendicularly whereas the numbers 19–36 denote the parallel scans. The colors of plots are typically related to the colors of filaments (however white filament is marked as blue and the silver one using black symbols for better visualization). The circles denote high quality prints whereas the crosses stand for low quality samples. The orange samples have varying quality and therefore big differences in their local entropy can be observed after the division

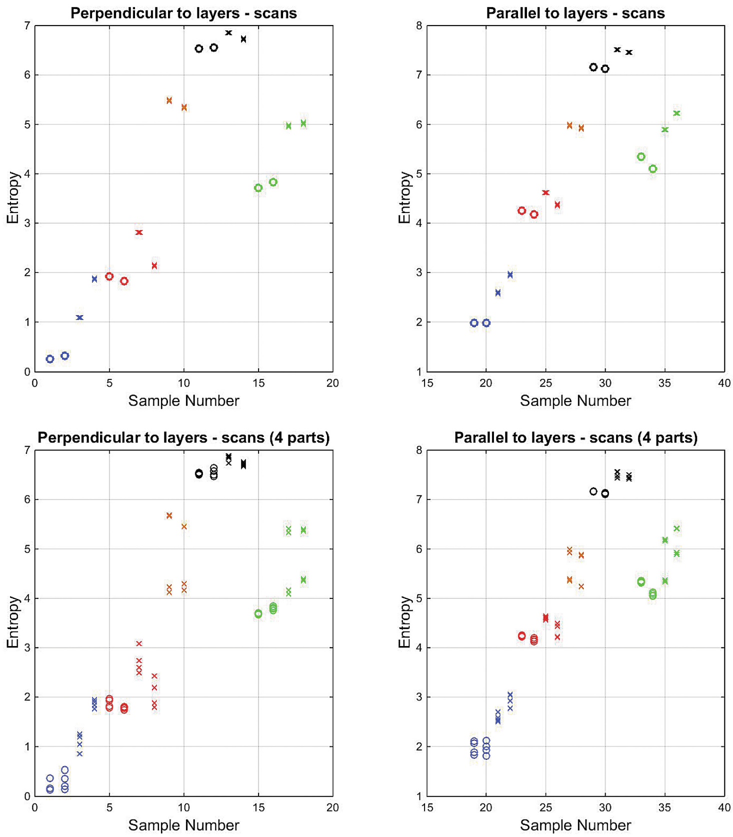

Fig. 3. Entropy values for different colors of samples and their local values obtained for division into 4 parts (o - high quality prints, x - low quality prints) using the grayscale conversion according to recommendation ITU BT.601-7.

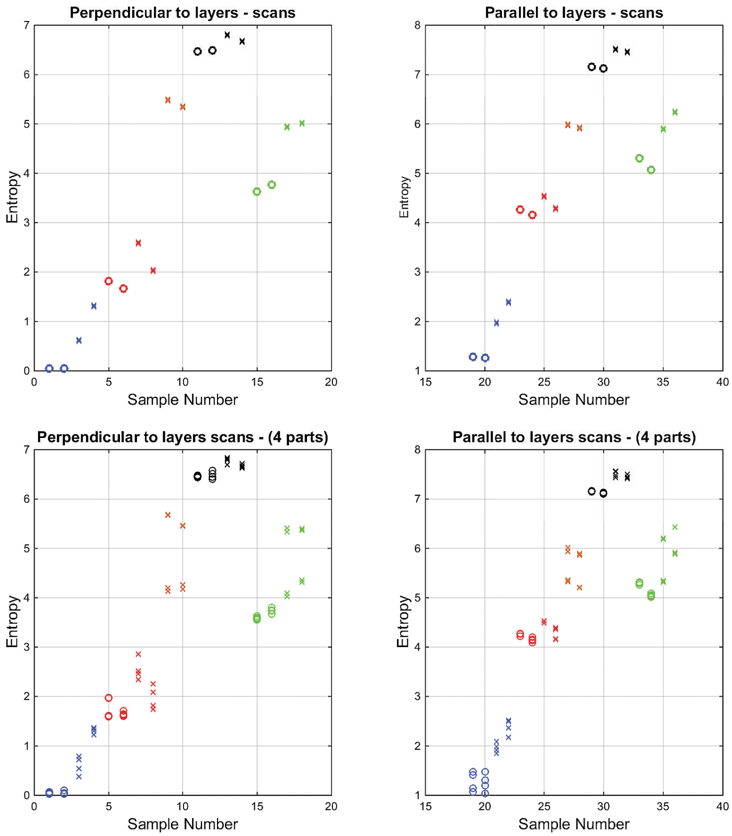

Fig. 4. Entropy values for different colors of samples and their local values obtained for division into 4 parts (o - high quality prints, x - low quality prints) using the grayscale conversion according to recommendation ITU BT.709-6.

of the scanned images into 4 or 16 regions. A similar effect, caused by the presence of local distortions not covering the whole surface, can also be observed for the red samples although the differences are not as high.

Results obtained for perpendicular and parallel scans as well as for different color to grayscale conversion methods differ noticeably but lead to similar conclusions. Nevertheless for perpendicular scans the differences between the entropy for high and low quality samples are higher allowing easier classification of samples.

Presented approach makes possible to identify the decrease of the 3D printed surface quality during the printing process assuming the possibility of mounting the camera such that the side view of the printed object can be observed. Since the color of the filament as well as color to grayscale conversion method have a great impact on the obtained absolute entropy values, the proposed method can be successfully implemented assuming the availability of the reference high

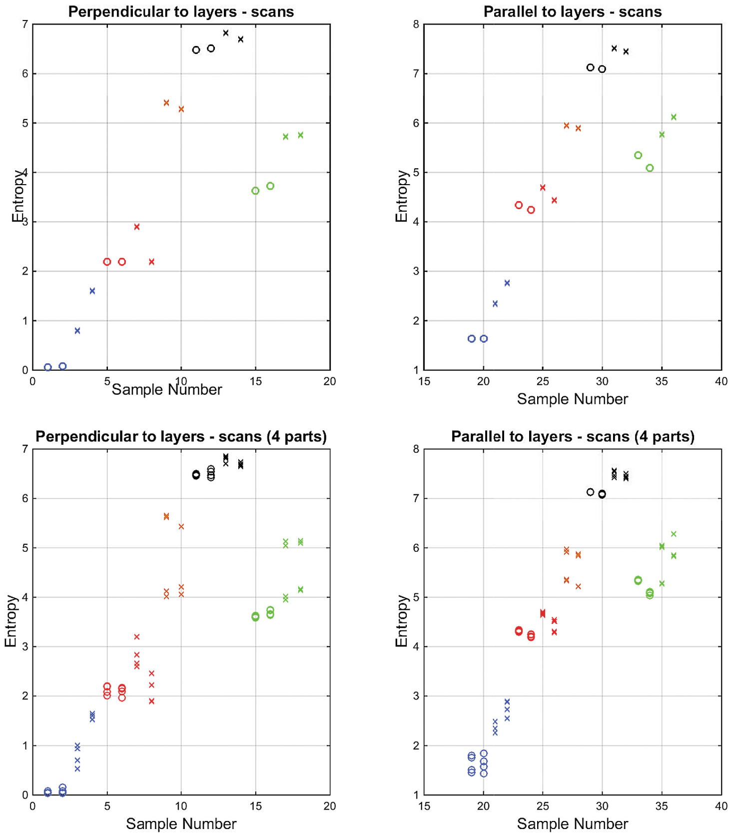

Fig. 5. Entropy values for different colors of samples and their local values obtained for division into 4 parts (o - high quality prints, x - low quality prints) using the grayscale conversion as the average of the RGB channels.

quality fragment of the printed surface using the same color of the filament. In many cases it can be just the bottom part of the printed sample.

Nevertheless a proper detection of the decreased quality or using the entropy values for the quality assessment in the continuous quality scale would require the knowledge of the reference entropy values for the perfect quality 3D print assuming the specified color of the filament and color to grayscale conversion method. At the current stage of research it seems to be one of the most relevant limitations of the proposed approach. Therefore one of the directions of our further experiments will be the implementation of the no-reference entropy based method for the quality assessment of the 3D prints where the expected entropy value should be predicted on the basis of the filament's color.

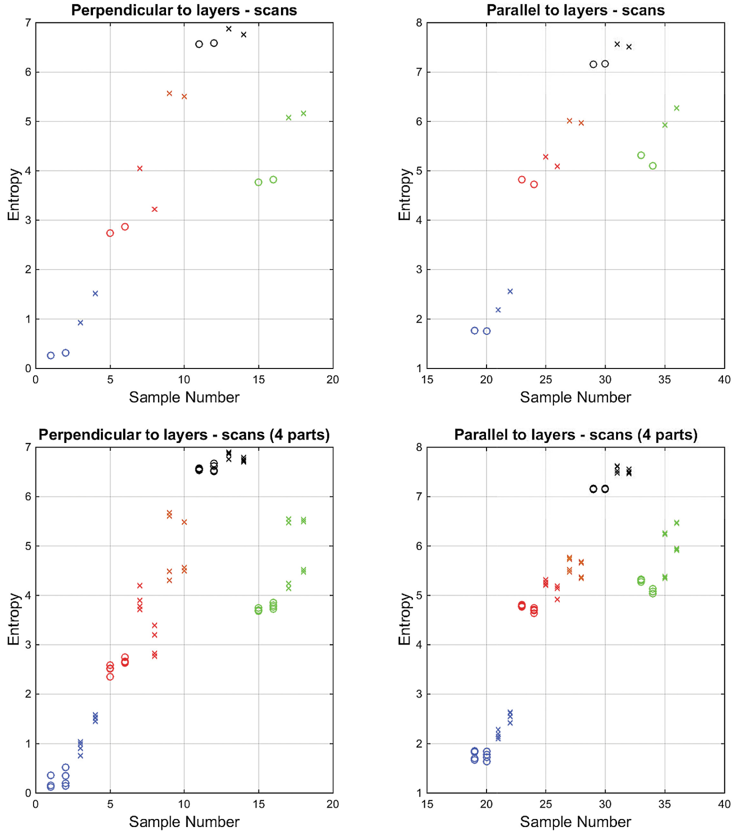

Fig. 6. Entropy values for different colors of samples and their local values obtained for division into 4 parts (o - high quality prints, x - low quality prints) using the grayscale conversion as the maximum of the RGB channels.

4 Concluding Remarks

Automatic visual quality assessment of the 3D prints still remains one of the challenges of image analysis especially in view of the most desired no-reference methods. Development of the universal method suitable for all types of 3D prints seems to be doubtful but some methods e.g. based on texture analysis can be successfully applied utilizing the specificity of the surface patterns obtained using the most popular PLA based devices.

The application of the entropy for such purposes leads to very promising results allowing not only the classification of the 3D prints into low and high quality prints but also the identification of the distorted fragments of the surface. Computing the local entropy values it is possible to obtain the quality map of the surface and, in the long run, express the quality of the surface in a continuous quality scale. In such solution the quality metric would give the information not only about the presence of distortions but also about their amount.

Although the presented approach have its limitations e.g. does not utilize shape information, it can be combined with some other methods. Such a combination, particularly with the texture analysis methods discussed in our earlier papers [8,14,16], will be one of the most important challenges of our further research.

References

1. Battisti, F., Bosc, E., Carli, M., Callet, P.L., Perugia, S.: Objective image quality assessment of 3D synthesized views. Sig. Process. Image Commun. **30**, 78–88 (2015)
2. Benoit, A., Le Callet, P., Campisi, P., Cousseau, R.: Quality assessment of stereoscopic images. EURASIP J. Image Video Process. **2008**(1), 659024 (2008)
3. Chauhan, V., Surgenor, B.: A comparative study of machine vision based methods for fault detection in an automated assembly machine. Procedia Manufact. **1**, 416–428 (2015)
4. Chen, M.J., Cormack, L.K., Bovik, A.C.: No-reference quality assessment of natural stereopairs. IEEE Trans. Image Process. **22**(9), 3379–3391 (2013)
5. Chen, M.J., Su, C.C., Kwon, D.K., Cormack, L.K., Bovik, A.C.: Full-reference quality assessment of stereopairs accounting for rivalry. Sig. Process. Image Commun. **28**(9), 1143–1155 (2013)
6. Cheng, Y., Jafari, M.A.: Vision-based online process control in manufacturing applications. IEEE Trans. Autom. Sci. Eng. **5**(1), 140–153 (2008)
7. Fang, T., Jafari, M.A., Bakhadyrov, I., Safari, A., Danforth, S., Langrana, N.: Online defect detection in layered manufacturing using process signature. In: Proceedings of IEEE International Conference on Systems, Man and Cybernetics, vol. 5, pp. 4373–4378, San Diego, California, USA (1998)
8. Fastowicz, J., Okarma, K.: Texture based quality assessment of 3D prints for different lighting conditions. In: Chmielewski, L.J., Datta, A., Kozera, R., Wojciechowski, K. (eds.) ICCVG 2016. LNCS, vol. 9972, pp. 17–28. Springer, Cham (2016). doi:10.1007/978-3-319-46418-3_2
9. Goldmann, L., Simone, F.D., Ebrahimi, T.: A comprehensive database and subjective evaluation methodology for quality of experience in stereoscopic video. In: 3D Image Processing (3DIP) and Applications, vol. 7526 in Proceedings of SPIE (2010)
10. Guo, J., Vidal, V., Cheng, I., Basu, A., Baskurt, A., Lavoue, G.: Subjective and objective visual quality assessment of textured 3D meshes. ACM Trans. Appl. Percept. **14**(2), 11:1–11:20 (2016)
11. International Telecommunication Union: Recommendation ITU-R BT.601-7 - Studio encoding parameters of digital television for standard 4:3 and wide-screen 16:9 aspect ratios (2011)
12. International Telecommunication Union: Recommendation ITU-R BT.709-6 - Parameter values for the HDTV standards for production and international programme exchange (2015)
13. Lin, Y., Wu, J.: Quality assessment of stereoscopic 3D image compression by binocular integration behaviors. IEEE Trans. Image Process. **23**(4), 1527–1542 (2014)

14. Okarma, K., Fastowicz, J.: No-reference quality assessment of 3D prints based on the GLCM analysis. In: 2016 21st International Conference on Methods and Models in Automation and Robotics (MMAR), pp. 788–793 (2016)
15. Okarma, K.: On the usefulness of combined metrics for 3D image quality assessment. In: Choraś, R.S. (ed.) Image Processing and Communications Challenges 6. AISC, vol. 313, pp. 137–144. Springer, Heidelberg (2015). doi:10.1007/978-3-319-10662-5_17
16. Okarma, K., Fastowicz, J.: Quality assessment of 3D prints based on feature similarity metrics. In: Choraś, R.S. (ed.) Image Processing and Communications Challenges 8, pp. 104–111. Springer, Heidelberg (2017). doi:10.1007/978-3-319-47274-4_12
17. Okarma, K., Fastowicz, J., Tecław, M.: Application of structural similarity based metrics for quality assessment of 3D prints. In: Chmielewski, L.J., Datta, A., Kozera, R., Wojciechowski, K. (eds.) ICCVG 2016. LNCS, vol. 9972, pp. 244–252. Springer, Cham (2016). doi:10.1007/978-3-319-46418-3_22
18. Starch, J., Kilner, J., Hilton, A.: Objective quality assessment in free-viewpoint video production. In: Proceedings of the 3DTV Conference: The True Vision - Capture. Transmission and Display of 3D Video, pp. 225–228, Istanbul, Turkey (2008)
19. Straub, J.: Initial work on the characterization of additive manufacturing (3D printing) using software image analysis. Machines **3**(2), 55–71 (2015)
20. Szkilnyk, G., Hughes, K., Surgenor, B.: Vision based fault detection of automated assembly equipment. In: Proceedings of ASME/IEEE International Conference on Mechatronic and Embedded Systems and Applications, Parts A and B, vol. 3, pp. 691–697, Washington, DC, USA (2011)
21. Tourloukis, G., Stoyanov, S., Tilford, T., Bailey, C.: Data driven approach to quality assessment of 3D printed electronic products. In: Proceedings of 38th International Spring Seminar on Electronics Technology (ISSE), pp. 300–305, Eger, Hungary, May 2015
22. Yang, J., Hou, C., Zhou, Y., Zhang, Z., Guo, J.: Objective quality assessment method of stereo images. In: Proceedings of the 3DTV Conference: The True Vision - Capture. Transmission and Display of 3D Video, pp. 1–4, Potsdam, Germany (2009)