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THE OVERVIEW OF NEURAL RENDERING
ОГЛЯД НЕЙРОННОГО РЕНДЕРИНГУ

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Abstract. *In the article the usage of neural networks for increasing image rendering efficiency was analyzed. The main characteristics of the most popular neural networks architectures are described. The common application areas of neural rendering are analyzed. The example of neural network for triangular mesh generation is examined. The neural implementation of the rendering system in overall is described. The neural networks usage for generating textures from photo and textures style transfer is described. The main features of reflectance models representation in the neural network form are given. The possibility of reflectance model formula learning by the neural network is analyzed. The information about neural networks usage for improving the image quality by anti-aliasing and determining the optimal surface polygon number is provided. The application of reverse neural rendering is examined using the example of object's polygonal reconstruction from the image. The characteristic feature of conducted neural rendering overview is its concentration on separate stages of three-dimensional scenes visualization.*

Key words: *neural rendering, neural network, BRDF, surface shading, rendering.*

Introduction. Neural networks [1] are the models that are used for learning the multi-layer representations of data. The three main neural networks architectures are densely-connected, convolutional and recurrent networks. Densely-connected networks [1] are characterized by the fact that each neuron of the layer is connected with each neuron of previous layer. This architecture is usually used for vector data. Convolutional neural networks (CNN) [1] consist of the series of convolution and pooling layers. They are usually used for the tasks with images and volumes.

Recurrent neural networks (RNN) [1] are based on the usage of hidden state and processing the input data by time steps. RNN are used for the processing of language and time-dependent data. One of the neural networks usage spheres is a computer graphics. The popular directions of neural networks application in computer graphics are direct generation of images and the improvement of three-dimensional rendering stages. For the direct image generation GAN (generative adversarial networks) are often used. GANs include two agents for image synthesis and determining if the image was generated. If the rendering stages include the usage of neural networks, such rendering is called neural [2].

The purpose of the work – to analyze the peculiarities of neural rendering usage for the tasks of computer graphics.

State-of-the-art of Neural Rendering The stage of geometrical transformations [3], that includes the triangulation process, is a preliminary stage before rendering. The triangulation lies in dividing the surface of three-dimensional object into set of triangles. PointTriNet [4] is among the triangulation neural networks. PointTriNet is composed of two neural networks. Both networks are multi-layer perceptrons. The first neural network for the proposed triangle predicts the probability of its belonging to the final mesh of primitives. The input of neural network contains the information about the 64 closest triangles and 64 closest points. One point near triangle is described by six parameters: three coordinates relative to the triangle's normal and edge, three barycentric coordinates of projected point into triangle. The triangle is presented by twelve parameters: the maximal and minimal values are selected from three triangle vertexes representations. The second neural network is used for neighboring figures proposing for each triangle's edge. The probability of triangle formation with the edge is calculated for the closest points. For each edge the determined number of most possible triangles is selected. At the first step of triangulation method the initial set of triangles is formed. The first neural network classifies if these triangles belong to final solution. For the selected triangles the second neural network proposes neighboring triangles. Then the first neural network filters the proposed triangles. After the few iterations the final triangle mesh is created. The training of this neural network belongs to unsupervised learning. The expected Chamfer distance (the distance between the predicted surface and the simplified object's surface (in the form of points set)), overlap kernel loss (used for eliminating the overlaps between triangles), watertight loss (used for eliminating gaps in the triangle mesh) are applied. The another approach to neural triangle mesh creation can lie in using supervised learning. In the training set the points can be used as input data, the target values in this case are created triangle meshes in respect to existing triangulation algorithms.

The rendering of scene is based on the created at the geometrical transformations stage mesh of primitives. The list of main rendering operations [3] includes rasterization, eliminating the hidden surfaces, texture mapping, surface shading [5,6], final image processing.

The neural network RenderNet [7] presents the full sequence of three-dimensional rendering stages. At the input of network the voxel grid and the information about the lighting, camera position are given. The transformation from world to camera coordinates is used. The block of three-dimensional convolution is applied to the three-dimensional data. The next in the architecture is the projection block that is used for the transition to two-dimensional tensor and calculating the visibility of scene components. The block of two-dimensional convolution provides the calculation of object's points colors. During the calculation of error function at the training stage the created and target images were compared. The neural network is capable of learning different shading methods, for example, the Phong shading.

Textures are the images used for mapping at the surfaces of objects. The convolutional neural network VGG-19 is used for texture generation [8] using the input photo. VGG-19 includes 16 convolution layers and 5 sampling layers. The input image is fed to convolution neural network. For each network layer the Gram matrix is formed, it shows the correlation between features maps. The image with white noise is also fed to convolution neural network. Similarly for each layer the Gram matrixes are formed. The error function is calculated using the weighted difference between two sets of Gram matrixes. During the gradient descent the second image is transformed until the Gram matrixes of both images will be similar. In the result, the texture is generated. Another direction of neural network usage is textures style transfer. For example, the painting of artist in particular style is given. The network transform the style of texture to the given one. The textures styles transfer can be implemented using VGG-19 [9]. Then the combined error function combines the error functions between input image, style image and output image.

The shading of geometrical surfaces includes the color intensity calculation for every pixel. One of the color intensity components is a specular component [10]. For its representation the bidirectional reflectance distribution function (BRDF) [11] value is calculated. BRDF can be represented in the form of neural network. For example, NBRDF [12] network is used for replacing the standard BRDF calculation during the rendering. The speed of network is comparable with theoretical reflectance models. NBRDF includes the input layer with six nodes, two hidden layers with 21 node and the output layer with three nodes. The network is fully-connected. The half-vector $\overline{H}$ (between incident and reflected light vector) and difference vector $\overline{D}$ (incident light vector in the coordinate system, where $\overline{H}$ points to northern pole) are fed into neural network input. At the output of neural network we have three values of color channels. In overall, NBRDF includes 675 parameters. The autoencoder was developed by the NBRDF authors in order to compress the information about neural network weights. The logarithm function was used as error function during the network training. The predicted NBRDF values and measured material data from MERL database are compared. The model can be applied to isotropic and anisotropic materials. The neural networks usage also allows to synthesize the BRDF calculation formula. One of the standard approaches to formula synthesis is combining the symbolic regression and genetic algorithms. The disadvantage of approach is a tendency to algorithm overfitting [13]. Therefore, the alternative approach includes neural network usage. The example of approach is general-purpose network EQL [13]. The distinctive feature of EQL is that instead of ordinary usage of one activation function for neuron layer the different mathematical functions and operations are applied. Based on the learned by neural network weight values the formula is synthesized using the special algorithm.

Anti-aliasing lies in “jaggies” removal from images. One of the applications of M-Net [14] neural network is the images anti-aliasing. M-Net is the variant of MR-Net neural network that is based on dividing the frequencies of input signal into stages depending on the level of detail. The network architecture is divided horizontally depending on the number of stages. The four blocks of layers are used: the first layer, hidden layers, linear layer (these three blocks are sinusoidal multi-layer perceptron), control layer (used for controlling the stages output values). The output of neural network combines the stages values. M-Net is characterized by the fact that the output of hidden layers block is connected with input of the same block at the next stage. Through combining the information about different levels of details the image anti-aliasing is provided. For each pixel (x, y) the level of detail parameter $\lambda(x, y)$ is calculated using the partial derivatives of texture mapping function. The output value of neural network is calculated using the formula [14]

$$f_\lambda = \sum_{i=1}^{N} \lambda_i g_i ,$$

where N - number of network stages, g_i - the output value of the $i-th$ stage, λ_i - the weight of the $i-th$ stage value (depends on the value of $\lambda - 1, 0$ or $\lambda - \lfloor \lambda \rfloor$).

The visualized image of scene corresponds to the particular camera and light source positions. After changing these parameters the image should be formed again. The alternative is the generation of image by neural network. The method, developed by B. Mildenhall et al. [15], lies in using neural radiance fields. The three-dimensional set of points is formed using the ray marching through the scene. The color intensity and volume density values are calculated using the neural network relative to points coordinates and their orientation to the viewer. These values form the neural radiance fields, on the basis of which the two-dimensional image is created by volume rendering methods. The neural network training is based on scene images under different views.

Neural networks allow to evaluate the quality of the formed image depending on the used rendering methods. K. T. Lwin et al. [16] have used the neural network for image quality evaluation depending on different resolutions, methods of shading and texture anti-aliasing. For example, the usage of flat shading method, Phong method, Gouraud method with different numbers of surface polygons were compared. For each pair of shading method and triangles number the percent of images for which the neural network correctly predicted the lighting direction was calculated. The best results were got for the Phong shading. Using the calculated percentages for different shading methods the maximum triangles numbers, at which the image quality improves, were determined.

For getting the information about scene lighting, surface geometry the inverse rendering is used. The method SoftRas [17] is used for polygonal mesh generation from the input image. At the first method step the displacement vectors are generated by the neural network, at the basis of which the polygon mesh is reconstructed. At the second method step the developed by authors rasterization method is applied, this method provides the calculation differentiability. For every triangle in mesh the probability map, that shows the probability of its coverage of particular image pixel, is created. After combining every probability map the mesh silhouette is formed. The silhouette of generated mesh is compared with the reference silhouette. In the result, gradually the mesh reconstruction becomes more accurate.

Summary and conclusions. Besides the direct image generation, neural networks are used at different rendering stages. At the tessellation stage (before rendering) the geometrical primitives mesh creation and the learning of existing tessellation algorithms are possible. The whole rendering process can be represented by neural network. For this at the neural network input the information about surface geometry, camera and the viewer are used, at the output the pixel color intensities are calculated. At the texture mapping stage the texture generation and texture modification to a given style are used. If the lighting directions and material data are set as neural network input values, the learning of BRDF values can be provided. The alternative to BRDF formula learning using symbolic regression is a neural network approach. The simplicity of execution of the reverse rendering and image quality evaluation processes can be increased using neural networks. Also, neural networks make it more easy to synthesize images under different lighting conditions and different camera views. In overall, the intellectual modification of rendering process is provided.

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Анотація. *У статті проаналізовано використання нейронних мереж для підвищення ефективності рендерингу зображень. Описано основні характеристики найпопулярніших архітектур нейронних мереж. Проаналізовано загальні області застосування нейронного рендерингу. Розглянуто приклад нейронної мережі для генерації сітки трикутників. Описано нейронну реалізацію системи рендерингу в цілому. Описано використання нейронних мереж для генерації текстур із фото та трансферу стилю текстур. Наведено основні особливості представлення моделей відбиття у формі нейронної мережі. Проаналізовано можливість вивчення формули моделі відбиття нейронною мережею. Наведено інформацію про використання нейронних мереж для покращення якості зображення шляхом антиаліайзингу та визначення оптимальної кількості полігонів поверхні. Застосування зворотного нейронного рендерингу розглядається на прикладі полігональної реконструкції об'єкта із зображення. Характерною особливістю проведеного огляду нейронного рендерингу є його концентрація на окремих етапах візуалізації тривимірних сцен.*

Ключові слова: *нейронний рендеринг, нейронна мережа, ДФВЗ, зафарбовування поверхні, рендеринг.*

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