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Neural implicit representation of time-varying surfaces

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1 Introduction

One of the problems that computer graphics deals with is methods of surface representation. In the case of a static surface, there are a number of possible approaches. The given surface can be described using parametric equations, implicit function, or, e.g., using polygonal meshes, where the surface is tesselated and approximated by a set of polygons.

Recent work has shown that neural networks can also be used to represent static surfaces. The DeepSDF method proposed by Jeong Joon Park et al. (2019) is based on the regression of the signed distance function (SDF) of a given surface using a multilayer perceptron (MLP). The SDF is a function that assigns to each point $\mathbf{x} \in \mathbb{R}^3$ a value that corresponds to the distance from the surface and whose sign determines whether the point is inside or outside the surface. From such a representation, the original surface can then be reconstructed by extracting an isosurface with an associated value of 0. The aim of this work was to generalize this representation for time-varying surfaces and to examine the properties of this representation.

2 Proposed representation

As with the representation of static surfaces, the MPL is used for regression of the SDF for dynamic surfaces. The proposed neural representation of time-varying surfaces is based on the DeepSDF concept for static surfaces. In order to perform the SDF regression, it is necessary to extend the feature space by the time coordinate because the SDF of a time-varying surface is a four-dimensional function $SDF(x, y, z, t)$. The MPL used is further formed by several inner layers with ReLU activation function and an output layer with one neuron and TanH activation function.

To achieve better results, the Fourier features mapping method was also used, which performs the extension of the feature space. Furthermore, a special loss function was proposed instead of the original mean absolute error, which allows assigning a larger error to points that are closer to the represented surface and therefore have a greater impact during surface reconstruction.

3 Experiments

Several experiments were designed and implemented to verify the properties of the proposed representation. Two different sequences of triangle meshes were used as input data to perform the experiments. The aim of the experiments was to verify the compression capabilities of the proposed representation, including another possibility of compression by quantizing the weights of the neural network. The dependence of the representation error on the number of

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samples used for neural network training was examined. Furthermore, the possibility of using a neural network to use for time super-resolution of the original surface was verified. An example of a comparison of the original surface and the surface reconstructed from the neural network prediction is shown in the Figure 1.

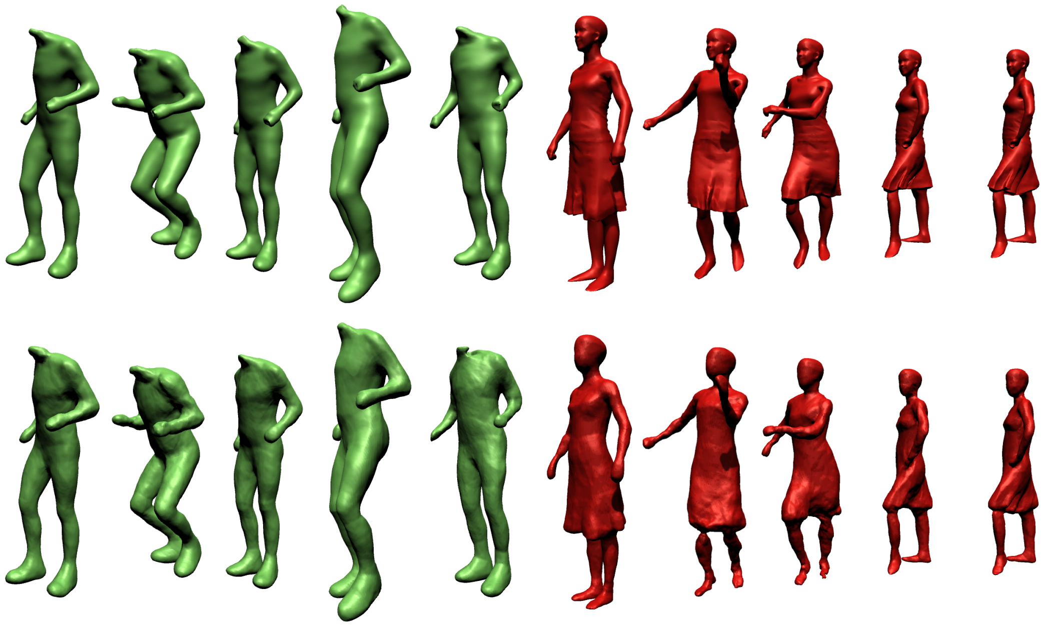

Figure 1: Comparison of the original and reconstructed surface. Top: original surface. Bottom: reconstructed surface. Left: jump dataset. Right: samba dataset.

4 Conclusion

Experiments have shown that the proposed neural representation can be used to represent time-varying surfaces. It has been shown that the proposed representation provides good compression ratios. A further improvement in the compression ratio was achieved by quantizing the neural network weights. Another advantage of the proposed representation is the possibility to use it for super-resolution of the original dynamic surface. One of the main advantages of neural representation is that it can work with sequences of neural networks that do not have constant connectivity and where we do not know the correspondence between its vertices. The advantages of using Fourier features mapping, and tailored loss function have also been demonstrated.

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References

Jeong Joon Park, Peter Florence, Julian Straub, Richard Newcombe, Steven Lovegrove (2019) DeepSDF: Learning Continuous Signed Distance Functions for Shape Representation. *Proceedings, The IEEE Conference on Computer Vision and Pattern Recognition (CVPR).*