Conformal Geometric Algebra, a mathematical framework for motion continuity in deep neural networks

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Generating human motion is one of the most challenging problems in computational modelling: movement is continuous, highly dimensional, and fundamentally expressive. Articulated motion is usually formulated by linking the skeleton bones of a character model in a hierarchical order (rigging), and then modifying the joint angles over time. Recent developments in deep learning and neural networks have shown promise in synthesizing and controlling articulated characters using convolutional, recurrent, or generative adversarial networks. Deep neural networks, though, work better on data with continuous representations, allowing efficient mapping between the tensor and real-world spaces. As shown in the literature (Zhou, et al. 2019) (Xiang and Li 2020), for 3d rotations, all representations are discontinuous in the real Euclidean spaces of four or fewer dimensions, making difficult for neural networks to learn; this discontinuity in the representation space generates motions with absurd and erroneous rotations. Currently, most of the deep neural network researchers turn to represent motion using positional data, but such a representation have ambiguity problems (roll axis is missing), and cannot ensure bone length violations, requiring the use of an additional Inverse Kinematics layer. In this work, we investigate the use of conformal geometric algebra (CGA), to ensure the continuity in motion representation when deep neural networks are used. We demonstrate the use of CGA and other mathematical frameworks (e.g., Euler angles, unit quaternions, 5d, 6d), comparing the smoothness in their synthesized motion. We also present an easy way to convert motion files (in .bvh format) in CGA representations, and vice versa, for an easy adaptation to neural networks.

References

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