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Spatial-temporal color mappings for recognizing 3D skeletal sign languages

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Abstract

As a result of their widespread availability, feature maps do not discriminate between similarly worded signs. When using unnormalized training maps, traditional CNNs struggle to isolate non-discriminatory features from feature maps due to the presence of vanishing gra dients. The loss of information caused by the vanishing gradients in the deeper CNN layers makes it challenging to develop discriminative features for recognition. In order to correctly represent 3D joint motions, we propose a novel color-coded feature map, joint angular velocity maps (JAVMs). We propose a new ResNet architecture, termed connived feature ResNet (CFR), as an alternative to standard convolutional neural networks. In comparison to other ResNet and CNN based architectures utilized for sign classification, this one does not employ dropout in the final layers and achieves the required result in a smaller number of iterations.

1.Introduction

The purpose of this study is to provide an original method of characterizing 3D sign (or action) data using spatio-temporal features. To describe the relative joint changes in 3D sign (or action) location data, current maps characterize ge ometric parameters such as joint lengths and angles or both. Joint angular velocity maps (JAVMs) are a new type of color-coded feature map proposed to better model 3D joint motions. We propose a new ResNet design, connived feature ResNet (CFR), which incorporates a CNN layer into the feedforward loop of the densely linked regular ResNet architecture. We demonstrate that this architecture outperforms competing ResNet and CNN based architectures for sign (activity) classification without resorting to dropout in the last layers, and does so in fewer iterations. When distances are mapped into images, they cause significant gradients in the feature data, which are commonly referred to as joint distance maps (JDM) [1], joint angular displacement maps (JADM) [2], or joint velocity maps (JVM) [3]. These maps are used for training and testing CNNs that will be used for gesture or action recognition. Cross-subject recognition

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rates for both sign language and action recognition hover around 60% after fine-tuning the hyperparameters.

2.Methodology

A study strategy with three goals has been developed for creating a 3D sign (activity) recognition system.

To determine the angular speeds of the joints from one frame to the next, using the derived joint angular velocity characteristics, create color-coded maps to Construct and evaluate a novel ResNet architecture for action recognition based on a fabricated feature model

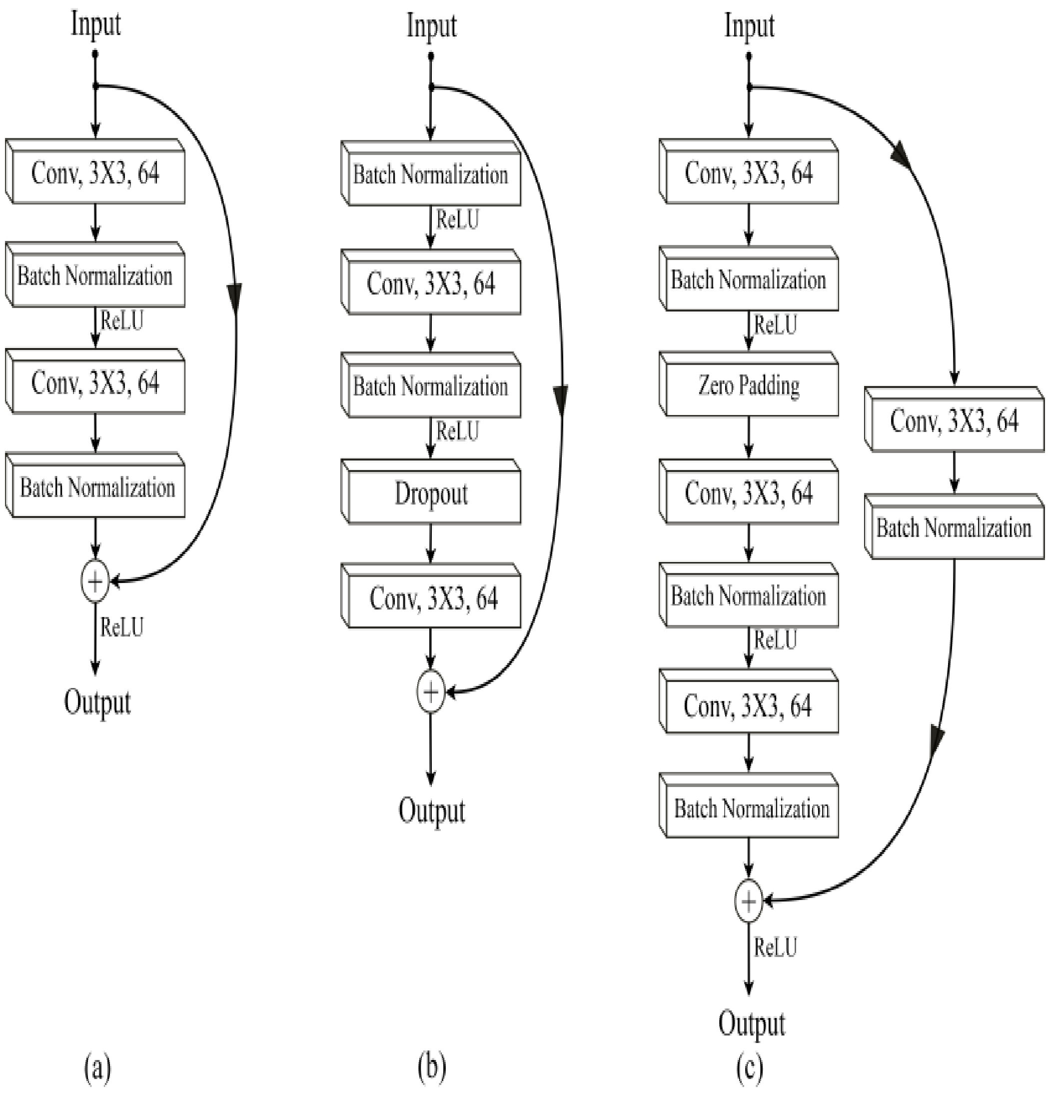

Fig. 2: ResNet architectures. (a) traditional ResNet, (b) densely connected ResNet and (c) the proposed connived feature ResNet.

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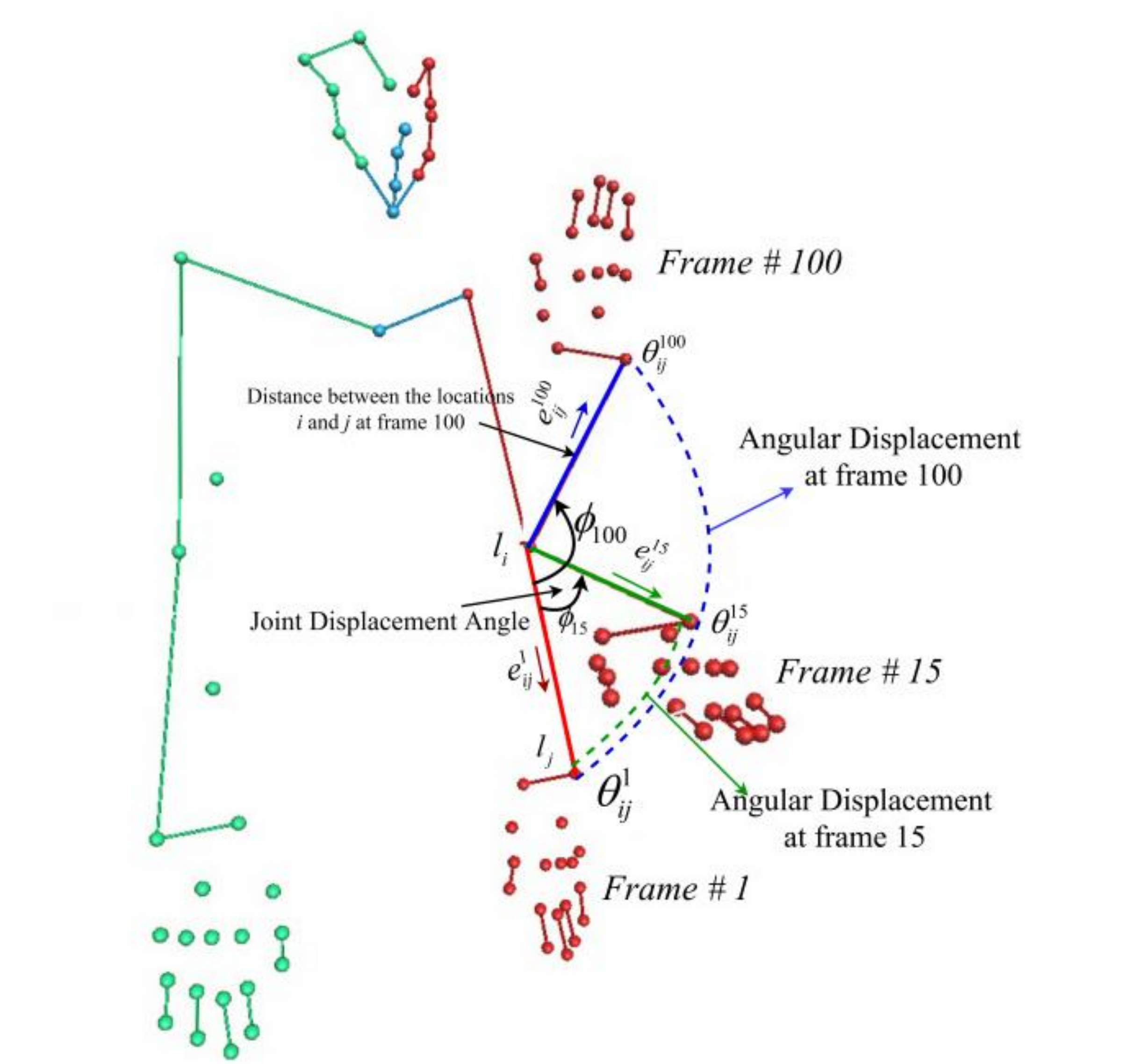

Fig. 3: Joint angular velocity feature computation on the skeleton.

Figure.2(a) shows a conventional ResNet, but the residual feature maps (figure.2(b)) keep the features that were lost during the ReLU operation. A CFR block is shown in figure.2(c), which transforms the l th layer input. The steps taken to derive joint angular velocity features from joint location data are depicted in Figure.3. We learned to use the CF ResNet structure depicted in figure.4. Fourth, network nodes act as ensembles for layer information. ResNet topologies typically have many Res blocks, anywhere from 20 to 121.

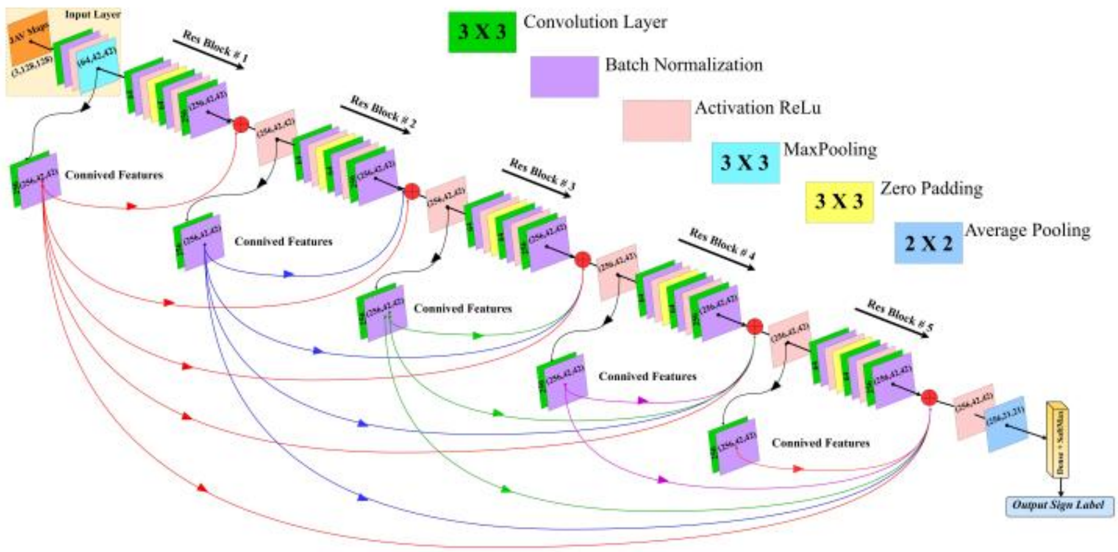

Fig. 4: Proposed connived feature ResNet (CF-ResNet)architecture.

3.Conclusion

Current models for representing 3D data, such as JDTDs, JATDs, and JADMs, are inadequate for characterizing subtle joint motions. Here, we introduce a new method of representing joint motion using angular velocities between two frames by designing joint angular velocity maps (JAVM). The CF ResNet framework was developed, trained, and tested on JAVMs for recognition.

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