**Skeleton-Based Action Recognition Using Few Shot Learning**

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Abstract

This paper presents a new action recognition method using the few shot learning. considered the skeleton sequence contain the temporal and spatial information, the proposed method encodes each of skeleton feature as an RGB image. Then a few shot learning method, prototypical network, is introduced to recognize the specific action of the RGB image stands for. Since a serial of dilated-densenet layers is utilized to map the feature image into embedding space, our method could extend the receptive field of feature points to whole the skeleton sequence (RGB image). Experiment result shows, our method achieved state-of-the art performance on a series of dataset. Besides that, our method is able to classify new classes that have not presented during the training phase with a few support samples.

**Index Terms:** skeleton sequence, dilated filter, few shot learning

# Introduction

Human action recognition has been widely researched for few decades. A lot of recognition methods are developed to serve the field of entertainment, surveillance and video analysis.

From the perspective of feature representation, these recognize methods could divide into three kinds: first, local feature-based method. Such methods design a set of 3D local invariant descriptor (3D-Hessia and 3D-Harris) to track the movement of human body. Then a machine learning model will be engaged to recognize the indeed action of the movement. Second, global feature-based method. It usually needs a descriptor to capture the whole motion of human body. Motion Energy Image (MEI) and Motion History Image (MHI) are two typical of global descriptor. The last type method is developed by the latest wave of deep learning model. Or it could interpret as a mixture of local and global feature descriptor method. deep learning models like 3D-CNN[1] and LSTM[2] had achieved state of the art performance in the action recognition filed. But these methods always consume large-scale datasets during training time. as human actions are varied, the demand of train sample will be exploded. Besides, when feed a new class of sample, the deep model need be re-trained to fit the changing distribution of the data.

To address these difficulties, a kind of Few-shot learning method are proposed. Non-parameter model from nearest neighbor to metric learning [3] have play a great role in the progress of this field. But seldom attention had paid to apply the few shot learning model to action recognition yet. for these reasons, we propose a method based on the few shot learning and global skeleton feature. Our method could also be considered as a kind of the global feature representation method. And The main contributions of this method are：

1. Only few skeleton sequences are needed to train an efficient action recognition model.
2. With few support samples, it is enough to recognize the action that had never seen before.
3. Dilated-densenet layer is embedded to extract the feature maps, which could enhance the robustness and diversity of our feature representation.

The remainder of the paper is organized as follows. In Sec.2 we briefly review methods proposed to deal with skeleton representation, few shot learning and dilated-dense layer. Then the inference and training algorithm about our method will be fully described. In Sec 4. we report the experiments results on a series of dataset to show the performance of the method. Finally, in Sec.5 we discuss propose research directions in the future.

# proposed method

## Feature image

It is common knowledge that a skeleton sequence can be represented as an RGB image []. consider a frame skeleton sequence action , each contains joints . And each is a 3-D coordinate point, which is corresponding to the RGB channel of a pixel in image . Thus, the skeleton sequence can be encoded as an feature image. a sort of variant RGB encoder had proposed to achieve the translation-scale invariant representation of the skeleton sequences [4][5]. But our method hasn’t taken advantage of these mechanism. Only a normalization, proposed by [6], is introduced.

Where and are the maximum and minimum value of the k-th channel (x; y; z) of the i-th skeleton.



Figure 1. the workflow of extracting a feature image from a skeleton sequence

## Prototypical network

A prototypical network[7] learn a metric space in which classification can be performed by computing distances to prototype representations of each class[7]. given K classes N labeled encoded image . each of class of image sample will be mapped by an embedding function and the prototype of each class is the mean of the mapped support sample belong to it.

when feed an unlabeled feature image , the label of image is decided by nearest prototype.

## dilated-densenet

we construct the as a CNN network. Since each pixel scatted in the image feature represent a skeleton join. We trend to expands the size of convolution kernel so that is could involve as much as pixels in the feature image. also, it will enlarge the receptive field of the CNN network. Besides that, Both the movement of skeleton joins in different frame and the distribution of the joints are the significates feature of the action. For these reasons, we considered to add dilated-densenet layers when construct the CNN network. And the dilated convolution kernel could enlarge the receptive filed of the CNN, the full connectivity of densenet could lead a variety of joints distribution descriptors and movement features.



Figure2． **CNN** architecture of the mapping function , The is corresponding to the weights and biases of the CNN network.

## The model

The output of prototypical network is SoftMax over the distance, it is defined as a:

where, is the prototypical of the model, is the train feature image sample, is the parameter of embedding function . Thus, the learnable part of this model can be solved via SGD optimization. For the sake of extending the receptive filed of the feature point and diversity feature representation, we had introduced the dilated-dense layers to construct the embedding function.

**Inference phase:** the inference phase of our model is similar to the nearest neighbor. Testing samples are divided into the support and test sets. samples from support set will be mapped into embedding space by . The prototype of our model is estimated by the mean of different class of mapped support samples. When a sample from test set is feed into our model, it will be mapped by same .then the assignment of the sample is depended on the model prototypes, from whom it had shortest distance. The algorithm 1 is a brief descript of the inference phase.



Figure3. The structure of the skeleton-based action recognition model. The sample x is assigned to the class, who had shortest distance from it

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| --- |
| **Algorithm 1: the inference process of action recognition model.** |
| **Input：** classes of support set , where each class of support set contains labeled samples. the unlabeled sample  **Output:** the assignment of unlabeled sample  **Foreach i in**    **End** |

**Training Phase:** the training algorithm of the skeleton-based action recognition method is provided in algorithm 2. The purpose of our training is to address the parameters of . the training samples are divided into support and query sets. Analogy to the inference, support sets is used to calculate the prototype of classes. The query sets, mapped into embedding space, will be used to adjust the parameter of . Figure 4 illustrate the detail computation of the cross-entropy loss of the model. Having the loss defined, the parameters can be updated by the gradient descent method on it.



Figure 4. The computational graph of model

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| --- |
| **Algorithm 2: the training process of action recognition model.** |
| **Input：** classes of action training set , where the i-th class of training sample is labeled as and contains samples. and are the number of support and query sample.  **Output:**    **Repeat:**  **Foreach i in**    **End**  **Foreach i in**        **End**  **Foreach i in**  **For each in**  **End**  **End**    **END** |

# Experiments (talk is cheap, show me your code)

The trainable part of our model is the mapping function . as mentioned before, we construction the as a CNN network. The architecture of the CNN is illustrated in Figure2. It composed of six layers: two dilated-dense layers, a convolution layer, a ReLU layer, a max-pool layer, a flatten layer. We implemented our method on Tensorflow with GeForce 920MX and evaluate it on series of datasets.

**Classify seen samples**

The UTD-MHAD dataset contains 27 classes of actions performed by 8 subjects (4 females and 4 males), Each subject repeated each action 4 times[]. So, we get 32 samples for each action. From each class, we select 8(4 support, 4 query) samples for model training, and leave out 24 samples for testing. Table1 shows the recognition accuracy of different methods on UTD-MHAD dataset.

|  |  |
| --- | --- |
| method | accuracy |
| ELC-KSVD | 76.19% |
| kinect & Inertial | 79.10% |
| Cov3DJ | 85.58% |
| SOS | 86.97% |
| JTM | 87.90% |
| TSIIM-MSDCNN | **96.27%** |
| Our method | 96% |

**Classify unseen samples**

To verify the ability of model of classifying the unseen samples, the whole dataset is divided into two unrelated training and inference sets. the training set contains 10 classes of the actions, and the inference set contains reminded 17 classes. During training phase, we select ( support, query) samples from each class of action , with which the parameters of the model are optimized. During the inference phase, we randomly select 5 samples from each remined class to calculate the prototype of them . and the rest 27 samples is used to verify the accuracy of our model. In this scenario, the training and inference samples are totally from different actions. Table2 shows the recognition accuracy of our model with different train setting.

|  |  |
| --- | --- |
| method | accuracy |
| query=5 support=5 n\_class =5 | 94% |
| query= support= n\_class = |  |
| query= support= n\_class = |  |
| query= support= n\_class = |  |

# Conclusion

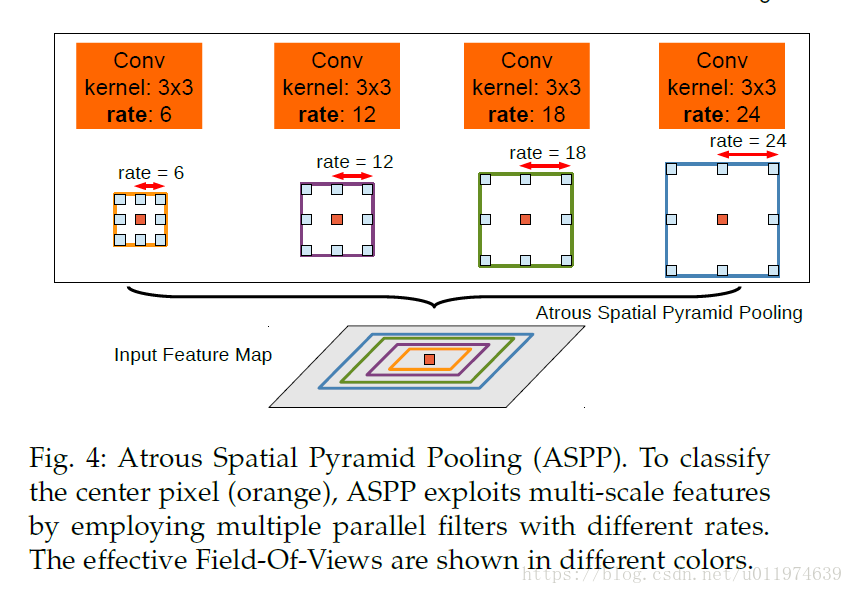
We present an action recognition method based on a few shot learning. It is able to classify the unseen classes with a few support samples. But, for a new coming sample, it could only be classified into a fixed number of classes, while the number of classes is always varied in practice. For future work, we will focus on to expand the model to automatic adjust the output number of class depend the indeed class number of the feed samples.

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# Other



The atrous spatial pyramid pooling. To classify the center pixel, ASPP exploits multi-scale features by employing multiple parallel filter with different rates. The effective of Field-of-view are shown in different colors.