Prototypical Contrast and Reverse Prediction: Unsupervised Skeleton Based Action Recognition

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Abstract—In this paper, we focus on unsupervised representation learning for skeleton-based action recognition. Existing approaches usually learn action representations by sequential prediction but they suffer from the inability to fully learn semantic information. To address this limitation, we propose a novel framework named Prototypical Contrast and Reverse Prediction (PCRP), which not only creates reverse sequential prediction to learn low-level information (e.g., body posture at every frame) and high-level pattern (e.g., motion order), but also devises action prototypes to implicitly encode semantic similarity shared among sequences. In general, we regard action prototypes as latent variables and formulate PCRP as an expectation-maximization task. Specifically, PCRP iteratively runs (1) E-step as determining the distribution of prototypes by clustering action encoding from the encoder, and (2) M-step as optimizing the encoder by minimizing the proposed ProtoMAE loss, which helps simultaneously pull the action encoding closer to its assigned prototype and perform reverse prediction task. Extensive experiments on N-UCLA, NTU 60, and NTU 120 dataset present that PCRP outperforms state-of-the-art unsupervised methods and even achieves superior performance over some of supervised methods. Codes are available at https://github.com/Mikexu007/PCRP.

I. INTRODUCTION

As an essential branch in computer vision, skeleton based action recognition has drawn broad attention due to the compact and effective skeletal representation of human body and its robustness against viewpoint variations and noisy backgrounds [5], [19], [32], [33].

Many of current skeleton-based works [5], [40], [42] for action recognition resort to supervised learning paradigms to learn action representations, which require massive annotated samples for training. However, the annotated information sometimes is not available or demand expensive labor force for labelling, which might face uncertain labelling or mislabelling challenges due to the high inter-class similarity of actions [7], [38]. From this perspective, exploiting the unlabeled data to learn effective action representations arouses considerable interests [15], [24].

In recent years, a stream of unsupervised learning methods have been introduced. Most of them [20], [22], [29], [34], [44] are built upon encoder-decoder structures [1] to yield discriminative action representations via sequential prediction/reconstruction or augmented sequence contrast. However, these methods suffer from a common significant disadvantage: Higher-level semantics (e.g., motion order, semantic similarity among sequences) is not fully explored. This issue derives from the instance-level situation that the sequential prediction task forces the predicted sequence to get closer to only the original one, but neglect the semantic similarity between various instances. Likewise, augmented sequence contrast is also restricted in pulling closer two augmented samples of one sequence regardless of others. Furthermore, this problem is worsened in large-scale datasets, since the correlation shared among numerous semantically similar samples cannot be fully exploited.

To address the challenges above, we rethink the encoder-decoder based sequential prediction in terms of expectation-maximization (EM) algorithm [6], and propose Prototypical Contrast and Reverse Prediction (PCRP) framework. Fig. 1 illustrates the proposed PCRP. An action prototype, similar to an image prototype [18], is a representative encoding for a bunch of semantically similar sequences. Instead of directly using encoder-decoder structure to obtain representation via data prediction, we exploit the EM algorithm to encode semantic structure of data into action representations by (1) implicitly learning semantic similarity between sequences to force the action encoding to approach their corresponding prototypes, and (2) learning high-level information (e.g., motion order) of sequences via predicting sequence in reverse order.

Specifically, we focus on the encoder parameter learning in the EM algorithm and regard action prototypes as additional latent variables. From this perspective, the EM algorithm attempts to find a maximum likelihood estimate of encoder parameters (see Fig. 2(a)), while the decoder keeps fixed for enhancing the encoder to learn representations [34]. Given the current encoder parameters, the expectation step (E-step) aims to estimate the probability of prototypes by performing k-means clustering on the action encoding (the output at final step) from the Uni-GRU encoder, and the maximization step (M-step) tries to update the encoder parameters by minimizing the proposed loss, namely, ProtoMAE (Sec. IV-B2). Minimizing ProtoMAE is equivalent to maximizing the estimated likelihood under the assumption that the distribution around each prototype is isotropic Gaussian [18]. It is also equivalent to help predict sequence reversely and simultaneously pull
the action encoding closer to its corresponding prototype compared to other prototypes (see Fig. 2(b)). The E-step and the M-step function iteratively. In this way, the encoder is able to learn discriminative action representations without labeled data, and after convergence, it can be used for other downstream tasks such as classification. The contributions of our work are listed as follows:

- We propose a novel framework named Prototypical Contrast and Reverse Prediction to explore high-level information of sequences and that of the global dataset. To our knowledge, this work is the first to introduce prototypical contrast and reverse prediction for unsupervised skeleton based action recognition.
- We formulate the PCRP into an EM iteration manner, in which the alternating steps of clustering and reverse prediction serve to approximate and maximize the log-likelihood function.
- We introduce ProtoMAE, an enhanced MAE loss that exploits contrastive loss to achieve high-level information learning as well as to adaptively estimate the tightness of the feature distribution around each prototype.
- Experiments on the N-UCLA, NTU RGB+D 60, and NTU RGB+D 120 dataset, show the superiority of our framework to other state-of-the-art unsupervised methods as well as some of supervised counterparts.

II. RELATED WORK

**Unsupervised action recognition:** While supervised methods [5], [19], [31] show great performance in skeleton based action recognition by using annotated information, unsupervised methods are advantageous at learning action representation without any labels. Zheng et al. [44] introduce a generative adversarial network (GAN) based encoder-decoder for skeletal sequence regeneration, and utilize the learned representation from encoders to identify actions. Su et al. [34] further devise predict&cluster (P&C) model with decoder-weakening mechanism to enhance the ability of the encoder to capture more discriminative action pattern. Rao et al. [29] propose skeleton augmentation strategies and apply momentum LSTM with contrastive learning to learn robust action representation. However, these methods ignore the semantic information between different sequences. In this paper, we adopt encoder-decoder structure with decoder-weakening strategy [34] as the backbone, and propose prototypical contrast for semantic learning and achieve sequential reverse prediction for enhancing representation learning.

**Unsupervised Action Clustering:** Many clustering based models have been introduced for unsupervised action clustering. Jones et al. [14] propose dual assignment k-means (DAKM) to achieve context learning for facilitating unsupervised action clustering. Bhatnagar et al. [2] devise weak learner based autoencoders to extract temporal features under different temporal resolutions. Peng et al. [28] establish a recursive constrained model by using the contextual motion and scene for unsupervised video action clustering. Nevertheless, these approaches only serve for RGB videos and yet the counterpart for skeleton action sequences is not developed.

In this proposed work, we for the first time explore the prototypical contrast for unsupervised skeleton based action recognition.

**Contrastive Learning:** In recent years, contrastive learning, a type of unsupervised (self-supervised) learning method, has attracted massive attention. Most of them [3], [4], [12], [18] learn effective representations by pretext tasks [39], [45] with contrastive losses [10], [11]. For example, Wu et al. [39] base an instance contrast task and noise-contrastive estimation (NCE) loss [10] to match positive pairs and push apart negative pairs. He et al. [12] propose momentum based encoder to learn more consistent representations. Nevertheless, these methods mainly focus on image representation learning. In this paper, we introduce prototypical contrast [18] to skeleton based action recognition and improve the sequential prediction task on high-level semantics learning.

III. PRELIMINARIES

We focus on the unsupervised representation learning using skeleton sequences. Then, we exploit the learned representations for skeleton-based action recognition. Given a training set \( \Phi = \{x(i)\}_{i=1}^{N} \) of \( N \) skeleton sequences, each sequence \( x \in \mathbb{R}^{T \times J \times 3} \) contains \( T \) skeleton frames and each frame has \( J \) body joints that are represented in 3D space. Our goal is to learn an encoder \( f_{E} \) (we employ Uni-GRU) that maps \( \Phi \) to action encoding set \( V = \{v(i)\}_{i=1}^{N} \), where \( v(i) \in \mathbb{R}^{C} \) is a discriminative action representation of \( x(i) \). Traditional encoder-decoder based models achieve this goal by sequential prediction as to optimize the loss function of mean square error (MSE) or mean absolute error (MAE) between the original sequence and its predicted one. MAE/MSE only focus on skeleton reconstruction within each single sequence and ignore the similarity of different sequences. In our proposed framework PCRP, we tackle this challenge by introducing action prototypical contrast paradigm (see Sec. IV-A1). Besides, we achieve sequential prediction in reverse order (see Sec. IV-B1) to enhance high-level information (e.g., motion pattern) learning. Fig. 2(a) illustrates our framework, where semantic learning and data reverse prediction are performed alternately at each epoch. The main algorithm of PCRP is shown in Algorithm 1.

Before introducing our proposed PCRP, we first have a brief review of the general encoder-decoder based sequential prediction task that we rely on.

### A. Sequential Prediction

Given a skeleton sequence \( x = \{x_{1}, \ldots, x_{T}\} \), the model is expected to output the predicted sequence \( \hat{x} = (\hat{x}_{1}, \ldots, \hat{x}_{T}) \) that gets closer as much as possible to \( x \). In training phase, the encoder (e.g., Uni-GRU) encodes every skeleton frame \( x_{t} (t \in \{1, \ldots, T\}) \) and the previous step’s latent state \( h_{t-1} (t-1 > 0) \) to determine the current output \( v_{t} \) and the current latent state \( h_{t} \):

\[
(v_{t}, h_{t}) = \begin{cases} f_{E}(x_{t}) & \text{if } t = 1 \\ f_{E}(h_{t-1}, x_{t}) & \text{if } t > 1 \end{cases}
\]  

(1)
Algorithm 1 Main algorithm of PCRP

Input: encoder $f_E$, decoder $f_D$, training dataset $\Phi$, number of clusters $K = \{k_m\}_{m=1}^M$

while not MaxEpoch do
  # E-step
  $V = f_E(\Phi)$
  # obtain action encoding for all training data
  for $m = 1$ to $M$ do
    # cluster $V$ into $k_m$ clusters and return prototypes.
    $Z^m = \text{k-means}(V, k_m)$
    # calculate the distribution tightness of each prototype with Eq. 8
    $\phi_m = \text{Tightness}(Z^m, V)$
  end for
  # M-step
  for a mini-batch $x$ in $\Phi$ do
    $v = f_E(x)$
    $\hat{x} = f_D(v)$
    $x = \text{Reverse}(x)$
    # compute loss with Eq. 13
    $L_{\text{ProtoMAE}}(v, x, \hat{x}, \{Z^m\}_{m=1}^M, \{\phi_m\}_{m=1}^M)$
    fix $f_D$
    # parameters of decoder do not evolve
    Update $f_E$ to minimize $L_{\text{ProtoMAE}}$ with Adam optimizer
  end for
end while

where $v_t, h_t \in \mathbb{R}^C$. Next, the decoder $f_D$ utilizes the output at final step $v_T$ from the encoder to perform prediction task:

$$
(\hat{x}_t, h_{t-1}) = \begin{cases} f_D(v_T) & \text{if } t = 1 \\ f_D(h_{t-1}) & \text{if } t > 1 \end{cases}
$$

(2)

Then MAE loss is applied on $x$ and $\hat{x}$ for model optimization. Therefore, $v_T$ is the action encoding (i.e., representation) of the sequence $x$.

IV. PROTOTYPICAL CONTRAST AND REVERSE PREDICTION AS EXPECTATION-MAXIMIZATION

Sequence prediction based PCRP aims to find the encoder parameters $\theta$ that maximizes the likelihood function of the $N$ observed sequences:

$$
\theta^* = \arg \max_{\theta} \sum_{i=1}^N \log p(x^{(i)} | \theta) = \arg \max_{\theta} \sum_{i=1}^N \log \prod_{t=1}^{T_{i}} p(x_t | x_{t-1}, \theta)
$$

(3)

Since the action prototypes are introduced but not directly observed, they are viewed as the latent variables of observed data given by $Z = \{z_i\}_{i=1}^K$ with $K$ action prototypes, where $z_i \in \mathbb{R}^C$. Thus the Eq. 3 is referred to as:

$$
\theta^* = \arg \max_{\theta} \sum_{i=1}^N \log \sum_{z_i \in Z} p(x^{(i)} | z_i, \theta)
$$

(4)

Achieving this function directly is challenging, and the only knowledge of action prototypes $Z$ is obtained in the posterior distribution $p(z_i | x^{(i)}, \theta)$. Under this circumstance, we first utilizes current parameters $\theta^{\text{old}}$ and the Jensen’s inequality to turn Eq. 4 into an expectation 1 $Q(\theta, \theta^{\text{old}})$ that needs to be maximized:

$$
\theta^* = \arg \max_{\theta} Q(\theta, \theta^{\text{old}}) = \arg \max_{\theta} \sum_{i=1}^N \sum_{z_i \in Z} p(z_i | x^{(i)}, \theta^{\text{old}}) \log p(x^{(i)}, z_i | \theta)
$$

(5)

Then we rely on the EM algorithm with E-step and M-step to achieve Eq. 5.

A. E-step

In this step, we attempt to estimate $p(z_i | x^{(i)}, \theta^{\text{old}})$ of Eq. 6 and introduce prototypical contrast.

1) Prototypical Contrast: The result of $p(z_i | x^{(i)}, \theta^{\text{old}})$ is based on the action prototype $z_i$. Along this line, we take advantage of the action encoding from encoder to obtain $z_i$. Specifically, we apply $k$-means algorithm on all action encoding $\{v_T^{(i)}\}_{i=1}^N$ (the final output) from $f_E$ to obtain $K$ clusters, in which we define prototype $z_i \in \mathbb{R}^C$ as the centroid of the $i$th cluster [18]. Therefore, we have

$$
p(z_i | x^{(i)}, \theta^{\text{old}}) = \begin{cases} 0 & \text{if } v_T^{(i)} \notin z_i \\ 1 & \text{if } v_T^{(i)} \in z_i \end{cases}
$$

(7)

Using the action encoding from encoder to achieve prototypical contrast is beneficial due to several aspects: (1) The action encoding is in low dimension compared with the whole

1More details are given in Supplementary Materials.
sequence. (2) The action encoding contains abundant context information of the action. (3) Semantic similarity between different samples is explored by pulling the action encoding closer to their corresponding prototypes (see Sec. IV-B2).

2) Tightness Estimation: To measure the cluster’s quality (feature distribution), we introduce the tightness $\phi \propto \sigma^2$ [18]. We first suppose a cluster has a prototype $z_i$ and contains $P$ action encoding vectors $\{v_T^{(i)}\}_{i=1}^P$, which are then used to compute $\phi$. Here a good $\phi$ is expected to be small and satisfy several requirements: (1) The average distance between each action encoding $v_T^{(i)}$ and their prototype $z_i$ is small. (2) A cluster covers more action encoding (i.e., $P$ is large). To achieve this goal, we define $\phi$ as follows:

$$\phi = \frac{\sum_{i=1}^P \|v_T^{(i)} - z_i\|^2_2}{P \log (P + \alpha)},$$

where $\alpha$ is a scaling parameter that avoids overwhelmingly large $\phi$. On the other hand, $\phi$ serves as a punishing factor in the loss objective (see Sec. IV-B2) to generate more balanced clusters with similar tightness.

B. M-step

Next, we try to estimate $p(x^{(i)}, z_i \mid \theta)$. Due to the uniform probability over cluster centroids, we set $p(z_i \mid \theta) = \frac{1}{K}$ and get:

$$p(x^{(i)}, z_i \mid \theta) = p(x^{(i)} \mid z_i, \theta)p(z_i \mid \theta) = \frac{1}{K}p(x^{(i)} \mid z_i, \theta).$$

To calculate Eq. 9, we assume that the distribution for each action prototype is an isotropic Gaussian [18], which results in:

$$p(x^{(i)} \mid z_i, \theta) = \frac{\exp \left( -\frac{(v_T^{(i)} - z_i)^2}{2\sigma^2} \right)}{\sum_{k=1}^K \exp \left( -\frac{(v_T^{(i)} - z_k)^2}{2\sigma^2} \right)},$$

where $v_T^{(i)} \in z_s$. Suppose $\ell_2$-normalization is applied to $v_T^{(i)}$ and $z_i$, then we have $(v_T^{(i)} - z_i)^2 = 2 - 2v_T^{(i)} \cdot z_i$. On the basis of Eq. 5, 6, 7, 9, 10, the maximum likelihood estimation is referred to as:

$$\theta^* = \arg\min_\theta \sum_{i=1}^N -\log \frac{\exp (v_T^{(i)} \cdot z_s/\phi_s)}{\sum_{k=1}^K \exp (v_T^{(i)} \cdot z_k/\phi_k)}.$$

1) Reverse Prediction: Instead of performing commonly-used plain sequential prediction (see Sec. III-A) for action representation learning, we propose reverse prediction as to learn more high-level information (e.g., movement order) that are meaningful to human perception. Hence, we expect our model is able to generate predicted sequence $\hat{x} = (x_1, \ldots, x_T)$ that get closer to $\overline{x} = (\overline{x}_1, \ldots, \overline{x}_T) = \{x_T, \ldots, x_1\}$, where $\overline{x}_t = x_{t-T+1}$. Then the MAE loss for reverse prediction is defined as:

$$\mathcal{L}_R = \frac{1}{T} \sum_{t=1}^T \sum_{j=1}^J |x_{t,j} - \hat{x}_{t,j}|.$$

2) ProtoMAE Loss: To this end, we combine Eq. 12 and Eq. 11 to form a new loss objective named ProtoMAE, defined as:

$$\mathcal{L}_{\text{ProtoMAE}} = \sum_{i=1}^N \left( \sum_{t=1}^T |x_{t,i} - \hat{x}_{t,i}| - \frac{1}{M} \sum_{m=1}^M \log \frac{\exp \left( \frac{w_T^{(i)} \cdot x_m}{\sigma_m} \right)}{\sum_{k=1}^K \exp \left( \frac{w_T^{(i)} \cdot x_k}{\sigma_k} \right)} \right),$$

which is to be minimized simultaneously achieve sequential reverse prediction and cluster the action encoding with semantic similarity. Note that in Eq. 13 large $\phi$ denotes the action encoding are in a loose cluster and small $\phi$ means they are in a tight cluster. Large $\phi$ weakens the affinity between the action encoding and the prototype, which drives the encoder to pull the action encoding closer to the prototype. In contrast, small $\phi$ does not compromise much to the affinity mentioned above, which less encourages the action encoding approach the prototype. Hence, learning with ProtoMAE generates more balanced clusters with similar tightness [18]. Besides, since the $K$ may be too large, we choose to sample $r$ prototypes, where $r < K$. We also attempt to cluster action encoding $M$ times with different number of clusters $K = \{k_m\}_{m=1}^M$ to provide more robust probability estimation of prototypes.

EM algorithm performs E-step and M-step alternately without supervision for a specific epochs. Then the quality of learned representations $v_T$ from the encoder are measured by linear evaluation protocol [44], where the learned representations are always kept frozen and a linear classifier is added on top of them for training and testing.

V. Experiments

Dataset: Experiments are based on three large action datasets and we use their skeleton sequences. (1) Northwestern-UCLA (N-UCLA) Multiview Action 3D dataset [37] consists of 10 classes of actions where every action is acted by 10 subjects. Three Kinect cameras record the action simultaneously and yield 1494 action videos in total. We adopt the same evaluation setting as in [43] by using samples from the first two views for training and the other for testing. (2) NTU RGB+D 60 (NTU 60) dataset [30] is popular for skeleton based action recognition due to its variety of actions (60 classes) and its large scale (56578 samples). We follow the provided evaluation protocol: (a) Cross-Subject (C-Sub) setting that separates 40091 samples into training set.
and the rest for testing set by different persons. (b) Cross-View (C-View) setting that covers 37646 samples captured by one camera for training and samples from the other camera are for testing. (3) **NTU RGB+D 120** (NTU 120) dataset [21] is NTU 60 based extension, whose scale is up to 120 classes of actions, 106 participants, and 113945 sequences in total. Similar as NTU 60, two validation protocols should be followed: (a) Cross-Subject (C-Sub) and (b) Cross-Setup (C-Set). In C-Sub, 63026 samples performed by 53 persons are for training and the others are for testing. In C-Set, all 32 setups are separated as a half for training and the other half for testing.

### A. Configuration Details

**Pre-processing:** To overcome the orientation misalignment of skeleton movements shown in Fig. 3(a), we transform the raw data into a view-invariant coordinate system [16] as illustrated in Fig. 3(b). The transformed joint coordinates are then given by:

\[
x_{t,j} = R^{-1} (x_{t,j} - o_R), \forall j \in J, \forall t \in T
\]

where \(x_{t,j} \in \mathbb{R}^{3 \times 1}\). The rotation \(R\) and the origin of rotation \(o_R\) are determined by:

\[
R = \begin{bmatrix}
u_1 \\
\|u_1\| \\
u_2 \\
\|u_2\| \\
u_1 \times u_2 \\
\|u_1 \times u_2\|
\end{bmatrix}, \quad o_R = x_{1,\text{root}}
\]

where \(u_1 = x_{1,\text{spine}} - x_{1,\text{root}}\) denotes the vector vertical to the floor and \(u_2 = \frac{u_2 - \text{Proj}_{u_1}(u_2)}{\|u_2 - \text{Proj}_{u_1}(u_2)\|}\) where \(u_2 = x_{1,\text{hip left}} - x_{1,\text{hip right}}\) denotes the difference vector between the left and right hip joints at the initial time step of each sample. \(\text{Proj}_{u_1}(u_2)\) represents the vector projection of \(u_2\) onto \(u_1\).

\(\times\) is the cross product and \(x_{1,\text{root}}\) is the spine base joint at the initial frame. The sequence length is fixed at 50 and we pad zeros if the sample is less than the fixed length.

PCRP is based on the encoder-decoder structure of [34] with fixed weights for the decoder, but we replace Bi-GRU stated in [34] with the Uni-GRU for the encoder. We pre-train PCRP for 50 epochs on the N-UCLA dataset and for 10 epochs on the NTU 60/120 dataset. The learning rate is 0.001 in pre-training stage. In the linear evaluation, we fix the encoder and train the linear classifier by 50 epochs on the N-UCAL dataset and by 30 epochs on the NTU 60/120 dataset. The learning rate is 0.01 in evaluation stage. Adam is applied for model optimization.

### B. Performance Comparison

We compare our PCRP with previous relevant unsupervised learning methods, supervised methods, and hand-crafted methods on three large datasets including N-UCLA dataset, NTU 60 dataset, and NTU 120 dataset. The performance comparisons are shown in Table I, II, III. For an unsupervised learning method P&C FW [34], we implement it on linear evaluation protocol instead of KNN evaluation, and also rid the auto-encoder part to be efficient in pre-training but not compromising much the performance.

1) **Comparison with Unsupervised Methods:** As shown in Table I on N-UCLA dataset, the proposed PCRP shows 3.7-24.5% margin over the state-of-the-art unsupervised methods (Id = 6, 7, 8, 9), which are also based on the encoder-decoder structure to learn action representation. Although they possess cross-view decoding [17], additional adversarial training strategies [44], decoder-weakening mechanism [34] or multi-task learning [20], they just aim at plain sequential prediction in order and do not consider high-level semantic information learning. In contrast, the proposed PCRP is able to simultaneously learn semantic similarity between sequences and enhance action representation learning via reverse prediction. In particular, our method achieves over 10% improvement than Li et al. (Id = 6) that focus on view-invariant action representation learning, which validates the superior robustness of our method to viewpoint variations. On the other hand, our approach takes skeleton sequences as inputs that are smaller sized than depth images, but it still significantly outperforms depth-image based methods (Id = 5, 6). Above advantages of our approach are also similarly shown on NTU 60 dataset (see Table II) and NTU 120 dataset (see Table III). These comparison results do show the effectiveness and efficacy of the proposed PCRP.

Since our work is based on P&C FW [34], we make further comparison of our PCRP with P&C FW on pre-training loss curves and evaluation accuracy curves. In Fig. 4(a) on N-UCLA dataset, we observe that PCRP shows increasing margin than P&C FW as epoch goes on. When it comes to larger scale datasets, i.e., NTU 60/120 dataset (see Fig. 4(b)-4(e)), the proposed work shows great superior over P&C FW that PCRP keeps high evaluation accuracy from the beginning while P&C FW’s accuracy grows increasingly. We here argue
TABLE II
COMPARISON WITH PRIOR METHODS ON NTU 60 DATASET. BOLD NUMBERS REFER TO THE BEST UNSUPERVISED PERFORMERS.

| Id  | Method                  | C-View Acc (%) | C-Sub Acc (%) |
|-----|-------------------------|----------------|---------------|
| 1   | *HOG$^2$ [27]           | 22.3           | 32.2          |
| 2   | *Super Normal Vector [41]| 13.6           | 31.8          |
| 3   | *HON$^4$D [25]          | 7.3            | 30.6          |
| 4   | Skeletal Quads [9]      | 41.4           | 38.6          |
| 5   | Lie Group [35]          | 52.8           | 50.1          |

| Id  | Method                  | C-View Acc (%) | C-Sub Acc (%) |
|-----|-------------------------|----------------|---------------|
| 6   | HBRNN [8]               | 64.0           | 59.1          |
| 7   | Deep RNN [30]           | 64.1           | 56.3          |

TABLE III
COMPARISON WITH SUPERVISED AND UNSUPERVISED METHODS ON NTU 120 DATASET. BOLD NUMBERS DENOTE THE BEST PERFORMERS.

| Id  | Method                  | C-Set Acc (%) | C-Sub Acc (%) |
|-----|-------------------------|---------------|---------------|
| 1   | Part-Aware LSTM [30]    | 26.3          | 25.5          |
| 2   | Soft RNN [13]           | 44.9          | 36.3          |

| Id  | Method                  | C-Set Acc (%) | C-Sub Acc (%) |
|-----|-------------------------|---------------|---------------|
| 3   | P&C FW [34]             | 42.7          | 41.7          |
| 4   | PCRP (Ours)             | 45.1          | 41.7          |

that excellent unsupervised learning methods should be of high efficiency that they do not require too many pre-training epochs to achieve high evaluation accuracy, and they are supposed to maintain it as the epoch increases. From this point, our method indeed performs better than P&C FW. We plot confusion matrix results in Fig. 5.

2) Comparison with Hand-Crafted and Supervised Methods: The proposed PCRP significantly surpasses several hand-crafted methods (Id = 1-2 in Table I) on the N-UCLA dataset and (Id = 1-5 in Table II) on the NTU 60 dataset. For instance in Table II, PCRP shows better results than Skeletal Quads (Id = 4) and Lie group (Id = 5) by at least 10.7% on the C-View protocol and 3.8% on the C-Sub protocol. In addition, the proposed work is competitive or superior compared with some prior supervised methods on three datasets: (1) For the N-UCLA dataset in Table I, the proposed work has 6.5% margin better than HBRNN (Id = 3). (2) For the NTU 60 dataset in Table II, our method shows comparable results with Deep RNN (Id = 7). (3) For the NTU 120 dataset in Table III, our proposed approach presents advantage over Part-Aware LSTM (Id = 1) and Soft RNN (Id = 2) by 0.2-18.8% on different evaluation settings.

C. Ablation Study

In this section, we conduct extensive ablation experiments on three datasets mentioned above to provide solid validation.
of our proposed work.

1) Analysis of PC and RP: In this part, we explore the role of prototypical contrast (PC) and reverse prediction (RP). The baseline is P&C FW [34] with Uni-GRU encoder instead of Bi-GRU stated in [34]. When the experiment is involved in PC, we run $M = 3$ times clustering with different cluster number (see Eq. 13).

In Table IV(a) for the N-UCLA dataset, compared with the baseline (Id = 1), RP (Id = 2) presents 0.9% improvement, which validates the effectiveness of RP in our framework. This effectiveness can also be observed from the comparison between (Id = 3) and (Id = 4). For the effective function of PC, the item (Id = 3) runs 3 times clustering with 40, 70, 100 clusters respectively and it shows superior performance over the baseline (Id = 1) by 2.5%. Besides, the item (Id = 4) also shows 2.8% margin higher than (Id = 2). Combing PC and RP, the final model (Id = 4) achieves the best result. In the larger datasets such as NTU 60/120 dataset, the effectiveness of PC and RP can also be demonstrated and shown in Table IV(b) and Table IV(c).

Furthermore, we plot evaluation accuracy curves of PCRP, PC, RP, and baseline on NTU 60/120 dataset. As shown in Table 6(a)-6(d), our approach PCRP (red line) is able to obtain high evaluation accuracy at beginning and then maintain it as the pre-training goes on, which shows its powerful and robust action representation learning.

2) Effects of Various Number of Clusters: To understand the effects of $M$ times running with different cluster number, we conduct ablation experiments on the N-UCLA dataset, the NTU 60 dataset in C-View setting, and the NTU 120 dataset in C-Set setting. As shown in Table V(a), $M = 1$ with 70 clusters for PC (Id = 2) obtains 87.0%, which outperforms $M = 3$ times running for PC (Id = 4-5). Likewise, Table V(c) has similar observation. In Table V(b), $M = 3$ with 90, 120, 150 (Id = 5) achieves 63.5%, the highest score among (Id = 1-6). Along this line, we can understand running larger $M$ with different cluster number does not necessarily guarantee better representation.

VI. CONCLUSION

This paper presents a novel framework named prototypical contrast and reverse prediction (PCRP) for skeleton-based action recognition. In the view of EM algorithm, PCRP alternately performs E-step as generating action prototypes by clustering action encoding from the encoder, and M-step as updating the encoder by contracting the distribution around the prototypes and simultaneously predicting sequences in reverse order. Experiments on three large datasets show that our work can learn distinct action representations and surpass previous unsupervised approaches.

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