Attention Module for Enhanced Posture Accurate in 2D-3D Pose Estimation Network

***Abstract*— Addressing the challenge of effectively reducing a redundant 2D pose sequence from a weak pose detector to create a representative 3D pose remains unresolved. To tackle this, the proposed method integrates an efficient system that incorporates the attention mechanism. This system deploys two main networks: a 2D pose detector and a 3D pose estimator. The 2D pose detector is enhanced with an attention module for precise joint detection, and a new attention module is implemented after 2 last blocks to improve accuracy. The 3D pose network also leverages a Transformer-based architecture with advanced attention mechanisms, including a new Transformer Encoder that applies spatial and temporal attention to capture long-range dependencies in 2D pose sequences. This proposed architecture has demonstrated good comparison performance on two benchmark datasets for 3D human pose estimation—Human3.6M and MPI-INF-3DHP—improving performance by 0.9% and 0.3% respectively over its closest counterpart, PoseFormer. Additionally, in terms of 2D pose estimation, the system surpasses existing methods on the COCO 2017 Microsoft Dataset. Link demo: demo vision**

***Index Terms*— 3D modeling, Pose estimation, Deep learning, Video surveillance.**

I. Introduction

A. Research Background

THREE Dimension human pose estimation (HPE) is a crucial topic in computer vision. This approach involves determining the three-dimensional locations of a human body joint from a two-dimensional image or set of photos. Many applications can be used for human pose estimation such as object recognition [1], [2], human-computer-interaction [3], activity recognition [4], [5] or robotic system [6], [7].

1) 2D Human Pose Network: In the field of 2D Human Pose Estimation, as outlined in the introduction, most techniques fall into two main categories: top-down and bottom-up. Recently, bottom-up methods [27] have become popular due to their efficiency. These methods predict keypoints directly from the input image without requiring person detection. However, because they do not focus specifically on human regions, their accuracy may be compromised. Conversely, top-down methods start with a human detector that identifies all individuals in an image, then performs single-person pose estimation for each detected subject, resulting in more accurate predictions. Notable techniques in this category include HRNet [18] and HRFormer [8]. This paper introduces a novel top-down approach that significantly enhances heatmap prediction by applying an attention mechanism between the characteristic functions of the predicted and ground truth (GT) heatmaps.

2) 3D Human Pose Network: Existing single-view 3D pose estimation methods can be divided into two mainstream types: one-stage approaches and two-stage methods. One-stage approaches directly infer 3D poses from input images without intermediate 2D pose representations [19], [29], while two-stage network first obtain 2D keypoints from pretrained 2D pose detections and then feed them into a 2D-to 3D lifting network to estimate 3D poses. Benefiting from the excellent performance of 2D HPE, this 2D-to-3D pose lifting method can efficiently and accurately regress 3D poses using detected 2D key points. Despite the promising results achieved by using temporal correlations from fully convolutional [4], [26] or graph-based [2] architectures, these methods are less efficient in capturing global-context information across frames.
Recently, vision transformers advanced all the visual recognition tasks [14]. Following PoseFormer [21], the transformer has been used to lift 2D poses to the corresponding 3D poses. To eliminate the redundancy in the sequence with temporal information, Li et al. [12] proposed a strided transformer network. spatial-temporal transformer is used for 3D HPE tasks. Using transformers in HPE showed significant improvement overall. However, pre-training on a large dataset is required to learn more representative and effective representations for the sequence HPE data. The proposed method is different from the previous methods in leveraging the cross-interaction between the joints of the body parts in the spatial and temporal domains.

B. Problem Statement and Technical Challenges

For the 2D Pose Estimator, deep convolutional neural networks have demonstrated exceptional performance. Typically, most existing approaches process the input through a network to enhance the resolution and subsequently apply 3D Human Pose Estimation (HPE) on the 2D results, as depicted in Fig.1. The 3D network, which uses a series of 2D points as input, generally consists of high-to-low resolution subnetworks arranged in sequence. For instance, the Hourglass model [11] employs a symmetric low-to-high resolution technique to regain high resolution, while Simple Baseline [27] utilizes a few transposed convolution layers to create high-resolution representations. Nevertheless, accurately lifting the 2D keypoints to a 3D model remains a significant challenge.

Recent advancements in 3D human posture encoding have been facilitated by deep neural networks [17], [22]. However, these networks encounter several challenges. First, improving the accuracy of various network types, such as real-time networks or networks that measure accuracy, is crucial. Second,

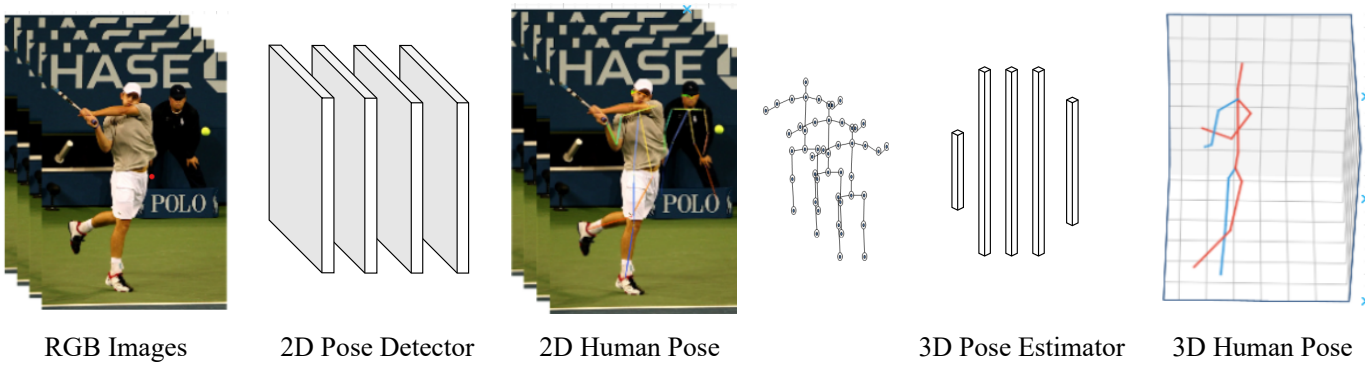

Fig. 1. The proposed system comprises two main components: the 2D Pose Detector and the 3D Pose Estimator. The 2D Pose Detector processes the input image to identify 2D human keypoints. Subsequently, the 3D Pose Estimator takes a sequence of these predicted 2D joints from the Detector and accurately estimates the final 3D pose of the human figure.

it is common practice to verify the accuracy of a network by using different 2D pose results. Finally, the current challenge for networks is to enhance accuracy while either maintaining or increasing processing speed. The proposed study introduces a novel network structure and evaluates it in terms of speed and accuracy. This experiment diverges from PoseFormer [21] by implementing a new attention mechanism known as spatial-temporal attention.

C. Attention in Human Pose Estimation Review

The attention mechanism has been widely adopted in natural language processing (NLP) tasks, achieving state-of-the-art performance in machine translation [5] and language understanding [21]. Recently, attention-aware features have also proved highly effective in computer vision tasks. For instance, Newel et al. [11] proposed a robust attention module that integrates an attention branch with an hourglass block, which is stacked multiple times to construct a deep convolutional neural network for image classification. Leveraging the self-attention mechanism, the network described in [13] captures rich contextual dependencies for scene segmentation. Similarly, Zhang et al. [17] and Yang et al. [21] have incorporated attention mechanisms into various convolutional neural networks to enhance human pose estimation. A prominent mechanism in this area is self-attention, also known as transformer-based attention, which enables the model to focus on different parts of the input and recognize long-range dependencies. This capability allows pose estimation models to dynamically prioritize the significance of different joints or body parts based on their interrelations.

Furthermore, spatial attention can be utilized to emphasize relevant spatial regions within an image, enhancing the model's focus on crucial areas for accurate pose estimation through technologies like spatial transformer networks or spatial attention modules.

D. Contribution of The Paper

Many papers have been researched on 2D and 3D human pose estimation over the past few years. However, less work has been deeply studied on attention mechanisms for both 2D and 3D networks. This article proposes a new attention mechanism for the whole network, which significantly improves the accuracy of the final 2D and 3D prediction results. In summary, the main contribution of the paper is described in three-fold:

1) This paper introduces and applies a novel attention mechanism to both the 2D pose detector and the 3D estimator, enhancing the network's ability to focus on and resolve occlusion issues. Within the 2D Pose Network, an attention module employing 1×1 depth-wise convolution across different channels effectively captures long-range dependency information. Additionally, a new spatial-temporal attention mechanism has been implemented in the 3D Network, significantly increasing the accuracy of 3D predictions.
2) The study presents a comprehensive system for Lifting 2D-3D Pose Estimation. The proposed architecture accurately predicts the final 3D human posture from the input image, incorporating several minor techniques to enhance both 2D and 3D results.
3) Our proposed method, straightforward and free from unnecessary complexities, surpasses the original methods in performance on benchmark datasets. For 2D, it is extensively compared with other methods on the Microsoft COCO 2017 benchmark. Additionally, it achieves competitive results on the Human3.6M and MPI-INF-3DHP datasets for the 3D Network.

II. Methodology

A. 2D Pose Estimator

1) Backbone network: The proposed system utilizes a benchmark composed of HighResolutionNet-W32 and HighResolutionNet-W48 [18], as depicted in Fig. 2, representing the complete network architecture. Each HighResolutionNet is organized into four stages, comprising four subnetworks that include skip connections and residual blocks. The default input image is resized to dimensions of 256×192 for both HighResolutionNet-W32 and HighResolutionNet-W48 models. The extracted features pass through each stage, with the initial dimensions of $H \times W$ being halved at every stage. Consequently, by the end of the backbone, the feature map

size is reduced to $\frac{W}{16} \times \frac{H}{16}$, and the number of channels at the final layer reaches 256. The architecture employs only the first subnet throughout, maintaining the dimension of $W \times H$ up to the conclusion of the regression process. Additionally, the dimension of the channels doubles at each level, with tensor channels increasing from 32 at the first stage to 256 at the final stage. The baseline architecture's primary function is to gather crucial information from the extracted tensor and integrate it into the training process, which predicts human joints using cross-entropy loss.

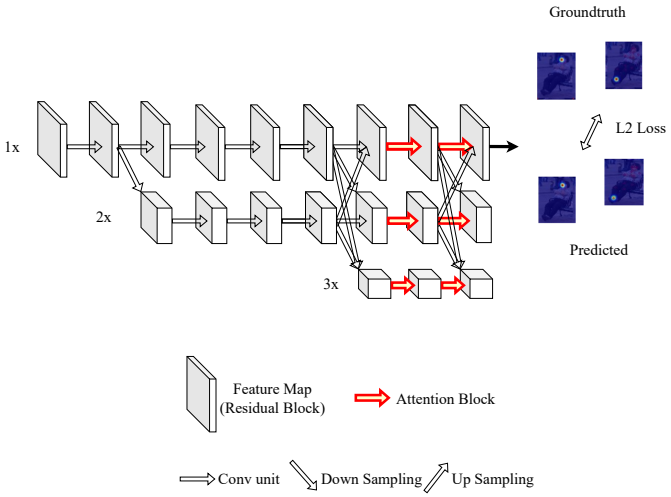

Fig. 2. The proposed 2D Pose Detector architecture incorporates a multi-resolution framework adapted from the original HRNet, which includes both downsampling and upsampling processes. The key modification in our design is the integration of an attention mechanism into the final layer of the last two residual blocks, enhancing the model's focus and performance in key areas.

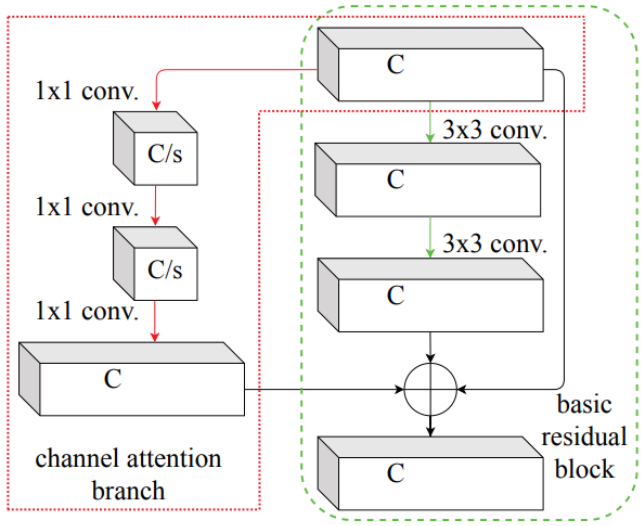

Fig. 3. Architecture of Attention module. The Attention was implemented on the last layer of the residual block

2) Attention Module: In the proposed 2D Pose Estimator, the Attention Mechanism was applied only to the last two blocks of each sub-network. As shown in Fig. 2, only six attention modules were employed to balance computational cost and accuracy. According to Fig. 3, the attention module employed is based on channel attention, as spatial attention was deemed inefficient for keypoints. After one residual block in the backbone network, the feature information is directed to the channel attention module where a 1×1 convolution is applied.

$$2 \times D_w \times D_h \times C \times \frac{C}{s} + \frac{C}{s} \times \frac{C}{s} \times D_w \times D_h, \quad (1)$$

$$\frac{2 \times D_w \times D_h \times \left(\frac{C}{4} + \frac{C}{4} \times \frac{C}{4} \times D_w \times D_h\right)}{2 \times 3 \times 3 \times D_w \times D_h \times C \times C} = \frac{1}{32}, \quad (2)$$

The tensor information in the Channel Attention Module (CAM) uses this convolution to reduce the channel dimension from C to $\frac{C}{s}$, where s, the shrinking ratio, is typically set to 4. This layer compresses the essential features into a tensor of size $1 \times 1 \times \frac{C}{s}$. The network then activates these parameters via the ReLU function within the channel mechanism.

B. 3D Pose Estimation Network

1) Baseline network: In this work, it adopt a Transformer-based architecture which in Fig. 4 since it performs well in long-range dependency modeling. Then first give a brief description of the basic components in the Transformer [13], including a multi-head self-attention(MSA) and a multi-layer perceptron (MLP). MSA. In the MSA, the inputs $x \in \mathbb{R}^{n \times d}$ are linearly mapped to queries $Q \in \mathbb{R}^{n \times d}$, keys $K \in \mathbb{R}^{n \times d}$, and values $V \in \mathbb{R}^{n \times d}$, where n is the sequence length, and d is the dimension. The scaled dot-product attention can be computed by:

$$Attention(Q, K, V) = Softmax(\frac{QK^T}{\sqrt{d_m}})V, \quad (3)$$

MSA splits the queries, keys, and values for h times as well as performs the attention in parallel. Then, the outputs of the attention heads are concatenated. The MLP consists of two linear layers, which are used for non-linearity and feature transformation:

$$MLP(x) = \alpha(xW_1 + a_1)W_2 + a_2, \quad (4)$$

where α denotes the GELU activation function, $W_1 \in \mathbb{R}^{d \times d_m}$ and $W_2 \in \mathbb{R}^{d_m \times d}$ are the weights of the two linear layers respectively, and $a_1 \in \mathbb{R}^{d_m}$ and $a_2 \in \mathbb{R}^d$ are the bias terms.

2) Spatial Attention (SA module): This module is inserted between the MSA layer and MLP for each block. The Spatial attention module consists of two depth-wise convolutions with kernel size 5, group normalization and non-linearity GELU. Also, the residual connection is added to the output of the module to avoid overfitting. The following operations on output of the patch embedding step P_0 can be described:

$$P = CONV(Norm(GELU(CONV(P)))) + P, \quad (5)$$

where $GELU$ refers to the non-linear layer, $CONV$ is the standard convolution layer with kernel 5 and Norm indicates th normalization used in [28]. Since the focus of the SA module is on the interaction between the joints, the output of the MSA part in Eq.2 has been transposed. That is, it becomes $P_0 \in R$

D×P . The spatial encoders for a transformer layer l cn then be represented by the following list of operations:

$$MLP(x_0) = \beta(xW_1 + a_1)W_2 + a_2, \tag{6}$$

where β denotes the P function in Eq.3

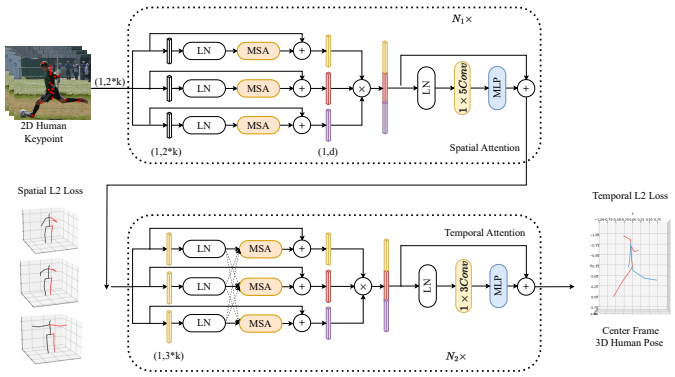

Fig. 4. Detailed Architecture of 3D Pose Estimator. The proposed network is based on the transformer. The new here is we apply the 1×1 conv with different channels for the Spatial and Temporal attention. In the case of Temporal attention, the attention-getting the interaction among multi feature

3) Temporal Attention (TA module): Same with SA module, The TA module learns pairwise feature correlations using the outer product. Each element of the correlation matrix $C_{ij} = \sum_F P_i P_j$ is a dot product of the corresponding embedded features of frames i and j and then it is sum-pooled, where $P_i \in R^{J \times D}$ is the input feature of frame i. More precisely, the input is transformed by combining the positional information with the frames where $P \in R^{F \times J \times D}$ and then using convolutions this paper extract K, Q, and V such that:

$$K = PW_k, Q = PW_q, V = PW_v \tag{7}$$

4) Regression Head: In the regression head, a linear transformation layer is applied on the output Z_{L3} to perform regression to produce pose sequence $\widehat{X} \in \mathbb{R}^{N \times J \times 3}$. Finally, the 3D pose of center frames $\widehat{X} \in \mathbb{R}^{J \times 3}$ is selected from $\widehat{X}$ as our final prediction

C. Loss Function

1) 2D Pose Estimator Loss: Heat maps are utilized in the proposed work to demonstrate body keypoint locations in the loss function. At the beginning, we set the ground-truth point by $m = \{m_n\}\, N = 1^N$, where $X_n = (x_n, y_n)$ is the geographical information of the n^{th} body keypoint for every image. The principles of Ground-truth heat map H_n is then built up by utilizing the Gaussian distribution and the mean a_n with variance σ as illustrated in the next equation.

$$H_n(p) \sim N(a_n, \sigma), \tag{8}$$

where $\mathbf{p} \in \mathbb{R}^2$ illustrate the coordinate, and σ is automatically decided as an identity matrix $\mathbf{I}$. The final layer of the proposed architecture generated J heat maps, *i.e.,* $\hat{S} = \hat{S}_b^a$ and $b = 1^B$ for B body joints. The mean square error for the loss function is defined, which is summarized as follows:

$$L = \frac{1}{AB} \sum_{A=1}^{A} \sum_{B=1}^{B} \left\| S_b^a - \hat{S}_b^a \right\|^2, \tag{9}$$

Where A denotes the number of selected in the training process, B denotes the number of joints. S_b^a and $\hat{S}_b^a$ is the predict and ground truth for 2D Keypoint.

2) 3D Loss: The entire 3D Estimator is trained in an end-to-end manner with a Mean Square Error loss for the Spatial module function defined by the mean of MPJPE, which is calculated as follows:

$$\mathcal{L}_s = \sum_{m=1}^{M} \sum_{j=1}^{J} \left\| S_j^m - \hat{S}_j^m \right\|_2, \tag{10}$$

Where M denotes the number of selected 2D Pose in the training process, J is the number of Joint. S_j^m is the predict 3D human pose joint and $\hat{S}_j^m$ is the ground truth 3D Pose. Same with the Spatial L2 Loss, The Temporal L2 Loss is calculated as follows:

$$\mathcal{L}_t = \sum_{N=1}^{N} \sum_{j=1}^{J} \left\| S_j^n - \hat{S}_j^n \right\|_2, \tag{11}$$

Where N denotes the number of selected predicted 3D Pose in the training process. The total loss for 3D network composed in:

$$\mathcal{L} = \lambda_s \mathcal{L}_s + \lambda_t \mathcal{L}_t, \tag{12}$$

While λ_s and λ_t is the weighted parameter for each loss

III. Experiment

A. Datasets and Evaluation Protocols

For the 2D human pose estimator, Microsoft COCO 2017 [3] was used for training and testing in the whole process.

1) Microsoft COCO 2017: was utilized through the training and testing process. This dataset is a challenging dataset for joint detection which comprises around 250K human labeled in 200K images, each human pose has 17 keypoint labels. The proposed research applies Object Keypoint Similarity (OKS) for Microsoft COCO2017 dataset with $OKS = \frac{\sum_i exp(-{d_i}^2/2s^2k_i^2)\delta(v_i>0)}{\sum_i \delta(v_i>0)}$ In the above function, The Euclidean distance between the groundtruth joint and the predicted joint is d_i, The target's visibility flag is v_i, The object scale is s, and k_i is one of seventeen joints in Microsoft COCO 2017 Benchmark. Hence, The standard average accuracy and recall value are then computed.

About the 3D human pose, this approach evaluate proposed model on two general datasets: Human3.6M [9], MPI-INF-3DHP [20] and Industrial dataset individually.

2) Human3.6M: is the most commonly used indoor dataset for the 3D human pose estimation tasks. Following the same policy of the base method [14], the 3D human pose in Human3.6M is adopted as a 17-joint skeleton, and the subjects S1, S5, S6, S7, S8 from the dataset are applied during training, the subjects S9 and S11 are used for testing. The two commonly used evaluation metrics (MPJPE and P-MPJPE) are involved in this dataset. In addition, mean per-joint velocity

TABLE I
COMPARISON RESULT ON COCO 2017 VALIDATION SET. PT = PRETRAIN THE BACKBONE ON THE IMAGENET CLASSIFICATION TASK

Methodology	Backbone	PT	#Parameters	Image dimension	AP	AR	AP^{50}	AP^{75}	AP^{L}	AP^{M}
Fine-tune Attention [26]	ResNet-50	N	31.2M	256×192	71.4	76.3	91.6	78.6	75.7	68.2
Fine-tune Attention [26]	ResNet-101	N	50.2M	256×192	72.3	77.1	92.0	79.4	77.1	68.3
High-Resolution Net [18]	HRNet-W32	N	28.5M	256×192	73.4	78.9	89.5	80.7	80.1	70.2
High-Resolution Net [18]	HRNet-W32	Y	28.5M	256×192	74.4	79.8	90.5	81.9	81.0	70.8
High-Resolution Net [18]	HRNet-W48	Y	63.6M	256×192	75.1	80.4	90.6	82.2	81.8	71.5
Zhang at al. [17]	HRNet-W32	N	29.2M	256×192	74.8	77.6	92.5	81.6	79.3	72.0
Zhang at al. [17]	Hourglass-8	N	25.8M	256×192	75.1	80.4	90.6	82.6	81.9	71.6
MogaNet-T [25]	MogaNet	N	8.1M	256×192	73.2	90.1	81.0	78.8	-	-
MogaNet-S [25]	MogaNet	N	29M	256×192	74.9	90.7	82.8	80.1	-	-
PPE-Net [24]	ResNeXt-101	Y	-	256×192	75.7	-	90.3	76.3	80.7	79.5
Our	HRNet-W32	N	29.5M	256×192	75.7	80.6	90.6	82.1	82.4	71.3
Our	HRNet-W48	N	66.2M	256×192	76.1	80.9	90.7	82.7	82.9	71.9

error (MPJVE) is applied to measure the smoothness of the prediction sequence.

3) MPI-INF-3DHP: is a recently proposed large-scale dataset, which consists of three scenes, i.e., green screen, non-green screen, and outdoor. By using 14 cameras, the dataset records 8 actors performing 8 activities for the training set and 7 activities for evaluation. Following the works [21], the proposed network adopts the MPJPE (P1), percentage of correct keypoints (PCK) with 150mm, and area under the curve (AUC) results as the evaluation metrics.

B. Implementation Details

The proposed model, implemented using PyTorch, utilizes 2D keypoints from HRNet [18], CPN Detector, or 2D ground truth to analyze performance. The 2D pose detector in this study is based on the AlphaPose [15] codebase, while the 3D pose estimator adopts the PoseFormer codebase [21]. Although the proposed model is capable of adapting to any length of the input sequence, for fairness in comparison, specific sequence lengths (T) were chosen for three datasets: Human3.6M (T=81, 243), and MPI-INF-3DHP (T=1, 27). Details regarding the selection of frame lengths are discussed in the ablation study (Section III.E.3). The batch size, dropout rate, and activation function are set at 1,024, 0.1, and GELU, respectively. All experiments were conducted on the PyTorch framework using two NVIDIA GeForce GTX 2080 Ti GPUs. The network training employs the Adam optimizer [10], with a learning rate of 0.001 and a decay factor of 0.95 applied every two epochs.

C. Comparison with the SOTA 2D Pose Methods

1) Result for COCO2017 dataset: The proposed result in Table I was estimated on the COCO validation dataset. In all instances, the accuracy in the proposed technique is larger than the Benchmark High-Resolution Network of 1.3 and 1.0 AP in backbone HRNet-32 and HRNet-W48 respectively. In addition, the average recall (AR) for HRNet-W32 is 0.5 points higher and 0.4 points higher for HRNet-W48. Overall, the experiment outcomes improved modestly in both AP and AR, showing that attention mechanisms affect the result. To ensure a fair comparison, we evaluated the results against networks without pretraining. Despite being only trained on COCO, the proposed network still surpasses the ImageNet-pretrained HRNet-W32 and HRNet-W48 by 1.3% and 1.6% in Average Precision (AP), respectively. This demonstrates that the integration of the attention mechanism can outperform models that rely on pretraining.

D. Comparison with the SOTA 3D Pose Methods

1) Result for Human3.6M dataset: For the 2D-to-3D pose lifting task, the accuracy of the 2D detections directly. To guarantee fair comparisons, the input is taken from CPN in the form of 2D keypoints for training and testing. Table II shows the comparison of the SOTA methods with the proposed method (81 frames). In Table II, the proposed method achieves the state-of-the-art on Human3.6 on all the metrics and it outperforms the state-of-the-art (Chen at al) with a considerable margin of 0.9%, 1.3% for Protocols 1 and 2, respectively. It is worth noting that the across-joint modules in the spatial and temporal cases are crucial to infer the body-joint dependencies. Comparing the proposed method with PoseFormer (with no pre-training used) shows the significance of the across-joint correlation modules. Our method outperforms with a large margin of 2% the SOTA. In terms of accuracy, it achieve 1% better than the second best accuracy. Additionally, the proposed method achieves the best performance amongst all the compared methods in protocol 2 in Table II (bottom). In some selected difficult poses such as walk together, walk, smoke, where the poses change very quickly, the proposed method showed a significant improvement ranging from 1.1% to 2.5% over the baseline. This highlights the ability of our method to encode the long-range interactions between the body joints. Considering the pre-trained baseline, the proposed method achieves better performance for all the actions. These results show the importance of plugging the Spatial-temporal attention modules in the transformers.

Further experiments on Human3.6 using ground-truth 2D poses as input have also been performed. This shows the power of the proposed method where there is no noise in the input as in the previous case. Table III shows the comparisons of our method and the baselines. Overall, the proposed method achieved the best performance amongst the baselines. It achieved 28.3% MPJPE, whereas the second-best approach achieved 31.0 with gain of 3%. The proposed method outperforms the baselines in all the actions with a considerable

TABLE II
QUANTITATIVE COMPARISONS WITH STATE-OF-THE-ART ON HUMAN3.6M DATASET USING CPN DETECTOR UNDER PROTOCOL #1 AND PROTOCOL #2 FOR FULLY-SUPERVISED METHODS. THE BOLD NUMBER IS THE BEST PERFORMANCE IN EACH CASE, ⋆ DENOTES THAT THE 2D KEYPOINT DETECTION IS THE CASCADED PYRAMID NETWORK(CPN) WHILE ∗, † REFERS TO 3D NETWORK APPLY TRANSFORMER-BASED MODEL

Protocol # 1 - CPN	Dir.	Disc	Eat	Greet	Phone	Photo	Pose	Punch	Sit	SitD.	Smoke	Wait	WalkD.	Walk	WalkT.	Avg.
Martinez *et al.* [16]	51.8	56.2	58.1	59.0	69.5	78.4	55.2	58.1	74.0	94.6	62.3	59.1	65.1	49.5	52.4	62.9
Fang *et al.* [22]	50.1	54.3	57.0	57.1	66.6	73.3	53.4	55.7	72.8	88.6	60.3	57.7	62.7	47.5	50.6	60.4
Li *et al.* [23]	47.0	**47.1**	49.3	50.5	**53.9**	**58.5**	48.8	45.5	**55.2**	68.6	50.8	**47.5**	53.6	42.3	45.6	50.9
Zhen [18]	45.4	49.2	45.7	49.4	50.4	58.2	**47.9**	46.0	57.5	63.0	49.7	46.6	52.2	**38.9**	40.8	49.4
Xu *et al.* [19]	45.2	49.9	47.5	50.9	54,9	66.1	**48.5**	46.3	59.7	71.5	51.4	48.6	53.9	**39.9**	44.1	51.9
Yang *et al.* [21]	41.5	44.8	39.8	42.5	46.5	**51.6**	42.1	42.0	53.3	60.7	45.5	43.3	46.1	31.8	32.2	**44.3**
Our	**45.0**	48.3	**46.6**	**49.8**	46.6	59.0	48.7	**41.9**	57.7	**60.2**	**45.1**	48.2	**45.8**	41.0	45.1	**43.1**
Protocol # 2 - CPN	Dir.	Disc	Eat	Greet	Phone	Photo	Pose	Punch	Sit	SitD.	Smoke	Wait	WalkD.	Walk	WalkT.	Avg.
Fang *et al.* [22]	38.2	41.7	43.7	44.9	48.5	55.3	40.2	38.2	54.5	64.4	47.2	44.3	47.3	36.7	41.7	45.7
Pavllo *et al.* [29] ⋆	34.1	36.1	34.4	**37.2**	36.4	42.2	34.4	33.6	45.0	52.5	37.4	33.8	37.8	25.6	27.3	36.5
Yang *et al.* [30]	**26.9**	**30.9**	**36.3**	39.9	43.9	47.4	**28.8**	**29.4**	**36.9**	58.4	41.5	**30.5**	**29.5**	42.5	**32.2**	**37.7**
Yang *et al.* [21]	30.0	33.6	29.9	31.0	30.2	35.4	37.4	34.5	46.9	**50.1**	40.5	36.1	41.0	29.6	33.2	39.0
Li *et al.* [23]	34.5	34.9	37.6	39.6	**38.8**	45.9	34.8	33.0	40.8	51.6	38.0	35.7	40.2	30.2	34.8	38.0
Our	34.1	36.0	36.4	39.9	39.4	**45.0**	35.9	32.8	43.1	52.1	**37.3**	36.6	39.7	30.2	35.8	38.3

TABLE III
QUANTITATIVE COMPARISONS WITH STATE-OF-THE-ART ON HUMAN3.6M DATASET USING GROUNDTRUTH AS 2D KEYPOINT UNDER PROTOCOL #1 WITH 2D GROUND-TRUTH INPUT. BOLD NUMBER IS THE BEST PERFORMANCE IN EACH CASE

Protocol # 1 - GrouthTruth	Dir.	Disc	Eat	Greet	Phone	Photo	Pose	Punch	Sit	SitD.	Smoke	Wait	WalkD.	Walk	WalkT.	Avg.
Martinez *et al.* [16]	37.7	44.4	40.3	42.1	48.2	54.9	44.4	42.1	54.6	58.0	45.1	46.4	47.6	36.4	40.4	45.5
Fang *et al.* [22]	32.1	36.6	34.3	37.8	44.5	49.9	40.9	36.2	44.1	45.6	35.3	35.9	30.3	37.6	35.6	38.4
Li *et al.* [23] †	32.9	38.7	32.9	37.0	37.3	44.8	38.8	36.1	41.2	45.6	36.8	37.7	37.7	29.5	31.6	37.2
Zhen [18]	45.4	49.2	45.7	49.4	50.4	58.2	47.9	31.7	38.5	45.5	35.4	36.6	36.2	28.9	30.8	35,8
Xu *et al.* [19]	35.8	38.1	47.5	31.4	39.6	35.8	45.5	35.8	40.7	41.4	33.0	33.8	33.0	26.6	26.9	34.7
Xue *et al.* [3]	35.0	37.2	46.6	30.8	38.7	35.1	44.3	34.9	40.1	41.0	32.1	33.6	32.5	26.0	26.1	33.3
Chen *et al.* [28]	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	32.3
Yang *et al.* [21]	34.8	32.1	29.8	31.5	36.9	35.6	30.5	30.5	38.9	40.5	32.5	31.0	29.9	22.5	24.6	32.0
Our	**27.9**	**29.9**	**26.6**	**27.8**	**28.6**	**32.8**	**31.1**	**26.7**	**36.5**	**35.5**	**30.0**	**29.8**	**27.5**	**19.6**	**19.7**	**31.0**

improvement range from 2.4% as the minimum difference and 4.8% for the largest.

2) Result for MPII-INF-3DHP dataset: The approach further compares the proposed methods to the baseline PoseFormer on MPP-INF-3DHP using 9 frames. This is important because it illustrates the ability of the proposed method to train with fewer training samples in outdoor settings. As Table IV shows, this paper obtains the best performance among the compared approaches.

TABLE IV
PERFORMANCE COMPARISION IN TERMS OF PCK, AUC AND P1 WITH THE STATE-OF-THE-ART METHODS ON MPI-INF-3DHP

Method	PCK ↑	AUC ↑	MPJPE ↓
Pavllo *et al*. [29] (f=81)	86.0	51.9	84.0
Lin *et al*. [13] (f=25)	83.6	51.4	79.8
Li *et al*. [23]	81.2	46.1	99.7
Chen *et al*. [28]	87.9	54.0	78.8
Yang *et al* [21] (f=9)	88.6	56.4	75.5
Our (f=9)	89.1	57.5	76.3

E. Ablation Study

1) Effect of attention in 2D Detector and 3D Estimator: In Table V, To evaluate the impact and performance of the 2D for the whole 3D model, The proposed network evaluates and investigates the result in the Human3.6M dataset. The result shows that applying the attention module in the 2D pose estimator makes the 2D input accurate and then helps the final 3D result. Fig.5 shows the impact of the attention mechanism when the arm in the picture is straight compared to the baseline HRNet looks folding the arms while in the testing image, the person is straight his arm.

TABLE V
COMPARISION RESULT FOR APPLYING THE ATTENTION MODULE IN HRNET WITH OTHER DETECTORS

Detector	Protocol #1	Protocol #2	MPJVE ↓
CPN	47.6	37.4	3.20
Detectron2 [30]	45.7	37	3.02
Hourglass [11]	52.3	41.2	4.11
HRNet-W32 [18]	45.1	36.3	2.91
HRNet-W32+AM (our)	43.6	35.1	2.77
GroundTruth	28.6	24.5	0.98

Table VI is a comparison of different module in a proposed system, focusing on the presence or absence of specific modules and their impact on the Mean Per Joint Position Error (MPJPE). The modules include 2D Attention, 3D SAM (Spatial Attention Module), and 3D TAM (Temporal Attention Module). Each row in the table corresponds to a specific configuration, indicating the presence or absence of these modules. The MPJPE values for each configuration serve as a quantitative measure of the accuracy of joint position predictions. Notably, the proposed method exhibits improved performance when incorporating all three modules simultaneously, achieving the lowest MPJPE at 42.2, which decreases by 3.2% in accuracy compared to the baseline.

2) Position of Attention Module in 2D Detector and 3D Estimator: Table VII investigates the result when applying different AM in each subnetwork and each stage in HRNet. In

TABLE VI
COMPARISION RESULT OF EACH MODULE IN THE PROPOSED SYSTEM

Method	2D Attention	3D SAM	3D TAM	MPJPE ↓
PoseFormer				44.3
Our	✓			43.6
Our		✓		43.7
Our			✓	43.8
Our		✓	✓	43.3
Our	✓	✓	✓	42.2

conclusion, the result when applied in the attention module in all stages (16 Attention modules got added) got the best result however it also got the highest number of parameters in the computational cost. Besides, Table VII also shows that AM had the most effect in the first sub and stage than in the remaining. Hence, this paper only applies the module for the first sub-network and stage (only 6 were added) to not only balance the computational cost but also keep the high accuracy.

TABLE VII
THE RESULT WHEN UTILIZING THE ATTENTION MECHANISM FOR EACH SUB-NETWORK AND EACH STAGE OF HRNET-W32

Backbone	Sub-Net	AP	#Param
HRnet-W32	-	73.4	28.5M
HRnet-W32	1	74.2	28.8M
HRnet-W32	2+1	75.9	29.3M
HRnet-W32	3+2+1	76.2	30.0M
Backbone	Stage	AP	#Param
HRnet-W32	1	74.3	28.9M
HRnet-W32	2+1	76.0	29.4M
HRnet-W32	3+2+1	76.2	30.0M

Table VIII showcases the influence of different positions of the Spatial Attention Module (SAM) and Temporal Attention Module (TAM) on Mean Per Joint Position Error (MPJPE). For SAM, positioning it after Multi-Head Self-Attention (MSA) or after Multi-Layer Perceptron (MLP) yields lower MPJPE (44.1 and 44.9) compared to before MSA (45.2). Similarly, for TAM, placing it after MSA results in the lowest MPJPE (44.9), while before MSA and after MLP have slightly higher errors (45.0 and 46.2, respectively). This highlights the importance of the relative positioning of attention modules in achieving optimal accuracy in joint position predictions. Hence, this paper decided to put SAM and TAM between the MSA and MLP.

TABLE VIII
THE RESULT WHEN APPLYING DIFFERENT POSITIONS OF 1×1 CONVOLUTION IN SAM AND TAM

Module	Before MSA	After MSA	After MLP	MPJPE ↓
SAM	✓			45.2
SAM		✓		44.1
SAM			✓	44.9
TAM	✓			45.0
TAM		✓		44.9
TAM			✓	46.2

3) Effect of modifying the setting in 3D network: Table IX presents a comparative evaluation of different backbone architectures for human pose estimation under varying stride frame configurations. Three methods, Pavllo et al.'s approach [29], PoseFormer by PoseFormer et al. [21], and a proposed method are analyzed. For Pavllo et al.'s method, adjusting the stride frame from the default 243 to 81 leads to a slight reduction in the number of parameters from 12.75M to 12.70M, with a marginal increase in the Mean Per Joint Position Error (MPJPE) from 47.5 mm to 47.9 mm. PoseFormer demonstrates improved accuracy with reduced MPJPE values when the stride frame is decreased from 81 to 27, resulting in MPJPE values of 44.3 mm and 44.6 mm, respectively. The proposed method ("Our") consistently outperforms the other methods, achieving lower MPJPE values as the stride frame decreases from 81 to 27 to 9, while maintaining a relatively stable parameter count of around 9.86M. This suggests that the proposed method is effective in producing accurate pose estimations with different stride frame configurations.

TABLE IX
THE RESULT FOR APPLYING DIFFERENT LEVELS OF FRAME. THE DEFAULT SETTING FOR LEARNING RATE IS 0.25

Method	Stride Frame	#Param (M)	MPJPE ↓
SimplePose *et al.* [29]	243 (default)	12.75M	47.5
SimplePose *et al.* [29]	81	12.70M	47.9
PoseFormer *et al.* [21]	81 (default)	9.59M	44.3
PoseFormer *et al.* [21]	27	9.60M	44.6
Our	9	9.85M	44.3
Our	27	9.86M	43.6
Our	81	9.86M	43.3

TABLE X
THE COMPARISON RESULT FOR APPLYING DIFFERENT LEARNING RATES FOR 3D MODEL. THE DEFAULT FRAME WAS SET AT 81 FOR ALL OF THE EXPERIMENT

Method	Learning rate	#Param (M)	MPJPE ↓
SimplePose *et al.* [29]	0.25 (default)	12.70M	47.9
SimplePose *et al.* [29]	0.1	12.70M	47.5
PoseFormer *et al.* [21]	0.25 (default)	9.60M	44.3
PoseFormer *et al.* [21]	0.1	9.60M	44.6
Our	0.25	9.86M	43.3
Our	0.2	9.86M	43.3
Our	0.1	9.86M	43.1
Our	0.05	9.86M	43.4

Table X shows the result when changing the learning rate setting. While other papers set the learning rate as 0.25 and do not consider this. This paper found based on the gradient descent, 0.1 in learning rate is truly a perfect match for 3D model. Only simple changing with our increase the computational cost but significantly improve the accuracy which decreases almost 1% of the error. The side effect of changing the learning rate is only making training time increase from 20 hours to 22 hours.

IV. CONCLUSION

This research explores the impact of attention mechanisms not only on the 2D Pose Detector but also on the 3D Pose Estimator, particularly in the context of constructing a full system from input to 3D result for the Industrial Environment. Additionally, this work illustrates that the attention module can yield significant benefits without substantially increasing computational costs. Extensive experiments demonstrate that the proposed network holds a fundamental advantage over

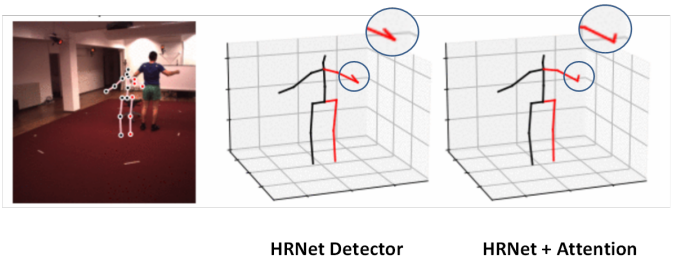

Fig. 5. 3D human pose estimation result come from 2D skeleton based on detector and detector with attention mechanism

baseline Transformers, achieving state-of-the-art performance on two benchmark datasets. The proposed method anticipate that our approach will stimulate further research in 2D to 3D pose lifting, considering various ambiguities.

However, the proposed model faces challenges that need to be considered in future work. Firstly, training and predicting occluded joints proved to be difficult for the architecture. Implementing techniques to handle the hypothesis of 3D Pose could address this issue. Secondly, the computational demands of end-to-end networks pose a hurdle for real-time applications due to their significant computational load. In future research, this paper aims to mitigate this computational cost and develop a lightweight system.

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