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## Deep temporal motion descriptor (DTMD) for human action recognition

NUDRAT Nida<sup>1</sup>, Muhammad HAROON Yousaf<sup>1,2\*</sup>, AUN Irtaza<sup>3</sup> and SERGIO A.Velastin<sup>4</sup>

<sup>1</sup>Department of Computer Engineering, UET, Taxila, Pakistan. orcid=0000-0003-1115-1413.

<sup>2</sup> Swarm Robotics Lab, National Centre of Robotics and Automation, Pakistan. orcid=0000-0001-8255-1145\*

<sup>3</sup>Department of Computer Science, UET, Taxila, Pakistan. orcid=0000-0001-7757-5839

<sup>4</sup>Cortexica Vision Systems Ltd., London, SE1 9LQ, UK

Department of Computer Science, Applied Artificial Intelligence Research Group,  
University Carlos III de Madrid, Madrid 28270, Spain

School of Electronic Engineering and Computer Science, Queen Mary University of London, London E1 4NS, UK.  
orcid=0000-0001-6775-1737

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**Abstract:** Spatiotemporal features have significant importance in human action recognition, as they provide the actor’s shape and motion characteristics specific to each action class. This paper presents a new deep spatiotemporal human action representation, “Deep Temporal Motion Descriptor (DTMD)”, which shares the attributes of holistic and deep learned features. To generate the DTMD descriptor, the actor’s silhouettes are gathered into single motion templates through applying motion history images. These motion templates capture the spatiotemporal movements of the actor and compactly represents the human actions using a single 2D template. Then, deep convolutional neural networks are used to compute discriminative deep features from motion history templates to produce DTMD. Later, DTMD is used for learn a model to recognise human actions using a softmax classifier. The advantage of DTMD comes from (i) DTMD is automatically learned from videos and contains higher dimensional discriminative spatiotemporal representation as compared to handcrafted features; (ii) DTMD reduces the computational complexity of human activity recognition as all the video frames are compactly represented as a single motion template; (iii) DTMD works effectively for single and multiview action recognition. We conducted experiments on three challenging datasets: MuHAVI-Uncut, iXMAS, and IAVID-1. The experimental findings reveal that DTMD outperforms previous methods and achieves the highest action prediction rate on the MuHAVI-Uncut dataset.

**Key words:** Human activity recognition, deep convolutional neural network, motion history images, Deep Temporal Motion Descriptor(DTMD), computer vision

### 1. Introduction

Human action recognition (HAR) is a significant research areas in computer vision for generating context-aware applications for human assistance. Human action recognition is utilized in various fields including video surveillance systems[1], group activity recognition[2], video summarization[3] and smart education[4, 5]. HAR is a challenging problem because of real-world constraints such as viewpoint variation, background clutter, changes in scale, partial occlusion, lighting, appearance and frame resolution that affect recognition accuracy. Similarly, describing behavioral components e.g. Gait style, gesture, posture and pose demand significant effort and tedious learning of a particular action. Moreover, certain actions are challenging to differentiate due to

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\*Correspondence: haroon.yousaf@uettaxila.edu.pk

visual similarities between them, like walking and jogging[6], etc. The way in which an action is performed also makes the action recognition difficult because actions are relative in nature. Moreover, due to fine-grained activities, action classes have less intra-class variability that can confuse the model as well. Another challenge in the action recognition domain is a scarcity of application-specific benchmark datasets to model the progressive movements of human activities.

Recent research in HAR can broadly be categorized into two classes: representation-based and deep network-based techniques [6]. Representation-based techniques use handcrafted features for classifying human actions into different action classes and can be further classified into the following sub-categories: spatiotemporal interest point extractors [7, 8], holistic representation [9–11] and motion trajectory extractors [12, 13]. The spatiotemporal interest points extractors consider the spatial interest points along with action-time to recognize certain actions [7]. However, such features generate a varying number of interest points for different video sequences and generate sparse representations. In [9], HOG (histogram of oriented gradients) features were extracted from the MHIs (motion history images) that were classified through an SVM (support vector machine) classifier for action recognition. However, the major limitation of the HOG based representation appears in action recognition when actors perform a similar action with different poses e.g. bending left, right, or in forwarding positions. The primary reason for performance deficit is that HOG based representations are not rotation invariant and even a slight change in pose results in different HOG representations. Later, motion trajectory extractors have been proposed in [12, 13], to encode the spatiotemporal action representation. These extractors capture pixel variations within the video sequences to discriminate actions. Among shallow handcrafted action representation, motion trajectories are proven to be one of the strongest descriptor for human action recognition[12]. In [14] HOG features are combined with the LBP (Linear Binary Pattern) descriptor and action recognition is performed through an SVM classifier. However, the technique results in degraded performance, due to the limited ability of HOG features to address various action poses. Moreover, the LBP is severely affected by noise and so classification performance significantly falls. On the other hand, silhouette extraction depends on accurate and robust segmentation techniques, which rely on-time evolution.

In addition to representation based HAR techniques, recently deep learning techniques have become popular, as deep learning networks can effectively handle nonlinear boundaries thus reducing misclassification rates. Recent works on deep action representation (DAR) can be categorized into various groups including static frame learning [15], transformed frames [16], 3D-CNN [17], multi-streams network [18, 19] and recurrent networks[20–22]. In static frame learning methods, the video frames are used to learn action sequences without capturing the temporal information [15]. Another limitation of the static frame learning technique is the requirement of a fixed number of video frames with consistent resolution. Transformed frames learning techniques can be used to overcome such limitations by incorporating a temporal representation of action sequences [16]. These techniques establish a generative probabilistic model for learning higher dimensional frame transformations and fuse the motion information from neighboring frames to capture temporal information. For the case of 3D-CNN models for HAR, convolutional operations are performed in a spatial and temporal dimension through 3D cubes that are constructed by assembling multiple simultaneous frames [17]. In [18] a two-stream network is used having two CNN networks, a spatial network and a temporal network, to extract a spatiotemporal action representation. In [19], optical flow is computed from successive video frames to train 2D CNN networks for human action recognition. However, the resulting method performed lower than handcrafted features due to the imprecise spatiotemporal representation of actions and less diversity of action datasets. The temporal information was extracted by transforming frames to a lower resolution to reduce computational

complexity [20]. However, the recognition performance of 3D-CNN is equivalent to 2D-CNN operated on spatial video frames, which indicates no significant performance improvement in motion information of 3D-CNN as compared to 2D-CNN for HAR. Moreover, the reported results of 3D-CNN are also lower than for some handcrafted- representations. Sun et al. [21] improved an LSTM (Long Short Term Memory) network to learn a model for activity recognition through encoding movement information at each pixel of the video frame. In [22], a Long-Term Recurrent Convolutional Network (LRCN) was presented for action recognition using LSTM on convolutional feature maps of RGB spatial frames or optical flow. Bilen et. al [23] used an LSTM network to generate a representation in the form of RGB images for action videos and encoded motion information across each pixel using rank pooling. Afterwards, the motion encoded RGB representations were used for action classification.

Overall, deep learning-based action techniques usually require powerful computational resources and a large amount of data. Action representation from the fusion of handcrafted and learned approach may achieve better prediction performance in HAR. Therefore, we have explored the fusion of spatiotemporal holistic motion templates and deep convolutional features to encode an actor’s motion representation for action recognition. For evaluation, we tested our scheme on the benchmark activity datasets MuHAVi-Uncut [24] and iXMAS. We also evaluated our technique on a newer video dataset, “Instructor Activity Video-1 (IAVID-1)”. Our contributions can be summarized as follows:

- (i) We propose a deep temporal motion descriptor (DTMD) for human action recognition using motion history images and a 2D CNN (Convolutional Neural Network). DTMD utilizes the CNN model to capture spatiotemporal deep representation from MHI using backpropagation algorithm. The proposed DTMD outperforms recent methods in silhouette-based activity recognition.
- (ii) Secondly, DTMD is capable to recognize human actions in a multiview scenario. Its spatiotemporal representation of actions improves performance under occlusion, scale, temporal variation, and viewpoint variation. This contribution is explored in the experiment section using the MuHAVI-Uncut and IXMAS multi-view action recognition datasets.
- (iii) DTMD reduces the computational complexity of human action recognition as all the video frames are compactly represented by a single holistic motion template. Then, these motion templates were used for DTMD computation.
- (iv) To evaluate the performance of the proposed approach, we performed a case study to recognize instructor actions within the lecture room using DTMD. The work illustrates how important it is to develop an autofeedback mechanism within the lecture rooms to improve the quality of lecture delivery within academic institutes. However, this goal cannot be achieved until and unless instructor actions are recognized. DTMD successfully recognizes the eight basic actions of the instructor within the classroom.

The rest of the paper is organized as follows. Section 2, introduces the proposed approach for human action recognition. Then, in section 3 experimental results and findings are discussed. Section 4 concludes the paper.

## 2. Deep temporal motion descriptor (DTMD) for action recognition

For training, we formed a set of the video  $V$  along with respective action labels  $L$  to build a model for action recognition using the  $DTMD$  descriptor. The  $DTMD_{v_t}$  descriptor gathers spatiotemporal information

to describe the action class, where  $v_t$  are the total training videos (Figure 1). There are four main steps for  $DTMD_{v_t}$  generation: silhouettes extraction and refinement, motion information gathering in the spatiotemporal template, deep spatiotemporal representation of the actor's motion template and, finally, recognition of human action classes using a softmax classifier as illustrated in Figure 1. The following subsections describe the methodology in more detail.

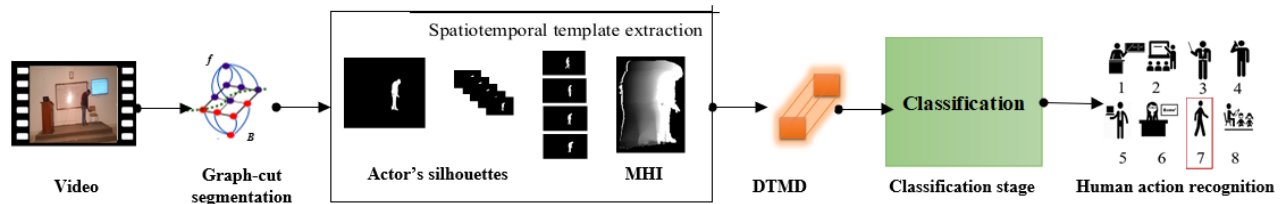


Figure 1. Architecture diagram of the proposed methodology.

## 2.1. Spatiotemporal template computation

The actor silhouettes are processed to form actor's motion templates through applying the holistic Motion History Images ( $MHI$ ) technique. Motion history images ( $MHI$ ) [25] are computed from the actor silhouettes  $f$  to produce a spatiotemporal information template.  $MHI$  is computed using eq. (1), where  $MHI$  is a spatiotemporal template of all the actor's silhouette frames  $f$  in the video, representing the object of interest, in this case an actor at time  $t$  on location  $(x,y)$  [9], as described in eq.(1).

$$MHI = \begin{cases} \tau & \text{if } f = 1 \\ \max(0, (f - 1)) & \text{otherwise} \end{cases} \quad (1)$$

Here,  $\tau$  is the total number of frames to generate  $MHI$  for each action sequence. The benefit of using  $MHI$  is to reduce the spatial and computational complexity of an action, as the entire human action video is represented by a 2-D single  $MHI$  image. The  $MHI$ s are centered and resized into fixed dimensions to eliminate redundant background information and to make them compatible for CNN as an input.  $MHI$  template intensities are normalized within the maximum range, to reduce more computation. Normalization also helps to overcome undesirable factors like non-uniform illumination and contrast variations [9].

These motion templates are not invariant to spatial location or viewpoint. Therefore, as the prime motive of the action recognition system is to identify an action irrespective of spatial location, normalization is applied to create correspondences between training and testing action templates [11]. Scale and spatial location constraints are minimized through centering the motion template with respect to the maximum occupied area and wrapping the silhouettes to a predefined template. In this way, the challenges of viewpoint, spatial location and scale are reduce through the spatiotemporal action template.

## 2.2. Deep representation of the actor's movement

The next step is the computation of deep features to represent each action class using CNN models. In CNN networks, the input layer receives the  $MHI$ s as input data and passes it to the next convolutional layer (conv layer). As the conv layer performs convolution of input data at the smaller region with weights to generate a feature map, the  $MHI$  is rescaled to  $N \times N$  dimensions, to make them compatible with the CNN

and generating spatiotemporal DTMD description. The intuition of using actor’s motion templates MHI for action representation is derived from the hypothesis that motion templates are not significantly affected by imperfect segmentation of silhouettes, less sensitive to noisy artifacts, shadows, and occluded body parts. MHI is robust to cater for variations in pose due to changes in direction of motion like walking left and walking right, therefore, MHIs are capable to recognize the same action in different directions, viewpoints, and scale[9]. AlexNet[26], VGG16[27], VGG-19[27], Squeezenet[28], GoogleNet[29] and ResNet[30] have been used here for DTMD extraction. The last layer of the network is a Soft-Max classification layer, which performs the task of action recognition as shown in (Figure 1).

### 3. Experiments

The proposed approach has been evaluated on the RGB IAVID-I, MuHAVI-Uncut and iXMAS datasets which are single and multi-view datasets captured from static cameras. IXMAS and MuHAVI-Uncut have been chosen for evaluation of DTMD because the proposed approach involves segmented actor’s silhouettes (provided by these standard datasets) with a static background. A set of experiments has been performed to evaluate the performance of DTMD using the following techniques:

- i Examine the impact of different types of CNN architectures on DTMD for HAR.
- ii Quantitative analysis.
- iii Case study: Instructor action recognition in lecture room scenario using DTMD.
- iv Comparison of the proposed approach with other state-of-the-art methods.

#### 3.1. Datasets

The new (IAVID-I) and the benchmark (MuHAVI-Uncut, IXMAS) action recognition datasets are used to evaluate DTMD. The main characteristics of the used datasets are listed below:

##### 3.1.1. IAVID-1

We have constructed the dataset of Instructor’s Action Videos IAVID-1 to evaluate the proposed scheme. Twelve actors participated in data recordings in a realistic lecture room environment. There are 100 videos having 1088x1920 high-resolution 24-bit RGB videos. 12 actors performed the 8 instructor actions and approximately 12 instances of each action class are present in the dataset. There are eight actions in this dataset, i.e. interacting or idle, pointing towards the board, pointing towards the screen, using a mobile phone, using a laptop, sitting, walking and writing on the board. IAVID-1 is a challenging dataset as it contains illumination and contrast variation, moving objects like an electric fan and multimedia slide transitions.

##### 3.1.2. MuHAVi Uncut

The MuHAVi-Uncut dataset is a multi-action recognition dataset acquired from multiple cameras. It constitutes 17 activities performed by 14 actors at multiple duration. The 8 CCTV cameras were mounted at 45° view difference to capture an action sequence. The MuHAVI-Uncut dataset is a large video dataset (2898 videos) and a single actor’s silhouettes are segmented.

### 3.1.3. IXMAS

INRIA Xmas Motion Acquisition Sequence (IXMAS) is a multi-view dataset constitutes of twelve human actions performed by twelve actors. DTMD requires an actor’s silhouettes to form motion templates since better silhouettes form better MHIs, therefore MuHAVI-Uncut and iXMAS are the most suitable dataset for evaluation of DTMD. Another benefit for DTMD’s evaluation is that MuHAVI-Uncut and iXMAS allow us to examine the performance of action prediction at multi-view setting and all the actions in these datasets are performed by a single actor with a static background.

### 3.2. Implementation details

In this section, we describe the optimal hyperparameters arrived at. The learning rate is set to 0.0001, while the batch size is set to 50 to train CNN models with 200 epochs using DTMD action representation. The batch size is set to 50 because there are 50 MHI training samples to optimize gradient loss and update the weight of pretrained CNNs using stochastic gradient descent algorithm in each epoch within 12 iterations for HAR. To evaluate the performance of DTMD we have used cross-validation splits, leave one actor out (LOAO), leave one camera out (LOCO) and leave one sequence out (LOSO) validation schemes for HAR.

CNN Type	DTMD	CNN models	Parameters	Prediction Accuracy		
				IAVID 2/3 splits	MuHAVi LOAO	IXMAS LOAO
Serial	DTMD11	Alexnet	60 K	75.09	70.90	63.78
	DTMD22	Alexnet	60 M	<b>78.13</b>	<b>89.66</b>	<b>70.70</b>
	DTMD38	VGG16	110 M	62.50	79.85	68.05
	DTMD44	VGG19	138 M	<b>78.13</b>	83.94	68.98
DAG	DTMD68	SqueezeNet	421,098	50.73	65.32	63.77
	DTMD99	GoogleNet	4 M	65.65	71.44	65.56
	DTMD175	ResNet50	25M	71.87	75.75	67.39
	DTMD205	ResNet101	44.5M	72.81	78.45	68.97

**Table 1.** Impact of CNN architecture on DTMD performance.

### 3.3. The impact of the type of CNN architecture on DTMD for HAR

To examine the performance of the proposed technique with respect to different types of CNNs, various serial and directed acyclic graph(DAG) based CNN networks (i.e. AlexNet[26], VGG16[27], VGG-19[27], Squeezenet[28], GoogleNet[29] and ResNet[30]) have been used.

Sequential CNN architecture designs such as Alexnet and VGG, follow a hierarchical sequential convolutional layer for computation of DTMD using a high-level representation of the input classes. On the other hand, based CNN models based directed acyclic graphs (DAGs), such as Squeezenet, GoogleNet and ResNet, use multiple CNN parallel layers to capture lower, middle and higher-level for DTMD extraction.

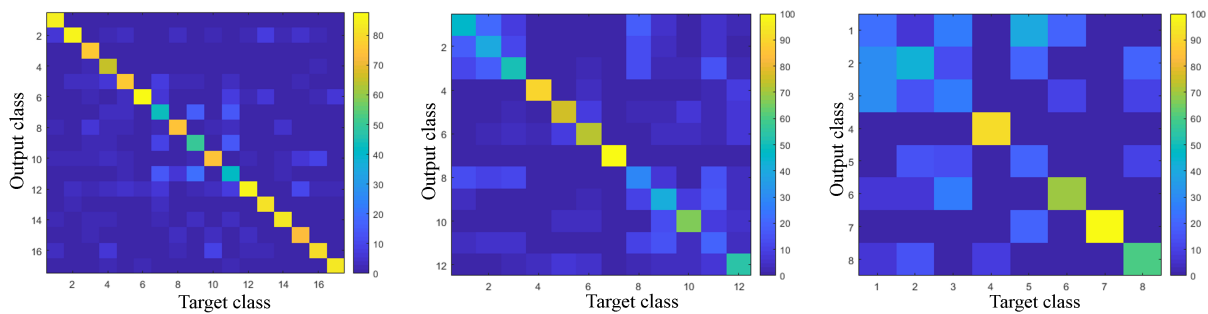
For simplicity, the DTMD obtained from AlexNet, VGG16, VGG-19 Squeezenet, GoogleNet and ResNet are denoted as DTMD11, DTMD22, DTMD38, DTMD44, DTMD68, DTMD99, and DTMD175, respectively, because DTMD11 is computed from the 11 layers of AlexNet, DTMD22 from the 22 layers of Alexnet, DTMD38 from the 38 layers of VGG16 and DTMD44 from the 44 layers of VGG19, and so on, The benefits of deep network transfer learning have been exploited by fine-tuning the pre-trained models for DTMD generation. The performance of the proposed DTMD descriptor is influenced by the quality of silhouettes, the span of

Dataset	DTMD Dimension	Accuracy
MuHAVi-Uncut	4096	89.66
IXMAS		70.70
IAVID-1		68.19

**Table 2.** DTMD performance on MuHAVi-Uncut, IXMAS, and IAVID-1 using LOAO validation scheme.

activities and the type of CNN architecture, as the quality of the actor’s silhouettes and span of actions are the essential factors for generating class specific MHI. The resultant MHI generated from short duration activities of visually similar actions or imprecise segmented silhouettes sometimes confuse the prediction of action recognition. Moreover, the type of CNN architecture for DTMD generation also affects the performance of action prediction.

It can be observed from Table 1 that DTMDs computed from sequential CNN models for HAR are generally better than DTMDs computed from DAG based CNN models, as the smaller sequential CNN models hold a smaller number of hyper-parameters helping the transfer learning training process, especially with modest amounts of data [28]. On the other hand, DAG-based CNN models used for DTMD generation, accumulate lower, middle and higher level representation of MHIs reducing granularity for precise action prediction. Among sequential CNN models, the DTMD extracted from Alexnet outperformed on IAVID-1, MuHAVi-Uncut and IXMAS datasets. The reason behind the good performance of Alexnet model within sequential CNN models is due to its capability to resolve non-saturating activation of nodes, and applying overlapping pooling, local response normalization and dropout regularization. After evaluation of the optimal model for DTMD computation, the rest of the experiments will consider DTMD22 extracted with Alexnet.



**Figure 2.** Confusion matrices for LOAO validation scheme on MuHAVi-Uncut, IXMAS, and IAVID-1 dataset using DTMD descriptor.

### 3.4. Quantitative evaluation of DTMD

#### 3.4.1. DTMD performance for person invariant HAR

The performance of DTMD is examined using the leave-one-actor-out (LOAO) validation scheme, using training video data of all the actors except one actor and using the remaining actor video sequences for testing. The entire process is repeated for all the actors and the average accuracy is reported. In MuHAVi-Uncut, IXMAS, and IAVID-1, there are fourteen, ten and twelve actors participated in the data acquisition process and these actors performed multiple actions several times.

The observations recorded in Table 2 show that DTMD overcomes the high intra-class variation that raises



due to multiple actors performing the same action multiple time and accurately recognizes human activities. MuHAVi-Uncut dataset has seventeen actions, performed by fourteen actors multiple times resulting in an action prediction rate of 89.66%, which is higher than state-of-the-art methods. IXMAS dataset has twelve activities performed by twelve actors multiple time and action prediction rate is 70.70%. Similarly, for IAVID-1 has eight activities performed by twelve actors multiple times and action prediction rate is 68.19%. The per-class accuracies for LOAO validation of MuHAVi-Uncut and IXMAS are illustrated in Figure 2.

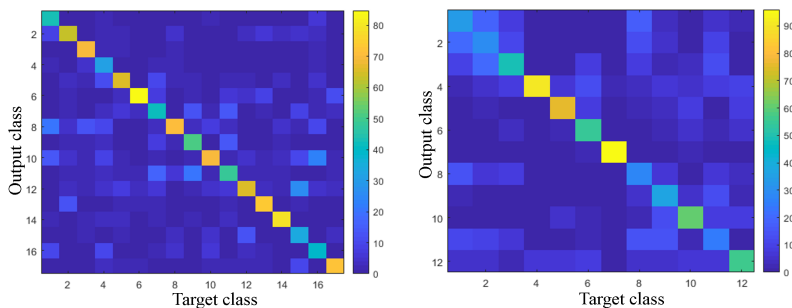
### 3.4.2. DTMD performance for view invariant HAR

The leave-one-camera (LOCO) validation scheme is used to estimate the stability of action recognition algorithm using video representation from multiple camera views. In LOCO, action videos from multiple cameras except one camera view are used for training and action videos from the remaining camera are used for testing. The process is repeated for all the camera views and average prediction accuracies are reported in Table 3.

Dataset	DTMD Dimension	Accuracy
MuHAVi-Uncut	4096	52.42%
IXMAS	4096	60.80%

**Table 3.** Performance evaluation of DTMD using LOCO validation scheme on MuHAVi-Uncut and IXMAS dataset.

The MuHAVi-Uncut and IXMAS datasets are captured from eight, and five cameras views. The observations recorded in Table 3 illustrates that DTMD does a reasonable job to deal with the high intra-class variation that raises due to multiple views of the same action. DTMD is able to recognize human actions in the multi-view setting because the deep spatiotemporal representation of action templates strengthens the learning model to predict actions from missing views. MuHAVi-Uncut dataset’s seventeen actions are predicted by 52.42%, which is higher than other state-of-the-art methods. IXMAS dataset has twelve activities captured from five camera views that are predicted by 60.8%. The confusion matrices of MuHAVi-Uncut and IXMAS are presented in Figure 3.



**Figure 3.** Confusion matrices for LOCO validation scheme on MuHAVi-Uncut (left) and IXMAS dataset (right) using DTMD descriptor.

### 3.4.3. DTMD performance for large training data

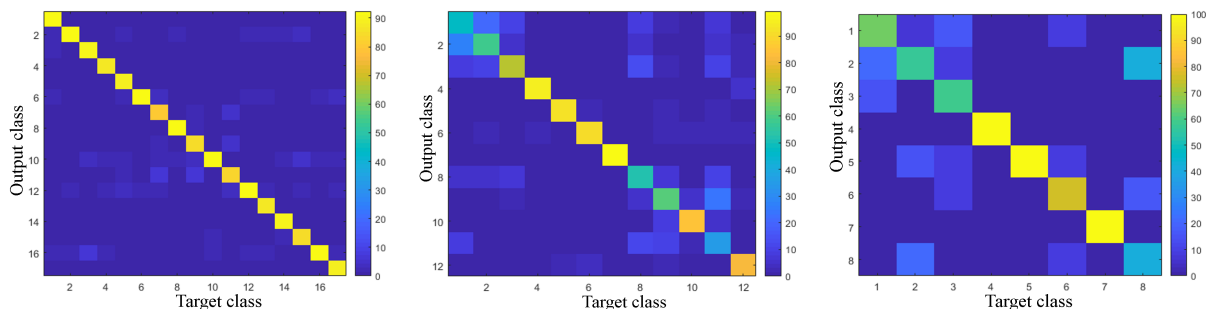
In leave one sequence out (LOSO) validation scheme, the DTMD descriptions for all the action sequences (except one) are used to generate the training model. The remaining action video sequence is used as a test sample.

Dataset	DTMD Dimension	Accuracy
MuHAVi-Uncut	4096	97.07%
IXMAS		70.83%
IAVID-1		71.42%

**Table 4.** Performance evaluation of DTMD using LOSO validation scheme on MuHAVi-Uncut, IXMAS and IAVID-1 dataset.

To determine the performance of the system, the process is repeated for all possible combinations and average accuracy is calculated, as illustrated in Table 4.

To examine the behavior of DTMD on the large training dataset, we evaluated the LOSO validation scheme on MuHAVi-Uncut, IXMAS and IAVID-1 datasets. The MuHAVi-Uncut, IXMAS and IAVID-1 datasets have 2898, 1800 and 100 action video samples for model learning, respectively. Table 4 shows that DTMD is capable to recognize human activities for a large amount of training data due to higher dimensional spatiotemporal representation. MuHAVi-Uncut dataset's seventeen actions for approximately 3000 videos samples are predicted by 97.07%, which is higher than state-of-the-art methods. IXMAS dataset has twelve activities for 1800 video samples which are predicted by 79.83%. The confusion matrices of MuHAVi-Uncut, IXMAS, and IAVID-1 are presented in Figure 4, which portrays the stability of DTMD for HAR on large training data. The per-class accuracies for LOSO validation of MuHAVi-Uncut and IXMAS are illustrated in confusion matrices in Figure 4.



**Figure 4.** The performance of DTMD using LOSO validation scheme on MuHAVi-Uncut, IXMAS, and IAVID-I dataset.

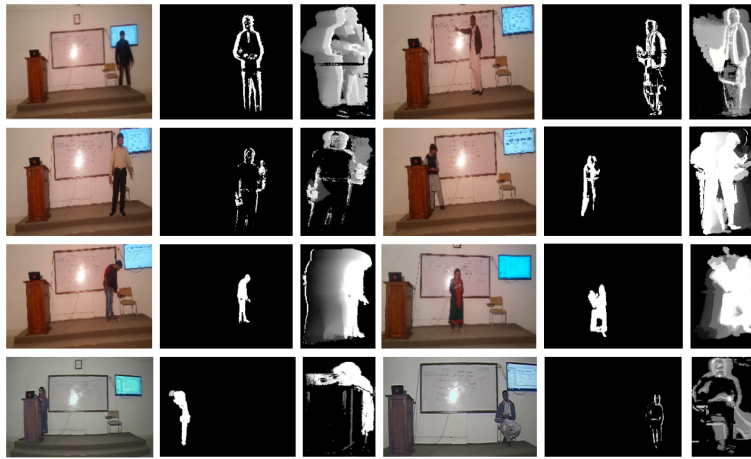
### 3.5. Case study: Instructor action recognition in lecture room scenario using DTMD

HAR techniques can be applied to applications for societal growth, like academic institutes for estimating the effectiveness of lecture delivery within the lecture room. The classroom visual information can be utilized to provide genuine feedback for the instructor to self-evaluate and plan for the next subsequent lectures. There is a need to utilize modern computer vision technology to evaluate instructor behavior within the lecture room for improving the quality of lecture delivery. Manual self-evaluation is tedious for teachers, as remembering all the details and shortcoming in lecture delivery is not possible or involves time analyzing video recordings. Peer-evaluation is also useful but time-consuming and may be biased. Therefore, automation using video analysis is useful for teachers or instructors [31, 32]. In this case study, input lecture video streams are captured in an uncontrolled realistic environment and the instructor action recognition methodology begins with foreground extraction and computing MHI for each video. Spatiotemporal characteristics are described using DTMD.

Validation schemes	DTMD Dimension	Accuracy
Cross-validation		78.13%
LOAO	4096	68.19%
LOSO		71.42%

**Table 5.** Performance of DTMD on IAVID-1 for instructor actions recognition.

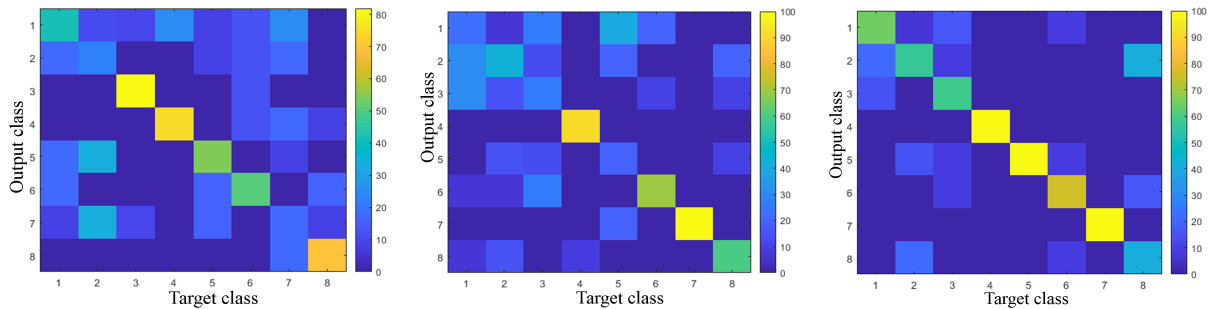
Although resulting silhouettes of IAVID-1 obtained from graph-cut segmentation[?] do not completely capture the instructor as its movement may become semi-static during lecture delivery, causing the partial segmentation of the instructor silhouettes, as shown in Figure 5. However, the working hypothesis is that the MHIs generated from these silhouettes are capable of representing the instructor action, as it overcomes the issues of under-segmentation of human silhouettes. The hypothesis is later tested in experiments.



**Figure 5.** Instructor actions of IAVID-1 within the classroom in column I and IV, and relevant silhouette representation in column II and V and resulting MHI in column III and VI.

The per class action recognition accuracy for cross-validation, LOAO, and LOSO validation schemes are sorryshown in Figure 6. From Figure 6, confusion matrix of 70:30 cross-validation, it can be observed that five instructor’s actions ‘Interacting or Idle’, ‘Pointing board or screen’, ‘Using laptop’, ‘Using phone’ and ‘Walking’ are classified accurately, whereas ‘pointing students’, ‘writing on board’, ‘sitting’ are misclassified with ‘using laptop’, ‘using phone’, ‘pointing towards board screen’, ‘interacting or idle’, respectively. The reason for misclassification of these actions is due to the existence of some visual similarity in their poses. Increasing the training sample will improve the recognition capability of DTMD. However, average action recognition accuracy is 78.13% for 70:30 cross-validation ratio, as shown in Table 5.

From the LOAO confusion matrix of IAVID-1 (Figure 6), it can be observed that the class *pointing towards board or screen* has the lowest prediction accuracy using LOAO scheme. This is because a comprehensive representation of actions from MHI requires a large ratio of motion variation. Consequently, actions that have a small span of motion are not effectively predicted by the softmax classifier due to visual similarity with other action classes like *sitting*, *using a laptop*, *using the phone* and *walking*. This issue could be resolved by increasing the training data. Average recognition accuracy is 68.19% for LOAO validation scheme, as shown in Table 5. The confusion matrix for LOSO validation scheme on IAVID-1 is given in Figure 6 for actions, *Interacting or idle*, *Pointing towards board or screen*, *Pointing students*, *Sitting*, *Using laptop*, *Using phone*, *Walking*, and



**Figure 6.** DTMD performance on IAVID-1 dataset for instructor analysis on 70-30 splits cross-validation, LOAO and LOSO validation scheme, respectively.

*Writing on board* are 75%, 91.7%, 57.15%, 64.35%, 100%, 100%, 58.3%, and 25% respectively. It is noted (Figure 6) that the class *Writing on board or screen* has the minimum recognition accuracy of 25% for the LOSO validation scheme while *Pointing board*, *Using laptop* and *Using phone* achieved a maximum recognition rate of 91.7%, 100%, and 100% respectively. Overall, the average recognition accuracy is 71.42% for LOSO validation scheme, as shown in Table 5.

### 3.6. Comparison of the proposed DTMD descriptor with state-of-the-art HAR techniques

In this section, the proposed approach is compared with relevant state-of-the-art. We have implemented the ones listed in Table 6. Action prediction accuracy of representation based (handcrafted) methods [9, 14] is lower than the proposed scheme, due to a low-dimension representation of motion templates. A Holistic motion template with handcrafted features was computed in [9, 14] but the fusion of holistic motion template and deep convolutional neural network enhances the performance of the proposed system due to the higher level action representation, as shown in Table 6. Comparing deep learning methods C3D [17] and LRCN[22] with handcrafted HAR techniques also has shown that the former performed better. However, the performance of deep learning methods is lower than that of the proposed DTMD, due to the fact that C3D performs similar to action recognition using 2D-CNN at frame level, and LRCN used optical flow to encode action motion information which is sensitive to noise and fails to encode long term temporal information. Conversely, the Deep Temporal Motion Descriptor (DTMD) due to the fusion of a motion template with numerous deep spatiotemporal features shows better performance.

The proposed technique is robust in addressing the challenges of action recognition in multi-view settings, due to the higher dimensional representation of actions. The problem of viewpoint dependency for action recognition was addressed in [11] using 3D human body modeling for action recognition. The major drawback of this method is that various fixed calibrated cameras are required for precise training and testing, which is difficult to obtain. The observed results validate DTMD’s view invariance properties. The experiments on MuHAVI-Uncut dataset revealed that in contrast to [33, 34], DTMD produces view-invariant human action representation that does not require multi-view feature fusion or calibrated cameras, hence a single viewpoint video is used for testing and the remaining views are used for training in leave one camera out (LOCO) validation scheme. Although most practical applications use single cameras, view invariance is important to minimize re-training when the views/cameras are changed.

The performance of DTMD on the iXMAS dataset has been evaluated as well. However, its prediction accuracy is not outstanding. This is due to the fact that iXMAS dataset is challenging and has inconsistent

Dataset	Validation scheme	Method	Accuracy
IAVID-I	Cross validation	Proposed technique	78.12
		Motion template and HOG description[9]	63.5
		Motion template and HOG-LBP descriptor[14]	50
		C3D features and CNN[17]	70
		LRCN[22]	70.05
MuHAVI-Uncut	LOAO	Proposed technique	89.66
		Motion template and HOG description[9]	84.1
		Observable Markov model[11]	83.9
		C3D features and CNN [17]	84.56
		LRCN[22]	86.87
	LOCO	Proposed technique	73.29
		Motion template and HOG description[9]	52.2
		C3D features and CNN[17]	72.98
		LRCN[22]	71.23
	LOSO	Proposed technique	97
		Motion template and HOG description[9]	96.6
		C3D features and CNN [17]	95.78
LRCN[22]		90.78	
IXMAS	LOSO	Proposed technique	70.83
		The sequence of the key poses[10]	85.9
		C3D features and CNN [17]	71.09
		Substructure and boundary modeling[33]	76.5
	LOCO	Proposed technique	71.92
		C3D features and CNN[17]	70.09
		LRCN[22]	69.43
		Spatiotemporal visual words to learn the SVM[34]	57.3

**Table 6.** Performance DTMD22 on action dataset.

angular positions of actors with respect to cameras views. As in IAVID-1, iXMAS action classes are fairly visually similar e.g. watching watch, stretching head and folding arms, etc. This variation in actor's pose causes no significant visual differences in MHI within each view and this is a major reason for lower action prediction accuracy. Nevertheless, still, the proposed technique recognizes actions of iXMAS to some extent, as shown in Table 6. As shown in the same Table 6, the method outperformed other state-of-the-art action recognition approaches in terms of accuracy.

It is notable from Table 6, that DTMD is capable of recognizing actions in single and multi-view setting and robust to recognizing actions performed by multiple actors. DTMD improved the baseline results on MuHAVI-Uncut dataset in LOCO scheme by 21.09%, LOAO scheme by approximately 5.56% and LOSO scheme by approximately 0.4% respectively. Thus, the improvement in performance validates the reliability of DTMD for multi-view and multiple actors in action recognition task. Moreover, improvements in the recognition rate on MuHAVI-Uncut also indicate the practical bearing of DTMD descriptor for action recognition task in another application domain.

#### 4. Conclusion

This paper has proposed a DTMD descriptor that is a deep spatiotemporal representation of action sequences for human action recognition. The method consists of actor's silhouettes extraction, followed by an actor's motion encoding in the form of motion history templates then described through a deep feature representation. DTMD

is capable of precise recognition of human actions performed by multiple actors in single or multi-view settings. In comparison to some handcrafted features and deep learning HAR approaches, DTMD has shown better performance on IAVID-1, as well as on standard action recognition datasets, due to the deep spatiotemporal representation of action templates. In IAVID-1, DTMD successfully recognizes the eight basic actions of the instructor, which indicates the practical application of the DTMD descriptor for action recognition task in another domain. In future, we plan to construct a larger instructor activity dataset to promote research in smart applications for educational institutes.

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