A Novel Approach for Robust Multi Human Action Detection and Recognition based on 3-Dimensional Convolutional Neural Networks

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ABSTRACT

In recent years, various attempts have been proposed to explore the use of spatial and temporal information for human action recognition using convolutional neural networks (CNNs). However, only a small number of methods are available for the recognition of many human actions performed by more than one person in the same surveillance video. This paper proposes a novel method for multiple human action recognition using a new architecture based on 3Dimensional deep learning with application to video surveillance systems. The first stage of the model uses a new representation of the data by extracting the sequence of each person acting in the scene. An analysis of each sequence to detect the corresponding actions is also proposed. KTH, Weizmann and UCF-ARG datasets were used for training, new datasets were also constructed which include a number of persons having multiple actions were used for testing the proposed algorithm. The results of this work revealed that the proposed method provides more accurate multi human action recognition achieving 98\%. Other videos were used for the evaluation including datasets (UCF101, Hollywood2, HDMB51 and YouTube) without any preprocessing and the results obtained suggest that that our proposed method clearly improves the performances when compared to state-of-the-art methods.

Keywords: Action recognition; multi human action recognition; motion detection and tracking; 3-dimensional convolutional neural networks

1. Introduction

A large number of videos that capture different events throughout the world are produced on a daily basis using different types of cameras (surveillance, phones, and filming crew). However, detecting the temporal and spatial events requires retrieving the required information contained in the captured videos. This process of creating useful information about the content of videos can be achieved through video content analysis [1] which has a wide range of applications including the retrieval of particular information, providing automatic alerts and data summarization. Human action recognition is another specific application of video content analysis which aims to recognize activities from a series of observations on actions of subjects and the surrounded environment and it is important for many other applications [2]. However, human action recognition is a complex technology due to the difficulty to extract information about person’s identity and their psychological states. Hence, human action recognition has gained the interest of researchers in the computer vision area and many approaches have been proposed for the aim developing this technology.

Human action recognition is an important task for many applications including video surveillance system, video indexing and retrieval, sport application, and multimedia. Action detection, recognition and summarization can be exploited to support many other tasks. For example, in sport applications, it can help to recognize and understand players’ poses allowing to make good decision on players’ fouls, especially for football games that require correct decisions in many situations. Each
human action has many characteristic patterns and appearances. In video processing, the effectiveness of such action recognition method is related to the chosen features [26–42]. Therefore, in order to recognize actions from video sequences, the existing algorithms available in the literature combine image action and spatiotemporal features, such that, the spatial features represent the visual appearance while the temporal one illustrates the dynamic motion.

Human action recognition approaches can be classified into two main categories: detection recognition and video classification. The detection recognition approaches start by first detecting the motion of the person’s action, followed by recognizing the action(s). These approaches are validated using popular surveillance datasets such as KTH [3], Weisman [4], IXMAS [5], UCF-ARG [6], PETS series [7]. These datasets were recorded in controlled conditions, such that an individual actor performs an action in a video clip in nearly an identical manner in terms of camera’s position, illumination variation with a simple static background; therefore, the recognition rate is very high (up to 90%) for almost all methods.

In the case of classification approaches, videos are classified according to the action a video contains. These approaches are evaluated using newly developed datasets with videos that are either gathered from the web, compiled from YouTube, or video clips that are recorded in realistic conditions where illumination conditions are not controlled, using moving cameras and unstated complex background. Datasets belonging to this category include Hollywood [8], Hollywood2 [9], UCF sport [10], UCF50 [11], UCF101 [12], HMDB51 [13], HMDB [14]. The diversity of clips content (scale of the actors, objects change positions, etc.), the variation in a camera’s motion and the background obsolete analysis of this category of dataset are explored.

The main goal of this paper is recognizing multiple human action for video surveillance videos. An additional part for recognizing action on video non-surveillance videos by testing our proposed CNN model on this kind of videos. The contribution of this paper relates to a new method for multiple human action detection and recognition is proposed. The main contributions of this paper can be summarized as follows: (i) motion detection and tracking of human motion in a scene using method and (ii) extraction of sequences of each human silhouette in each time, (Each sequence is exploited to recognize the action using a 3-dimensional CNN model.

The remainder of the paper is organized as follows. The literature overview including sequential-based and CNN-based methods related to our work are presented in section 2. The proposed method is presented in section 3. Experiments performed to validate the proposed method are discussed in section 4. The conclusion and future works are provided in section 5.

2. Related works

To improve the action recognition performance, recent works have employed various deep learning models [17], [18]. Since human actions are extracted from multiple movements of human body or some parts of it, it is necessary that the recognition process should involve video browsing over time to learn the patterns of the visual appearance changes [19]. To achieve this, existing deep learning models based on 2D convolutional networks can be extended into 3D domain to capture the temporal information [20]. For example, the authors in [21] use the motion in consecutive frames to extract information for action recognition using a two-stream ConvNet architecture that incorporates both spatial and temporal networks.

In the same context, authors in [22] proposed a 3D CNN-based method using stacked frame cubes of actions to capture 3D spatial-temporal action signals. In addition, Wang et al. [23] built up a temporal pyramid pooling based CNNs for action representation comprising an encoding, a pyramid pooling and a concatenation layer, which can transform both motion and appearance features. Moreover, in [24], trajectory-pooled CNNs was designed by fusing Improved Trajectories into CNNs architecture, while an adaptive recurrent convolutional hybrid networks was proposed consisting of a data module and a learning module.

For the same reason, many methods use several input videos for deep learning modelling in order to recognize the human action. In [25], Wang el. use a combination of saliency-aware, 3D CNN model and long short-term memory (LSTM) to recognize human action. Another example of many features used with CNN model was proposed in [26] where the authors exploit the original frames, optical flow, and motion stacked difference image (MSDI) as inputs of CNN model for human action recognition. Ma et al. [27] propose CNN-based methods for action recognition that use six-stream features in order to use a general action recognition where many inputs are used including the full images, human image representing just the human body, operation region represent the part of body in action, and the optical flow result of each one of the previous features. In the same category of methods that use multi-stream CNN-based technic, Tu et al. [28] propose a multi-stream convolutional neural network architecture to recognize human action. The proposed approach detects human body in action and the region of interest corresponding to the moving parts. The fusion of all CNN results is used to recognize the human action. Other methods use infrared images to recognize the human action [29]. In order to summarize the sport player actions, authors in [31] use a 3D CNN model with two streams as input the first represented the video of human body skeleton and the second represent the video of segmented data.

3. Proposed approach

This section introduces the proposed approach which consists of four phases as illustrated in figure 1. In the first stage (i.e., the preprocessing phase), we extract detected and tracked persons to generate target-region sequences from the videos. Then, the proposed convolutional neural network architecture which includes both a 3-dimensional and 2-dimensional networks where the 3DCNN is used to recognize action from the generated sequence videos of each person while the 2D counterpart is used to recognize the actions based on the Motion History Images (MHIs) of the detected action(s). The third phase, referred to as the post-processing stage, is a presentation.
of a multi action detection and recognition method for many targets in a video. In the last section (action classification), the proposed approach uses our proposed 3DCNN without any pre-processing on videos collected from web and YouTube specially to deal with the more complex video contents.

3.1. Pre-processing stage

In this work, we introduce a new representation of data to be suitable for multiple recognition of human action(s). The proposed representation is tailored towards surveillance videos captured by a fixed camera installed in private or public scene with moving objects targeting surveillance video to recognize human actions. In addition, we are interested in the human motion regions because the human body can occupy a small and specific region in the video while the existing approaches use the entire video sequences to recognize human actions.

3.2. 3DCNN Model

Depending on the applications, the selection of the optimal CNN architecture is challenging. The proposed deep learning-based approach involves the preprocessing of action videos before feeding them to the convolution neural network. The pre-processing consists of extracting the target region that contains human bodies in action, followed by resizing the data before creating NumPy video. A 3-Dimensional Convolution Neural Network (3DCNN), which is a supervised learning with multi-stage deep learning network, has been implemented. 3DCNN is capable to learn multiple invariant features from the input’s videos. Convolution and pooling are the main layers in a CNN model.

Fig. 3. The proposed 3DCNN architecture with detailed representation.

The architecture of our model, as illustrated in figure 3, is composed of two 3D convolution-pooling units, two convolutional layers and two MaxPooling layers, one flattened layer and two fully connected layers. The output layers consist of ten neurons that represent the number of actions.

We introduce a 3D convolution neural network with the following notations: I(x,y,d) as an input video with a size of x y and d the temporal depth; Conv(x,y,d,f) is convolutional layer and pooling Mpool(x,y,d,k) where x and y are video dimension d the temporal depth, f is the number of channels , and k number of kernels. PReLU represents Parametric the Rectified Linear Unit, FC(n) is a fully connected layer with n neurons, and D(r) is a dropout layer with the dropout ratio r. Using the above notations, the proposed 3DCNN model can be described as follows:

\[ I(32,32,10), \text{conv}(32,32,10,1), \text{Mpool}(10,10,3,64), \text{conv}(10,10,3,64), \text{Mpool}(3,1,64), \text{flatten}(576), \text{FC}(128), D(0.5) \text{and } FC(\text{number of actions}). \]

We have used a parametric Rectified Linear Unit (PReLU) as the activation function, which is a generalized parametric formulation of ReLU. This activation function adaptively learns the parameters of rectifiers and improves the accuracy at negligible extra computational cost [33]. Only positive values are fed to the ReLU activation function while all negative values are set to zero. PReLU assumes that a penalty for negative values, and it should be parametric. The PReLU function can be defined as:

\[ f(y) = \begin{cases} y_i if y_i > 0 \\ a_i y_i if y_i \leq 0 \end{cases} \]

where \( a_i \) controlling the slope of the negative part. When \( a_i = 0 \), it operates as an ReLU; when \( a_i \) is a learnable parameter, it
is referred to as Parametric ReLU (PReLU). Figure 4 shows the shape of PReLU activation. If \( a_i \) is a small fixed value, PReLU becomes LReLU \( (a_i = 0.01) \). As shown in [32] PReLU can be trained using the backpropagation concept.

![Activation functions of ReLU and PReLU](Image)

**Fig. 4.** Activation functions of ReLU and PReLU. (Left) ReLU. (Right) PReLU. In the case of PReLU, the coefficient \( a \) is learned from the data.

The input of our system is a video of the background subtraction results with a resolution of 32x32 pixels and a temporal depth of 10. For the training and testing, we have used the pre-processed data from KTH, Weizmann, and UCF-ARG datasets. The model is trained using CrossEntropy with a batch size of 128 examples, a learning rate of 1.

3.3. Multi-Action Detection and Recognition and Post-processing.

In the case of many moving objects or persons in the scene, we detect and track each person in the scene to generate a sequence of each one of them. To achieve this, we have used the extended version of kernelized correlation filter (KCF) based method for tracking [16]. From the tracking results, we are able to extract and generate the sequence of each person which represents the human body actions. Recognizing the activity of different persons in one scene has the added advantage of extracting a sequence for each person.

The proposed approach using the proposed pre-processing can be applied for the recognition of each of these actions.

After the extraction of each person sequence the recognition is performed using the proposed 3DCNN architecture using the sequence as input. Each RGB video (or sequence) may contain some redundant (non-useful) information like the static background. For that we apply the 3DCNN also on the RGB sequence without background called BS-video. Also, in order to minimize time of recognition we use Motion History Images (MHI) extracted from BS-video and apply 2DCNN version of the proposed architecture. The use of the MHI improve the recognition rate.

3.4. Action Classification.

The main difference between surveillance videos and other types of videos from movies, phone cameras etc. is related to the stability of the camera as well as the coverage scope. Surveillance video focuses to place that can be widely covered. For the other category of videos collected form Web and YouTube or movies usually consist of crowded videos and videos with large variations of action categories. For these kinds of videos, the content is very difficult to be analyzed making the extraction of patterns and the recognition of the action extremely very difficult. Various researchers have attempted to classify these videos using several datasets, including YouTube, UCF101, HMDB51 contains millions of videos been constructed.

This paper proposes to recognize the action from these videos using our proposed 3DCNN model. The videos are introduced to the neural network without any preprocessing and the recognition is made by learning the patterns using all the datasets. From the experimental results the proposed model provides an improved recognition rate compared to the state of the arts methods.

4. Experimental Results

The following section presents the evaluation of the proposed approach for action recognition. The experimentation was carried out using well known KTH, Weizmann, and UCF-ARG datasets. In addition, the 3DCNN and 2DCNN models were tested on UCF101, Hollywood, MHAD datasets. The 3DCNN model, with the new representation, was then evaluated in terms of the detection and recognition performances of multiple person actions at the same time. Further, the accuracy of the proposed method was evaluated using three different inputs such as RGB video, background subtraction video (BS-video) also MHI images using 2DCNN version of our model. Results of the proposed method were then compared with state-of-the-art method that are based on surveillance videos, as well as methods based on video classification.

To recognize human actions using the proposed model only regions of interest from each video, in the three datasets KTH, Weizmann and UCF-ARG, were extracted. This provides a new representation of data before the recognition process using deep learning model. Each video was divided into shorts clips of 1 second that can represent the time of an action then converted to an NPZ file.

In order to test the proposed action recognition method, we have used our own dataset named Multi Human Action Datasets (MHAD) [34]. MHAD dataset contains many actions made by many actors in the same video. On one hand, and related to video surveillance needs, each subject in a scene can carry many actions. Thus, this dataset can be useful for many tasks in computer vision [35]. On the other hand, many subjects can be found in the same video in action. Compared to the existing video surveillance dataset (that contains moving objects in the scene but with one action like walking), the proposed dataset provides many persons acting different actions in the same video.

The constructed dataset can help computer vision researchers, especially those working on video summarization, motion detection and tracking, real-time human action recognition and many related tasks. The proposed dataset includes a set of human actions representing usual human activities. MHAD composed of 10 actions, including: boxing, walking, running, hand clapping, jogging, carrying, standing, backpack carrying, and two persons fighting.

The generated videos contain from 3 to 5 persons acting in the scene. In addition, three of the videos are taken in an outdoor environment with one in an indoor setup. The background
is generated for each video and annotations of each moving actor is provided.

| Training setting | Accuracy (%) | Accuracy with data augmentation |
|------------------|--------------|--------------------------------|
| 3DCNN (RGB video) | 84.38%       | 90.63%                         |
| 3DCNN (BS video) | 94.53%       | 95.31%                         |
| CNN (MHI)        | 91.41%       | 98.44%                         |

To ensure a good detection and recognition performance, the new presentation of the three datasets was used by dividing data between training, validation and testing. 80% of the data are used for training, 10% for validation and 10% if data for testing. The used data is augmented, and another split is used giving 90% of data for training, 5% for validation and finally 5% for testing as shown in Table 1. Also, to represent each action by many different situations, a set of videos with individual actions made by different actors was used.

![Fig. 5. Training and validation evaluation results.](image)

Based on different features used as inputs for our 3DCNN and 2DCNN models, the accuracy increases when using simpler feature (sequence of motion of each person without background as input of 3DCNN model and motion history images of each person sequence as input of 2DCNN model) with our representation of data. The RGB video and background subtraction video were used to evaluate the robustness and accuracy of the proposed approach. For that, results shown in Table 2 show the accuracy of human action recognition using the proposed model. From the table it can be clearly observed that the accuracy increases from 84% to 94% when the background is subtracted from the RGB video and use the results (video without background) as input. However, the background might contain non-useful information, therefore, removal of background may result in a decrease of the accuracy. With the 2D version of our CNN model, the Motion History Image was used, represented a summarization of the motion in the video, as input for the CNN model. The performance accuracy is better that the background subtraction counterpart; however, depending on the information (the content of the image) in each MHI that can be different from an action to another. For example, the motion history of the action of walking where all body move is different of the action of waving two hands where just the two hands is moving. The accuracy increases also when we augment the number of training data, as we can see the accuracy improved by 6% for (3DCNN- RGB video) and by 7% for 2DCNN+MHI.

The proposed system has been implemented with python programming language using a laptop with GPU NVIDIA 1070 GTX. The evaluation has been made using the new representation of data of four dataset KTH, Weizmann, UCF-ARG and our dataset MHAD. For the training phase we use two splits 80% and 90% of data where 10% and 5% of data is for validation and 10% and 5% for testing. Using 1000 epochs, the accuracy of the proposed 3DCNN-based approach reaches a good accuracy using different inputs respectively. Figure 5 illustrates two graphs that represent training and validation loss and training and validation accuracy, respectively. In addition, figure 6 shows the average accuracy graphs using the proposed approach for different inputs including RGB video, Background subtraction video and MHI when the average recognition rates are 90.63%, 95.31% and 98.44%, respectively. By removing the background from RGB video, the accuracy is increased.

![Fig. 6. Accuracy of the proposed model using different inputs](image)

A comparative study against some state-of-the-art-methods that use the same datasets is shown in Table 3 where it can be observed that the proposed method results are improved and more effective. The obtained results are mainly due to the use of the new representation of the data and the deployment of spatiotemporal features represented by 3DCNN.

| Methods               | Accuracy (%) |
|-----------------------|--------------|
| Jin et al. [18]       | 96% (KTH)    |
| Akula et al. [22]     | 87.44%       |
| Ours (3DCNN+RGB video)| 90.63%       |
| Ours (3DCNN+BS video) | 95.31%       |
| Ours (3DCNN+MHI)      | 98.44%       |

The 3DCNN model allows the system to recognize the action of each one of the human presents in the scene. Figure 8 shows some examples of detected persons and their actions. Tests are made on three videos from MHAD dataset and one video from PETS2009 dataset. The visualized results and accuracy results, shown in Figure 7 and Table 2, reveal that the proposed approach detects and recognizes multiple human actions with an attractive accuracy. In addition, the proposed approach can be
improved to be used to recognize the multiple human action in real time.

Fig. 7. Detection and recognition results from MHAD and PETS datasets. The block represents the detected human action and the corresponding action. (a), (b) and (c) videos from MHAD dataset. (d) video from PETS 2009 dataset.

As represented in figure 8, in the testing part a sequence of each detected person is generated each time and the action in each is recognized using the proposed model. The succession of analysis (motion detection, motion tracking and the proposed architecture) provides a multi human action recognition. After that, each action can be represented at the original video. Also, in order to summarize the detected and recognized actions during the entire time of a video, Figure 8 represents a summarization using graphs of the recognized actions of each person during his presence in the scene.

Fig. 8. Summarization of actions made by each person during his presence in the scene. First row: actions recognition and summarization for video 1. Second row: actions recognition and summarization for video 2.

Because of the complexity of the Movies or YouTube videos captured by moving cameras, the variation of points of view, the illuminations changes and video produced by a jitter camera. Many approaches use the entire video to classify the action in it without analyzing the content of the videos. This work proposes to deploy our 3DCNN architecture to recognize the actions in these videos. To validate and evaluate our proposed method for video classification we exploit the other datasets collected from Movie and YouTube and use the video as there are without any preprocessing (no analysis of content of the videos). We do our test on UCF101, UCF sport, YouTube and HMDB51 datasets. Obtained results were compared with state of art methods (video classification approaches) shown in the table 3. From accuracy results in table 3, we can observe that the proposed methods can recognize action even without preprocessing. In addition, the recognition rates reach 91%, 71% and 89% for UCF101, Hollywood and YouTube datasets respectively.

Table 3. Action recognition results on UCF101, Hollywood2, HMDB51 and YouTube datasets comparing with the state-of-the-art methods

| Method | UCF101 Accuracy (%) | Hollywood2 Accuracy (%) | HMDB51 Accuracy (%) | YouTube Accuracy (%) |
|--------|---------------------|-------------------------|---------------------|----------------------|
| [17]   | 65.4%               | -                       | -                   | -                    |
| [19]   | 88.1%               | -                       | 59.1%               | -                    |
| [20]   | 92.0%               | -                       | 64.5%               | -                    |
| [21]   | 88%                 | -                       | 59.4%               | -                    |
| [23]   | -                   | 67.5%                   | 59.7%               | -                    |
| [24]   | 91.5%               | -                       | 65.9%               | -                    |
| [25]   | 84.0%               | -                       | 55.1%               | -                    |
| [26]   | 89.7%               | 70.6%                   | 61.3%               | 78.2%                |
| [27]   | -                   | -                       | 76.9% (JHMDB)       | -                    |
| [28]   | 94.5%               | -                       | 69.8%               | -                    |
| [30]   | 92.6%               | -                       | -                   | -                    |
| Ours   | 91.41%              | 71.88%                  | 66.65%              | 89.06%               |

5. Conclusions

This paper proposes a 3DCNN-based multi human action recognition method which is able to simultaneously detect and recognize actions made by many persons in the same video. For video surveillance systems, our approach enables a real-time human action recognition in public areas where people simultaneously act in the scene. With the proposed representation of data, which was performed prior to the recognition phase, our model accurately recognizes most actions. Our model is robust for real-time multi-human action recognition. The advantage of this new 3DCNN model is that it can be tested without preprocessing. For YouTube and movie videos, in most methods, the videos are classified to extract the actions in them. Compared with the results of existing methods, our results are attractive.

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