
# HUMAN ACTIVITY RECOGNITION USING OPENCV AND PYTHON

**A Project Report of Capstone Project - 2**

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# SCHOOL OF COMPUTING AND SCIENCE AND ENGINEERING

## BONAFIDE CERTIFICATE

Certified that this project report "HUMAN ACTIVITY RECOGNITION USING OPENCV AND PYTHON." is the bonafide work of "SIDDHARTH SHARMA(1613101737)" who carried out the project work under my supervision.

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# ABSTRACT

The purpose of this study is to determine whether current video datasets have sufficient data for training very deep convolutional neural networks (CNNs) with spatio-temporal three-dimensional (3D) kernels. Recently, the performance levels of 3D CNNs in the field of action recognition have improved significantly. However, to date, conventional research has only explored relatively shallow 3D architectures. We examine the architectures of various 3D CNNs from relatively shallow to very deep ones on current video datasets. Based on the results of those experiments, the following conclusions could be obtained: (i) ResNet-18 training resulted in significant overfitting for UCF-101, HMDB-51, and ActivityNet but not for Kinetics. (ii) The Kinetics dataset has sufficient data for training of deep 3D CNNs, and enables training of up to 152 ResNets layers, interestingly similar to 2D ResNets on ImageNet. ResNeXt-101 achieved 78.4% average accuracy on the Kinetics test set. (iii) Kinetics pretrained simple 3D architectures outperforms complex 2D architectures, and the pretrained ResNeXt-101 achieved 94.5% and 70.2% on UCF-101 and HMDB-51, respectively. The use of 2D CNNs trained on ImageNet has produced significant progress in various tasks in image. We believe that using deep 3D CNNs together with Kinetics will retrace the successful history of 2D CNNs and ImageNet, and stimulate advances in computer vision for videos. The codes and pretrained models used in this study are publicly available

# I.INTRODUCTION

Human action recognition has been an active research field in computer vision, which has great application prospects in intelligent video surveillance, human-computer interaction and so on. In recent years, data-driven deep learning has benefited from the upgrading of computer performance and explosion of video data on the internet, as a result, deep learning human action recognition methods have outperformed traditional hand-crafted features baseline and have become the mainstream research direction. Some literature [1][2][3][4] also survey human action recognition research with deep learning, but all of them don't refer to the detailed approaches on skeleton sequences and depth maps. In fact, capturing human actions in the full 3D space can provide more comprehensive information and the research of action recognition based on RGB-D data has attracted the interest of many scholars. The fundamental of human action recognition is capturing the spatial body features and its temporal evolution of a video. Fig. 1 gives a taxonomy from spatial-temporal viewpoint on color videos, skeletal sequences and depth maps respectively. Considering that spatial information is same relatively simple in skeleton sequences and depth maps and the methods on them are similarly, so we introduce them together

# II. LITERATURE SURVEY

## 2.1 TWO-STREAM CONVOLUTIONAL NETWORKS FOR ACTION RECOGNITION IN VIDEOS A. Authors (Karen Simonyan, Andrew Zisserman)

**Overview:**

The authors of this paper investigated architectures that are trained on deep Convolutional Networks for action recognition in video. The challenge in this problem is to capture the complementary information on appearance from still frames and motion between frames. Their aim is to generalise the best performing hand-crafted features within a data-driven framework. Their main contribution is that they were first to propose a two-stream ConvNet architecture which incorporates spatial and temporal networks. They showed that a ConvNet trained on a multi-frame dense optical flow is able to achieve very good performance in spite of limited training data and they demonstrated that multi-task learning applied to two different action classification datasets can be used to increase the amount of training data and improve the performance of both. Each stream is implemented using a deep ConvNet, softmax scores of which are combined by late fusion. They consider two fusion methods: averaging and training a multi-class linear SVM on stacked L2 Normalised softmax scores as features. The architecture corresponds to CNN-M-2048 and all hidden weight layers use the rectification (ReLU) activation function, max pooling is performed over 3*3 spatial windows with stride 2. The only difference between the spatial and temporal ConvNet configuration is that they are the second normalisation layer from the temporal to reduce memory consumption.

## 2.2 ACTION VLAD: LEARNING SPATIO-TEMPORAL AGGREGATION FOR ACTION CLASSIFICATION A. Authors (Rohit Girdhar,Deva Ramanan, Abhinav Gupta, Josef Sivic, Bryan Russell)

**Overview:**

In this work, the most notable contribution by the authors is the usage of learnable feature aggregation (VLAD) as compared to normal aggregation using maxpool or avgpool. The aggregation technique is akin to a bag of visual words. There are multiple learned anchor-point (say c1, ck) based vocabulary representing k typical action (or sub-action) related spatiotemporal features. The output from each stream in two stream architecture is encoded in terms of k-space action words features - each feature being difference of the output from the corresponding anchor-point for any given spatial or temporal location. They train all their networks with a single-layer linear classifier on top of ActionVLAD representation. Throughout, they use $K = 64$ and a high value for $\alpha = 1000.0$. Since the output feature dimensionality can be large, they use a dropout of 0.5 over the representation to avoid overfitting to small action classification datasets. They train the network with cross-entropy loss, where the probabilities are obtained through a softmax. Similar to a two stream network, they decouple ActionVLAD parameters ck used to compute the soft assignment and the residual to simplify learning.

## 2.3 TEMPORAL 3D CONVNETS: NEW ARCHITECTURE AND TRANSFER LEARNING FOR VIDEO CLASSIFICATION A. Authors (Ali Diba, Mohsen Fayyaz, Vivek Sharma, Amir Hossein Karami, Mohammad Mahdi Arzani, Rahman Yousefzadeh, Luc Van Gool)

### Overview

The authors of this paper introduced a new temporal layer that models variable temporal convolution kernel depths. They embedded a new temporal layer in the proposed 3D CNN. They extended the DenseNet architecture - which normally is 2D - with 3D filters and pooling kernels. They called their video convolutional network Temporal 3D ConvNet (T3D) and its new temporal layer Temporal Transition Layer (TTL). Their experiments show that T3D outperforms the current state of-the-art methods on the HMDB51, UCF101 and Kinetics Datasets. They employed a simple and effective technique to transfer knowledge from a pre-trained 2D CNN to a randomly initialized 3D CNN for a stable weight initialization. This allowed them to significantly reduce the number of training samples for 3D CNNs. Their goal was to capture short, mid and long term dynamics for a video representation that embodies more semantic information. Inspired by the idea of GoogleNet they proposed Temporal Transition Layer(TTL). It consists of several 3D convolution kernels, with diverse temporal depths. The TTL output feature maps are densely fed forward to all subsequent layers, and are learned end-to-end. The major contribution of their work is supervision and knowledge transfer between cross architectures from 2D to 3D ConvNets thus avoiding the need to train 3D ConvNets from scratch.

## 2.4. HUMAN ACTIVITY RECOGNITION AND PREDICTION

### Authors (Kong, Yu, and Yun Fu)

### Overview

In this paper, the authors talk about the two major problems that are action recognition and action prediction. In the action recognition task, there are two major types of techniques that can be followed. First is the Shallow Approaches. Shallow Approaches flowchart has two major components one is action representation and the next task is the action classification. Action Representation can be done using Holistic Approaches, Localization Approaches or Trajectory based Approaches. Action classification can be done using Bag-of-the-words approach or sequential approach which uses off the shelf classification algorithms like SVM, kNN. In the Deep Learning Approach, this paper categorises as Space-Time Networks where they talk about 3D ConvNets, C3D, etc., Secondly, Multi-stream Networks where they introduced the famous Two Stream Network and how the development of pooling layer by fusion to improve the interaction between the two layers were proposed and the best pooling layer ActionVLAD is also introduced. Thirdly, Hybrid Networks where they introduced LRCN hybrid of Convnets and LSTMs. In the Action Prediction, There are two major categories. One is Short-term prediction and the other is long-term prediction. The authors talk about a paper by Ryoo which proposed integral bag-of-words(IBoW) and dynamic bag-of words(DBoW) approach, Cao et al built action models by learning feature bases using sparse coding. Li et a explored long-term accuracy prediction problem. Lan et al developed hierarchical movements for action prediction. There were deep learning approaches were also discussed in which a new monotonically decreasing loss function in learning LSTMs for action prediction was used. Inspired by that idea the authors implemented an autoencoder to model sequential context information for action prediction.

# III.PROBLEM STATEMENT

Many researchers have contributed innovative algorithms and approaches in the area of human action recognition system and have conducted experiments on individual data sets by considering accuracy and computation. In spite of their efforts, this field requires high accuracy with less computational complexity. The existing techniques are inadequate in accuracy due to assumptions regarding clothing style, view angle and environment. Hence, the main objective of this thesis is to develop an efficient multi-view based human action recognition system using shape features. During the development phase, the following two objectives have been conceived in the proposed approach: Primary Objective – to develop an efficient human action recognition system using multiple views. Secondary Objective – to understand human behavior model using probabilistic action graph.

## 3.1 PROBLEM STATEMENT OF PRIMARY OBJECTIVE

The existing boundary based features are insufficient to represent the shape information due to high dimensionality and computational complexity. To solve this problem, problem statement 1 is formulated. 41 Problem Statement 1: To propose a simple and suitable scheme for extracting boundary based shape features to obtain robustness against occlusion and noise. The solution to this problem is attained by combining the novel triangulated shape orientation context based shape features and centroid orientation context based shape features. They discriminate the human posture correctly even though intra-class variability exists. Also, the experimental results using a variety of datasets are analyzed to prove robustness. Likewise, camera view angle and clothing styles limit the recognition accuracy during the implementation phase. To overcome this problem, problem statement 2 is formulated. Problem Statement 2: To develop a multi-view based human action recognition system irrespective of actor's style, clothing style and ethnicity. This problem can be solved by developing Discrete Hidden Markov Model based classification method.

### 3.2 PROBLEM STATEMENT OF SECONDARY OBJECTIVE

It has been found that most of the existing human behavior modeling techniques deal with post processing approaches to detect abnormality. But, they lose the correspondence between adjacent frames of learning behavior transitions. So, the problem statement 3 is formulated to overcome the drawbacks. Problem Statement 3: To construct a model for understanding human behavior using posture sequence transitions. To solve this problem a state space approach based on probability of occurrence is applied. The proposed approach improves the interpretation of temporal actions as either ‘normal’ or ‘abnormal’.

# IV.PROPOSED METHODOLOGY

## 4.1. OPENCV AND PYTHON:

Human activity Recognition can be done using one of the 2 techniques.

(i)Template Matching Technique: The template matching technique convert an picture(image) sequence

into a static shape pattern here instead of using GMM we will use HMM(Hidden Markov Model and

optical flow For defining the sequence of the data in the separated frames.) and then compare the value of

the static picture with that of the values previously stored in the trained data-set, when the value of the

data set matches the value of the data the blobs displays the derived result. The advantage of using the

template matching procedure is that it takes less computational power of the system but it is still reactive

to the temporal anomaly discussed above.

(ii)State-Space Model defines each Stationary static pose as a single state. This stationary pose is relevant

to each frame formed by HMM These states are connected by certain Possibilities such as the activities

will all have a predefined number and other activities surrounding that number will form a chain of events

likely to happen and hence increasing the probability of recognition and also making prediction a

reality. Any motion sequence taken into account as a tour going through these states. Joint expectation is

to be calculated through all these tours and the value cost maximum and closest to the values in the

data-set is chosen as the criteria for classifying activities. In such a scenario, temporal anomaly of motion

does not raise any issue because each state on loop visits itself in repetition. Hence this method of

state-space The model is reliable against temporary anomalies. below are the broad steps of the projected

technique :

(1)Pre processing

(2)Feature Extraction

(3)Human activity Recognition

**4.2.IMPLEMENTATION:**

This whole model is based on python openCv2 (CvHMM version) which makes use of the Hidden Markov Model. The pretrained data set is taken into consideration from Microsoft Kinects which in broad sense just involves basic movements. Also the KTH data set seemed useful so we made an adjustment to even use it. In the Specificity of the order of the technique we have around 5 steps which are mentioned below.

(i)Grabbing Video

(ii)Preprocessing

(iii)Construction of frames

(iii a)testing frame (in accordance to data set)

(iv)Feature Extraction

(v)Human Activity Recognition

(v a)Classification of human activity(in acc. To data-set)

**(A)Video Grabbing:**

The video data from the dataset or recorded surveillance vedios is taken into consideration.

It is a finding that if the data is supervised the results will be better than that of the unsupervised data(video).

**(B)Pre-Processing:**

The process leads on with the first step of importing necessary packages of numpy, argparse, imutils, sys, opencv2, after which the construction of the argument parser to parse the arguments takes

place, using cvHMM version will eventually provide us with the preconfigured code settings for the dataset.

**(C)Construction of The Frames/blobs:** 2D blobs are the most commonly used feature (low level) for recognition of human activity, that is why we generally come across it as the first stage.

The dilution in blob is for the enhancement of the frame, dilution can be done easily via masking or by applying a filter it is only after dilation that we obtain a 2D blob. Blob segments the frame(here we are taking one frame of the video set in consideration) into foreground and Background & the net median numerical video. Blobs are multidimensional arrays or data.

**(C(I))Testing Of The Frames:** after loading the contents of the class label, it is advisable to define the sample duration that is defining the number if frames for classification and sample size just to save the computational costs. loading it into human activity recognition model in order to test the data, after this it would provide a better gui experience for the user as well.

**(D)Feature Extraction:** After the classification of the segments in the blob the next stage in the sequel is of feature extraction, here the numerical median of the blob in motion is taken into consideration as the value for the recognition of activity is best described by the blob rather than the colour or the size of the actor. Here the feature of" Motion/Activity/Movement" of the actor in the blob is done.

Here as previously mentioned to go from one video frame to another we use optical flow which is nothing but the usage of the HMM in between of the frames, following are the popular methods for finding optical flow

(i)Horn-Schunck Technique

(ii) Lucas-Kanade Technique

Horn Schunck technique is used for floating point input & Lucas-Kanade for otherwise (I.e for fixed point input. )

Here in this paper we have made use of the Lucas Kanade method.

**(E)Action Recognition:** This in Sequence is after the 'Feature Extraction" where the activity/Movement which was the median numerical number of the blob is extracted, here then by using the optical flow of the Lucas kanade Method & also for human activity recognition we use Hidden Markov Model.

**(E(I))Action classification:** The "Activity/Motion/Movement" is classified due to the median of the blob which is then compared to the already stored numerical values of the pre-trained data-set. each activity has a corresponding numerical value to it, which when matched with the value given by the blobs results in itself classifying the activity in Observation.

# V. CODE

## 5.1. GUI.py:

```
import sys

import os

from tkinter import *

window=Tk()

window.title("Running Python Script")

window.geometry('550x200')

def run():

os.system('python main.py --model train.onnx --classes a_kinetics.txt --input
dataset1.mp4')

btn = Button(window, text="Video1", bg="black", fg="white",command=run)

btn.grid(column=0, row=0)

def run1():

os.system('python main.py --model train.onnx --classes a_kinetics.txt --input v.mp4')

btn1 = Button(window, text="Video2", bg="red", fg="white",command=run1)

btn1.grid(column=20, row=0)

def run2():

os.system('python main.py --model train.onnx --classes a_kinetics.txt --input sk.avi')
```

```
btn2 = Button(window, text="Video3", bg="blue", fg="white",command=run2)

btn2.grid(column=30, row=0)

window.mainloop()
```

## 5.2.Main.py:

```
# import the necessary packages

import numpy as np

import argparse

import imutils

import sys

import cv2

# construct the argument parser and parse the arguments

ap = argparse.ArgumentParser()

ap.add_argument("-m", "--model", required=True,

help="path to trained human activity recognition model")

ap.add_argument("-c", "--classes", required=True,

help="path to class labels file")

ap.add_argument("-i", "--input", type=str, default="",

help="optional path to video file")

args = vars(ap.parse_args())

# load the contents of the class labels file, then define the sample

# duration (i.e., # of frames for classification) and sample size

# (i.e., the spatial dimensions of the frame)
```

```
CLASSES = open(args["classes"]).read().strip().split("\n")

SAMPLE_DURATION = 16

SAMPLE_SIZE = 112

# load the human activity recognition model

print("[INFO] loading human activity recognition model...")

net = cv2.dnn.readNet(args["model"])

# grab a pointer to the input video stream

print("[INFO] accessing video stream...")

vs = cv2.VideoCapture(args["input"] if args["input"] else 0)

# loop until we explicitly break from it

while True:

# initialize the batch of frames that will be passed through the

# model

frames = []

# loop over the number of required sample frames

for i in range(0, SAMPLE_DURATION):

# read a frame from the video stream

(grabbed, frame) = vs.read()

# if the frame was not grabbed then we've reached the end of
```

```
# the video stream so exit the script

if not grabbed:

print("[INFO] no frame read from stream - exiting")

sys.exit(0)

# otherwise, the frame was read so resize it and add it to

# our frames list

frame = imutils.resize(frame, width=400)

frames.append(frame)

# now that our frames array is filled we can construct our blob

blob = cv2.dnn.blobFromImages(frames, 1.0,

(SAMPLE_SIZE, SAMPLE_SIZE), (114.7748, 107.7354, 99.4750),

swapRB=True, crop=True)

blob = np.transpose(blob, (1, 0, 2, 3))

blob = np.expand_dims(blob, axis=0)

# pass the blob through the network to obtain our human activity

# recognition predictions

net.setInput(blob)

outputs = net.forward()

label = CLASSES[np.argmax(outputs)]
```

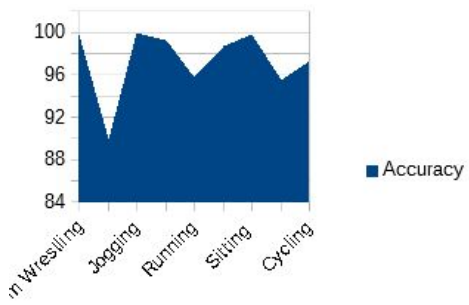
```
# loop over our frames

for frame in frames:

# draw the predicted activity on the frame

cv2.rectangle(frame, (0, 0), (300, 40), (0, 0, 0), -1)

cv2.putText(frame, label, (10, 25), cv2.FONT_HERSHEY_SIMPLEX,

0.8, (255, 255, 255), 2)

# display the frame to our screen

cv2.imshow("Activity Recognition", frame)

key = cv2.waitKey(1) & 0xFF

# if the `q` key was pressed, break from the loop

if key == ord("q"):

Break
```

# VI.RESULT:

The approach provided by this paper is based for action recognition. It has a 2D blob using Lucas kanade method of optical flow . the motion parameters are transformed into symbol sequence using HMM

The Hmm is then trained to get the maximum likelihood of the model; this is selected as a recognition result. The average success using these data sets using this technique for various activities is given in the chart below.

| Types of Sequence | Accuracy |
|---|---|
| Arm Wrestling | 99.78 |
| Boxing | 89.94 |
| Jogging | 100 |
| Cigarette | 99.28 |
| Running | 95.78 |
| Walking | 98.67 |
| Sitting | 99.83 |
| Drinking | 95.43 |
| Cycling | 97.37 |



# VII. SUMMARY

In this paper we learned how to perform human activity recognition using OpenCV and Deep Learning.

To accomplish this task, we leveraged a human activity recognition model pre-trained on the Kinetics dataset, which includes 400-700 human activities (depending on which version of the dataset you're using) and over 300,000 video clips.

The model we utilized was of ResNet, but with a twist — the model architecture had been modified to utilize 3D kernels rather than the standard 2D filters, enabling the model to include a temporal component for activity recognition.

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