Hybrid deep learning and HOF for Anomaly Detection

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***Abstract*— Anomalies detection in video footage is a daunting task treated with many challenges in crowded scenes. In this paper, we propose an efficient method based on deep learning and handcrafted spatio-temporal feature extraction for anomaly detection using a pre-trained CNN (convolution neural network) and HOF (Histogram of Optical Flow) features. Abnormal motion is picked by relative thresholding. One-class SVM is trained with spatial features for robust classification of abnormal shapes. Moreover, a decision function is applied to correct the false alarms and the miss detections. Our method has a high performance in terms of speed and accuracy. It achieved anomaly detection with good efficiency in challenging datasets and reduced computational complexity compared to state-of-the-art methods.**

I. INTRODUCTION

In recent years the surveillance cameras are more widely used, it proved their effectiveness in various field, such as malicious detection, traffic monitoring, health monitoring and intrusion detection. However, this intensive use generates a great amount of data and poses the problem of their treatment and exploitation in an efficient manner. The human being has natural abilities to recognize an important range of data, allowing him to analyze and understand a complex event in a fraction of a second. These skills allow him to understand the normal behavior of a supervised scene and detect an abnormal event that may represent a security risk. Nevertheless, the large amount of data that needs to be analyzed complicates the task for the human operators and can lead to security breaches. Therefore, the development of automated systems for abnormal event detection is paramount in order to solve these problems. These systems must be able to learn the normal events of a monitored scene and detect in real time any deviant behavior that may represent a security risk. The contextual nature of the event combined with the difficulty to generate abnormal training samples makes the detection task challenging. Given what is at stake in this area and the complexity of this work, abnormal event detection is an open search task that generates excitement in the scientific community, which led to the development of various methods. The main of them use in the training phase only normal samples and consider in the testing phase any event with a low probability of occurrence as abnormal. Among these approaches, many works focus on the extraction of handcrafted features [1]–[4]. Low local features such as Histogram of Oriented Gradients (HOG), Histogram of Optical Flow (HOF), Dynamic textures (DTs) or spatio-temporal oriented energy where used to extract representations and construct the model of normal events. Although these methods are effective in extracting spatio-temporal representations, they require prior knowledge to match the features with the targeted events and are usually too local to describe effectively complex events. Trajectory-based methods have also been widely explored [5]–[7]. During the training phase, the trajectory of moving objects are evaluated to construct a model. In the testing phase, new target is labeled as abnormal if its trajectory deviates from the model. Despite the fact that these methods have demonstrated their effectiveness in anomaly detection in non-crowded scene it remains unusable in crowded scenes, since it requires generally accurate tracking techniques with a high computational complexity. These methods are also ineffective for detecting abnormal objects with little or no movements.

In recent years, deep learning methods have greatly improved the results of signal processing tasks and more particularly computer vision. Their results rely principally on the fact that they are not based on handcrafted features and does not require prior knowledge to extract robust representations. Instead, they are able to learn features directly from raw data. The success of deep learning in computer vision favored the emergence of deep learning based methods for abnormal events detection. These methods fall into two categories: supervised learning methods [11] and unsupervised learning methods [12]–[16]. The first ones are mainly based on convolutional neuronal networks and try to classify the events in two categories normal and abnormal. During the learning process these methods require training samples from each class. Despite the undeniable results of these methods, their use in real-world applications for abnormal events detection remains unlikely given their supervised nature. As mentioned earlier is difficult to provide training examples for all abnormal events that can occur in a monitored scene. The second one, aims to extract robust representation, using neural networks learned only on normal data. These methods use unsupervised neural networks such as convolutional auto-encoders (CAEs), generative adversarial networks (GAN) or pre-trained convolutional networks. These methods have achieved good results on abnormal event detection and overcome the drawbacks of the first category, since they use only normal training examples during the training process.

In this paper, we propose new method based on a combination between pre-trained CNN VGG16 and Histogram of Optical Flow to extract robust representations related to shape and motion. We use one class SVM to classify these representations as normal or abnormal. We also propose an intuitive post-processing based on the assumption "an abnormal event cannot appear or disappear abruptly" to improve the results of our method and reduce the errors that may occur.

II. STATE OF THE ART

Abnormal event detection is challenging task in computer vision. Usually, state-of-the-art methods learn reference model to represent the normal events that occur during the training phase and consider every event that not occur during the training as abnormal.

Some methods were introduced using low-level features to construct the behavior model. [1] used the Histogram of Oriented Social Force (HOSF) to represent the events and construct dictionary during the training phase. The dictionary is then used to evaluate the potential abnormality of each new testing event. [2] proposed multiples features extraction (size, texture and motion) on small regions of the input frames obtained by foreground segmentation technique. Multiple classifier (one for each feature) are used to decide if a region is normal or abnormal. [3] used Histograms of Optical Flow (HOF) to represent the motion information of each frame and one class Support Vector Machine (SVM) to dissociate between normal and abnormal events. In [4], based on the assumption: "usual events in a video are more likely reconstructible from a normal event dictionary compared to unusual events", the author proposed to learn dictionary from the training frames using sparse coding. In the testing phase, the dictionary is used to obtain reconstruction weight vector and compute normality score for each new event in order to separate normal and abnormal ones. Meanwhile, other trajectory-based methods have been applied in order to recognize unusual trajectories in monitored scene. [5] proposed to represent trajectories by Kanade Lucas-Tomasi Feature Tracker (KLT) and used Multi-Observation Hidden Markov Model (MOHMM) to determine if trajectory are normal or not. [6] learned One-Class Support Vector Machine to recognize the normal and abnormal trajectories. [7] combined vector quantization and neural networks to extract robust representation of the events. Recently, several researches based on deep learning have obtained great result on various applications such as object detection [8], action recognition [9] and face recognition [10]. Methods based on deep learning owe their success to their ability to learn non-linear and complex representations from raw images, which is important since real-world data contain many non-linear relationships. These methods also have a good property of generalization: they can be applied on data unused during the learning process. The author of [11] proposed to apply optical flow to extract spatial–temporal volumes of interest (SVOI) and used them to train a spatial–temporal convolutional neural network to classify events as normal or abnormal. [12] combined pre-trained CNN completed with Binary Quantization Layer (BQL) and optical flow to detect local anomalies. [13] proposed a Generative Adversarial Network (GAN) learned on normal images and corresponding optical-flow representation to detect local abnormal events. [14] proposed a method based on two neural networks: a Stacked Fully Connected Variational Auto-Encoder (VAE) and a Skip Convolutional VAE to detect both local and global abnormal events. The first network is used to filter and eliminate the obvious normal events and the second for accurately locating the abnormal ones. [15] proposed spatio-temporal architecture composed of Convolutional Auto-Encoder to extract the spatial features of frames and convolutional temporal auto-encoder to learn temporal representations. The reconstruction error is then used to establish if frame is normal or not. The author of [16], integrated One-Class Support Vector Machine (OC-SVM) into Convolutional Neural Network (CNN) to obtain end-to-end deep one-class learning framework adapted for abnormal event detection. In [17], 3D Auto-Encoder is used for early differentiation of normal and suspicious patches. The suspicious patches are then evaluated by more accurate and deeper 3D convolutional neural network.

III. PROPOSED METHOD

Abnormal event can be defined as rare motion or rare shapes in video footage. Our work is mainly based on extracting two robust descriptors to represent spatio-temporal behavior of each frame; The first using a pre-trained CNN (Convolution Neural Network) capable of describing the shapes and the second able to describe the movement of the video using the HOF (Histogram of Optical Flow). Then, a thresholding and non linear SVM are combined to classify the frames as abnormal or normal. At the end, our algorithm is enhanced by post-processing to decrease the number of the false alarms and the miss detections.

A. *Features extraction*

VGG16 [18] (Visual Geometry Group) is robust ConvNet developed and trained by University of Oxford. It achieved very good performance of about 94% accuracy on the ImageNet dataset. In Deep Learning Images Processing (DLIS), the fully connected layers hold a reduced and a deeper representation of Feature Maps (FMs) generated by the convolutions layers to describe the whole frame. Therefore, we extract a deep features of the shape (Fig. 1) from the two last fully connected layers FC1 and FC2 of VGG16 ConvNet contain 4096 neurons combined to be able to decide if the frame contained abnormal shapes or not. A Clip is applied to each feature vector to improve consistency between data.

Initialization:
N=number of Frames
$Train_1 = [\ ]$
$Train_2 = [\ ]$
for *i=1:N* **do**
  # F_i: The ith Frame
  $D1 = Feature\_extraction\_shapes\_FC1(F_i)$
  $Train_1 = [Train_1; D1]$
  #$size(Train_1) = N$ vectors of 4096 values
  $D2 = Feature\_extraction\_shapes\_FC2(F_i)$
  $Train_2 = [Train_2; D2]$
  #$size(Train_2) = N$ vectors of 4096 values
  $HOF_{Train} = Feature\_extraction\_motion(F_{i-1}, F_i)$
  #$size(HOF_{Train}) = N$ vectors of 2 values
end
$Model1 = Train\_OC\_SVM(Train_1)$
$Model2 = Train\_OC\_SVM(Train_2)$
Anomaly detection:
for *Each new Frame* F_i' **do**
  $D1_{Test} = Feature\_extraction\_shapes\_FC1(F_i')$
  $D2_{Test} = Feature\_extraction\_shapes\_FC2(F_i')$
  $HOF_{Test} = Feature\_extraction\_motion(F_{i-1}', F_i')$
  #Abnormal shapes detection
  $Label1 = Predict(Model1, D1_{Test})$
  $Label2 = Predict(Model2, D2_{Test})$
  #Abnormal motion detection
  if $HOF_{Test}[2] > Threshold$ **then**
    *Label*3=*Abnormal*
  else
    *Label*3=*Normal*
  end
end
if *(*$Label1 = Abnormal$ *Or* $Label2 = Abnormal$ *Or* $Label3 = Abnormal$*)* **then**
  $Label = Abnormal$
else
  $Label = Normal$
end
$Label = Post\_processing(Label)$

Algorithm 1: Algorithm of Anomaly Detection

However, the VGG16 CNN does not take into account the motion concept. That is why, we propose handcrafted method to extract feature motion to pick up any abnormal movement into video in the following way: First we calculate a dense Optical flow (OF) (1) with Farnebäck [19] algorithm at every frame of the video describing the motion at each pixel. Each flow vector is composed according to its magnitude R and primary angle from the horizontal axis. Then, we establish the histogram of quantity motion depending on the magnitude R (2) only with two bins (3) the first bin represents the Low Motion Level (LML) and the second contains information about the High Motion Level (HML):

$$u = \frac{dx}{dt}, v = \frac{dy}{dt} \tag{1}$$

Where dx and dy represent the motion taken after dt time from frame to another. u and v respectively represent horizontal and vertical movements between two consecutive images.

$$R = \sqrt{u^2 + v^2} \tag{2}$$

$$F_i \longmapsto HOF = [B_0, B_1]_{i \in [|1,n|]} \tag{3}$$

F_i : The ith frame in video
B_0 : Low motion, first component of HOF
B_1 : High motion, second component of HOF

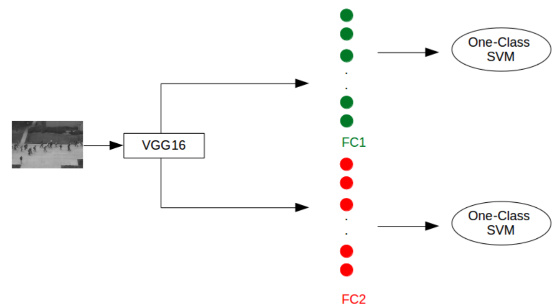

Fig. 1: Feature of shapes

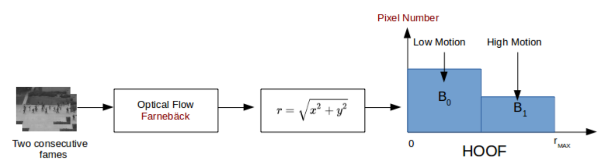

Fig. 2: Feature of motion

B. Classification

In this section, we explain how we can classify our features in order to determine the abnormal images. One-Class SVM (Support Vector Machine) is used to classify our feature shapes within unsupervised learning mode, which is coherent with our problem as we use only the normal event for training task. Moreover, a classification by thresholding is used to pick any anomalies in motions.

Support Vector Machine is statistical learning method adapted to non-linear problems with using kernel methods [20] for both regression and classification problems (4):

$$N(X, X') = \Theta(X).\Theta(X') \tag{4}$$

Where $\Theta(X)$ is the projection of input data X to the new space H where the problem have a linear solution.

The target of this learning method is to find a separator "hyper-plane" to classify our data (5). The optimal classifier can be determined by maximizing the margin and it is represented by minimization problem shown in (6).

$$f(X) = W.X + b \tag{5}$$

$$Min\frac{1}{2}||W||^2 \tag{6}$$

subject to:

$$Y_i \times (W.X_i + b) \geq 1, i \in [|1,n|] \tag{7}$$

where n is the size of input training data and Y_i is data label (-1 or +1) defined by (8).

$$y(X) = sign(f(X)) \tag{8}$$

Moreover, in one-class SVM, the data from only one class are available which is consistent with our problem framework as only the normal event examples should be used for training. On another hand, a classification by thresholding (Fig. 2) is proposed to determine abnormal motions. As we explain in the previous section, the motion information at each frame is represented by a HOF with 2 bins, the first describes the low motion and the second describes the high motion (3). We fix the threshold 'S' as the maximum high motion in the training phase (9). Then, we compare the high motion B'_{1i} of each new frame F'_i with the threshold 'S' to decide if the frame contained abnormal motion or not as it is shown in (Fig. 3).

$$S = Max(B_{1i}, B_{12}, ..., B_{1i}, B_{1n}) \tag{9}$$

B_{1i} : High motion in ith frame at Train phase

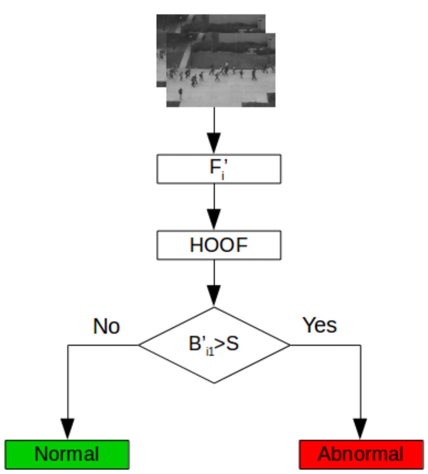

Fig. 3: Motion classification

C. Post-processing

Moreover, we propose a post-processing to decrease the erroneous decisions taken by each classifier. So, we define a new decision function D_{in} based on the n previous decisions taken classification noted T_i and based on hypothesis that an anomaly can not appear or disappear abruptly (Fig. 4). The following TABLE I summarizes all the possibilities for n=3.

TABLE I: Table of truth

T_{i-2}	T_{i-1}	T_i	D_{i3}
0	0	0	0
0	0	1	0
0	1	0	0
0	1	1	1
1	0	0	0
1	0	1	1
1	1	0	1
1	1	1	1

- 0 : Frame contains anomaly
- 1 : Frame does not contain anomaly

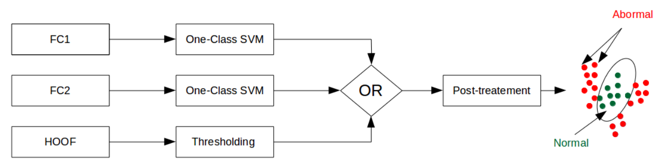

Fig. 4: Flowchart of the proposed method

IV. EXPERIMENT RESULTS

UCSD Peds2 and UMN [29] are two different anomaly detection datasets. UCSD Peds2 consists of a video footages of crowded pedestrian walkway. It contains both normal and abnormal events like walking movement of bikers, skaters, cyclist and small carts. In the walkways, the motion of the pedestrians in an unexpected area is also considered as an anomalous event. It contains 16 training and 12 testing video samples and provides frame-level ground truth which helps us to evaluate the detection performance with comparing our method with others stat-of-the-art anomaly detection methods. In the other hand, The UMN dataset is consisted of 3 scenes: lawn (1450 frames), indoor (4415 frames) and plaza (2145 frames). It has two events: people walking which is considered as normal event and people running which is considered as abnormal event. The ground truth is provided in the video frames that need to be extracted to evaluate the performance.

A. Performance evaluation

In order to evaluate the performance of the proposed method, we used the measure of EER (Equal Error Rate), calculated with the following equation :

$$EER = \frac{FP + NF}{FN} \tag{10}$$

- FP : False Positive, representing the false alarm.
- FN : False Negative, representing the miss detection.
- NF : Number of frames in each folder.

Our results in each folder of USCD Ped 2 is presented in the following table :

TABLE II: Results in USCD Ped 2 dataset

Folder	nbr frames train	nbr frames test	FP	FN	EER
1	120	180	12	0	6.6%
2	150	180	95	0	52.7%
3	150	150	3	0	2%
4	180	180	20	0	11.11%
5	180	150	20	0	13.3%
6	150	180	20	4	13.3%
7	150	180	45	0	25%
8	120	180	0	0	0%
9	180	120	0	0	0%
10	180	150	0	2	1.3%
11	180	180	0	0	0%
12	180	180	88	0	48.8%

It could also be noted for each test folder that we have used the images of corresponding train folder. Despite we have trained the SVM with a small dataset around 150 frames at each folder, our method achieved good results comparing with others method summarized in TABLE III. It is reached a high performance and proved its efficiency comparing with the most of the state-of-the-art methods. The one-class SVM classifier is robust to the training dataset size, which allows its applicability for very large video datasets. Moreover, this hybrid system decreases the false negatives (miss detections) by dissociating of all descriptors decisions.

TABLE III: EER comparison of UCSD Peds2

Method	EER
Mehran. [21]	42.00%
Kim(MPCCA). [22]	30.00%
Bertini. [23]	30.00%
Zhou. [24]	24.40%
Bouindour. [25]	24.20%
Li. [26]	18.50%
Chong. [27]	12.00%
Tan Xiao. [28]	10.00%
Ours	14.50%

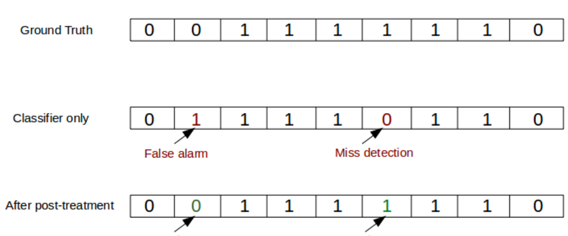

Fig. 5: Example of post-processing

The post-processing has proven its efficiency by decreasing the error by 1.2% for UCSD Peds2 dataset and 1.7% for UMN dataset. It enhances the stability of our classify to detect the anomalies (Fig. 5). To evaluate the using of two fully connected layers the TABLE IV summarizes the results on UCSD Ped2 dataset using only one fully connected layer at each time. We note that using two fully connected layers has more efficiency and enhance our results by decreasing the total error by 3.45% at average. However, it should be noted that we can not use the third fully connected layer because it represents the probability membership vector for each 1000 classes.

TABLE IV: FC1 and FC2 performance on USCD Peds2

Method	ERR
FC1+HOF	16.3%
FC2+HOF	20.19%

Our results in scene of UMN is presented in the following table :

TABLE V: Results in UMN dataset

Scene	EER
Lawn	3.25%
Indoor	3.25%
Plaza	4%

TABLE VI: ERR comparison of UMN dataset

Method	EER
Mehran. [21]	12.60%
Chaotic invariants. [30]	5.30%
Li. [26]	3.70%
Saligrama et al. [31]	3.40%
Sparse. [32]	2.80%
Ours	3.50%

These both tables (TABLE V and the TABLE VI) summarize the results on UMN dataset and show high performance of our method in anomaly detection compared with state-of-the-art methods.

V. CONCLUSIONS

In this paper, we have proposed a novel approach based on coupling deep learning CNN and handcrafted spatial and temporal feature extraction for anomaly detection. Moreover we have proposed a post-processing to rectify the classification decisions. This method proves robustness to occlusion and high performance in anomaly detection compared with state-of-the-art methods. Moreover, it decreases considerably the false negatives, which allow us to treat the localization issues more efficiently. Our future work is to add an effective strategy to our algorithm for anomaly localization taken in account more additional challenges as scaling and mobile cameras.

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