PAT: Pseudo-Adversarial Training For Detecting Adversarial Videos

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ABSTRACT
Extensive research has demonstrated that deep neural networks (DNNs) are prone to adversarial attacks. Although various defense mechanisms have been proposed for image classification networks, fewer approaches exist for video-based models that are used in security-sensitive applications like surveillance. In this paper, we propose a novel yet simple algorithm called Pseudo-Adversarial Training (PAT), to detect the adversarial frames in a video without requiring knowledge of the attack. Our approach generates ‘transition frames’ that capture critical deviation from the original frames and eliminate the components insignificant to the detection task. To avoid the necessity of knowing the attack model, we produce ‘pseudo perturbations’ to train our detection network. Adversarial detection is then achieved through the use of the detected frames. Experimental results on UCF-101 and 20BN-Jester datasets show that PAT can detect the adversarial video frames and videos with a high detection rate. We also unveil the potential reasons for the effectiveness of the transition frames and pseudo perturbations through extensive experiments.

KEYWORDS
Adversarial, defense, video action recognition, attack

1 INTRODUCTION
Deep neural networks (DNNs) have proven to be excellent learners for various tasks like image classification and video action recognition. Recent studies have also shown the vulnerability of DNNs to adversarial attacks [4, 6, 21]. An example is when the input is altered subtly, leading to misclassification by the DNN. This has drawn a lot of attention as DNNs are being used for applications like surveillance [35], autonomous vehicles [23, 45], facial recognition [13, 30], etc., where resilience to adversarial attacks is of utmost importance.

While the current literature documents extensive research related to adversarial learning in image-based applications, [1, 2, 11, 21, 34, 43], the adversarial vulnerability of video-based DNNs remains a less explored area. This poses a pressing practical challenge, as DNNs are widely deployed in various video-analysis tasks [3, 5, 22, 31, 38, 39]. Although the video-based DNNs are more difficult to attack due to the additional temporal dimension, [40] showcased the susceptibility of video action recognition models to adversarial attacks.

The attacks on such models can be categorized into two types - (1) sparse attack where either minimum number of frames are perturbed or minimum amount of perturbations are added to each frame like [40], (2) dense attack where perturbations are added to all the frames like in [12].

There are plenty of defenses designed to defend image attacks [16, 19, 27, 32, 37]. However, in general, they cannot be directly applied to videos as they do not take temporal information into account. Often, defenses for videos need to be computationally efficient, in order to handle the volume of data. The temporal redundancy present in videos can lead to a significant waste of computation if one simply applies an image-based approach on a frame-by-frame basis. To overcome these challenges, we suggest that the detection of adversarial videos will be a better alternative as compared to techniques involving intensive training, changes to network parameters or reconstructing the frames [15].

In this paper, we propose a novel defense strategy, Pseudo-Adversarial Training (PAT), for video action recognition networks which can detect the adversarial frames without any prior knowledge of the perturbations. It is called ‘pseudo’ because the network is not trained on the actual perturbations. The detection network is trained on transition frames and pseudo perturbations to detect the perturbed frames. The transition frames, constructed from the neighboring frames, make the otherwise finely blended perturbations noticeable. The pseudo perturbations enable the network to learn about potential deviations from authentic frames, without the need to know specific attack models.

We summarize our contributions as follows:

- We propose a new technique, Pseudo-Adversarial Training (PAT) to detect the adversarial frames in a video. This strategy does not need prior knowledge of the attack scheme or the added perturbations, and can defend both the sparse as well as the dense attacks.
- We define and use the transition frames so that the detection network can focus on perturbations that are more relevant to the detection of the adversarial frames rather than other elements in the frame.
- We also propose to generate pseudo perturbations and use them to train our detection network. These perturbations are generated such that the network can learn to handle varying perturbations due to adversarials.

2 RELATED WORK
Ever since the adversarial attacks were discovered by [36], they have been researched extensively [6, 20, 26, 46] for various computer vision tasks. Early attacks like [2, 6, 21] used the gradient information of the image models to generate the perturbations. As having the access to the network parameters is a strong assumption, the black-box attacks like [14, 25] on the image models were designed which used the principle of transferability [24] to fool the network. To defend these attacks, one simple technique was to retrain the network with the adversarial images [17]. As the attacks

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The focus on the spatial information of the images in the image-based defenses makes them non-applicable to video-based models. [42] designed a defense for video-based models, where the optical flow is used to generate the current frame based on the previous. The video is then passed through the target network to check for temporal consistency.

[8] also use the concept of temporal consistency to determine the perturbed frames in a video. They use a well-trained network to determine the labels of each frame and a frame is considered adversarial if its label is different from its adjacent frames. [15] presents a defense method that replaces the batch normalization layers in the action recognition network with their module named MultiBN. They adversarially train this modified network to defend against adversarial attacks.

PAT avoids the complex tasks of frame reconstruction and optical flow estimation by using instead the ‘transition frames’, which are computed by a much simpler process. PAT neither introduces any hyperparameters for detection (like that in [8]) nor requires retraining the target classifier (like that in [15]) and hence reduces the overhead of learning.

### 3 METHODOLOGY

#### 3.1 Problem Definition

Without loss of generality, we consider video action recognition models in this work but it can be easily extended to other video-related tasks. Let \( X_1, X_2, ..., X_t, X_{t+1} \) be the image frames of a video with \( X_t \) being the target frame. Let \( D \) be the classifier model and the prediction output of \( X_t \) be \( Y_t (D(X_t) = Y_t) \). An attacker aims to generate an adversarial frame \( X_t^* \) by adding a small perturbation \( \epsilon \) to the target frame \( X_t \) such that \( D(X_t^*) = Y_t^* \), where \( Y_t^* \) is the adversarial target output. Our aim is to detect the adversarial frame \( X_t^* \) without any knowledge of the attacking algorithm besides the two frames \( X_{t-1} \) and \( X_{t+1} \). Also, there is no definite knowledge if \( X_{t-1} \) and \( X_{t+1} \) are clean or perturbed frames.

#### 3.2 Pseudo-Adversarial Training (PAT)

The Pseudo-Adversarial Training (PAT) strategy consists of three key components: transition frame generation, pseudo-perturbation generation and training the detection network using the clean transition frames and pseudo-adversarial transition frames. (b) shows transition frame generation. (c) shows the detection network architecture.

![Image](image_url)

**Figure 1:** Overview of the Pseudo-Adversarial Training (PAT) approach. (a) shows the key components - transition frames generation, pseudo-perturbation generation and training the detection network using the clean transition frames and pseudo-adversarial transition frames. (b) shows transition frame generation. (c) shows the detection network architecture.
sense throughout this paper, and it is supposed to capture underlying dynamics. Similarly, the motion $M_2$ between $X_t$ and $X_{t+1}$ is $M_2 = X_{t+1} - X_t$. Now, the motion between $M_1$ and $M_2$ is given by:

$$M_2 - M_1 = X_{t+1} - X_t - X_t + X_{t-1}$$  \hspace{1cm} (1)

Eq. 1 reduces to the transition frame equation (Eq. 2). These equations show how the transition frame is able to capture the motion from the three frames used to create it. It is generated using two simple operations only - average and difference, making it computationally inexpensive.

$$X_{tr} = \frac{X_{t-1} + X_{t+1}}{2} - X_t$$  \hspace{1cm} (2)

There are two special cases - the first and the last frame of the video. The first frame does not have the previous frame and the last frame does not have the next frame. Thus, we replace the average frame for first and last frames by the second frame and the second last frame in the video respectively.

Fig. 2 shows the original frames, their average and the transition frames for the current frames. It is clear from the transition frame that it gets rid of most of the static background. It only contains the main object and the motion around it. Elimination of the passive elements does not hamper the detection process as they are not relevant to our detection task. As a result, the perturbations become visible prominently in the transition frames.

3.2.2 Pseudo Perturbations Generation. For training the detection network, we need clean and adversarial samples. As there is no prior knowledge of the perturbations being added or the attack algorithm, we propose a way to generate on-the-go pseudo perturbations. These perturbations are not actual perturbations as they are not generated using an attack strategy. But, when added to the transition frames, they are enough to let the network learn about the actual perturbations in the video frames.

To generate the pseudo perturbations, we use a varying magnitude of Gaussian noise by changing the standard deviation $\sigma$ of the Gaussian distribution. We generate Gaussian noise mask $X_n \sim N(0, \sigma)$ where $\sigma \sim \mathcal{U}(0.0001, 0.05)$. It is of the same shape as that of the transition frame (Eq. 3 where $X_{adv}$ represents the pseudo-adversarial transition frame). We choose this particular range for the value of $\sigma$ because it covers a wide variety of magnitude. For the values below 0.0001, the noise does not make any significant impact on the image. The values above 0.05 completely disrupt the transition frame and will turn it into noise only. For every transition frame, a different value of $\sigma$ is picked randomly. This varying noise mask added to the transition frames is essential to train the detection network such that it can identify a variety of perturbations.

$$X_{tr} = \frac{X_{t-1} + X_{t+1}}{2} - X_t + X_n$$  \hspace{1cm} (3)

3.2.3 Training the detection network. We use a convolutional neural network (architecture shown in Fig. 1 (c)) for binary classification as the detection network. The transition frames for the clean class are obtained from the original videos. For adversarial class, the transition frames are obtained by adding the pseudo perturbations to the clean transition frames. Our approach is summarized in Algorithm 1.

4 EXPERIMENTS AND RESULTS

In this section, we start with the discussion of the experimental settings and the metrics used for evaluation. We also discuss the two

Figure 2: Sample original frames, the average frames and the transition frames. The first 3 columns show the original frames of videos. The 4th column is the average of the previous and the next frames. The last column shows the transition frames for the current original frames. The transition frames eliminate most of the background and retain the object and the surrounding motion only. The frames in the 1st row belong to UCF-101 dataset and the ones in the 2nd row belong to 20-BN Jester dataset.
We achieve a test accuracy of 91.09%. The target network for Jester is the pretrained ResNet152 followed by a layer of LSTM, plus two fully-connected layers and the final classification using softmax.

4.1 Experimental Settings

4.1.1 Datasets and Target Networks. We chose UCF-101 [33] and Jester [18] dataset for our experiments to showcase that our approach works for both coarse-grained action recognition and fine-grained action recognition data. UCF-101 dataset contains 101 human-action classes (coarse-grained) like playing cello, applying lipstick, hammering etc. It contains variations in terms of illumination conditions, background, camera etc. The dataset comes with 3 different train-test splits. We use split 1 consisting of 9,537 training videos, 14,787 validation videos and 14,743 testing videos. As the labels for testset are not available, we provide the results on the validation set.

4.1.2 Attack Baselines. We consider two attacks to evaluate our approach. Sparse Adversarial Perturbations [40] perturbs only a small percentage of frames from the entire video using an $l_{2,1}$ optimization loss and temporal mask. As the perturbations are sparse, we refer to it as 'sparse attack' for the rest of the paper. For our experiments, we perturb pre-determined 22.5% (9 out of 40 frames) and 20% (4 out of 16 frames) of the total frames for UCF-101 and Jester dataset respectively.

The other attack [12] perturbs all the frames in a video using a generative model. As all the frames are perturbed, we refer to it as 'dense attack'. With these two attacks, we show that our method can detect adversarial frames containing a variety of perturbations.

4.1.3 Evaluation metrics. Two evaluation metrics are used in our experiments: 1) Frame Detection Rate -

$$FDR = \frac{\sum_{i=0}^{N} D(X_i) = Y_i}{N}$$

where $X_i$ is the input frame, $Y_i \in \{0, 1\}$ is the ground truth for frame detection, $D$ is Detection network and $N$ is the total number of frames; 2) Video Detection Rate -

$$VDR = \frac{\sum_{i=0}^{M} \left(\prod_{j=0}^{N} D(X_{ij})\right) = Y_i}{M}$$

where $X_{ij}$ is the $j^{th}$ frame in $i^{th}$ video, $Y_i \in \{0, 1\}$ is the ground truth for video detection, $D$ is Detection network, $N$ is the number of frames and $M$ is the number of videos.

We also calculate Area under Receiver Operating Characteristic (ROC), shortly known as AUC on UCF-101 dataset for comparison purposes. AUC represents the degree to which the model can distinguish between two classes and ROC is a probability curve. Higher the Area under Curve (AUC), better is the capability of the model to distinguish between the two classes.

4.2 Adversarial Detection Results

Table 1 summarizes our results for adversarial detection on both the datasets. From the FDR column, it is clear that PAT detects adversarial frames from both types of attacks with high rate. This demonstrates that PAT can detect different types and magnitude of perturbations without having any prior knowledge about them. Also, PAT works well for both the datasets showing that it can handle coarse-grained and fine-grained classification data. This makes it a very promising approach for detecting the adversarial frames. Based on the detected adversarial frames, the adversarial video input can be detected. The frame detection rate obtained by PAT is enough to detect most of the adversarial videos with ease.

The sparse attack showed that even if one frame is perturbed, a success rate of 60% is achieved. Therefore, even if one adversarial frame is detected in the entire video sequence, the video can be categorized as an adversarial one. However, to accommodate the scenario of having false positives, we use a threshold of 3 adversarial frames i.e we consider a video to be adversarial when at least 3 frames are classified as adversarial by the detection network. See Table 1 for the adversarial VDR results for PAT.

We tried different values of the threshold for adversarial frames to determine an adversarial video. We found empirically that a value of 3 for the threshold maintained a balance between false positives and true negatives.
Table 1: Adversarial Frame detection rate (FDR) and video detection rate (VDR) for PAT on UCF-101 and 20BN-Jester Dataset for different attacks.

| Attack Algorithm | FDR   | VDR   |
|------------------|-------|-------|
| UCF-101          |       |       |
| Sparse Attack    | 83.62%| 92.86%|
| Dense Attack     | 83.46%| 88.25%|
| 20BN-Jester      |       |       |
| Sparse Attack    | 75.9% | 80.7% |

positives and false negatives. Higher values of threshold led to higher number of adversarial videos being misclassified as clean which can pose a threat to the network. On the other hand, lower values of threshold led to higher number of clean videos being classified as adversarial, which is not desirable too.

Figure 3: Confusion matrix of PAT for the adversarial video detection when the adversarial videos are generated by both sparse and dense attack.

Fig. 3 shows the confusion matrix for detecting adversarial video using PAT on UCF-101 dataset. The adversarial videos contain a mix of videos generated by sparse and dense attack. The high true positives and true negatives along with low misclassification of videos for both the classes indicate the ability of PAT to detect adversarial videos without any prior knowledge of perturbations.

We also evaluate PAT using Area under Receiver Operating Characteristic curve (AUC) for comparing with other baselines. Table 2 shows the AUC results and the ROC curve for PAT is displayed in Fig. 4. This curve indicates that our approach has a high capability in differentiating between clean and adversarial videos. PAT achieves AUC of 94.2% on clean and adversarial (generated using both sparse and dense attack) videos.

In Table 2, the first row determines the performance of PAT when it is trained using the clean and adversarial videos. It is not surprising that the performance on both the attacks is high in this case as the network is aware of the perturbations. PAT can achieve almost as good performance (94.2% AUC which is just ∼ 5% lower) as the first case in Table 2, without actually having the knowledge of the real perturbations. Our method also outperforms [8] and [42] with an improvement of approximately 17% and 0.6% respectively.

Table 2: Comparison of PAT with other defenses (AUC) on UCF-101 dataset. The first column determines the type of defense mechanism used for defending the network against the adversarial videos. The last 3 columns determine the attack used to generate the test adversarial videos. The second last row is when the detection network is trained on set of clean and adversarial videos generated from sparse and dense attack, while the last row shows the results for the proposed method.

| Defense                   | Sparse | Dense | Sparse+Dense |
|---------------------------|--------|-------|--------------|
| Temporal+Spatial[8]       |   -    |   -   |    77%        |
| AdvIT[42]                 | 97%    |  -    |   -           |
| PAT (Adversarial data)    | 93.4%  | 99.8% | 99.8%         |
| PAT                       | 97.6%  | 94.1% | 94.2%         |

5 ABLATION STUDY

In this section, we showcase the importance of the two major components of the PAT algorithm - the transition frames and the varying value of standard deviation to generate the pseudo perturbations. We show how crucial these components are towards making our approach work well while being computationally inexpensive, effective, simple to implement at the same time using UCF-101 dataset.

5.1 Input Frame Analysis

Factors like color, texture and background add complexity to a frame. The attackers take advantage of such components to blend
Varying\* Dense 63.98% 0.01 52.31% 49.6%
Sparse 51.12% 0.0001 Varying\* 64.65%
80.12% 83.62% 83.46%

Table 3: Adversarial FDR showing the importance of key components of PAT using UCF-101. Sparse and Dense are the two attack baselines. PAT with transition frames and varying $\sigma$ outperform all other cases. *$\sigma$ varies between 0.0001-0.05.

| Frame Type | $\sigma$ | Sparse | Dense |
|------------|----------|--------|-------|
| Original   | Varying* | 92.31% | 51.12%|
| Transition | 0.0001   | 63.98% | 49.6% |
| Transition | 0.01     | 80.12% | 64.65%|
| Transition | Varying* | 83.62% | 83.46%|

in the added perturbations. This is where the transition frames play a major role in bringing the perturbations into the light. The transition frames, calculated using Eq. 2, eliminate the passive components in a frame and focus on the objects and their motion only. As a result, the perturbations have no way to blend in and therefore are clearly visible.

Fig. 5 shows an adversarial frame from a video belonging to UCF-101 dataset and its corresponding transition frame. The perturbations in the left image do not stand out while being prominently visible in the transition frame (on the right). As our main goal is to detect the adversarial frame, many components like the background become insignificant. As such insignificant components are removed in the transition frame, the perturbations can be viewed as well as processed by a network easily. This also helps in keeping the detection network architecture small reducing the training and inference time. For all the above reasons, transition frames are an essential part of keeping the PAT algorithm simple and accurate.

The 1st row of Table 3 shows the detection rate when original frames are used to train the detection network instead of the transition frames. The detection rate is almost equal to a random guess for both the attacks. This is because the original frames have a lot of information irrelevant for the detection task which acts as a perfect disguise for the perturbations. On the contrary, the transition frame keeps only relevant elements and has a higher adversarial frame detection rate.

5.2 Pseudo Perturbations Analysis
In PAT, the pseudo adversarial transition frames are generated using the Eq. 3. The standard deviation $\sigma$ is drawn from a uniform distribution and is different for every frame for each training epoch. This is crucial because the PAT can handle adversarial input with different perturbations.

The last 3 rows of Table 3 show the effect of different values of $\sigma$ on the adversarial FDR with transition frames as input to the detection network. The adversarial FDR when the value of $\sigma$ is fixed throughout the training process is lower as compared to the one when the value of $\sigma$ varies for every frame and epoch during training since the fixed values do not cover the variations in the actual perturbations. With varying standard deviation, the network learns from a different version of the same transition frame during every epoch. Also, we observed that in some cases of fixed $\sigma$, the network overfits at some point of time. For fixed $\sigma$ value of 0.01, the performance on the sparse attack is close to the best case FDR but the performance on the dense attack is poor. Thus, to achieve good performance on both the attacks, the transition frames and the varying standard deviation of Gaussian noise are both essential.

5.3 Run-time Analysis
To showcase that PAT is computationally inexpensive, we empirically measure the running time for the our detection process using Nvidia Titan XP GPU. We use a mix of both clean and adversarial (sparse as well as dense attack) videos to determine the average detection time for PAT. Our approach takes 0.01 seconds on an average to determine whether a video is adversarial, which is extremely low overhead to the existing action recognition systems.

5.4 Conclusion
We proposed a novel approach, PAT to detect the adversarial frames in a video efficiently and keep the video-based networks secure from different types of attacks. We achieve good detection rate without having any access to the attack or the perturbations, which is generally the case in real-world applications. Our experiments on UCF-101 and Jester datasets demonstrate that the approach is highly accurate in detecting the adversarial input produced by different attacks. We also show the detection of adversarial video based on the PAT detected frames. Furthermore, we demonstrated the importance of transition frames and the varying Gaussian noise to generate pseudo perturbations in achieving a good frame detection rate.

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