Sparse Adversarial Perturbations for Videos

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Abstract

Although adversarial samples of deep neural networks (DNNs) have been intensively studied on static images, their extensions in videos are never explored. Compared with images, attacking a video needs to consider not only spatial cues but also temporal cues. Moreover, to improve the imperceptibility as well as reduce the computation cost, perturbations should be added on as fewer frames as possible, i.e., adversarial perturbations are temporally sparse. This further motivates the propagation of perturbations, which denotes that perturbations added on the current frame can transfer to the next frames via their temporal interactions. Thus, no (or few) extra perturbations are needed for these frames to misclassify them. To this end, we propose an $l_{2,1}$-norm based optimization algorithm to compute the sparse adversarial perturbations for videos. We choose the action recognition as the targeted task, and networks with a CNN+RNN architecture as threat models to verify our method. Thanks to the propagation, we can compute perturbations on a shortened version video, and then adapt them to the long version video to fool DNNs. Experimental results on the UCF101 dataset demonstrate that even only one frame in a video is perturbed, the fooling rate can still reach 59.7%.

1 Introduction

In the past decade, Deep Neural Networks (DNNs) have shown great superiority in computer vision tasks, like image recognition [He et al., 2016], image restoration [Dong et al., 2014] and visual tracking [Wang and Yeung, 2013]. Although DNNs obtain the state-of-the-art performance in these tasks, they are known to be vulnerable to adversarial samples [Szegedy et al., 2013], i.e., the images with visually imperceptible perturbations that can mislead the network to produce wrong predictions. The adversarial samples are usually calculated by the Fast Gradient Sign Method (FGSM) [Goodfellow et al., 2014] and optimization-based methods [Moosavi-Dezfooli et al., 2016a]. One reason for adversarial samples is considered to be that they are fell on some areas in the high-dimensional feature space which are not explored during training. Thus, investigating adversarial samples not only helps understand the working mechanism of deep networks, but also provides opportunities to improve the networks’ robustness [Xie et al., 2017; Dong et al., 2017].

Up to now, many studies about adversarial samples have been investigated, such as adversarial perturbations for a single image [Moosavi-Dezfooli et al., 2016b], universal adversarial perturbations [Moosavi-Dezfooli et al., 2016a] and adversarial samples for object detection and segmentation [Xie et al., 2017]. However, these studies are all based on images, while leaving videos unexplored. Investigating adversarial
samples on videos is of both theoretical and practical values, as deep neural networks have been widely applied in video analysis tasks [Donahue et al., 2017; Nguyen et al., 2015; Wang et al., 2016].

Technically, the main difference between videos and images lies in the temporal structure contained in videos. Therefore, a properly designed attacking method should explore the temporal information to achieve efficiency and effectiveness. We expect that the perturbations added on one frame can propagate to other frames via temporal interactions, which will be called the propagation of perturbations. Besides, a video has many frames, computing perturbations for each frame is time-consuming, and actually not necessary. Whether it is possible that perturbations are added on only a few frames, and then are propagated to other frames to misclassify the whole video. In this way, the generated adversarial videos also have high imperceptibility and are hard to be detected. Because perturbations are added on sparse frames rather than the whole video, we call it the sparsity of perturbations. Actually, the propagation and sparsity interact with each other, propagation helps boost the sparsity, meanwhile the sparsity constraint will lead to better propagation.

For these reasons, in this paper, we aim to attack the video action recognition task [Poppe, 2010], where the temporal cue is a key component for the predicted label. This is naturally suitable to explore the temporal adversarial perturbations. For the threat model, we choose the networks with deep learning and adversarial attack.

The $l_{2,1}$-norm uses the $l_1$ norm across frames, and thus, enforces to select few key frames to add perturbations. As for propagation, we find perturbations show good propagation under the $l_{2,1}$ constraint within the recurrent neural network (such as Vanilla RNN, LSTM and GRU) because of the interaction with sparsity. Another advantage of the propagation is that we can compute perturbations on a shortened version video, and then adapt them to the long version video to fool DNNs, which provides a more efficient method to attack videos. The illustrations of our output and method are given in Fig. 1 and Fig. 2 respectively.

In summary, this paper has the following contributions:

- To our knowledge, we are the first to explore adversarial samples in videos. Considering the specific sparsity and propagation of video adversarial perturbations, we propose an $l_{2,1}$-norm regularization based optimization algorithm. We verify our method and evaluate its transferability on the UCF101 dataset.

- We give a comprehensive evaluation of the sparsity and propagation of perturbations, and furthermore, propose the propagation-based method for adversarial videos, i.e., computing perturbations on a shortened version video, and then adapt them to the long version video. We also find that LSTM and GRU are easier to be attacked than Vanilla RNN, because LSTM and GRU can represent long memory, which is favor to the perturbation propagation (see experiments).

The rest of this paper is organized as follows. In Section 2, we briefly review the related work. We present our algorithm in Section 3. Section 4 reports all experimental results. Finally, we summarize the conclusions in Section 5.

2 Related Work

The related work comes from two aspects: action recognition with deep learning and adversarial attack.

2.1 Action Recognition with Deep Learning

Action recognition is a core task in computer vision, where its goal is to predict a video-level label when given a video clip [Poppe, 2010]. With the rise of deep convolutional neural networks (CNNs) achieving state-of-the-art performance on image recognition, many works have looked into designing effective deep CNNs for action recognition. For instance, various approaches of fusing CNN features computed on RGB frames over the temporal dimension are explored on the Sport1M dataset [Karpathy et al., 2014]. To integrate the temporal information, CNN+LSTM based models, which use a CNN to extract frame features and an LSTM to integrate features over time, are also presented to recognize activities in videos [Donahue et al., 2017; Nguyen et al., 2015]. Optical flow is also useful to encode the temporal cue. For this, two stream CNNs with one stream of static images and the other stream of optical flows are proposed to fuse the information of object appearance and short-term motions [Simonyan and Zisserman, 2014]. Temporal Segment Networks sample frames and optical flow on different time segments to extract information for activity recognition [Wang et al.,]
In our paper, to better explore how the perturbations change along with the time, we choose the networks with a CNN+RNN architecture as the threat model.

2.2 Adversarial Attack

Generating adversarial examples for classification has been extensively studied in many different ways recently. Szegedy et al. [2013] first show that adversarial examples, computed by adding visually imperceptible perturbations to the original images, make CNNs predict a wrong label with high confidence. Goodfellow et al. [2014] propose a simple and fast gradient sign method to generate adversarial examples based on the linear nature of CNNs. Moosavi-Dezfooli et al. [2016b] propose a simple algorithm to compute the minimal adversarial perturbation by assuming that the loss function can be linearized around the current data point at each iteration. Moosavi-Dezfooli et al. [2016a] show the existence of universal (image-agnostic) adversarial perturbations.

Baluja and Fischer [2017] train a network to generate adversarial examples for a particular target model (without using gradients). Kurakin et al. [2016] show that the adversarial examples for machine learning systems also exist in the physical world. Liu et al. [2016] study the transferability of both non-targeted and targeted adversarial examples, and proposed an ensemble-based approaches to generate adversarial examples with stronger transferability. The above papers are all based on images, while we focus on video adversarial samples, which have new challenges.

3 Methodology

In this section, we introduce the proposed $l_{2,1}$-norm based algorithm for video adversarial samples. Our method is an optimization-based approach.

Let $X \in \mathbb{R}^{T \times W \times H \times C}$ denote a clean video, and $\hat{X}$ denote its adversarial video, where $T$ is the number of frames, $W, H, C$ are the width, height, and channel for a specific frame, respectively. $E = \hat{X} - X$ is the adversarial perturbations. To generate non-targeted adversarial examples, we approximate the solution to the following objective function:

$$\arg\min_{\lambda \in \mathbb{R}} |E|_p - \ell(Y, \theta(\hat{X})),$$  \hspace{1cm} (1)

where $\ell(\cdot, \cdot)$ is the loss function to measure the difference between the prediction and the ground truth label. In this paper, we choose the widely used cross-entropy function $\ell(u, v) = \log(1 - u + v)$, which is shown to be effective [Carlini and Wagner, 2017]. $J_\theta(\cdot)$ is the threat model with parameters $\theta$. $Y_i$ is the one-hot encoding of the ground truth label $y_i$. $|E|_p$ is the $l_p$ norm of $E$, which is a metric to quantify the magnitude of the perturbation. $\lambda$ is a constant to balance the two terms in the objective.

To obtain a universal adversarial perturbation across videos, we solve the following problem:

$$\arg\min_{\lambda \in \mathbb{R}} |E|_p - \frac{1}{N} \sum_{i=1}^{N} \ell(Y_i, \theta(\hat{X}_i)),$$  \hspace{1cm} (2)

where $N$ is the total number of training videos, and $\hat{X}_i$ is the $i$-th adversarial video.

To better control the sparsity and study the perturbation propagation across frames, we add a temporal mask on the video to enforce some frames having no perturbations. The problem is modified as follows:

$$\arg\min_{\lambda \in \mathbb{R}} |M \cdot E|_p - \frac{1}{N} \sum_{i=1}^{N} \ell(Y_i, \theta(X_i + |M| \cdot E)),$$  \hspace{1cm} (3)

where $M \in \{0, 1\}^{T \times W \times H \times C}$ is the temporal mask. We let $\theta(\cdot)$ be the set of frame indices, $\Theta$ is a subset within $\theta(\cdot)$ having $K$ elements, and $\Psi = \theta(\cdot)$. If $t \in \Theta$, we set $M_t = 0$, and if $t \in \Psi$, $M_t = 1$, where $M_t = \{0, 1\}^{W \times H \times C}$ is the $t$-th frame in $M$. In this way, we enforce the computed perturbations to be added only on the selected video frames. We here regard $\frac{\lambda}{2}$ as the sparsity.

If the goal is to generate targeted adversarial examples (i.e., the misclassified label is set to the pre-fixed label, which is called target label), the problem can be modified as follows:

$$\arg\min_{\lambda \in \mathbb{R}} |M \cdot E|_p + \frac{1}{N} \sum_{i=1}^{N} \ell(Y^*_i, \theta(X_i + |M| \cdot E)),$$  \hspace{1cm} (4)

where $y^*_i$ is the targeted label. Eq.(4) outputs the perturbations to make $J_\theta(\cdot)$ predict $y^*_i$ with a high probability.

Perturbation Regularization

The $l_p$-norm in problem (1) is a metric to quantify the magnitude of the perturbation. As mentioned before, we hope that the perturbations are added on as fewer frames as possible. Therefore, we choose $l_{2,1}$ norm to meet this goal, where $\lambda$ is widely used in sparse coding methods [Wright et al., 2009].

Yang et al., 2010. $||E||_{l_1} = \sum_t^{T} ||E_t||_2$, where $E_t \in \mathbb{R}^{W \times H \times C}$ is the $t$-th frame in $E$. $l_{2,1}$ norm apply the $l_1$ norm across the frames, and thus, can ensure the sparsity of generated perturbations. In the experiment, we also show the results using $l_2$ norm, as the comparison with the $l_{2,1}$ norm.

 Threat Model

In action recognition, the current state-of-the-art approach is the two-stream model [Donahue et al., 2017], i.e., one stream is to capture the RGB frames, and another stream is to capture the optical flow images (motion information) between two adjacent RGB frames. The outputs from these two streams are fused to predict the final label with various kinds of fusion methods. These two streams usually have the same network architecture, where one choice is CNN+Pooling, and another is CNN+RNN architecture. Compared with CNN+Pooling, CNN+RNN can encode the temporal information. In our paper, we regard the networks with CNN+RNN architecture as the threat model $J_\theta(\cdot)$. The results of attacking CNN+Pooling also are reported for comparisons. We give the illustration of the CNN+RNN model in Fig. 2. Note that, the CNN and RNN in the figure are the general terms for the spatial and temporal networks, respectively. CNN can be specified as ResNet, Inception V3, etc, and RNN as LSTM, GRU, etc.

Training

Problems (1)(2)(3) are easy to solve. Any Stochastic Gradient Descent (SGD) algorithm can solve them. Here, we use the Adam [Kingma and Ba, 2014] algorithm to get the results.
Because $l_{2,1}$ norm is used, initializing the perturbations with zeros will lead to NaN values. We instead initialize them using a small value. In the experiments, we use 0.0001. After some iterations, the perturbations will converge to a sparse result. $\lambda$ in problem (1,2,3,4) is set to a constant, which is tuned in the training set. Temporal mask $M$ is predefined according to the needed sparsity. We investigate some choices, and give the corresponding discussions about its impact to the proposed method (see experiments).

4 Experiments

In this section, we give the experiments from three aspects.

4.1 Datasets and Metrics

Datasets: We choose the widely used dataset in action recognition: UCF101 dataset [Soomro et al., 2012]. It contains 13,320 videos with 101 action classes covering a broad set of activities such as sports, musical instruments, body-motion, human-human interaction, human-object interaction. The dataset splits more than 8000 videos in the training set, and more than 3000 videos in the testing set.

Because there are no other existing methods for video adversarial samples, we can only compare with the methods based on images, i.e., computing perturbations for each frame [Moosavi-Dezfooli et al., 2016b] in a video. This setting is coincident with the outputs using Eq.(1) with $l_2$ norm, which are reported as the comparisons.

Metrics: We use three metrics to evaluate various aspects.

Fooling ratio (F): is defined as the percentage of adversarial videos that are successfully misclassified [Moosavi-Dezfooli et al., 2016a].

Perceptibility (P): denotes the proportion of frames that are perceptible.

Sparsity (S): denotes the proportion of frames with no perturbations (clean frames) versus all the frames in a specific video to fool DNNs. $S = \frac{K}{T}$, where $K$ is the number of clean frames, and $T$ is the total number of frames in a video.

4.2 Perturbation Propagation

In this section, we give the experimental results about the perturbation propagation.

Visualization for Perturbations

We firstly give the visualization of perturbations computed using Eq.(2) with $l_{2,1}$ norm, which are universal perturbations across videos. In Fig. 3, we see that the adversarial videos are not distorted by the perturbations, and are imperceptible to human eyes. Furthermore, the perturbations show the sparse property (black means no perturbations), i.e., they are reduced across frames along with the time, which is owing to the used $l_{2,1}$ norm. In the next section, we will discuss the propagation of perturbations, inspired by these sparse results.

Perturbation Propagation

To show the perturbation propagation, we give four examples outputted by Eq.(1) with $l_{2,1}$ norm in Fig.4 (see the blue line with stars), where we see the computed perturbations successfully fool the action recognition networks (for example, in the first case, a clean video with label of Bench Press is identified as Lunges after adding perturbations). Correspondingly, the original frame-level labels (red dotted line) are also misclassified as wrong labels (black dotted line). By contrast, the Mean Absolute Perturbation (MAP) value of each frame is reduced significantly along with the time. In the last few frames, they fall into almost zeros. That’s to say, although few perturbations are added on these frames, the perturbations from the previous frames propagate here, and help fool the DNNs. As a comparison, we also list the results of Eq.(1) with $l_2$ norm in Fig.4 (see the magenta line with circles). In this figure, the MAP value is also reduced across frames, which further demonstrates the perturbation propagation. The
Figure 4: Four examples for showing perturbation propagation on UCF101 dataset. The x-axis denotes the frame indices in a video. The left y-axis denotes the Mean Absolute Perturbation (MAP) value of each frame’s perturbations, and the right y-axis is the label indices. The blue line with stars is the curve of MAP values with $l_{2,1}$ norm, and magenta line with circles is the result with $l_2$ norm. The red dotted line is the predicted frame-level label indices for the clean video, and black dotted line is the predicted frame-level label indices for the adversarial video, both by the action recognition networks (the video-level labels are listed in the top of each figure with the same color). In the bottom of each figure, we give the corresponding video frames. For detailed discussions, please see the texts.

Figure 5: Four examples of showing perturbation propagation on UCF101 dataset. The difference with Fig. 4 lies in the integration of temporal mask proposed in Eq. (3). For detailed discussions, please see the texts.

difference is, the output of $l_{2,1}$ norm is sparse, which reveals that the frames ranking behind the video line actually need few (even no) perturbations to fool DNNs with the help of propagation. But $l_2$ norm cannot show this property.

Inspired by the sparsity of $l_{2,1}$ norm, we directly enforce perturbations not to be added on the frames ranking behind the video line. To this end, we add the temporal mask during the optimization process using Eq.(3). Here we only select the top 8 frames to compute their perturbations, and let the other frames be clean. The experimental results on the same videos are listed in Fig. 5. We find that the frames are still predicted as wrong labels. Furthermore, the MAP values of these frames also show a decreasing trend. It is further demonstrated the propagation of perturbations. Otherwise, these clean frames cannot be predicted as wrong labels. Note that in the forth case in Fig. 5 the final 4 frames have correct labels, which shows perturbations will reduce its effect along with the time, and cannot propagate forever.

Table 1: The results of fooling rates versus different sparsities.

| S    | 0%(40) | 80%(8) | 90%(4) | 97.5%(4) |
|------|--------|--------|--------|----------|
| F    | 100%   | 100%   | 91.8%  | 59.7%    |
| P    | 0.0698 | 0.6145 | 1.0504 | 1.9319   |

We now gradually enlarge the sparsity $S$ in Eq.(3), and observe the change of Fooling ratio $F$ in the testing set on UCF101 dataset. High sparsity $S$ means more clean frames, and less adversarial frames in the video. We give the quantitative results of fooling rates versus different sparsities in Table. 1. In the table, we list four sparsities ($S$) and their corresponding Fooling rates ($F$) as well as perceptibility scores ($P$). Taking $90\% (4)$ as an example, $90\% = 1 - \frac{4}{40}$, where 4 is top four polluted frames, and 40 is the total number of frames in the video. The results in Table 1 show that even only one frame is polluted ($S = 97.5\%$), the Fooling rate can also reach 59.7%. To achieve the 100% fooling rate, the least number of polluted frames is 8 ($S = 80\%$) on the used dataset. We also see that the perceptibility score is gradually increasing with the rise of sparsity score, and reach the top in $S = 97.5\%$. This is reasonable because large perturbations can spread to more frames. The polluted top one frames in $S = 97.5\%$ and their corresponding clean frames
are illustrated in Fig. 6, where we see that despite the largest $P = 1.9319$, the adversarial frames are the same to the clean frames, which are not perceptible to human eyes.

**Adversarial Video based on Propagation**

Thanks to the perturbation propagation, we don’t need to compute perturbations based on the whole video. Instead, we can compute perturbations on a shorten version video, and then adapt them to the long version video. In this way, the computation cost is reduced significantly. We report the time of computing perturbations for various frames in Table 2 where we see the computing time is linearly reduced with the rise of sparsity, showing that computing perturbations on a shorten version video can reduce computation cost.

Specifically, to fool the action recognition network for a given video, we first choose the top $N$ frames $\{F_1, ..., F_N\}$ from the original video, and then use Eq. (1) (for a single video) or Eq. (2) (for getting universal perturbations) with $l_2$ norm to compute their adversarial frames $\{\hat{F}_1, ..., \hat{F}_N\}$. Finally, we replace $\{F_1, ..., F_N\}$ with $\{\hat{F}_1, ..., \hat{F}_N\}$ in the original video. This modified video is then input to the action recognition networks. Note that, here we don’t use the $l_{2,1}$ norm. Because the $l_{2,1}$ norm will result in the sparse perturbations during these $N$ frames, which are not good for further propagation to the rest clean frames. We plot the comparisons between $l_2$ and $l_{2,1}$ norm in this setting in Fig. 7. In this figure, we see the performance of $l_2$ norm is advantageous to $l_{2,1}$ norm. In the next section, we will give the detailed evaluations and discussions of this method. In default, we set $N = 20$ and use $l_2$ norm in the following experiments.

Table 2: Time for computing perturbations in one iteration.

| $S$  | 0%  | 50%  | 75%  | 87.5% | 97.5% |
|------|-----|------|------|-------|-------|
| Time | 2.853s | 1.367s | 0.612s | 0.346s | 0.0947s |

4.3 Performance and Transferability

In this section, we evaluate the performance and transferability of the propagation based method.

**Transferability across Models**

We firstly evaluate the transferability of computed perturbations. Because the transferability of CNN networks has been studied in many literatures, we here mainly explore the RNN networks, including Vanilla RNN, LSTM, and GRU. Besides, the results of CNN + Average Pooling (removing the RNN layer in Fig. 2) are also reported. The Fooling rates in different settings are given in Table 3 where we use the networks in rows to generate perturbations, and networks in columns evaluate the transferability. Form the table, we draw the following conclusions: 1. The diagonals have largest values. It is reasonable because they perform the white-box attack in this setting. 2. In the off-diagonals, the values are all above 65%, which shows perturbations in videos have good transferability, especially in the RNN models. 3. In the off-diagonals, the Pooling column has the poor performance. Pooling method has no memory like LSTM or GRU, and thus, the perturbations cannot propagate to other frames, resulting in the poor performance. 4. By contrast, the GRU and LSTM columns have better performance than VanillaRNN. As we known, GRU and LSTM can represent long memory, this demonstrates long memory is favor to the propagation of perturbations, and thus GRU and LSTM are easier to be attacked than VanillaRNN.

Figure 7: Comparisons between $l_2$ and $l_{2,1}$ norm versus Fooling rate on UCF101 dataset. We here report the results when $N = 1, 5, 10, 20, 40$, respectively. The total number of frames is 40.

Table 3: Fooling rates in different settings on UCF101 dataset.

| Models    | VanillaRNN | LSTM | GRU | Pooling |
|-----------|-------------|------|-----|---------|
| Fooling   | 95.2%       | 95.2%| 95.2%| 71.0%   |
| LSTM      | 84.1%       | 100% | 97.1%| 76.8%   |
| GRU       | 81.8%       | 92.4%| 100% | 66.7%   |
| Pooling   | 84.1%       | 96.8%| 95.2%| 87.3%   |

5 Conclusions

In this paper, we explored the adversarial perturbations for videos. An $l_{2,1}$-norm based optimization algorithm was proposed to solve this problem. The $l_{2,1}$ norm applied the $l_1$ norm across frames, and thus, can ensure the sparsity of perturbations. A serial of experiments conducted on UCF101 dataset demonstrated that our method had better transferability across models and videos. More importantly, our method showed the propagation of perturbations under the $l_{2,1}$ constraint within the CNN+RNN architecture. According to this observation, we further presented the efficient method for adversarial videos based on the perturbation propagation.
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