Using LIP to Gloss Over Faces in Single-Stage Face Detection Networks

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Abstract

This work shows that it is possible to fool/attack recent state-of-the-art face detectors which are based on the single-stage networks. Successfully attacking face detectors could be a serious malware vulnerability when deploying a smart surveillance system utilizing face detectors. We show that existing adversarial perturbation methods are not effective to perform such an attack, especially when there are multiple faces in the input image. This is because the adversarial perturbation specifically generated for one face may disrupt the adversarial perturbation for another face. In this paper, we call this problem the Instance Perturbation Interference (IPI) problem. This IPI problem is addressed by studying the relationship between the deep neural network receptive field and the adversarial perturbation. As such, we propose the Localized Instance Perturbation (LIP) that uses adversarial perturbation constrained to the Effective Receptive Field (ERF) of a target to perform the attack. Experiment results show the LIP method massively outperforms existing adversarial perturbation generation methods – often by a factor of 2 to 10.

1. Introduction

Deep neural networks have achieved great success in recent years on many applications [26, 9, 5, 24, 13, 23, 6, 31, 15]. However, it has been demonstrated in various works that by adding tiny, imperceptible perturbations onto the image, the network output can be changed significantly [27, 4, 14, 21, 19, 10, 28, 17]. These perturbations are often referred to as adversarial perturbations [4].

Developing methods to generate adversarial perturbations that can effectively fool or attack a neural network is still an active research area [27, 4, 14, 21, 19, 10, 28, 17]. Most prior works are primarily aimed at generating adversarial perturbations to fool neural networks for image classification tasks [27, 4, 14, 21, 19, 10, 18]. It is relatively easier to attack these networks as the perturbations need to change only one network decision for each image containing an instance/object of interest. This means, there is only a single target and the target is the entire image.

Recently, several methods have been proposed on more challenging attacks to deep networks for segmentation and object detection tasks where there are significantly more targets to attack within the input image [28, 17, 3, 2]. In [17, 3, 2], adversarial generation methods are proposed to fool semantic segmentation networks in 2017. Xie et al. [28] proposed an approach to attack a Faster-RCNN network [24] trained for object detection tasks.

Inspired by the above research, in this work, we tackle the problem of generating effective adversarial perturbations for face detection networks. Deep neural networks have been shown to be extremely effective in detecting faces, especially in the unconstrained environment [11, 22, 31, 29, 1, 12, 6, 20, 32]. However, successfully fooling these networks could pose a serious security vulnerability for deploying the solution in real scenarios. This is because one could potentially use a black box or malware that adds imperceptible perturbation signals into a CCTV camera feed. In this work, we show that it is possible to perform an attack to disable the ability of the face detector to detect faces. To the best of our knowledge, this is the first study that attempts to perform such an attack on a single-stage network face detector.

In recent years, several deep network based methods are proposed for face detection that can handle challenging cases such as tiny face detection [6, 20, 32]. In [8], Faster-RCNN is used for face detection where a shallow region proposal network is applied to generate candidates and a deep classification network is utilized for the final decision. The Single-Stage (SS) network has been previously studied in object detection [13, 23], which is similar to the region proposal network in Faster-RCNN [24] but performs both object classification and localization simultaneously. By utilizing the Single-Stage network...
architecture, recent detectors [6, 20, 32] can detect faces on various scales with a much faster running time. Due to their excellent performance, we confine this paper to attacking the most recent face detectors utilizing Single-Stage network.

Unfortunately, attacking a Single-Stage detector is challenging because of the Instance Perturbation Interference (IPI) problem. The IPI problem can be briefly explained as cross-channel interference between the perturbation required to attack one instance and the perturbation required to attack a nearby instance. Since the recent adversarial perturbation methods [28, 17] do not consider this problem, they become quite ineffective in attacking SS face detector networks.

In this work, we attribute the IPI problem to the receptive field of deep neural networks. Recent works show that the receptive field follows a 2D Gaussian distribution, where the set of input image pixels closer to an output neuron have higher impact on the neuron decision. The area where high impact pixels are concentrated is referred to as the Effective Receptive Field (ERF) [16]. As illustrated in Figure 1, if two faces are close to each other, the perturbation generated to attack one face will reside in the ERF of another face, which significantly hampers the success of attacking the other face. In other words, the IPI problem happens when the interfering perturbations disrupt the adversarial perturbations generated for the neighboring faces. This IPI problem will become more serious when multiple faces exist in close proximity. We believe this is the first work that describes and addresses the IPI problem.

Contributions - We list our contributions as follows: (1) We describe the Instance Perturbation Interference problem that makes the existing adversarial perturbation generation method fail to attack the SS face detector networks when multiple faces exist; (2) This is the first study to show that it is possible to attack deep neural network based face detector. More specifically, we show that it is possible to attack Single-Stage based face detector networks. (3) To perform the attack, we address the IPI problem by generating instance based perturbations that are confined inside each instance ERF. We call our proposed method Localized Instance Perturbation (LIP).

We continue our paper as follows. We discuss related work and background in Section 2. Then we describe the Instance Perturbation Interference problem in Section 3. The proposed Localized Instance Perturbation is described in Section 4 followed by the validation experiments in Section 5. Finally, we draw our conclusions in Section 6.

2. Background

In this section, we will discuss recent studies on adversarial attacks and the loss function.

2.1. Adversarial Perturbation

As mentioned, attacking a network means attempting to change the network decision on a particular target. A target \( t \) is defined as a region in the input image where the generated adversarial perturbation is added to change the network decision corresponding to this region. Generally a target covers an instance of interest. For example, the target \( t \) for attacking an image classification network is the entire image.
The adversarial perturbation concept was first introduced for attacking image classification networks in [27, 4, 14, 21, 19, 10, 18]. Szegedy et al. [27] showed that by adding imperceptible perturbations to the input images, one could make the Convolutional Neural Network (CNN) predict the wrong class label with high confidence. Goodfellow et al. [4] explained that the vulnerability of the neural networks to the adversarial perturbations is caused by the linear nature of the neural networks. They proposed a fast method to generate such adversarial perturbations, naming the method Fast Gradient Sign Method (FGSM) defined by:

$$\xi = \alpha \text{sign}(\nabla_X \ell(f_\theta(X), y_{\text{true}})),$$

where $\alpha$ was a hyper-parameter [4]. The gradient was computed with respect to the entire input image $X \in \mathbb{R}^{w \times h}$ by back-propagation and the function sign() is the $L_{\infty}$ norm. Following this, Kurakin et al. [10] proposed to extend FGSM by iteratively generating the adversarial perturbations. At each iteration, the values of the perturbations were clipped to control perceptibility. To reduce perceptibility, Moosavi-Dezfooli et al. [19] proposed to iteratively add the minimal adversarial perturbations to the images by assuming the classifier was linear at each iteration. The existence of universal perturbations for image classification was shown in [18]. We note that, in this work, we do not aim to generate universal perturbations.

More recently, adversarial examples were extended into various applications such as semantic segmentation [28, 17, 2, 3] and object detection [28]. Metzen et al. [17] adapted an approach described in [10] into the semantic segmentation domain, where every pixel was a target. They demonstrated that the gradients of the loss for different target pixels might point to the opposite directions.

In object detection, the instances of interest are the detected objects. Thus, the targets are the detected region proposals containing the object. An approach for generating adversarial perturbations for object detection is proposed in [28]. They claimed that generating adversarial perturbations in object detection was more difficult than in the semantic segmentation task. In order to successfully attack a detected object, one needs to ensure all the region proposals associated with the object/instance are successfully attacked. For example, if only $K$ out of $R$ region proposals are successfully attacked, the detector can still detect the object by using the other high-confidence-score region proposals that are not successfully attacked.

Note that we talk about the above approaches use whole image perturbations which have the same size as the input image. This is because these perturbations are generated by calculating the gradient with respect to the entire image. Thus, a generated perturbation for one target may disrupt the perturbations generated for other targets. To contrast these methods with our work, we categorize these methods as **Image based Perturbation (IMP)** methods.

### 2.2. Loss function

In general, the perturbations are generated by optimizing a specific objective function. Let $\mathcal{L} = \sum_{t=1}^{T} \mathcal{L}_{t_i}$ be the loss function to optimize. The objective function is defined as follows:

$$\arg \min_{\xi} \sum_{t=1}^{T} \mathcal{L}_{t_i}(\xi),$$

where $T$ is the number of targets; $\mathcal{L}_{t_i}$ is the loss function for each individual target $t_i$; and $\xi \in \mathbb{R}^{w \times h}$ is the adversarial perturbation which will be added into the input image $X$.

According to the goals of adversarial attacks, the attacks can be categorized into **non-targeted adversarial attacks** [4, 18, 28] and **targeted adversarial attacks** [10, 17]. For non-targeted adversarial attacks, the goal is to reduce the probability of truth class $y_{\text{true}}$ of the given target $t$ and to make the network predict any arbitrary class, whereas the goal of targeted adversarial attacks is to ensure the network predict the target class $y_{\text{target}}$ for the target $t$. The objective function of the targeted attacks can be summarized into the following formula:

$$\arg \min_{\xi} \mathcal{L}_{t_i} = \ell(f_\theta(X + \xi, t_i), y_{\text{target}}) - \ell(f_\theta(X, t), \mathcal{L}_{t_i}(\xi)), y_{\text{true}}).$$

where, $\xi$ is the optimum adversarial perturbation; $f_\theta$ is the network function that admits the perturbed image and the target region; and $f$ is the network loss function.

In general, the face detection problem is considered as a binary classification problem, which aims at classifying a region as face (+1) or non-face (-1) (i.e. $y_{\text{target}} = \{+1, -1\}$). However, in order to detect faces in various scales, especially for tiny faces, recent face detectors utilizing Single-Stage networks [6, 20, 32] divide the face detection problem into multiple scale-specific binary classification problems, and learn their loss functions jointly. The objective function to attack such a network is defined as:

$$\arg \min_{\xi} \mathcal{L}_{t_i} = \sum_{j=1}^{S} \ell_{s_j}(f_\theta(X + \xi, t_i), y_{\text{target}}).$$
| N | 1 | 9 | 81 |
|---|---|---|---|
| Distance | 40 | 160 | 240 |
| IMP | 100 | 51.5 | 63.9 |

Table 1. The IMP attack success rate (in %) on the synthetic images with respect to the number of faces and distances among faces. N is the number of faces. The IMP can achieve 100% attack success rate when there is one face per image. The attack success rate drops significantly when the number of faces is increased. With the same number of faces, the attack success rate can be increased as the distance among faces increases.

where, $S$ is the number of scales; and $\ell_{s_j}$ is the scale-specific detector loss function. Compared to Eq. 3, the above objective is more challenging. This is because a single face not only can be detected by multiple region proposals/targets, it can also be detected by multiple scale-specific detectors. Thus, one can only successfully attack a face when the adversarial perturbation fools all the scale-specific detectors.

Finally, as our main aim is to prevent faces being detected, then our objective function is formally defined as:

$$L = \sum_{i=1}^{T} \sum_{j=1}^{S} \ell_{s_j}(f_{\theta}(X + \xi, t_i), -1).$$

(5)

In this work, we use the recent state-of-the-art Single-Stage face detector, HR [6], which jointly learns 25 different scale-specific detectors, i.e., $S = 25$. Note that since our aim is to fail detection, we set the target label as $-1$.

### 3. Instance Perturbations Interference

When performing an attack using the existing adversarial perturbation approaches [10, 17], the Instance Perturbations Interference (IPI) problem appears when multiple faces exist in the input image. In short, the IPI problem refers to the conditions where successfully attacking one instance of interest can reduce the chance of attacking the other instances of interest. For the face detection task, the instance of interest is a face. If not addressed, the IPI problem will significantly reduce the overall attack success rate.

To show the existence of the IPI problem, we perform an experiment using synthetic images. In this experiment, we apply an adaptation of the existing perturbation methods generated by minimizing Eq. 5.

#### 3.1. Image based perturbation

As mentioned, we categorize the previous methods as Image based Perturbation as they use whole image perturbation to perform the attack. Here we adapt one of the existing methods in [10] by optimizing Eq. 5. Following [10], the adversarial perturbation is generated by using a gradient descent approach. In each iteration, the gradient with respect to the input image, $\nabla_X L(f_{\theta}(X), y^{true})$, is generated via back-propagating the network with the loss function in Eq. 5. The aim is to minimize the loss of predicting incorrect labels, i.e., non-face. Thus, we iteratively update the adversarial perturbation as follows:

$$\xi^{(n+1)} = \text{Clip}_{\varepsilon}\{\xi^{(n)} - \alpha \text{sign}(\nabla_X L(f_{\theta}(X) + \xi^{(n)}, -1)\}.$$

(6)

where the step rate $\alpha = 1$; the epsilon $\varepsilon$ is the maximum absolute magnitude to clip; and $\xi^{(0)} = 0$. Note that in Eq. 5, the loss function is a summation of the loss of all targets. Thus, the aggregate gradient, $\nabla_X L$, can be rewritten as:

$$\nabla_X L(f_{\theta}(X + \xi^{(n)}, -1) = \sum_{i=1}^{T} \sum_{j=1}^{S} \nabla_X \ell_{s_j}(f_{\theta}(X + \xi^{(n)}, t_i), -1).$$

(7)

As we assume $f_{\theta}$ is a deep neural network, then the aggregate gradient $\nabla_X L$ can be obtained by back-propagating all of the targets at once.

After obtaining the final adversarial perturbation $\xi$, the perturbed image, $X^{adv}$, is then generated by:

$$X^{adv} = X + \xi.$$

(8)
3.2. Existence of the IPI problem

To show the existence of the IPI problem, we construct a set of synthetic images by controlling the number of faces and distances between them: (1) an image containing only one face; (2) an image containing multiple faces closely located in a grid and (3) using image (2) but increasing the distance between the faces. Examples are shown in Figure 2. For this experiment, we use the recent state-of-the-art face detector HR-ResNet101 [6]. The synthetic images are constructed by randomly selecting 50 faces from the WIDER FACE dataset [30]. Experimental details are given in Section 5.2. We generate the adversarial perturbations using the IMP approach.

The attack success rate is calculated as follows: \[
\text{Attack success rate} = \frac{\text{#Face removed}}{\text{#Detected face}}
\]

Table 1 reports the results. For the first synthetic case where an image only contains one face, IMP is able attack the face detector with a 100% attack success rate. The IMP method is only partially successful on the second case where the number of faces is increased to 9. The attack success rate decreases significantly to only 18.3% when \(N = 81\). The IMP method attack success rate significantly increases when the distances between faces are increased significantly.

These results suggest the following: (1) IMP is effective when only a single face exists; (2) IMP is ineffective when multiple faces exist close to each other and (3) the distance between faces significantly affects the attack performance. There are two questions that arise from these results: (1) why is the attack affected by the number of faces? and (2) why does the distance between faces affect the attack success rate? We address these two questions in the next section.

4. Proposed method

We first elaborate on the relationship between the Effective Receptive Field and the IPI problem. Then, the proposed Localized Instance Perturbation (LIP) method is outlined.
4.1. Effective Receptive Field (ERF)

The receptive field of a neuron in a neural network is the set of pixels in the input image that impact the neuron decision \([16]\). In CNNs, it has been shown in \([16]\) that the distribution of impact within the Theoretical Receptive Field (TRF) of a neuron follows a 2D Gaussian distribution in many cases. This means most pixels that have significant impact to the neuron decision are concentrated near the neuron. In addition, the impact decays quickly away from the center of the TRF. In \([16]\), the area where pixels still have significant impact to the neuron decision is defined as the Effective Receptive Field (ERF). The ERF only takes up a fraction of the TRF and pixels within the ERF will generate non-negligible impacts on the final outputs. We argue that understanding ERF and TRF is important for addressing the IPI problem. This is because the adversarial perturbation is aimed at changing a network decision at one or more neurons. This means, all pixels in the input image that impact the decision must be considered when determining the perturbation.

In this paper, we denote the distribution of impacts in the TRF as DI-TRF for simplicity. The DI-TRF is measured by calculating the partial derivative of the central pixel on the output layer via back-propagation. Following the notations in our paper, let us denote the central pixel as \(t_c\), then the partial derivative of the central pixel is \(\frac{\partial f_\theta(X,t_c)}{\partial X}\), which is the DI-TRF. According to the chain rule, we have the gradient of the target \(t_c\) \([16]\) as:

\[
\nabla_X \mathcal{L}(f_\theta(X,t_c), y_{\text{target}}) = \frac{\partial \mathcal{L}(f_\theta(X,t_c), y_{\text{target}})}{\partial f_\theta(X,t_c)} \frac{\partial f_\theta(X,t_c)}{\partial X} ,
\]

where the \(\frac{\partial \mathcal{L}(f_\theta(X,t_c), y_{\text{target}})}{\partial f_\theta(X,t_c)}\) is set to 1.

Comparing the gradient of a target pixel for the adversarial perturbations in Eq. 7, the only difference with the DI-TRF is in the partial derivative of the loss function \(\frac{\partial \mathcal{L}(f_\theta(X,t_c), y_{\text{target}})}{\partial f_\theta(X,t_c)}\), which is a scalar for one target pixel. In our work, the scalar, \(\frac{\partial \mathcal{L}(f_\theta(X,t_c), y_{\text{target}})}{\partial f_\theta(X,t_c)}\), measures the loss between the prediction label and the target label. The logistic loss is used for the binary classification of each scale-specific detector, \(i.e.\) the \(\ell_s(f_\theta(X,t_c), y_{\text{target}})\) in Eq. 5). Therefore, our adversarial perturbation for one target can be considered as a scaled distribution of the DI-TRF. Since DI-TRF follows a 2D Gaussian distribution \([16]\), then the adversarial perturbation to change a single neuron decision is also a 2D Gaussian.

We explain the IPI problem as follows. Since an adversarial perturbation to attack a single neuron follows a 2D Gaussian, then the perturbation is mainly spread over the ERF and will have a non-zero tail outside the ERF. From the experiment, we observed that the perturbations generated to attack multiple faces in the image may interfere with other. More specifically, when these perturbations overlap with the neighboring face ERF, they may be sufficient enough to disrupt the adversarial perturbation generated to attack this neighboring face. In other words, when multiple attacks are applied simultaneously, these attacks may corrupt each other, leading to a lower attack rate. We name the part of a perturbation interfering with the other perturbations for other faces as the interfering perturbation.

This also explains why the IPI is affected by the distance between faces. The closer the faces, the more chance the interfering perturbations with a larger magnitude overlap with the neighboring face ERF. When distances between faces increase, the magnitude of the interfering perturbations that overlap with the neighboring ERFs may not be strong enough to disrupt attacks for neighboring faces.

**Algorithm 1** The proposed LIP algorithm

**Input:** Input image \(X \in \mathbb{R}^{w \times h}\), instances \(\{m_i\}_{i=1}^N\) \(\text{ERF} \{e_i\}_{i=1}^N\), maximum iteration \(N_0\)

**Output:** output adversarial perturbation \(R \in \mathbb{R}^{w \times h}\)

1: Initialize \(R \leftarrow 0\)
2: while \(n < N_0\) do
3: Initialize \(R^{(n)} \leftarrow 0\)
4: for each instance \(m_i\) do
5: Generate the instance perturbation by using Eq. 12 or Eq. 13
\(\nabla_X \mathcal{L}_{m_i}(f_\theta(X, m_i), y_{\text{target}})\)
6: Crop the gradient w.r.t the ERF \(e_i\)
\(R_{m_i} = -C_{e_i} \cdot \nabla_X \mathcal{L}_{m_i}(f_\theta(X, m_i), y_{\text{target}})\)
7: \(R^{(n)} = R^{(n)} + R_{m_i}\)
8: end for
9: \(R^{(n)} = \alpha \text{sign}(R^{(n)})\)
10: Update the \(R \leftarrow R + R^{(n)}\)
11: Clip the value \(R \leftarrow \text{Clip}_x(R)\)
12: end while
4.2. Localized Instance Perturbation (LIP)

To address the IPI problem, we argue that the generated adversarial perturbations of one instance should be exclusively confined within the instance ERF. As such, we call our method as the Localized Instance Perturbation (LIP).

The LIP comprises two main components: (1) methods to eliminate any possible interfering perturbation and (2) methods to generate the perturbation. The proposed LIP algorithm is depicted in Algorithm 1.

4.2.1 Eliminating the interfering perturbation

To eliminate the interference between perturbations, we attempt to constrain the generated perturbation for each instance individually inside the ERF. Let us consider that an image $X$, with $w \times h$ pixels, contains $N$ instances $\{m_i\}_{i=1}^N$. Each instance $m_i$ has its corresponding ERF, $e_i$, and we have $\{e_i\}_{i=1}^N$. For each instance, there are a set of corresponding targets represented as object proposals, $\{p_j\}_{j=1}^P$. We denote the final perturbation for the $i$th instance as $R_{m_i}$, and the final combination of the perturbation of all the instances as $R$. Similar to the IMP method, once the final perturbation, $R$, has been computed, then we add the perturbation into the image $X_{adv} = X + R$.

**Perturbation cropping** – This step is to limit the perturbations inside the instance ERF. This is done by cropping the perturbation according to the corresponding instance ERF. Let us define a binary matrix $C_{e_i}$ as the cropping matrix for the ERF, $e_i$. The matrix $C_{e_i}$ is defined as follows:

$$C_{e_i}(w, h) = \begin{cases} 1, & (w, h) \in e_i \\ 0, & \text{otherwise} \end{cases}$$

where $(w, h)$ is a pixel location. The cropping operation is computed by a element-wise dot product of the mask $C_{e_i}$ and the gradient w.r.t. the input images $X$, is defined as:

$$R_{m_i} = C_{e_i} \cdot \nabla_X \mathcal{L}_{m_i},$$

where $\mathcal{L}_{m_i}$ is the loss function of the $i$-th instance. $\mathcal{L}_{m_i}$ will be described in the next sub-section.

**Individual instance perturbation** – It is possible to compute the perturbation of multiple instances simultaneously. However, the interfering perturbation can still exist and may impact the attack. To that end, we propose to separately compute the perturbation for each instance, $\nabla_X \mathcal{L}_{m_i}$, before cropping.

After the cropping step is applied to each instance perturbation, the final perturbation of all instances is combined via:

$$R = \sum_{i=1}^N C_{e_i} \cdot \nabla_X \mathcal{L}_{m_i}.$$  

We then normalize the final perturbation, $R$, via: $R = \alpha \text{ sign}(R)$.

4.2.2 Perturbation generation

Given a set of region proposals corresponding to an instance, there are at least two methods of generating the instance perturbation $R_{m_i}$: (1) All proposal based generation and (2) Highest Confidence proposal based generation.

**All proposal based generation** – In the first method, we utilize all the region proposals to generate the perturbation $R_{m_i}$. Thus, the $\mathcal{L}_{m_i}$ in Eq. 10 can be defined as a summation of the loss function of all the region proposals $\mathcal{L}_{p_j}$ belong to the instance:

$$\mathcal{L}_{m_i} = \sum_{j=1}^P \mathcal{L}_{p_j}.$$  

**Highest confidence proposal based generation** – In online hard example mining [25], Shrivastava et al. showed the efficiency of using the hard examples to generate the gradients for updating the networks. The hard examples are the high-loss object proposals chosen by the non-maximum suppression. Non-Maximum Suppression (NMS) is similar to max-pooling, which selects the object proposal with the highest score (i.e. selecting the proposal with the highest loss).

Inspired by this, instead of attacking all of the object proposals corresponding to a single instance, we can use NMS to select the one with highest loss to compute the back-propagation. Then $\mathcal{L}_{m_i}$ can be rewritten as:

$$\mathcal{L}_{m_i} = \max(\mathcal{L}_{p_j}).$$

5. Experiments

In this section, we first describe the implementation details and then evaluate our proposed adversarial attacks on the state-of-the-art face detection datasets.
5.1. Implementation Details

For this study, we utilize recent state-of-the-art face detector, HR [6]. In particular, HR-ResNet101 is used. Image pyramids are utilized in HR, i.e. downsampling/interpolating the input image into multiple sizes. Therefore, for every image in the pyramid, we generate corresponding adversarial examples. The detection results of the image pyramid are combined together with Non-Maximum Suppression (NMS). The chosen thresholds of NMS and classification are 0.1 and 0.5 respectively.

Imperceptibility is one of the important concerns when generating adversarial perturbations. We found that by zero-paddings the small input images can reduce the magnitude of the gradient. In this work, we zero pad the small images to 1000 × 1000 pixels. In addition, as the input images of the detection networks can be arbitrary sizes, we do not follow existing methods [18, 17] that resize the input images into a canonical size.

Note that we cannot simply crop the input image to generate a successful adversarial perturbation. This is because the perturbation may be incomplete as it does not include the context information obtained from neighboring instances. An example of two non-normalized perturbations in absolute value generated with and without context is shown in Figure 3.

For determining the perturbation cropping size, we follow the work of Luo et al. [16] which computes the gradient of the central pixel of an instance on the output feature map to obtain the distribution of the ERF. We average the gradients over multiple instances. The perturbation crop size is set to 80 × 80 pixels for small faces and 140 × 140 pixels for large faces. The maximum noise value \( \varepsilon \) is 20 and the maximum number of iterations \( N_0 \) is 40. The \( \alpha \) is set to 1 in this work.

Perturbation Generation Methods – In our work, we compared our proposed Localized Instance Perturbation (LIP) approach with the IMage Perturbation (IMP) and Localized Perturbation (LP). The details of the perturbation generation methods evaluated are listed as follow:

Localized Instance Perturbation using All proposal generation (LIP-A) – The proposed LIP-A is a variant of our proposed LIP method in Section 4.2. As mentioned, the loss function of one instance is the summation of all proposals (refer to Eq. 12).

Localized Instance Perturbation using Highest confidence proposal generation (LIP-H) – The LIP-H is another variant of our proposed LIP with the loss function of Eq. 13. The loss function of one instance consists of only one loss of the highest confidence proposal.

IMage Perturbation (IMP) – The IMP method refers to the generation method in Section 3.1 which applies the perturbation without cropping it. This perturbation generation method follows the previous work [17].

1These perturbation are not normalized for the sake of illustration.
| Perturbations | none | IMP | LP | LIP-A | LIP-H |
|---------------|------|-----|----|------|------|
| Detection Rate | 95.7 | 44.1 | 4.8 | 5.1  | 5.9  |
| Attack Success Rate | – | 53.9 | 94.9 | 94.6 | 93.8 |

Table 2. The attack success rates and detection rates (in %) on FDDB dataset [7].

**Localized Perturbation (LP)** – The LP is the localized perturbation which also crops the image perturbation. The main difference to the proposed LIP is that it computes the gradients of all the instances simultaneously before perturbation cropping. In contrast to Eq. 11, the final perturbation is obtained by:

\[ R = \bigcup_{i=1}^{N} C_{e_i} \times \sum_{i=1}^{N} \nabla_{X} L_{m_i} \text{.} \tag{14} \]

where \( \bigcup_{i=1}^{N} C_{e_i} \) is the union of all binary matrices. The advantage of this method is that current deep learning toolboxes can calculate the summation of the gradients of all instances, \( (i.e. \sum_{i=1}^{N} \nabla_{X} L_{m_i}) \), simultaneously by back-propagating the network only once.

**Benchmark Datasets** – We evaluate our proposed adversarial perturbations on two recent popular face detection benchmark datasets: (1) **FDDB dataset** [7]: The FDDB dataset is designed to benchmark face detectors in unconstrained environments. The dataset includes images of faces with a wide range of difficulties such as occlusions, difficult poses, low resolution and out-of-focus faces. It contains 2,845 images with a total of 5,171 faces labelled; and (2) **WIDER FACE dataset** [30]: The WIDER FACE dataset is currently the most challenging face detection benchmark dataset. It comprises 32,203 images and 393,703 annotated faces based on 61 events collected from the Internet. The images of some events, e.g. parade, contain a large number of faces. According to the difficulties of the occlusions, poses and scales, the faces are grouped into three sets: 'Easy', 'Medium' and 'Hard'. As for the experiments, we randomly choose 1,000 images from the validation set.

**Evaluation Metrics** – The metrics for evaluating the adversarial attacks against face detection are attack success rate and detection rate defined as follows: (1) **Attack Success Rate**: The attack success rate is the ratio between the number of faces that are successfully attacked and the number of detected faces before the attacks; and (2) **Detection Rate**: The detection rate is the ratio between the number of detected faces and the number of faces in the images.

### 5.2. Evaluation on synthetic data

As discussed in Section 3, due to the IPI problem, the IMP does not perform well on the cases where (1) the number of faces per image is large; and (2) the faces are close to each other. Here, we contrast IMP with LP and LIP-H.

We randomly selected 50 faces from the WIDER FACE dataset [30]. These faces were first resized into a canonical size of 30 \( \times \) 30 pixels. Each face was then duplicated and inserted into a blank image in a rectangular grid manner (e.g. \( 3 \times 3 = 9 \)). The number of duplicates and the distance between the duplicates were controlled during the experiment. In total there were 50 images and the attack success rate was then averaged across 50 images. Some examples of the synthetic images are shown in Figure 2.

**The effect of the number of faces** – we progressively increased the number of duplication for each synthetic image from \( 1 \times 1 \) to \( 9 \times 9 = 81 \) duplicates. We fixed the distance between duplicates to 40 pixels. The quantitative results are shown in Figure 4. From this figure, we can see that the IMP attack success rate significantly drops from 100% to 20% as the number of faces is increased. On the contrary, both LP and LIP-H can achieve significantly higher attack success rate than IMP. This is because both LP and LIP-H only use the generated perturbation within the corresponding instance ERF by cropping it before applying. Note that, when the number of faces is more than 36, the LP attack success rate drops from 85% (\( N = 36 \)) to 51% (\( N = 81 \)), whereas the LIP-H can still achieve more than 90% success rate. Since LP processes all the instances simultaneously, the accumulation of the interfering perturbations within each instance ERF will become more significant when the number of faces is increased.

**The effect of distance between faces** – In this experiment the number of faces duplication was fixed to 9. Then we modified the distance between face duplicates to 40 pixels, 160 and 240 pixels. It can be seen from Figure 4 that the attack success rate for IMP increases as the distance between faces is increased. The performance of both LP and LIP-H are not affected.

### 5.3. Evaluation on face detection datasets

We contrasted LIP-A and LIP-H with IMP and LP using the recent face detection datasets. The experiments were run on the entire FDDB [7] and 1,000 randomly selected images in the validation set of WIDER FACE [30].
Figure 4. The attack success rate with respect to: (a) the number of faces. The distance was fixed to 40 pixels; and (b) the distance between faces. Nine face duplicates were used in this result.

|                  | Detection Rate | Attack Success Rate |
|------------------|----------------|---------------------|
|                  | easy | medium | hard | easy | medium | hard |
| none             | 87.8 | 85.8   | 68.7 | –   | –      | –    |
| IMP              | 46.2 | 50.7   | 45.9 | 47.3 | 40.9   | 33.2 |
| LP               | 30.1 | 34.7   | 29.3 | 65.7 | 59.5   | 57.4 |
| LIP-A            | 28.2 | 32.2   | 23.6 | 67.9 | 62.5   | 65.7 |
| LIP-H            | 26.5 | 31.1   | 26.6 | 69.8 | 63.7   | 61.4 |

Table 3. The attack success rate and detection rate (in %) on WIDER FACE validation set [30].

The results are reported in Table 2 and Table 3 respectively. On the FDD dataset (in Table 2), the face detector, HR [6], achieves 95.7% detection rate. The LP, LIP-A and LIP-H can significantly reduce the detection rate to around 5% with the attack success rate of 94.9%, 94.6% and 93.8% respectively. On the other hand, the IMP can only achieve 53.9% attack success rate (i.e. significantly lower than the LP, LIP-A, LIP-H performance). This signifies the importance of the perturbation cropping to eliminate the interfering perturbations. Due to the IPI problem, the interfering perturbations from the other instances will affect the adversarial attacks of the target instance. This results in the low attack success rate of the IMP. This is because to generate the perturbations, the IMP simply sums up the all perturbations including the interfering perturbations. We note that the performance of LP, LIP-A and LIP-H are on par in the FDDB dataset. This could be due to the low number of faces per image for this dataset.

However, when the number of faces per image increases significantly, LIP shows its advantages. This can be observed in the WIDER FACE dataset where LIP-A and LIP-H outperform LP by 4 percentage points. the LIP-H can achieve attack success rates of (69.8%, 63.7%, 61.4%) on the (easy, medium, hard) sets, while the LP can only obtain attack success rate (65.7%, 59.5%, 57.4%). As the LP processes all the instances together, the interfering perturbations are accumulated within the ERF before the cropping step. Note that the interfering perturbations may have low magnitude, however, when they are accumulated due to the number of neighboring instances then disruption could be significant.

These results also suggest that we do not necessarily need to attack all the region proposals as the performance of LIP-H is on par with LIP-A.

5.4. Perceptibility

Following [27, 28], we measure the perceptibility of an adversarial perturbation by: \( p = \left( \frac{1}{K} \sum \|R\|^2 \right)^{\frac{1}{2}} \), where \( K \) is the number of pixels in one image and \( R \) is the adversarial perturbation for one image. The pixel intensities are normalized from the RGB color space into [0,1]. The perceptibility is averaged over the images in each dataset. Here, the maximum absolute value of the noise, \( \varepsilon \), is set to 20. The perceptibility of different perturbation generation methods is shown in Table 4. Some examples are shown in Figure 5. We can see that the LIP method can achieve good imperceptibility on both datasets.
Figure 5. An example of Perceptibility of the LIP-H compared with the IMP. The LIP-H is successfully attack all the faces, whereas some faces are still detected when IMP method is used.

| Perceptibility | IMP | LP | LIP-A | LIP-H |
|----------------|-----|----|-------|-------|
| FDDDB          | 0.0177 | 0.019 | 0.0188 | 0.0196 |
| WIDER          | 0.0204 | 0.0092 | 0.0086 | 0.0129 |

Table 4. The perceptibility values of compared methods in FDDB and WIDER datasets.

6. Conclusions

In this paper we presented an adversarial perturbation method to fool a recent state-of-the-art face detector utilizing the single-stage network. We described and addressed the Instance Perturbation Interference (IPI) problem which was the root cause for the failure of the existing adversarial perturbation generation methods to attack multiple faces simultaneously. We found that it was sufficient to only use the generated perturbations within an instance/face Effective Receptive Field (ERF) to perform an effective attack. In addition, it was important to exclude perturbations outside the ERF to avoid disrupting other instance perturbations. We thus proposed the Localized Instance Perturbation (LIP) approach that only used the perturbation within the ERF. Experiments showed that the proposed LIP successfully generated perturbations for multiple faces simultaneously to fool the face detection network and significantly outperformed existing adversarial generation methods.

As currently the perturbations are generated specifically to each face, we plan to develop a universal perturbation generation method which can attack many faces with a general perturbation.

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