ICIP 2019

MultiDrone

ADVERSARIAL FACE DE-IDENTIFICATION

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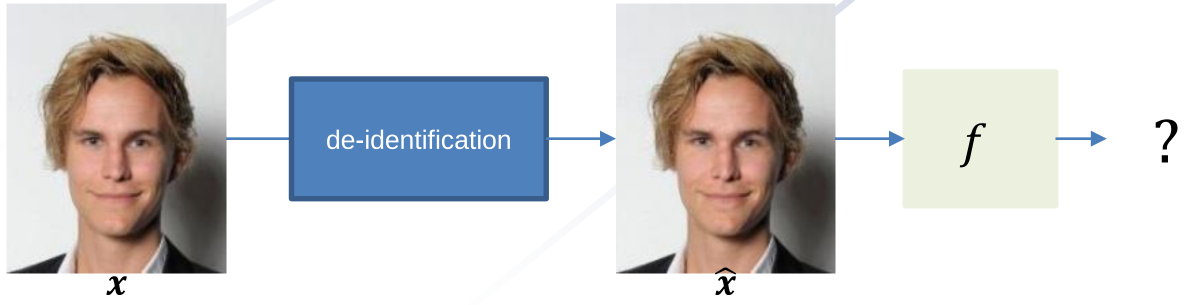
Adversarial Face De-Identification

Face de-Identification problem

- Face recognition systems f take a facial image $\boldsymbol{x}$ as input and predict its corresponding identity y, $f(\boldsymbol{x}) \rightarrow y$.
- Therefore, **face de-identification** methods aim to alter the original facial image $\boldsymbol{x}$ and produce a de-identified image $\widehat{\boldsymbol{x}}$ that can no longer be identified by face recognition systems, $f(\boldsymbol{x}) \rightarrow ?$.



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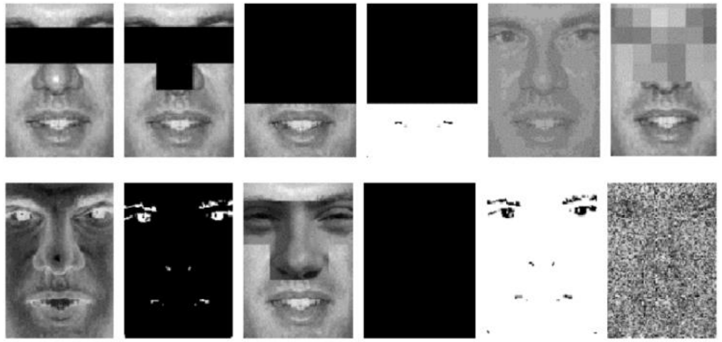
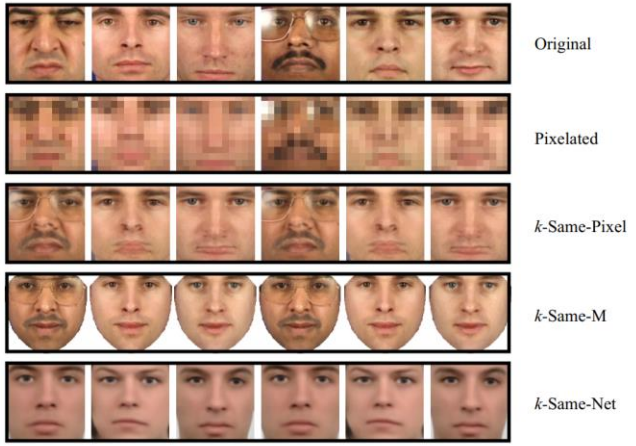
Adversarial Face De-Identification

Motivation - Drawbacks of previous methods

- Privacy protection on images and videos.
- Previous face de-identification methods strongly alter original images.
- De-identified image should retain the original facial image unique characteristics (e.g. race, gender, age, expression, pose).





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Motivation - Face recognition systems

- Modern face recognition systems are robust to ad-hoc de-identification methods (mask, blur, pixelization, random noise etc.).
- Wide variety of face recognition systems with different internal functionality.

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Contribution

- A new face de-identification method that uses adversarial examples.
- A novel penalty term in the objective function.
- Increased misclassification rate (protection) than previous face de-identification methods.
- Minimal image distortion between original and de-identified images.
- The non-identity facial characteristics are preserved in the de-identified images.

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Adversarial examples

- Adversarial examples are carefully constructed inputs that result to incorrect classification.
- Let f be a deep neural network classifier trained on a dataset and $\{\boldsymbol{x}_i, y_i\}$ is a dataset entry, with $\boldsymbol{x}_i \in \boldsymbol{X} \subseteq \boldsymbol{R}^n$ being a facial image and $y_i \in \boldsymbol{Y}$ the corresponding ground truth label.
- If $\boldsymbol{x}$ is an instance with ground truth label y, then an adversarial example $\hat{\boldsymbol{x}}$ can be crafted by adding a small perturbation to $\boldsymbol{x}$, so that $f(\hat{\boldsymbol{x}}) \neq y$.
- The added perturbation can be measured as $\boldsymbol{p} = \|\hat{\boldsymbol{x}} - \boldsymbol{x}\|_p$, where $\|\cdot\|_p$ is the p-norm.

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Adversarial attacks

- Fast gradient-based adversarial example generation methods generate adversarial examples by using the gradient $\nabla_x l_f$ of the loss function l_f of the classifier f w.r.t. an input $\boldsymbol{x}$.
- Iterative Fast Gradient Sign Method (I-FGVM) changes the input $\boldsymbol{x}$ in the direction of the gradient $\nabla_x l_f$.
- Iterative Fast Gradient Sign Method (I-FGSM) uses only the sign of the gradient $\nabla_x l_f$ to change the input $\boldsymbol{x}$.

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Adversarial attacks

- Targeted adversarial attacks: generate adversarial examples that are misclassified as a specific label $\hat{y}$, $f(\hat{\mathbf{x}}) = \hat{y}$.
- Non-targeted adversarial attacks: generate adversarial examples that are misclassified in a label different than the ground truth label y, $f(\hat{\mathbf{x}}) \neq y$.

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I-FGVM

- Gradient descent update equations of the I-FGVM.

$$\hat{\boldsymbol{x}}_0 = \boldsymbol{x},$$
$$\hat{\boldsymbol{x}}_{i+1} = clip_{[0,1]}(clip_{[\boldsymbol{x}-\varepsilon,\, \boldsymbol{x}+\varepsilon]}(\hat{\boldsymbol{x}}_i - \alpha \cdot \nabla_x l_f(\hat{\boldsymbol{x}}_i, \hat{y})))$$

- α is the step size, $\boldsymbol{x}$ is the original image, $\hat{\boldsymbol{x}}_i$ is the adversarial image at step i, $\nabla_x l_f(\hat{\boldsymbol{x}}_i, \hat{y})$ is the first-order gradient term of the adversarial loss, $\hat{y}$ is the target class label and $clip_{[a,b]}$ is a constraint that keeps pixel values in the $[a, b]$ range.

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I-FGSM

- Gradient descent update equations of the I-FGSM.

$$\widehat{\boldsymbol{x}}_0 = \boldsymbol{x},$$
$$\widehat{\boldsymbol{x}}_{i+1} = clip_{[0,1]}(clip_{[\boldsymbol{x}-\varepsilon,\, \boldsymbol{x}+\varepsilon]}(\widehat{\boldsymbol{x}}_i - \alpha \cdot sign\left(\nabla_x l_f(\widehat{\boldsymbol{x}}_i, \hat{y})\right)))$$

- α is the step size, $\boldsymbol{x}$ is the original image, $\widehat{\boldsymbol{x}}_i$ is the adversarial image at step i, $\nabla_x l_f(\widehat{\boldsymbol{x}}_i, \hat{y})$ is the first-order gradient term of the adversarial loss, $\hat{y}$ is the target class label, $clip_{[a,b]}$ is a constraint that keeps pixel values in the $[a, b]$ range and $sign(\cdot)$ is the sign function.

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Adversarial Face De-Identification

Proposed face de-identification method

- Penalized Fast Gradient Value Method (P-FGVM).
- A novel face de-identification method based on adversarial examples.
- Inspired by the adversarial attack method I-FGVM.
- Combines an adversarial loss term and a ‘realism’ loss term in the objective function.

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Adversarial Face De-Identification

Proposed method – P-FGVM

- Gradient descent update equations of the P-FGVM.

$$\hat{\boldsymbol{x}}_0 = \boldsymbol{x},$$
$$\hat{\boldsymbol{x}}_{i+1} = clip_{[0,1]}(\hat{\boldsymbol{x}}_i - \alpha \cdot \left(\nabla_x l_f(\hat{\boldsymbol{x}}_i, \hat{y}) + \lambda \cdot (\hat{\boldsymbol{x}}_i - \boldsymbol{x})\right))$$

- α is the step size, $\boldsymbol{x}$ is the original image, $\hat{\boldsymbol{x}}_i$ is the adversarial image at step i, $\nabla_x l_f(\hat{\boldsymbol{x}}_i, \hat{y})$ is the first-order gradient term of the adversarial loss, $\hat{y}$ is the target class label, λ is a weight coefficient, $clip_{[a,b]}$ is a constraint that keeps pixel values in the $[a, b]$ range and $sign(\cdot)$ is the sign function.

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Proposed method – P-FGVM advantages

- De-identified images are imperceptibly different from original images.
- Can be used to attack any deep neural network classifier.
- The novel objective function leads to higher misclassification rate compared to simple adversarial attack methods (I-FGVM, I-FGSM).

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Experiments

- Experimental evaluation of the proposed P-FGVM method and the baseline adversarial attack methods I-FGVM and I-FGSM.
- Two deep convolutional neural networks were used as target models.
- Both models were pre-trained on a subset of the CelebA dataset.
- The CelebA subset contains 900 random, aligned, cropped RGB facial images of 30 different persons.

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Experiments - Models

- Model A has a simple architecture consisting of two convolution layers and two fully connected layers.
- Model B is the state-of-the-art VGG-Face convolutional neural network, which utilizes the VGG-16 architecture.

Model A
Conv(32, Kernel(5, 5), Padding(Same), L2Regularizer(1e-3))
BatchNormalization+Relu
MaxPooling(PoolSize(2, 2), Strides(2, 2))
Conv(64, Kernel(5, 5), Padding(Same), L2Regularizer(1e-3))
BatchNormalization+Relu
MaxPooling(PoolSize(2, 2), Strides(2, 2))
FC(512, L2Regularizer(1e-3))
BatchNormalization+Relu
Dropout(0.9)
FC(30)+Softmax

Model B
VGG-Face CNN descriptor (VGG-16)
FC(256, L2Regularizer(1e-3))
BatchNormalization+Relu
FC(30)+Softmax

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Evaluation metrics

- L_2-norm of the adversarial perturbation, $L2 = ||\hat{\boldsymbol{x}} - \boldsymbol{x}||_2$.
- Mean Structural Similarity Index (MSSIM) between the original and the de-identified facial image.
- Misclassification Rate (MR) of the pre-trained models when tested with the de-identified facial images.

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Results

- Comparison between the proposed P-FGVM method and the baseline I-FGVM, I-FGSM methods using the evaluation metrics L2, MSSIM, MR.

Model A			Model B		
L2	SI	MR	L2	SI	MR
Experimental Results					
P-FGVM					
3.38	0.986	99.6%	2.11	0.995	96.0%
I-FGVM					
5.31	0.963	99.4%	2.67	0.993	93.2%
I-FGSM					
5.68	0.962	98.9%	5.74	0.968	94.4%
Percentage Improvement					
I-FGVM					
36.3%	2.3%	0.2%	20.9%	0.2%	3.0%
I-FGSM					
40.4%	2.4%	0.7%	63.2%	2.7%	1.7%

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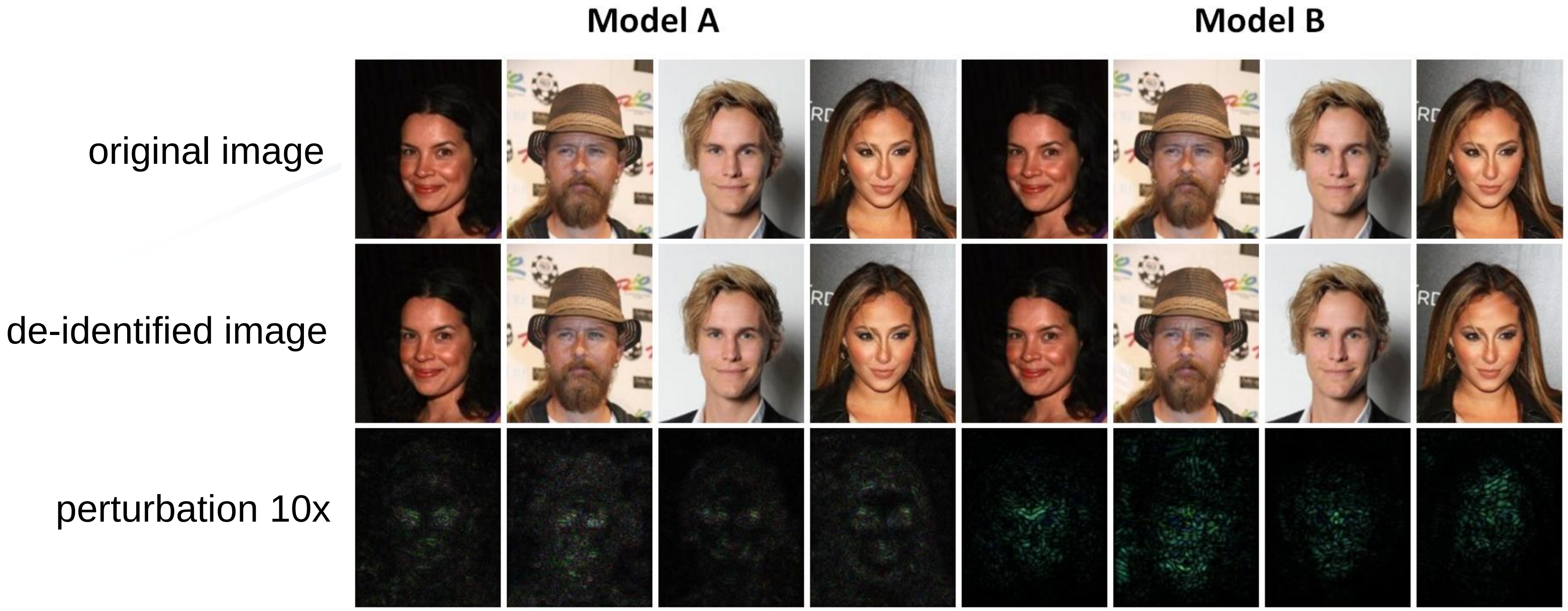
Results

- Examples of de-identified images generated using the proposed P-FGVM method and the adversarial perturbation.



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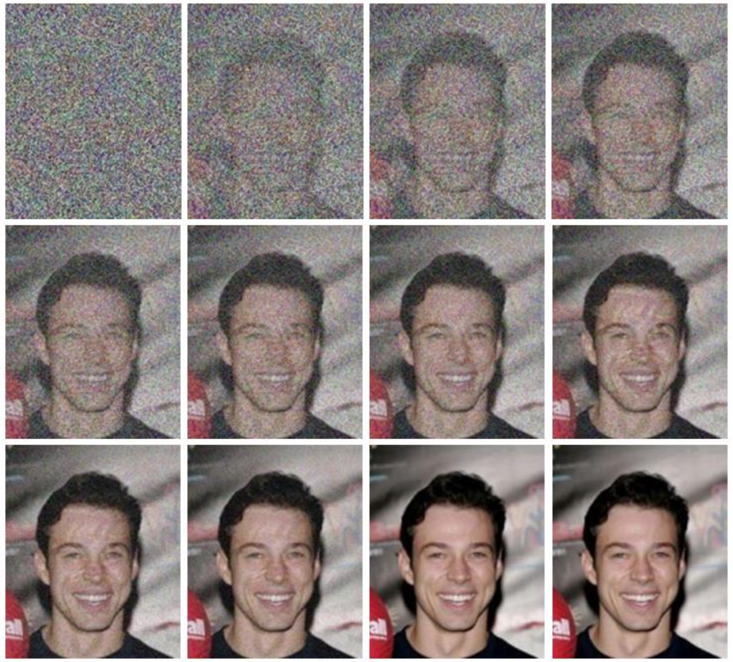
Results

- Evolution of an example de-identified facial image generated by the proposed de-identification method P-FGVM using as input Gaussian random noise.



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Conclusions

- P-FGVM is a novel adversarial attack method for face de-identification.
- The proposed P-FGVM method generates realistic, visually imperceptible de-identified images.
- Higher misclassification rate compared to previous methods.
- Successfully fool various deep convolutional neural network face classifiers.

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Q & A

Thank you very much for your attention!

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