Stable Diffusion Laundering Attacks

Trends & Applications of Computer Vision

2024/2025

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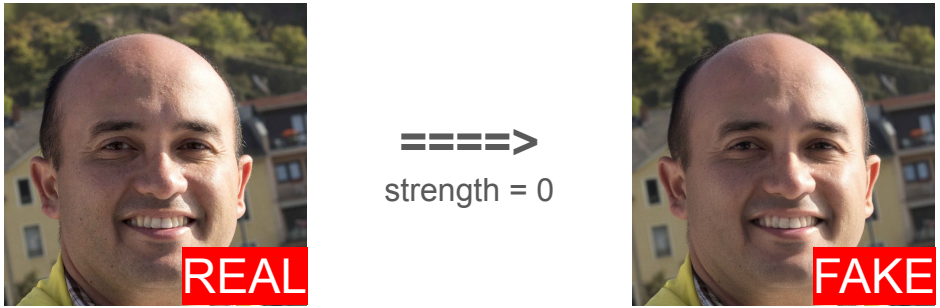
Our idea

- Explore more in depth the approaches proposed in Mandelli's paper[A]:
  - Verify the **capabilities** of the SD-based laundering attack using the MMLAB dataset
  - Explore possible **methodologies** of SD-based laundering attack
  - Verify the **robustness** of the detector proposed in [A]

[A] Mandelli, S., Bestagini, P., & Tubaro, S. (2024). When Synthetic Traces Hide Real Content: Analysis of Stable Diffusion Image Laundering. arXiv preprint arXiv:2407.10736.

Recap: Image Laundering Problem

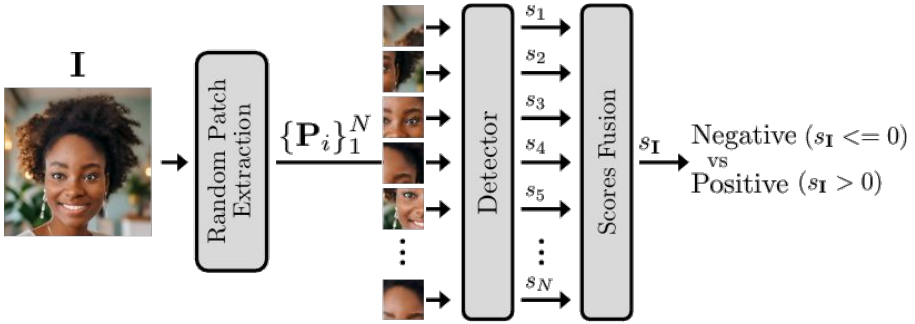


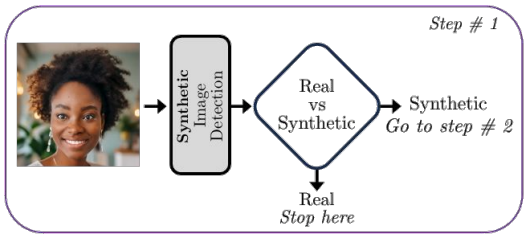
- What's happening:
  - The real image is encoded in the latent space using the SD encoder
  - Given the strength = 0, no noise is added and no denoising steps are performed
  - Then the the image is decoded using the SD decoder, introducing some **invisible artifacts**
- This is a problem:
  - the laundered image has no real forgery
  - despite this, it is classified as fake by many SoTA detectors
  - this approach could conceal nasty stuff as fake, despite being highly real

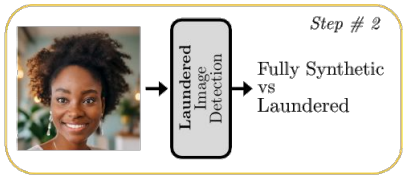
Mandelli, S., Bestagini, P., & Tubaro, S. (2024). When Synthetic Traces Hide Real Content: Analysis of Stable Diffusion Image Laundering. arXiv preprint arXiv:2407.10736.

Recap: How To Address the Laundering Problem

- Problems with backbone:
  - architecture perform only **real vs. synthetic**
  - laundered images detected as fully synthetic
  - trained only on real and fully synthetic images
- Solution (Two Stage Architecture):
  - a first stage to discriminate **real images from all the others** (both synthetic and laundered)
  - a second stage to discriminate fully synthetic from laundered images







Mandelli, S., Bestagini, P., & Tubaro, S. (2024). When Synthetic Traces Hide Real Content: Analysis of Stable Diffusion Image Laundering. arXiv preprint arXiv:2407.10736.
Mandelli, S., Bonettini, N., Bestagini, P., & Tubaro, S. (2022, October). Detecting gan-generated images by orthogonal training of multiple cnns. In 2022 IEEE International Conference on Image Processing (ICIP) (pp. 3091-3095). IEEE.

Our Dataset

(based on MMLAB's TrueFake)

Dataset

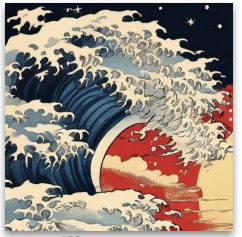
- The MMLAB dataset is composed by around 750K images:
  - Real Images
  - Synthetic images generated by different families of generators
  - Images generated at half precision (Float16)

- Due to computational limitations, we created our own MMLAB-based dataset:
  - 2.5K synthetic images generated by FLUX.1, SD2, SD3, SDXL, StyleGAN3
  - 1K real images
  - 18K laundered images

Parameters Explanation

- **Inference Steps:**
  - number of image refinement iterations
  - lower values produce faster but worse results
  - higher values produce slower but, generally, better results

steps:10



steps:100

- **Guidance Scale:**
  - how strongly the image should conform to textual prompt
  - lower values produce more creative results
  - higher values tend to adhere more to the textual prompt

guidance scale: 1

guidance scale: 20

- **Strength:**
  - how much the generated image deviates from the input image
  - ranges between 0 and 1
  - value 0 produces minor non-visible changes
  - value 1 produces highly unrelated images
  - values lower than 1.0 automatically reduce inference steps

original image

strength: 0.5

strength: 1

Our Approach to Laundering

- General parameters:
  - StableDiffusionXL model
  - Blank positive/negative prompt
  - Guidance scale: 10
  - Inference steps: 50
  - Images 1024x1024 resolution
- Attack methodologies
  - Multiple strength values [0.00, 0.05, 0.10, 0.15, 0.20]
  - Multiple iterations on strength = 0 [passages 1-5]
  - Different precision values [Float16, Float32]

Visual differences: multiple iterations

original

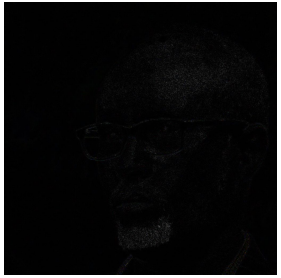
str=0, 1 iteration

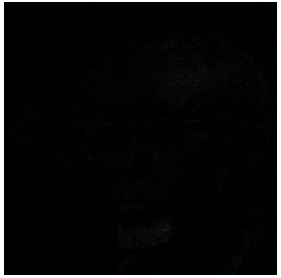
str=0, 2 iterations

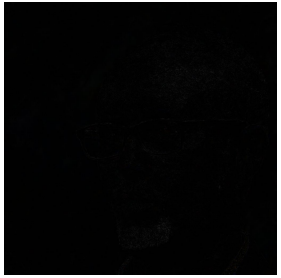
str=0, 3 iterations

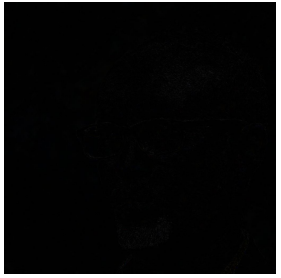
str=0, 4 iterations

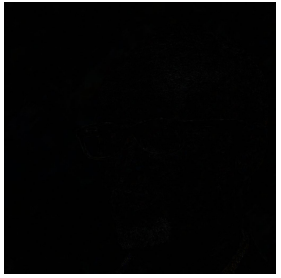
str=0, 5 iterations











Pixel level differences between current and previous iteration

Visual differences: multiple strengths


original

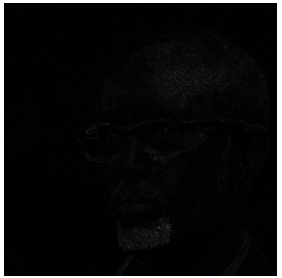

str=0

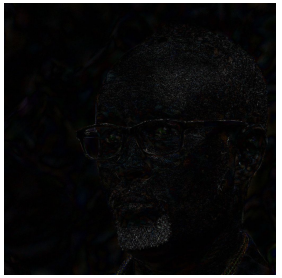

str=0.05


str=0.10


str=0.15


str=0.20





Pixel level differences between laundered and original image

Stable Diffusion UI

- The laundering through SD-based Hugging Face pipeline yielded an error:

```
RuntimeError: cannot reshape tensor of 0 elements into shape [0, -1, 1, 512]
 because the unspecified dimension size -1 can be any value and is ambiguous
```

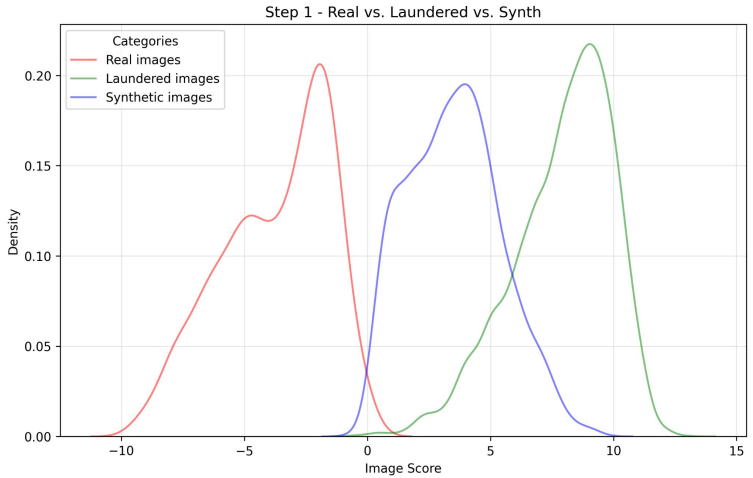
- To solve it, we used the web UI[A] from *Automatic1111*:
  - not usable on MMLAB machine via CLI
  - one of the most used tools in the SD community
  - useful to impersonate a possible attacker
  - usable only for Float32 generation on SDXL
  - CLI parameters used: --xformers, --no-half, --medvram

[A] https://github.com/AUTOMATIC1111/stable-diffusion-webui

Our Results

Results: general categories

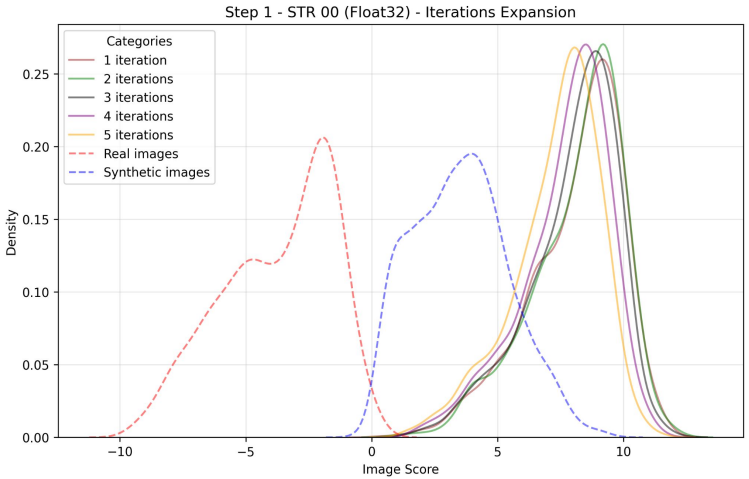
- Over our categories Real, Laundered, (Fully) Synthetic:
  - generally coherent behaviour with results proposed in [A] for Step 1
  - important overlap between Laundered and Synthetic for Step 2

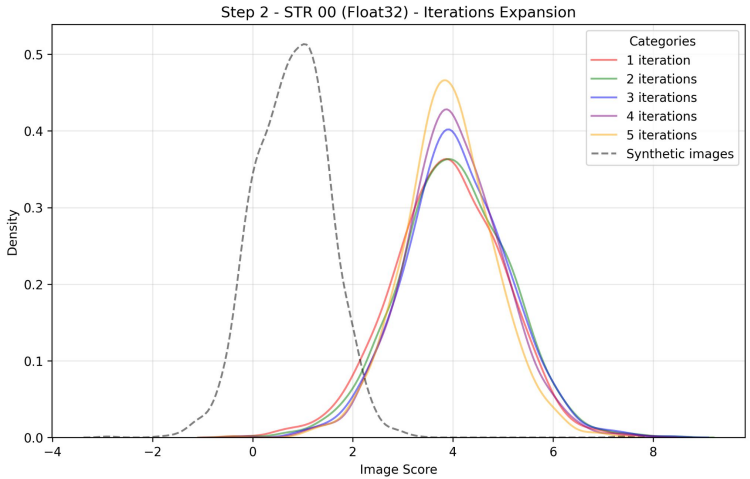


[A] Mandelli, S., Bestagini, P., & Tubaro, S. (2024). When Synthetic Traces Hide Real Content: Analysis of Stable Diffusion Image Laundering. arXiv preprint arXiv:2407.10736.

Results: strength = 0, multiple iterations

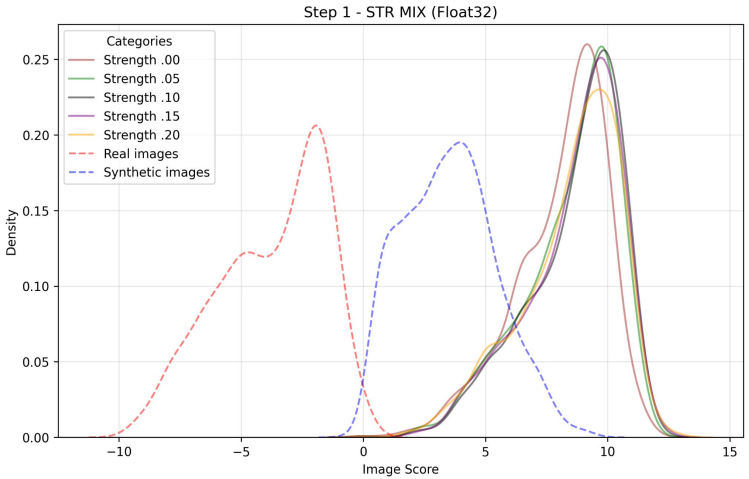
- Over multiple laundering iterations with strength 0 (precision Float32):
  - average score slightly decreasing over higher iteration values for Step 1
  - similar scores for Step 2

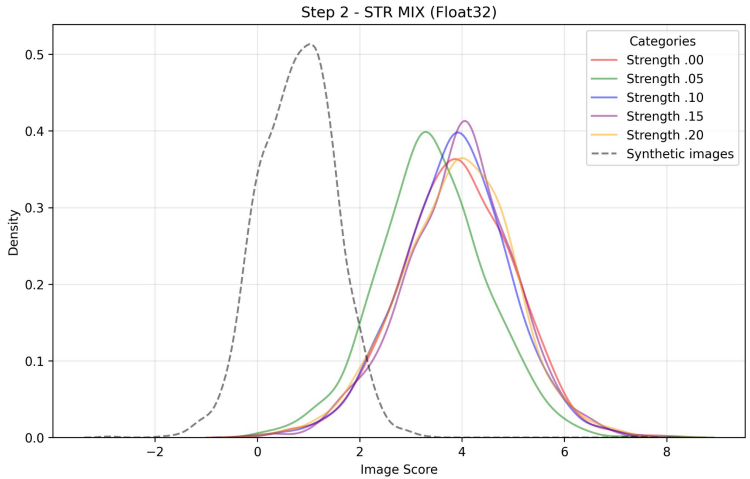




Results: different strength values

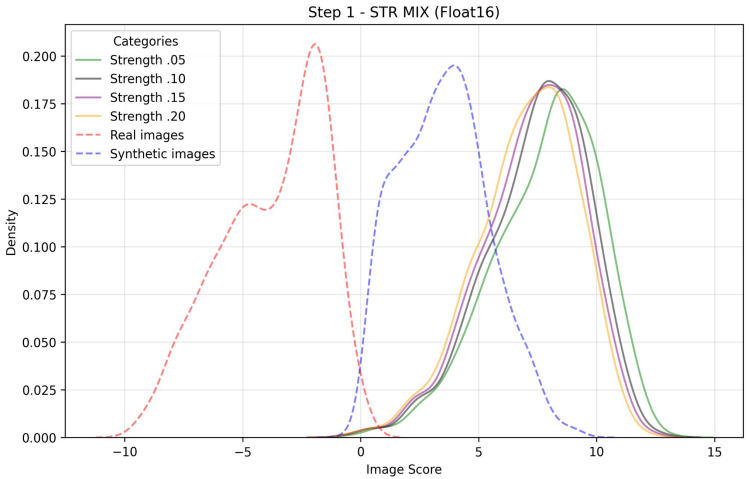
- Over laundering with multiple strength values (precision Float32):
  - no noticeable differences between Step 1 and Step 2

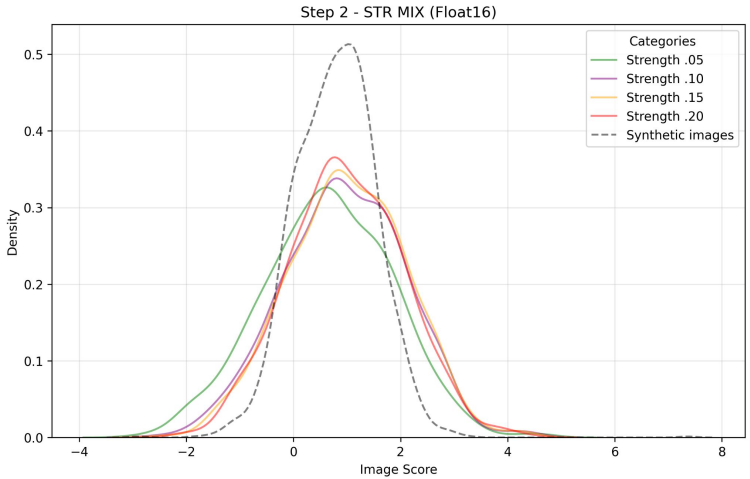




Results: precision

- Over laundering with multiple strength values (precision Float16):
  - no important differences in Step 1 compared to Float32
  - perfect overlap between fully synthetic and laundered images for all strength values!





Results: Float16 vs Float32

Float16, strength = 0.05

Float32, strength = 0.05

Conclusion

- Multiple Float32 laundering iterations at strength = 0:
  - minor decrease of Step 1 score with higher iterations
- Float32 laundering at different strength values:
  - no visible results in both Step 1 and 2
- Float16 images:
  - both laundered and fully synthetic yields similar scores in Step 2, independently from the strength
  - We assume the same behaviour with strength = 0 laundering
  - This results suggest a possible bias in the Step 2 detector from [A]

[A] Mandelli, S., Bestagini, P., & Tubaro, S. (2024). When Synthetic Traces Hide Real Content: Analysis of Stable Diffusion Image Laundering. arXiv preprint arXiv:2407.10736.

Other open challenges

- Explore a possible integration of the Mimicry Attack[A] with the SD-based laundering attack[B]
- Solve the “strength = 0 laundering problem”
- Launder and test strength = 0 Float16 images
- Investigate possible biases in the detector from [B] between Float32 and Float16 images
- Verify possible effects of higher iteration numbers in the strength = 0 laundering

[A] Boato, G., De Natale, F. G., De Stefano, G., Pasquini, C., & Roli, F. (2024). Adversarial mimicry attacks against image splicing forensics: An approach for jointly hiding manipulations and creating false detections. Pattern Recognition Letters, 179, 73-79.
[B] Mandelli, S., Bestagini, P., & Tubaro, S. (2024). When Synthetic Traces Hide Real Content: Analysis of Stable Diffusion Image Laundering. arXiv preprint arXiv:2407.10736.

Thanks for the attention