Clonability of printable graphical codes

a machine learning approach

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Outline

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Machine learning based attacks

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Authentication results

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ID docs



Electronics



Luxury objects

Art objects



Risks of counterfeiting

- Danger for life
- Market loss
- Damage of brand reputation •
- etc.





Certificates



Banknotes



Packaging



- **Risks of counterfeiting**
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 - increases the product cost
 - + expensive & difficult for copying



Luxury objects

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- Unclonable Physical Functions (PUFs) [VDB⁺12, WW15]
 - verification often requires special equipment
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- Anti-copying Pattern [Pic04, WB08]
 - + claimed to be unclonable





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- Anti-copying Pattern [Pic04, WB08]
 - ? is it really unclonable?





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- However they are clonable





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- These codes referred to as Printable Graphical Codes (PGC) are used to distinguish authentic product from fakes and are claimed to be unclonable under hand-crafted attacks
- What about machine learning based attacks?



Machine learning based attacks



Figure 3: Training procedure based on training samples $\{\mathbf{x}_i, \mathbf{y}_i^p\}_{i=1}^M$ (*p* - printer type, *M* - number of training samples and *T* - thresholding).



Machine learning based attacks



Figure 3: Training procedure based on training samples $\{\mathbf{x}_i, \mathbf{y}_i^{\rho}\}_{i=1}^{M}$ (p - printer type, M - number of training samples and T - thresholding).

$$\hat{\theta}^{\rho} = \operatorname*{arg\,min}_{\theta^{\rho}} \sum_{i=1}^{M} \mathcal{L}\big(\mathbf{x}_{i}, T(\phi_{\theta^{\rho}}(\mathbf{y}_{i}^{\rho}))\big) + \lambda \Upsilon_{\theta^{\rho}}(\theta^{\rho}) \tag{1}$$

where $\mathcal{L}(.)$ is a loss function, $\phi_{\theta^{p}}$ is a trained model, θ^{p} represents the parameters of the trained model for a printer p and $\Upsilon_{\theta^{p}}(.)$ is a regularizer for the model parameters.



Training:

Dataset of DataMatrix codes

- Printers:
 - Laser: Samsung Xpress 430 (SA) 600 dpi
 - Laser: Lexmark CS310 (LX) 1200 dpi
 - Inkjet: Canon PIXMA iP7200 (CA) 600 dpi
 - Inkjet: HP OfficeJet Pro 8210 (HP) 1200 dpi



LX

SA





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- Scanners:
 - Epson V850 Pro at 1200 ppi
- ▶ 384 codes of size 384 ×384 per printer
 - training 100 images: 25600 sub-images of size 24×24
 - validation 50 images: 12800 sub-images of size 24×24
 - test 224 images: 59904 sub-images of size 24×24



LX

SA







Figure 6: FC 4 layers.



Deep BN regenrator



Figure 7: Deep BN regenrator architecture.



Regeneration metrics

► Hamming distance: $\mathbf{x} \in \{0, 1\}^{n \times m}$, $\mathbf{y}^p \in \mathbb{R}^{n \times m}$, $T_{t^p}(.)$ - binarization function: ("hard" coding)

$$d(\mathbf{x}, \mathbf{y}^{\rho}) = \frac{1}{n \cdot m} \sum_{j=1}^{n \cdot m} \mathbf{x}(j) \oplus \mathcal{T}_{t^{\rho}}(\mathbf{y}^{\rho}(j))$$
(2)



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$$d(\mathbf{x}, \mathbf{y}^{p}) = \frac{1}{n \cdot m} \sum_{j=1}^{n \cdot m} \mathbf{x}(j) \oplus T_{t^{p}}(\mathbf{y}^{p}(j))$$
(2)

▶ Pearson correlation [PHMHSB13]: $\mathbf{x} \in \{0, 1\}^{n \times m}$, $\mathbf{y}^p \in \mathbb{R}^{n \times m}$: ("soft" coding)

$$\rho(\mathbf{x}, \mathbf{y}^{p}) = \frac{\operatorname{cov}(\mathbf{x}, \mathbf{y}^{p})}{\sigma_{\mathbf{x}} \sigma_{\mathbf{y}^{p}}}$$
(3)



Regeneration results

Method	SA	LX	HP	CA			
Pearson correlation							
Thr	0.774	0.766	0.742	0.704			
FC 2	0.995	0.994	0.982	0.981			
<i>FC</i> 3	0.994	0.994	0.982	0.983			
FC 4	0.994	0.995	0.981	0.982			
BN	0.996	0.996	0.986	0.984			
normalized Hamming distance							
Thr	11	12	13	15			
FC 2	0.22	0.24	0.93	0.98			
<i>FC</i> 3	0.23	0.24	0.90	0.85			
FC 4	0.24	0.23	0.95	0.90			
BN	0.21	0.22	0.69	0.76			

Table 1: Regeneration results with respect to original codes.



Results visualisation

	Printer	Original	Scanned original	Reconstructed (BN)	Difference
inters	SA				
Laser pi	LX				•
Inkjet printers	HP				
	CA				· ·

Table 2: Examples of attacks against PGC: two samples of scanned codes, the estimates produced by *BN* model and the difference between the original and attacked codes.



Authentication metrics

$$P_{d} = \Pr\{\alpha \cdot d(\mathbf{x}_{i}, \mathbf{y}_{i}^{p}) \leq \gamma | \mathcal{H}_{0}\}$$

$$P_{fa} = \Pr\{\alpha \cdot d(\mathbf{x}_{i}, \mathbf{y}_{i}^{p}) < \gamma | \mathcal{H}_{1}\},$$
(4)

where γ is the threshold, d(.) is a similarity measure between the original and printed codes, \mathcal{H}_0 corresponds to the hypothesis that \mathbf{y}_i^{ρ} is an authentic code and \mathcal{H}_1 is the hypothesis that \mathbf{y}_i^{ρ} is a fake (cloned) code, α equals to -1 for the *Pearson correlation* and to 1 for *Hamming distance*.





Figure 8: The ROC curves for *Hamming distance* between the original and fake printed codes estimated via *Thr* methods. P_d denotes the probability of the correct detection and P_{fa} is the probability of false acceptance.





Figure 9: The ROC curves for *Hamming distance* between the original and fake printed codes estimated via *BN* and *Thr* methods. P_d denotes the probability of the correct detection and P_{fa} is the probability of false acceptance.





Figure 10: The ROC curves for *Pearson correlation* between the original and fake printed codes estimated via *Thr* methods. P_d denotes the probability of the correct detection and P_{fa} is the probability of false acceptance.





Figure 11: The ROC curves for *Pearson correlation* between the original and fake printed codes estimated via *BN* and *Thr* methods. P_d denotes the probability of the correct detection and P_{fa} is the probability of false acceptance.



Conclusions

- we investigated the clonability of generic printable graphical codes using machine learning based attacks
- we examined the proposed framework on real printed codes reproduced with 4 printers
- we demonstrated a possibility of sufficiently accurate cloning of the PGC from their printed counterparts
- this should serve as a warning that more research are needed on the colonability of PGC



web-page:

http://sip.unige.ch/projects/snf-it-dis/publications/icassp-2019

GitHub:

https://github.com/taranO/clonability-of-printable-graphical-codes

Dataset:

http://sip.unige.ch/projects/snf-it-dis/datasets/dpOe/



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