Image Forensic: Face Spoofing

Alex Kot
ROSE Lab, CoE
Nanyang Technological University
Singapore

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Yunnan Garden Campus
Are these photos captured directly from natural scenes?
Image Forensic: Image Recapturing Threat

- Artificial display media:
  - LCD and LED display, high-quality printing, photos, videos, projection...
- We study prevention of image recapturing threat using the common and ubiquitous LCD as the display media
Finely Recaptured Image Dataset

Examples of our finely recaptured images:

- Canon DSC + Acer LCD
- Olympus Mju DSC + NEC LCD
- Olympus E500 DSLR + Philips LCD

Our Recaptured Image Dataset:

- 9 camera-LCD combinations with 3 cameras and 3 LCDs
- A total of 2700 images

<table>
<thead>
<tr>
<th>Camera</th>
<th>LCD Brand</th>
<th>Resolution</th>
</tr>
</thead>
<tbody>
<tr>
<td>Canon Powershot A620</td>
<td>Philips 19CB6CG (19 Inch)</td>
<td>300</td>
</tr>
<tr>
<td>Olympus Mju 300</td>
<td>NEC AccuSync LCD 72VXM (17 Inch)</td>
<td>300</td>
</tr>
<tr>
<td>Olympus E500 DSLR</td>
<td>Acer AL712 (17 inch)</td>
<td>300</td>
</tr>
</tbody>
</table>

Rapid-Rich Object Search Lab
Human Identification of Carefully Recaptured Images

Survey steps:

- Introduction and training
- Inspection and decisions

50 Test photos (Mixture of natural and recaptured photos):

No Constraints on time, browsing tool and visual inspection methods
Human Classification Result

- 30 survey participants (mainly university staffs and students)
- Findings:
  - Human beings are poor in this classification, especially in identification of the recaptured images
  - The finely recaptured photos post a threat to fool both human eyes and image forensic systems

On average, 4 out of 20 Type-I errors
Ave Type-I Err Rate: 20%
Std dev: 12.8%

On average, 15 out of 30 Type-II errors
Ave. Type-II Err Rate: 51%
Std dev: 18.3%
Artifacts of a Casually Recaptured Image on a LCD Screen

• Visible artifacts:
  – Textures
  – Loss of fine details
  – Color degradation

• Casually recapture often lead poor perceptual quality of the recaptured images
Local Binary Pattern (LBP)

The value of the LBP code of a pixel \((x_c, y_c)\) is given by:

\[
LBP_{P,R} = \sum_{p=0}^{P-1} s(g_p - g_c)2^p
\]

\[
s(x) = \begin{cases} 
1, & \text{if } x \geq 0; \\
0, & \text{otherwise}.
\end{cases}
\]

Example of LBP calculation

\[LBP = (10110010)_2 = (53)_{10}\]
Example of an input image, the corresponding LBP image and histogram

Input image

LBP image

LBP histogram

Courtesy from Abdenour Hadid
✓ Invariance to any monotonic gray level change
✓ High discriminative power
✓ Computational simplicity

Courtesy from Abdenour Hadid
Proposed Features for Computer Identification of Recaptured Photos - [Cao & Kot IEEE ICASSP 2010]

- **Local Binary Patterns (LBP) [1]**
  - To measure the texture patterns
  - 80 features

- **Multi-Scale Wavelet Statistics (MSWS)**
  - To measure the loss of fine details characteristics
  - 54 features

- **Color Features (CF) [2, 3]**
  - To measure the color anomalies
  - 21 features

1. Ojala *et al.* PAMI, 2002
2. Memon *et al.* ICIP 2004
3. Ma *et al.* ICME, 2006
Computer Classification Results

Image Datasets:
• 2100 **recaptured** images and 2000 natural images (1024 × 1024) from 12 cameras
• 80% for training and 20% for testing;
• Five random apportions of training and test images
• Probabilistic Support Vector Machine (PSVM) Classifier

<table>
<thead>
<tr>
<th>Features</th>
<th>Dimension</th>
<th>EER (%)</th>
<th>EER Threshold</th>
</tr>
</thead>
<tbody>
<tr>
<td>LBP</td>
<td>80</td>
<td>0.9</td>
<td>0.55</td>
</tr>
<tr>
<td>MSWS</td>
<td>54</td>
<td>1.1</td>
<td>0.35</td>
</tr>
<tr>
<td>CF</td>
<td>21</td>
<td>17.4</td>
<td>0.47</td>
</tr>
<tr>
<td>LBP+MSWS</td>
<td>134</td>
<td>0.7</td>
<td>0.43</td>
</tr>
<tr>
<td>LBP+MSWS+CF</td>
<td>155</td>
<td>0.5</td>
<td>0.50</td>
</tr>
<tr>
<td>Wavelet Stats</td>
<td>216</td>
<td>3.4</td>
<td>0.43</td>
</tr>
</tbody>
</table>

Image Forensic: Recapturing → Face spoofing

Biometric verification is becoming more and more popular. However, it is vulnerable being attacked.

- Printed Photo Attack
- Replay Video Attack
- Mask Attack

User Authorization
Alipay: Smile to Pay

Face Verification

User Authentication

https://intl.alipay.com/
Face Spoofing Detection

• Distortion based approaches

• Temporal information based approaches

• Deep learning approaches
  – Yang et al. Learn Convolutional Neural Network for Face Anti-Spoofing, arXiv, 2014

• Domain adaptation based approaches
  – Yang et al. Person-Specific Face Antispoofing With Subject Domain Adaptation, IEEE-TIFS 2015

• Texture based approaches
  – Boulkenafet et al. Face Anti-spoofing using Speed-Up Robust Features and Fisher Vector Encoding, IEEE-SPL 2017
## Evaluation Datasets
### Summary of 2D face spoofing datasets

<table>
<thead>
<tr>
<th>Dataset</th>
<th>Year of Release</th>
<th># Subj</th>
<th>#Samples (Live, Spoof)</th>
<th>Attack Type</th>
</tr>
</thead>
<tbody>
<tr>
<td>IDIAP Replay-attack [EPFL]</td>
<td>2012</td>
<td>50</td>
<td>(200,1000)</td>
<td>Paper recapture attack Video recapture attack Image recapture attack</td>
</tr>
<tr>
<td>CASIA [CAS]</td>
<td>2012</td>
<td>50</td>
<td>(200, 450)</td>
<td>Paper recapture attack Video recapture attack Cut photo mask attack</td>
</tr>
<tr>
<td>USSA [MSU]</td>
<td>2016 (internet photos)</td>
<td>1140</td>
<td>(1140, 9120)</td>
<td>Paper recapture attack Image recapture attack</td>
</tr>
<tr>
<td>UVAD [CAMPINES]</td>
<td>2015 (not mobile camera)</td>
<td>404</td>
<td>(808, 16268)</td>
<td>Video recapture attack</td>
</tr>
<tr>
<td>ROSE-Youtu [NTU/Tencent]</td>
<td>2017 (real scenarios)</td>
<td>25</td>
<td>(570, 3430)</td>
<td>Paper recapture attack Video recapture attack Cut photo mask attack</td>
</tr>
</tbody>
</table>
Image Quality Assessment for Fake Biometric Detection: Application to Iris, Fingerprint, and Face Recognition

[Galbally, Marcel and Fierrez, TIP, 2014]

• Features
  – 25 image quality assessment scores
    • 20 full reference algorithms:
      – MSE, PSNR, SSIM, NAE, VIF....
      – Gaussian smoothing is employed to generate image pairs
    • 1 reduced reference algorithms
      – RRED
      – Gaussian smoothing is employed to generate image pairs
    • 4 no reference algorithms
      – JQI & HLFI (without training)
      – BIQI & NIQE (Training based approaches)

• Classifier
  – Linear discriminant analysis (LDA)

• Limitation
  – Acquisition environments are different
  – IQA is designed based on perceptual cues of human visual system

MSE: mean square error
PSNR: peak-signal-to-noise-ratio
SSIM: structural similarity
NAE: normalized absolute error
VIF: visual information fidelity
RRED: reduce reference entropic difference
JQI: jpeg image quality index
HLFI: high low frequency index
BIQI: blind image quality index
NIQE: natural image quality evaluator
Image Quality Assessment for Fake Biometric Detection: Application to Iris, Fingerprint, and Face Recognition
[Galbally, Marcel and Fierrez, TIP, 2014]

- Image quality scores are employed as features
- Directly connects image quality assessment (IQA) and spoofing detection
- The proposed scheme is effective for iris, fingerprint and face spoofing
- 15.2% HTER for the Replay-attack database

Framework of the anti-spoofing scheme with image quality assessment
Face Spoof Detection with Image Distortion Analysis
[Wen, Han and Jain, TIFS, 2015]

• Features
  – Specular Reflection
    • Specular pixel percentage
    • Mean and variance of specular pixels
  – Blurriness
    • Difference between original input and blurred version
    • Average edge depth
  – Chromatic Moment
    • HSV mean, deviation and skewness
    • Percentage of pixels in the minimal and maximal histogram bins
  – Color Diversity
    • The histogram bin counts of the top 100 most frequently appearing colors
    • The number of distinct colors appearing in the normalized face image

• Classifier
  – Ensemble Classifier
    • Divide the training set according to the attack type
    • Min rule for score fusion
Face Spoof Detection with Image Distortion Analysis

[Wen, Han and Jain, TIFS, 2015]

- Distortion based approach for face spoofing
- Four distortion relevant features are adopted
- Ensemble classifier is used for spoofing detection
- Achieves the performance (HTER = 7.4%) on Idiap replay-attack database
Secure Face Unlock: Spoof Detection on Smartphones
[Patel, Han and Jain, TIFS 2016]

- Rejection
  - Inter Pupilliary Distance (IPD) Constraint
    - IPD represents the distance between the center of the right eye to the center of the left eye
    - Faces that are either small or large are rejected
  - Bezel detection
    - Detect fairly constant colors along the top, bottom, right and left edges
- Complementary Features
  - Face texture analysis
    - LBP feature
  - Different color distribution of spoof and genuine faces
    - Color moment
- Classifier
  - SVM
- Voting
  - Two or more frames in a 3-frame sequence is live (majority voting)
Secure Face Unlock: Spoof Detection on Smartphones

[Patel, Han and Jain, TIFS 2016]

- A new database for smartphone spoof attack database (>1000 subjects)
- A novel spoofing pipeline with rejection, complementary feature representation and multi-frame voting
- Under the smartphone protocol for face unlock, the proposed approach achieves 0% HTER on Idiap Replay-Attack, 1.67% EER on CASIA FASD, and 2.67% EER on MSU-MFSD databases

Framework of the face anti-spoofing scheme with rejection, complementary feature representation and multi-frame voting
Using Visual Rhythms for Detecting Video-Based Facial Spoof Attacks
[Pinto, Schwartz, Pedrini and Rocha, TIFS, 2015]

- Features
  - Noise signature extraction
    - Subtracting original image with the blurred version
  - Fourier Spectrum
    - Calculating the Fourier Spectrum of the noise signature video
  - Visual Rhythms
    - Rotate the video and view the temporal-spatial information
  - Feature extraction
    - Gray-Level Co-occurrence Matrices (GLCM)
    - LBP, HOG

- Classifier
  - SVM

\[ V_{RN} = V - h(V) \]
(h is the Gaussian filter)

\[ |F(u, v)| = \sqrt{R(u, v)^2 + I(u, v)^2} \]
\[ V_{FS} = \log(1 + |F(u, v)|) \]
(R and I are real and imaginary parts of the Fourier transform)
Using Visual Rhythms for Detecting Video-Based Facial Spoof Attacks
[Pinto, Schwartz, Pedrini and Rocha, TIFS, 2015]

- Propose a video based face spoofing detection scheme by utilizing the temporal info
- Employ Fourier analysis of noise signature to extract features based on visual rhythms
- The classification accuracy 14.27% (HTER) is achieved for Replay-Attack Database

Framework of the anti-spoofing scheme with Fourier spectrum of noise residual signal (source: Ref [6]).
Face Spoofing Detection Through Visual Codebooks of Spectral Temporal Cubes
[Pinto, Pedrini, Schwartz and Rocha, TIP, 2015]

• Features
  – Noise signature extraction
    • Subtracting original image with the blurred version
  – Fourier Spectrum
    • Calculating the Fourier magnitude and phase spectrum of the noise signature video
  – Time-Spectral descriptor
    • Intra: energy and entropy
    • Inter: correlation and mutual information
  – Mid level description
    • Bag of words
      – Selection of the visual words: random selection and clustering based selection
      – Visual words coding: hard-assignment and soft-assignment

• Classifier
  – SVM

\[ V_{RN} = V - h(V) \]
\[(h \text{ is the Gaussian filter)}\]

\[ |F(u,v)| = \sqrt{R(u,v)^2 + I(u,v)^2} \]
\[ V_{PS} = \log(1 + |F(u,v)|) \]
\[ V_{PS} = \arctan\left(\frac{I(u,v)}{R(u,v)}\right) \]
\[(R \text{ and } I \text{ are real and imaginary parts of the Fourier transform)}\]
Face Spoofing Detection Through Visual Codebooks of Spectral Temporal Cubes
[Pinto, Pedrini, Schwartz and Rocha, TIP, 2015]

- Combine low level and mid level features for face spoofing detection
- Temporal and spectral information are gathered
- An HTER of 2.75% and EER of 14.0% for Replay-attack and CASIA datasets

Framework of the visual codebook based face spoofing detection scheme.

The low-level representation of the videos is computed based on spectrum analysis of the noise signature.

The mid-level representation of the videos is computed based on building the time-spectral visual words.
Learn Convolutional Neural Network for Face Anti-Spoofing [Yang, Lei and Li, arXiv 2014]

- Pioneer method for deep learning based face spoofing
- Propose a CNN based face anti-spoofing pipeline

- CNN Architecture
  - AlexNet

- Training
  - Spatial data augmentation
    - Background regions are also contained
  - Temporal data augmentation
    - Multiple frames are fed into the network

- Classifier
  - Apply SVM on the last fully-connected layer

Achieved less than 5% HTER for CASIA & Replay-Attack datasets
Deep Representations for Iris, Face, and Fingerprint Spoofing Detection

[Menotti, Chiachia, Pinto, Schwartz, Pedrini, Falcao and Rocha TIFS-2015]

• Propose a spoof-net for iris, face and fingerprint spoofing
• Propose the architecture optimization and filter optimization schemes
• 0.75% HTER for Replay-attack database

AO: determine the network structure based on existing structure and domain knowledge (spoofnet)

FO: determine the filter parameters based on backward propagation

Deep learning based scheme for spoofing detection (source: Ref [8])
Person-Specific Face Antispoofing With Subject Domain Adaptation [Yang, Lei, Yi and Li, TIFS 2015]

- Subject domain adaptation
  - Given two subjects $a$ and $b$
    - Establishing the relationship between two subject domains
    - Synthesize the fake features for target domain with the relationship
    - For each subject, train a classifier
- Features
  - MS-LBP (Multiscale-LBP)
  - HOG (Histogram of Gradient)
- Face spoofing
  - Face recognition to detect the face and classifier
  - Spoofing detection with the classifier of the subject
- Classifier
  - SVM (linear)
- Limitations
  - Assumptions in person specific transformation
  - Requires identical acquisition environment for source and target domains
**Person-Specific Face Antispoofing With Subject Domain Adaptation** [Yang, Lei, Yi and Li, TIFS, 2015]

- **Motivation**
  - The genuine samples of one subject overlap the fake samples of another subject
  - The relationship between two genuine is similar to that between two fake samples
Face Spoofing Detection Using Colour Texture Analysis
[Boulkenafet, Komulainen and Hadid, TIFS 2016]

– Consider colour space info being affected in face spoofing detection
– Five features: LBP, COALBP, LPQ, BSIF, SID
– Significant performance improvement for intra-database (EER: from 0 to 3.5 % for Replay-Attack, CASIA, MSU databases)

\[
d_X(H_X, H_G, H_F) = d_{\chi^2}(H_X, H_G) - d_{\chi^2}(H_X, H_F)
\]

\[H_X, H_G, H_F: \text{Histograms of test, genuine and fake samples}
\]

\[d_{\chi^2}: \text{Chi-square distance}
\]

The distribution of the real and attack scores on the Replay-Attack Database (source: Ref [1]).
Left: gray scale (overlapped); Right: color channel (better separated)
Face Spoofing Detection Using Colour Texture Analysis
[Boulkenafet, Komulainen and Hadid, TIFS 2016]

Framework of the face anti-spoofing scheme with five colour texture features (LBP, COALBP, LPQ, BSIF, SID)

Color spaces: YCbCr (Y: Luma, Cb: blue-difference, Cr: red-difference)
          HSV (hue-saturation-value)
          RGB (red, green, blue)

Combination of YCbCr and HSV can achieve the best performance
Face Anti-spoofing Using Speed-Up Robust Features and Fisher Vector Encoding
[Boulkenafet, Komulainen and Hadid, SPL 2017]

- Features
  - SURF descriptor
    - Based on the sum of Haar wavelet around point of interest
    - Provides robust description of the texture with fast computation speed
  - Fisher Vector
    - The local SURF features are aggregated to Fisher Vector
    - Provides summary of the image based on the GMM

- Classifier
  - Softmax classifier with cross entropy loss

\[
V_j = \left[\sum d_x, \sum d_y, \Sigma|d_x|, \Sigma|d_y|\right]
\]

\[
\text{SURF} = [V_1, \ldots, V_{16}]
\]

\[
d_x, d_y: \text{Haar wavelet responses}
\]

\[
\phi_k^1 = \frac{1}{T \cdot \omega_k} \sum_{t=1}^{T} \alpha_t(k) \left( \frac{x_t - \mu_k}{\sigma_k} \right)
\]

\[
\phi_k^2 = \frac{1}{T \cdot \omega_k^2} \sum_{t=1}^{T} \alpha_t(k) \left( \frac{(x_t - \mu_k)^2}{\sigma_k^2} - 1 \right)
\]

\[
\text{Input:}
\begin{align*}
\omega_k, \mu_k, \sigma_k: & \text{GMM mode parameters} \\
x_k: & \text{SURF feature} \\
\alpha_t(k): & \text{Soft assignment weight in GMM} \\
T: & \text{The number of features}
\end{align*}
\]

\[
\text{Output:} \quad \phi_k^1 \text{ and } \phi_k^2
\]
Face Anti-spoofing Using Speed-Up Robust Features and Fisher Vector Encoding

[Boulkenafet, Komulainen and Hadid, SPL 2017]

- A texture based approach with SURF and FV for spoofing detection
- Strong generation ability to unseen attacks
- **Cross-database performance improvement** (19.1% to 31.8% HTER for cross-database evaluation)

![Framework of the face anti-spoofing scheme with SURF and FV](source: Ref [2])

HSV-YCbCr color space achieves the best performance
Unsupervised domain adaptation for face anti-spoofing
Current Research Status and Motivation

- Both hand-crafted features (e.g. Color Texture) and CNN based methods can achieve very good performance when training data and testing are coming from the same ‘domain’.
- When the training data and testing are captured from different domains, the detection ability suffers from a large performance drop.
- It is impossible to capture training data under all conditions.
Problem Definition

• How can we train a more robust classifier based on training data with labeled information and testing data without label information?
  – e.g. Training samples are captured by several types of camera model, but testing samples are captured by the models which are not the same as the training ones.

Mobile phones for training

Mobile phones for testing
Motivation

• Training data and Testing data have different distributions. A classifier trained on training data can not be generalized to testing data.
• By mapping the training data to a new space, we expect that the distribution of training and testing data are more similar.
• What are we going to do
  – How to model the distribution based on a specific problem (face anti-spoofing)?
  – How to reduce the distribution dissimilarity thus a more robust classifier can be trained?
Approach: unsupervised domain adaptation framework

The generalization and adaptation ability of state-of-the-art features are analyzed.
Framework

Feature Extraction
- Multiscale Wavelet
- CoALBP (HSV, YCbCr)
- LPQ (HSV, YCbCr)
Eigenspace Computing: Noise factors can be modeled in low-dimension linear subspace
- Facial Appearance
- Illumination

\[ \phi : \hat{X}_s \Rightarrow U_s, \quad X_t \Rightarrow U_t \]
\[ U_s = \arg \max_{\|U\|=1} \{U^T \hat{X}_s^T \hat{X}_s U \} \]
\[ U_t = \arg \max_{\|U\|=1} \{U^T X_t^T X_t U \} \]

- Maximum Mean Discrepancy Measurement:
\[ D(\hat{X}_s, X_t) = \|U_s - U_t\|_F^2 \]
Framework

Mapping (Subspace Alignment):

\[ M^* = \arg\min_M \| U_s M - U_t \|_F^2 \]

\[ M = U_s^T U_t \]
Framework

Classifier: Support Vector Machine

Training Kernel:
\[ K_{ss} = \hat{X}_s U_s U_s^T U_t U_t^T U_s U_s^T \hat{X}_s \]

Testing Kernel:
\[ K_{st} = \hat{X}_s U_s U_s^T U_t U_t^T X_t \]
Experiment Setting

• Features:
  – Multiscale Wavelet (mean and deviation of Wavelet Subbands in different scale) [1]
  – Co-occurance of Adjacent Local Binary Pattern (CoALBP) in HSV and YCbCr space [2]
  – Local Phase Quantization (LPQ) in HSV and YCbCr space [3]
• Database:
  – Idiap REPLAY-ATTACK (I) [4]
  – CASIA Face AntiSpoofing (C) [5]
  – MSU Mobile Face Spoofing (M) [6]
• Evaluation: Half Total Error Rate (HTER)
## Results

(submitted & under revision)

- **C**: CASIA database, **I**: Idiap REPLAY-ATTACK database, **M**: MSU mobile face spoofing database
- **A → B**: Training on ‘A’ and evaluating on ‘B’

<table>
<thead>
<tr>
<th>Method</th>
<th>C → I</th>
<th>C → M</th>
<th>I → C</th>
<th>I → M</th>
<th>M → C</th>
<th>M → I</th>
</tr>
</thead>
<tbody>
<tr>
<td>Wavelet</td>
<td>W/O DA</td>
<td>49.9%</td>
<td>49.2%</td>
<td>47.7%</td>
<td>48.6%</td>
<td>49.1%</td>
</tr>
<tr>
<td></td>
<td>DA</td>
<td>33.1%</td>
<td>19.1%</td>
<td>32.1%</td>
<td>31.3%</td>
<td>41.2%</td>
</tr>
<tr>
<td>CoALBP (HSV)</td>
<td>W/O DA</td>
<td>50.3%</td>
<td>24.9%</td>
<td>50.0%</td>
<td>50.0%</td>
<td>50.0%</td>
</tr>
<tr>
<td></td>
<td>DA</td>
<td>33.4%</td>
<td>20.9%</td>
<td>33.2%</td>
<td>29.0%</td>
<td>34.2%</td>
</tr>
<tr>
<td>CoALBP (YCbCr)</td>
<td>W/O DA</td>
<td>50.0%</td>
<td>15.1%</td>
<td>50.1%</td>
<td>50.0%</td>
<td>44.8%</td>
</tr>
<tr>
<td></td>
<td>DA</td>
<td>35.1%</td>
<td><strong>14.9%</strong></td>
<td>34.5%</td>
<td>29.0%</td>
<td>34.2%</td>
</tr>
<tr>
<td>LPQ (HSV)</td>
<td>W/O DA</td>
<td>45.5%</td>
<td>54.9%</td>
<td>43.7%</td>
<td>53.5%</td>
<td>58.7%</td>
</tr>
<tr>
<td></td>
<td>DA</td>
<td>33.4%</td>
<td>21.2%</td>
<td>39.0%</td>
<td>24.9%</td>
<td>39.8%</td>
</tr>
<tr>
<td>LPQ (YCbCr)</td>
<td>W/O DA</td>
<td>43.9%</td>
<td>44.3%</td>
<td>49.9%</td>
<td>46.2%</td>
<td>46.8%</td>
</tr>
<tr>
<td></td>
<td>DA</td>
<td><strong>40.7%</strong></td>
<td>16.3%</td>
<td><strong>33.1%</strong></td>
<td>27.8%</td>
<td><strong>33.3%</strong></td>
</tr>
</tbody>
</table>
Thank You
References


References


Validation Protocols

• Criterions
  – Receiver operating characteristic (ROC)
  – Half total error rate (HTER)
  – Equal error rate (EER)
  – Computational complexity (frame rate)

• Testing Protocols
  – Intra database
  – Cross(Inter) database
Backup Slide

• When a threshold is given, Half Total Error Rate is computed as the average of FAR and FRR.

• For face anti-spoofing problem, after training a classifier on training set, we first compute the threshold which minimize Equal Error Rate (EER) on development set

\[ \tau_{\text{EER}_\omega}^* = \arg \min_\tau |\text{FAR}_\omega(\tau, \mathcal{D}_{\text{dev}}) - \text{FRR}(\tau, \mathcal{D}_{\text{dev}})| \]

• Then, we can use the threshold to compute the HTER on Testing set

\[ \text{HTER}(\tau, \mathcal{D}_{\text{test}}) = \frac{\text{FPR}(\tau, \mathcal{D}_{\text{test}}) + \text{FNR}(\tau, \mathcal{D}_{\text{test}})}{2} \quad [\%] \]

Deep Representations for Iris, Face, and Fingerprint Spoofing Detection

[Menotti, Chiachia, Pinto, Schwartz, Pedrini, Falcao and Rocha TIFS-2015]

Architecture of CNN (source: [8])

- Architecture optimization
  - Incorporate the domain knowledge and CF10-11 neural network structure
  - Two convolutional layers and one fully connected layer
- Filter optimization
  - Back propagation
  - Data augmentation is performed for training
- Limitation
  - Deep learning may easily cause overfitting

Pooling: aggregating activations from the filter in a given region.
Local normalization: normalize the output feature based on the local feature energy
Specular Reflection (Backup Slides for TIFS2015)

• Specular Reflection
  – The immediately reflected light rays are called specular or interface reflections, while those that have penetrated and then reflected back into the air are called diffuse or body reflections. [Tan and Ikeuchi, 2005, TPAMI]

Left: Textured input image, Right: Specular-free image (source: [Tan and Ikeuchi, 2005])

Left: genuine face and specular reflection component Right: fake face and specular reflection component (source: Ref [4])