Detecting Manipulated Facial Videos: A Time Series Solution

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Manipulated Video Detection Problems



Challenges:

Huge datasets with various manipulate generation methods

Poor robustness on unseen cases, slow inference speed

Related Works: Facial Forgery Detection Method

[Pan et al., 2007] Eye-Blinking Model

[Afchar et al., 2018] CNN-Based Model

[Ferrara et al., 2012] Color-based Model

[Li et al., 2018] LSTM-CNN Model

Our approaches: FA/DFA-LSTM Simple yet Effective



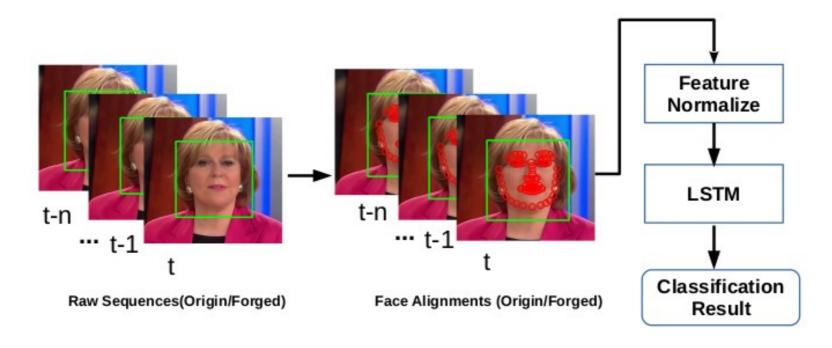


Figure 1: Framework of the proposed FA-LSTM model.

 $I \subseteq R^{n \times 136}$, in which n denotes the window length of LSTM. Note that n also equals to one slice of the input sequences with the range [t-n, t]

Feature Project: Dense Face Alignment



3D Morphable Model: $oldsymbol{S} = ar{oldsymbol{S}} + oldsymbol{A}_{shp} + oldsymbol{A}_{exp} oldsymbol{lpha}_{exp}$

Texture Model: $T = \bar{T} + B_{shp}\beta_{shp}$

Projected 3D facial vertices: $V(p) = s \cdot \mathbf{P_r} \cdot R(\bar{S} + A_{shp}\alpha_{shp} + A_{exp}\alpha_{exp}) + t_x$

Parameters: $p = [s, R, t_x, \alpha_{shp}, \alpha_{exp}]$

PAF: 3D vertex => $64 \times 64 \times 2$ feature anchors

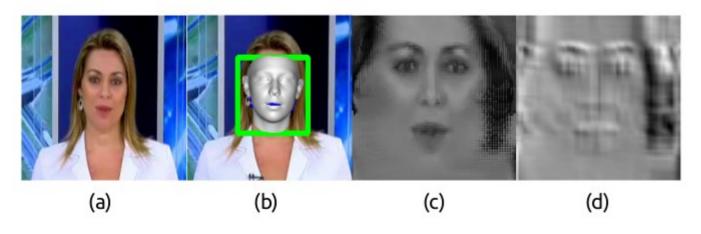


Figure 4: Illustrations of different feature types. (a) raw sequence image. (b) 3D vertices mask of a facial surface. (c) PAF of a facial surface. (d) PAC of a facial surface.

DFA-LSTM



DFA-Features
$$\xrightarrow{D \times N}$$
 PCA $\xrightarrow{L \times N}$ Bi-LSTM \longrightarrow Output

$$J(\boldsymbol{W}, \boldsymbol{Z}) = \parallel \boldsymbol{X} - \boldsymbol{W} \boldsymbol{Z} \parallel_F^2$$
 $\mathbf{Z} \in \mathbb{R}^{L \times N} \; \boldsymbol{W} \in \mathbb{R}^{D \times L}$

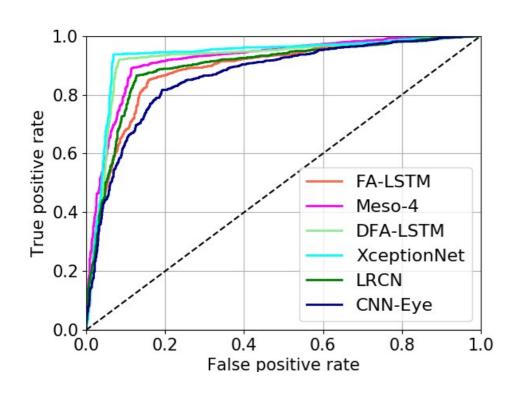
$$\begin{cases} \boldsymbol{\Sigma} = 1/N \sum_{i=1}^{N} \boldsymbol{x}_i \boldsymbol{x}_i^T \\ \boldsymbol{\Sigma} \boldsymbol{w}_i = \lambda_i \boldsymbol{w}_i. \end{cases}$$

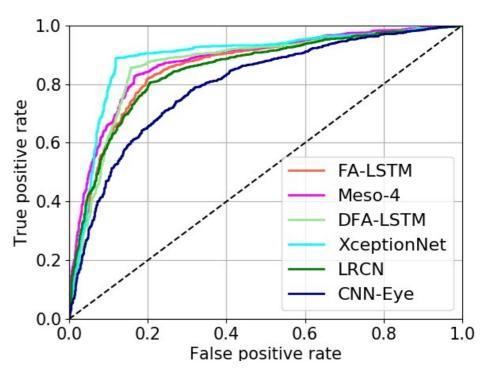
Wi , $0 \le i \le N$ is computed as an eigenvector of the covariance matrix Σ with the eigenvalue λi

Loss Function: $\mathcal{L}(\widehat{y_i}, y_i) = -w_i[y_i \log \widehat{y_i} + (1 - y_i) \log(1 - \widehat{y_i})]$



ROC curve for forgeries detection method on FaceForensics++ dataSet. Compression Level: 23 and 40





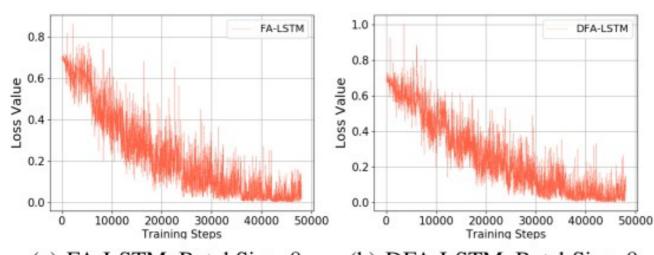


Inference Speed and Accuracy Test

Methods	CPU	GPU
Meso-4[Afchar <i>et al.</i> , 2018]	43.251ms	16.344ms
XceptionNet[Chollet, 2017]	166.021ms	38.130ms
LRCN[Li et al., 2018]	38.260ms	13.974ms
CNN-Eye[Kim et al., 2017]	18.362ms	6.611ms
FA-LSTM	16.125ms	5.314ms
DFA-LSTM	37.320ms	10.253ms

Methods	Accuracy		Runtime	
	$C_{-}23$	$C_{-}40$	CPU	GPU
FA-LSTM	0.825	0.689	16.125m	s 5.314ms
FA-LSTM + Atten-	0.879	0.721	20.025m	s7.221ms
tion				
Meso-4[Afchar et	0.830	0.702	43.251m	s 16.344ms
al., 2018]				

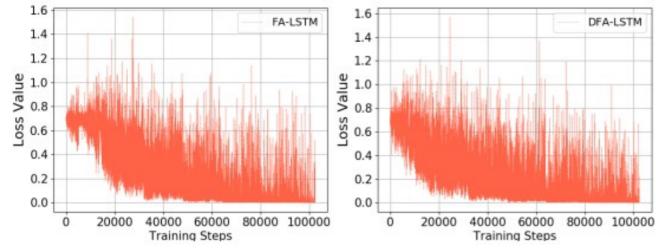




Training Convergence Analysis for DFA/FA LSTM Method with Various Batch-Size

(a) FA-LSTM, BatchSize=8

(b) DFA-LSTM, BatchSize=8



(c) FA-LSTM, BatchSize=1

(d) DFA-LSTM, BatchSize=1



Visual Effect Demo for Facial Forgery Detection



Example sequences of failure detection cases. #1, #3, #5:
Misclassification samples of FA-LSTM generated by DeepFake. #2, #4, #6: Improved results of #1, #3, #5 after introducing the attention layer. #1, #2 are forged samples, whereas #3-#6 are original samples.



THANKS