Face Familiarity in Deep Convolutional Neural Networks

Introduction

State-of-the-art Deep Convolutional Neural Networks (DCNNs) perform with

- high accuracy on face identification tasks (e.g. Taigman et al. 2014).
- good generalization across viewpoint, illumination, and appearance.

To date, DCNN performance tested only with 'cooperative' images. DCNN performance for disguised faces is unknown.

Here we test identification performance of a state-of-the art DCNN on disguised face images (Sankaranarayanan et al. 2016).

DCNNs – are they impaired by evasion and impersonation disguise? Humans are strongly impaired by evasion disguise; less impaired by impersonation (Noyes & Jenkins, submitted)

DCNN performance for disguised faces – do they improve with identity **familiarization**? Humans -> more accurate for **familiar** disguised faces (Noyes & Jenkins, submitted).

Stimuli

- Stimuli FAÇADE image dataset (26 models)
- Conditions No Disguise and 3 Disguise types

Evasion: model photographed to look unlike self.

Impersonation Similar: model photographed to look like a 'similar' person.

Impersonation Random: model photographed to look like a 'random' person.



1. FAÇADE

algorithm

images input to

DCNN Similarity Procedure







3. 'Feature

generated

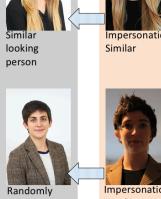
vectors'

for each

image

IMPERSONATION





4. Similarity

computed

scores

Methods

Results

Main Premise

- •

- •

•

(Sankaranarayanan et al. 2016)

2. Processed.

If similarity scores > criterion = same identity, if not = different identity

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Human & Machine: Face Matching (Noyes & Jenkins, submitted; Noyes et al. 2017)	2 Methods of Familiarity	
	Averaging Method of Familiarity	Contrast Method of Familiarity
ImageSame identity?ImageFeference ImageModel Image	Verage Representation of Reference IdentitySame identity?Model Image	SVM 1 SVM 2 SVM 3 SVM 3
 Paired matching task on humans (Noyes & Jenkins, submitted). DCNN matching performance computed by calculating similarity score between Reference Image and Model Image for each image pair. Similarity score compared against criterion to determine same/different identity response. 	 When people learn a face, they may create an average image- based representation for multiple images of the face (Kramer, Ritchie & Burton, 2016). <u>Alternative model</u>: Average <i>DCNN face representation</i>: Varied number (N= 0-100) of no disguise images of each model submitted to DCNN. Similarity score calculated by comparing Average Representation with Model Image. 	 Familiarity depends on learning within-identity variation and between-identity contrasts. Trained SVM classifiers for each identity. DCNN learned many images of each identity, and how each identity differed from all other identities. All images compared to SVMs. Dot product for each image pair calculated to produce similarity score.
% of correct responses Image: Correct responses Unfamiliar Human Familiar Human Participants Participants No Disguise Disguise No Disguise Disguise Same 96 60 98 87 100 50 Evasion Image: Different 92 82 99 98 100 96 Imp. Sim.	% of correct responses 3 Images 5 Images 10 Images 20 Images All Images All Images Same No Disguise 100.0 100.0 100.0 100.0 100.0 100.0 100.0 Same Disguise 50.0 46.9 52.3 64.6 65.4 69.2 Different Similar No Disguise 100.0 99.2 98.5 96.2 96.2 96.2 Different Similar Disguise 96.2 95.4 87.7 85.4 87.7 84.6	% of correct responses 3 images 5 images 10 images 20 Images All Images Same No Disguise 99.2 99.2 100.0 100.0 96.0 Same Disguise 40.0 43.9 44.6 46.2 57.6 Different Similar No Disguise 99.2 100.0 100.0 100.0 100.0 Different Similar Disguise 99.2 100.0 100.0 100.0 100.0 Different Similar No Disguise 99.2 100.0 100.0 100.0 100.0 Different Similar No Disguise 99.2 100.0 100.0 100.0 100.0 100.0 Different Similar No Disguise 99.2 100.0 100.0 100.0 100.0 100.0

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Different 98 89 100 98 100 92 Imp. Rand Random	Different Random No Disguise100.0100.0100.0100.0100.0Different Random Disguise92.396.295.495.496.296.2	No Disguise 100.0 100.0 100.0 100.0 100.0 Different Random 99.2 100.0 100.0 100.0 96.0	

Unfamiliar

Humans : No Disguise > Impersonation >>> Evasion DCNN : No Disguise > Impersonation >>> Evasion

Familiar

Humans : No Disguise > Impersonation > Evasion DCNN : ????

'Averaging' Method Results:

- Increased performance on Evasion trials
- But... *decreased* performance on different-identity face pairs



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'Contrast' Method Results:

- Increased performance on Evasion trials
- Maintained high performance on different-identity face pairs



Conclusions

- DCNN (and human) identification performance impaired by Evasion Disguise.
- Averaging Method improved Evasion Disguise but reduced performance on different-identity trials.
- Contrast Method improved Evasion Disguise and maintained high performance of different identity trials. 🗸

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