Supplementary Material

Anonymous ECCV submission

Paper ID 3004

1 Additional Network Details

The network used for spoof traces classification in Sec.4-4 is shown in Fig. 1. It consists of 5 conv layers and 3 fully connected layers. For each layer, we concatenate with a Leaky ReLU and a Batch Normalization layer. For the first 2 fully connected layer, we apply a dropout of 0.3.

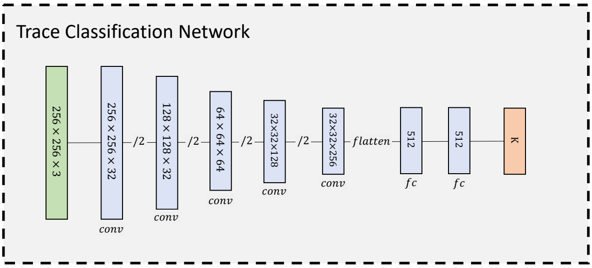

Fig. 1: The network architecture of Trace Classification Network used in Spoof Traces Classification, Sec. 4-4.

2 Spoof Traces Classification

We also execute the spoof traces classification task in Sec.4-4 on more spoof types in SiW-M database. We leverage the train/test split on SiW-M Protocol 1. We first train the STDN till convergence, and use the estimated traces from training set to train the trace classification network. We explore both 6-class scenario and 14-class scenario and the results are shown in Tab. 1. Our 6-class model and 14-class model can achieve classification accuracy of 91.6% and 92.0% respectively. Since the traces are more distinct among different spoof types, those performances are even better than fewer-class classification on print/replay scenario in Oulu-NPU Protocol 1). This further demonstrates that the STDN can estimate spoof traces that contain significant information of spoof mediums and can be applied to multiple spoof types.

3 Examples of the disentangled spoof trace elements

Shown in Fig. 2, we illustrate the effects of each element in spoof trace disentanglement by progressively removing the elements one by one. For the replay attack, the spoof

Label \ Predict	Live	Print	Replay	Masks	Makeup	Partial
Live	116	6	6	3	0	0
Print	1	40	1	3	0	1
Replay	3	1	32	1	0	1
Masks	3	1	1	90	0	3
Makeup	3	0	0	0	36	0
Partial	2	0	0	2	0	146

Label \ Predict	Live	Print	Replay	Half	Silic.	Trans.	Paper Mask	Mann.	Ob.	Im.	Cos.	Fun.	Paper Glass	Partial Paper
Live	129	0	1	0	0	0	0	0	0	0	0	0	0	1
Print	4	40	1	0	0	0	0	0	1	0	0	0	0	0
Replay	2	2	34	0	0	0	0	0	0	0	0	0	0	0
Half	1	0	0	25	0	0	0	0	0	0	0	2	0	1
Manne.	2	1	0	0	12	0	0	1	0	0	0	0	0	0
Paper	1	0	0	0	0	6	0	0	0	0	0	0	0	0
Silic.	2	0	0	0	0	0	9	0	0	0	0	0	0	0
Trans.	2	0	0	0	0	0	0	33	0	0	0	0	0	0
Im.	1	0	0	0	0	0	0	0	23	0	0	0	0	0
Cos.	4	0	0	0	0	0	0	0	0	2	0	0	0	0
Ob.	3	0	0	0	0	0	0	0	0	0	6	0	0	0
Papergls.	4	0	1	0	0	0	0	0	0	0	0	46	0	0
Fun.	1	0	0	0	0	0	0	0	0	0	0	0	63	0
Partial Paper	1	0	0	0	0	0	0	0	0	0	0	0	0	34

Table 1: Confusion matrices of spoof traces classification on SiW-M database. The left table is 6-class classification, and the right is 14-class classification.

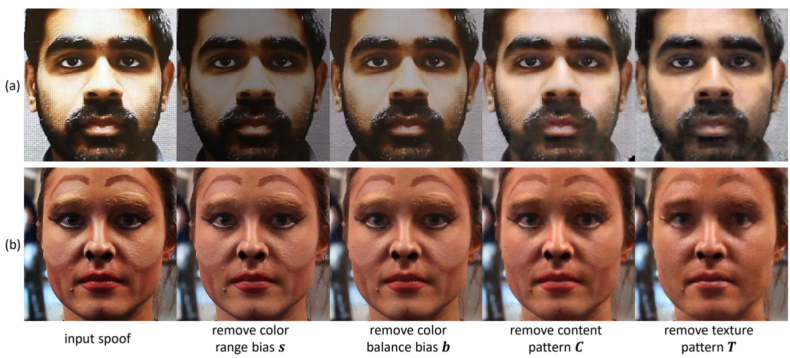

Fig. 2: The example of each disentangled spoof trace element. The estimated spoof trace elements of input spoof (first colum) are progressively removed in the order of $\mathbf{s}$, $\mathbf{b}$, $\mathbf{C}$, $\mathbf{T}$. (a) Replay attack; (b) Makeup attack.

samples comes with strong over-exposure as well as clear Moiré pattern. Removing the color range and balance bias can effectively correct the over-exposure and color distortion caused by the digital screen. Removing the content pattern can further correct the bright spots in the forehead and cheek, while still having the Moiré pattern left. And removing the texture pattern can peel off the high-frequency grid effect and reconstruct the live counterpart.

For the makeup attack, since there is no strong color range bias, removing estimated color range and balance bias would bring few changes to the input face. Next, while removing content pattern, the shadow on the cheek and the fake eyebrows are adequately lightened. Finally, removing the texture pattern would significantly correct the spoof traces from artificial wax, eyeliner and shadow on the cheek.