LIKELIHOOD RATIO BASED LOSS TO FINETUNE CNNS FOR VERY LOW RESOLUTION FACE VERIFICATION

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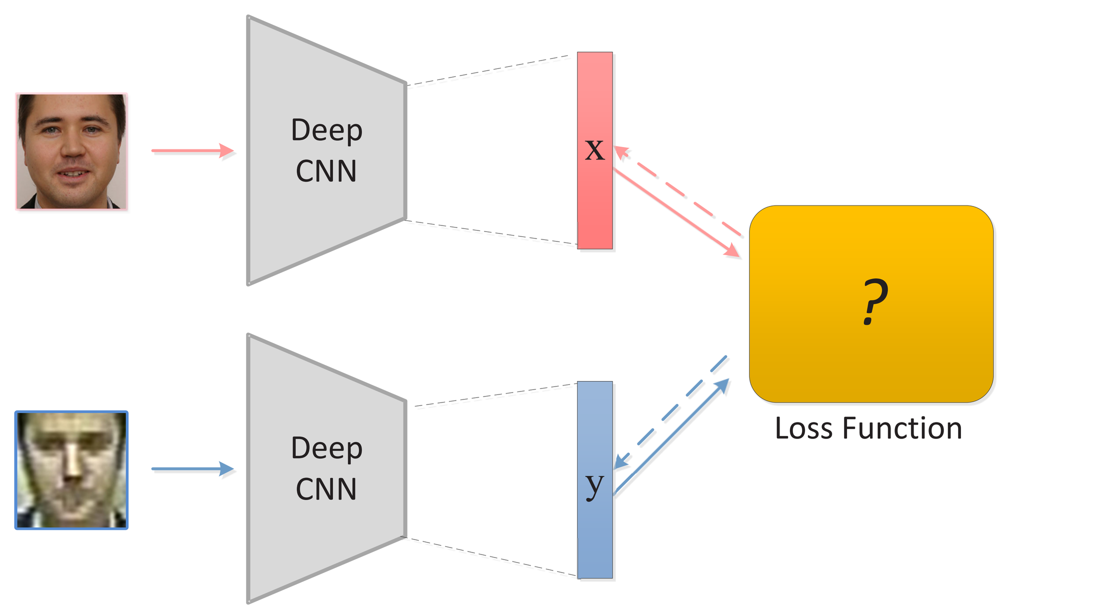
PROBLEM

How to build a better loss function for the face verification problem?

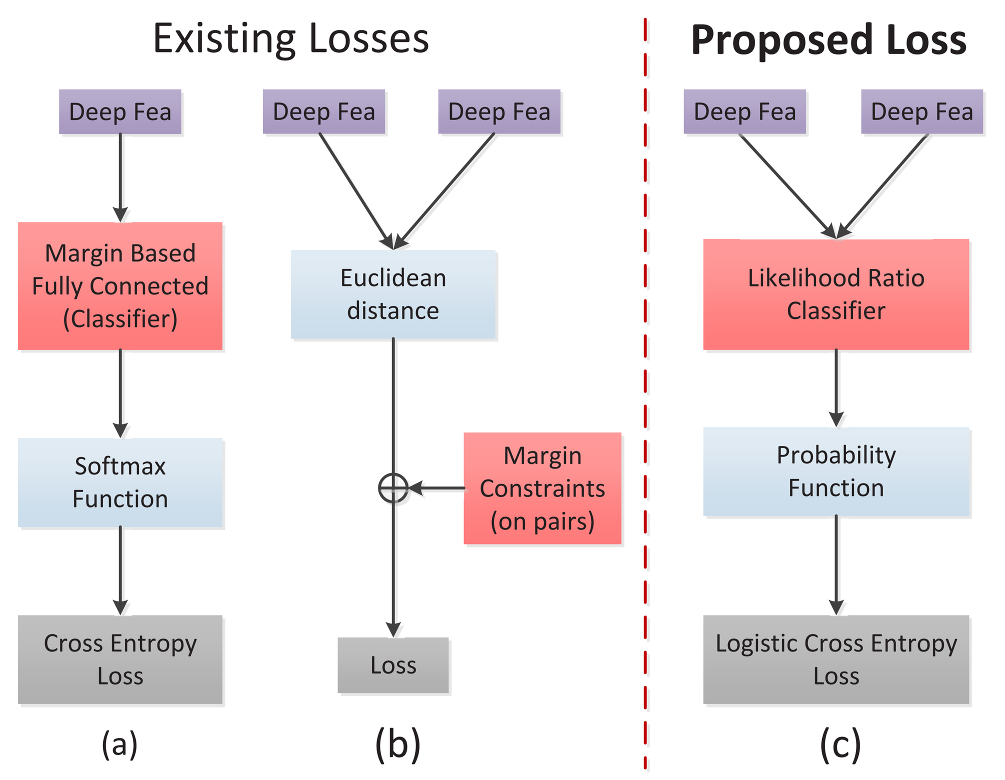


CONTRIBUTIONS

We apply the proposed loss function to address very low resolution (VLR) face recognition with the resolution of VLR face lower than 16×16. The main contributions of this paper are

1. A likelihood ratio based loss function
2. A training procedure to fine tune CNNs trained on arbitrary losses with limited data
3. State of the art results on VLR Scface dataset

MOTIVATION



(a) Margin-based softmax loss intends to improve the classifier part i.e., fully connected layer by imposing margin constraints.

(b) Image pair margin based loss employs constraints on image pairs rather than the single image, a intuitive way for biometrics verification.

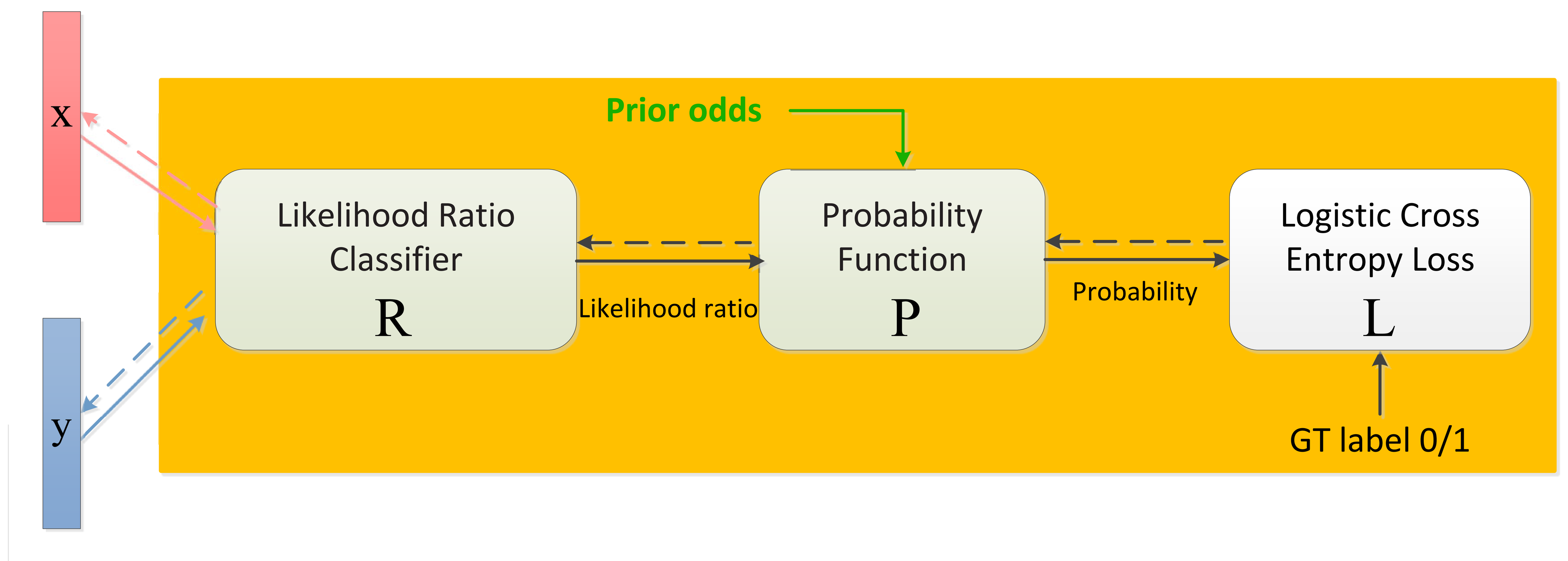
(c) The proposed loss is based on likelihood ratio classifier *which is an optimal classifier in Neyman-Pearson sense*. Besides, it directly optimizes the constraints between image pairs which is *very intuitive*.

REFERENCES

[1] D. Zeng, H. Chen and Q. Zhao. Towards resolution invariant face recognition in uncontrolled scenarios. In *ICB '2016*

[2] Y. Peng, L. Spreeuwers and R. Veldhuis. Low-resolution face alignment and recognition using mixed-resolution classifiers. IET biometrics 2017

METHODS



The likelihood ratio based loss function consists of three parts.

(1) *Likelihood ratio classifier* R takes the deep feature pair and obtain its likelihood ratio

(2) *Probability function* P explores the situation-relevant prior odds to predict the probability

(3) *Logistic cross entropy loss* L calculates the loss based on the predicted probability

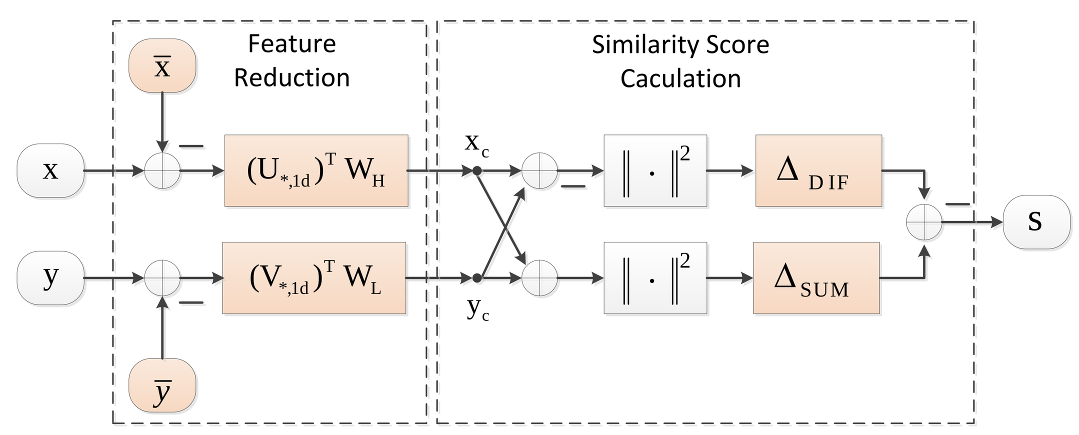
The training procedure for VLR face verification including,

- Training the deep CNN (use RIDN [1] deep model)
- Training the likelihood ratio classifier
- Apply the proposed loss to finetune the deep CNN

More detail about proposed loss is illustrated in the 'proposed loss' session.

PROPOSED LOSS

(1) *Likelihood ratio classifier*

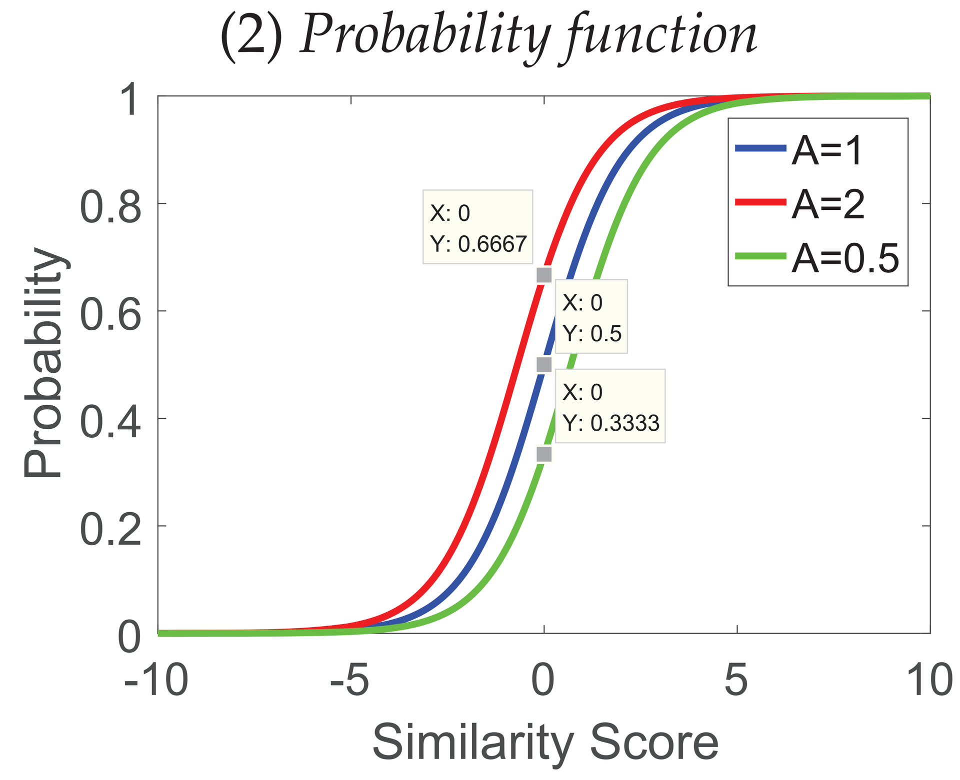


Likelihood ratio score s obtained by likelihood ratio classifier [2] is denoted as,

$$s = \mathrm{R}(\mathbf{x}, \mathbf{y}; \mathbf{W}).$$

Where **x** and **y** are the initial deep features of the HR and VLR faces. **W** needs to be estimated during a training process.

(2) *Probability function*



The figure shows how the prior odds A (a hyper-parameter) affects the predicted probability based on the obtained score s. When A equals 1, the probability function degrades to the **sigmoid** function.

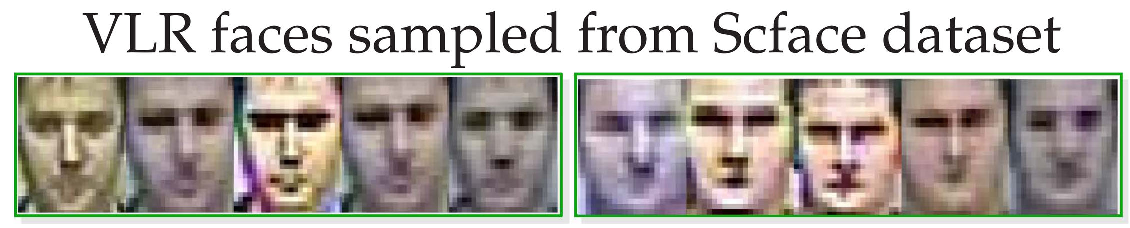
(3) *Logistic cross entropy loss*

$$L = -\mathrm{P}\log\hat{\mathrm{P}} - (1 - \mathrm{P})\log(1 - \hat{\mathrm{P}}),$$

where P is the target probability from GT label, $\hat{\mathrm{P}}$ represents the predicted probability.

RESULTS

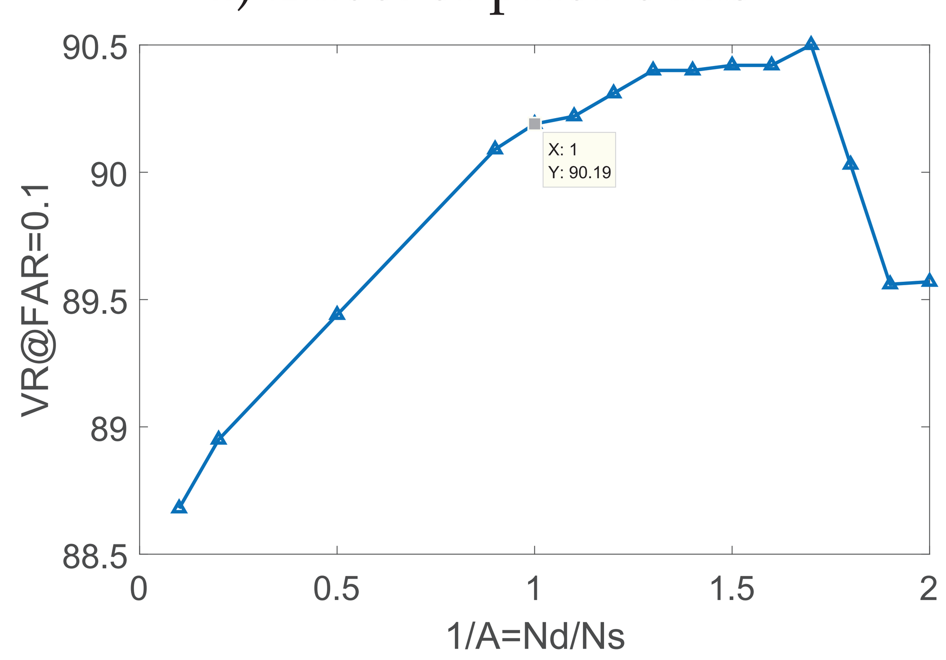
VLR faces sampled from Scface dataset



Experiments Results

We have explored the effect of prior odds and the number of training image pairs. Finally, the comparison performance with SOTA methods on Scface are given.

1) Effect of prior odds



2) Effect of number of training pairs

# genuine pairs	# impostor pairs	VR@FAR=0.1
100	100	88.47%
200	200	89.90%
300	300	**90.19%**
400	400	89.15%
500	500	89.73%

3) Comparison with SOTA methods

Methods	VR@FAR=0.1
RIDN [1]	70(3)%
MRC [2]	73(6)%
Proposed Baseline	87.65%
Proposed Loss	**90.50%**