



Irish Machine Vision and Image  
Processing Conference 2018

# A Minkowski Distance-based Generalisation Method for Improving Centre Loss for Deep Face Recognition

Xin Wei, Hui Wang, Huan Wan and Bryan Scotney

[ulster.ac.uk](http://ulster.ac.uk)

IMVIP 2018

August 29-31, 2018

# Outline:

1. Introduction
2. The proposed method
3. Conclusion and future works



# 1. Introduction

# 1. Introduction

Facial recognition system:

a technology capable of identifying or verifying a person from a digital image or a video frame [1].



1. Wikipedia contributors. (2018, August 27). Facial recognition system. In Wikipedia, The Free Encyclopedia. Retrieved 09:49, August 28, 2018, from [https://en.wikipedia.org/w/index.php?title=Facial\\_recognition\\_system&oldid=856753855](https://en.wikipedia.org/w/index.php?title=Facial_recognition_system&oldid=856753855)

# 1. Introduction

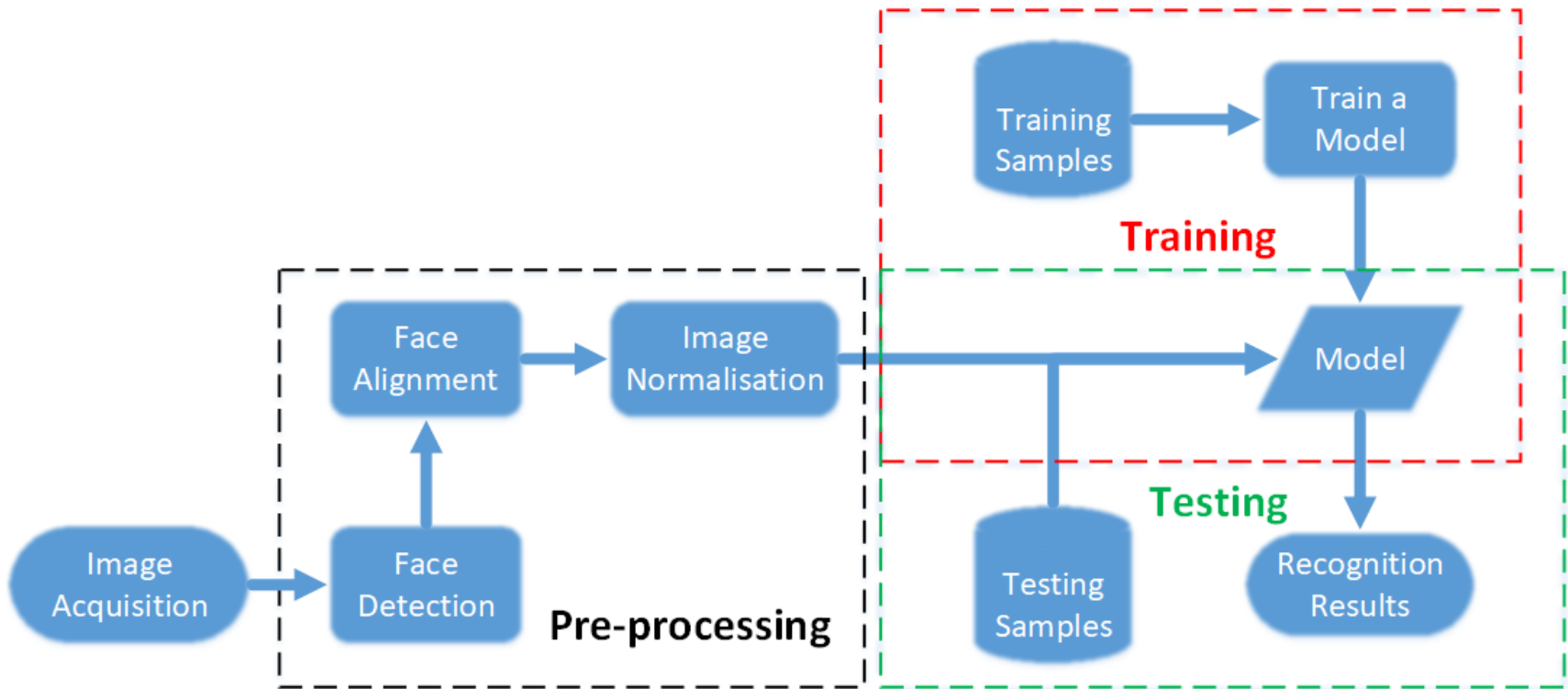
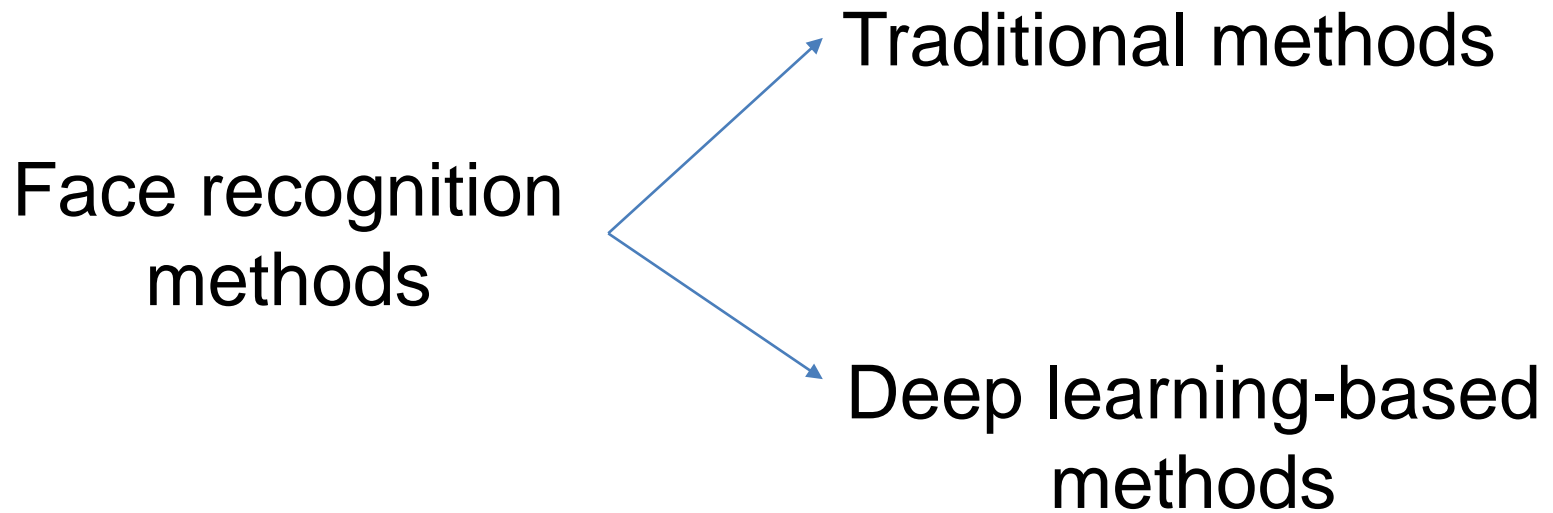


Fig. 1. The basic framework of a face recognition system.

# 1 Introduction



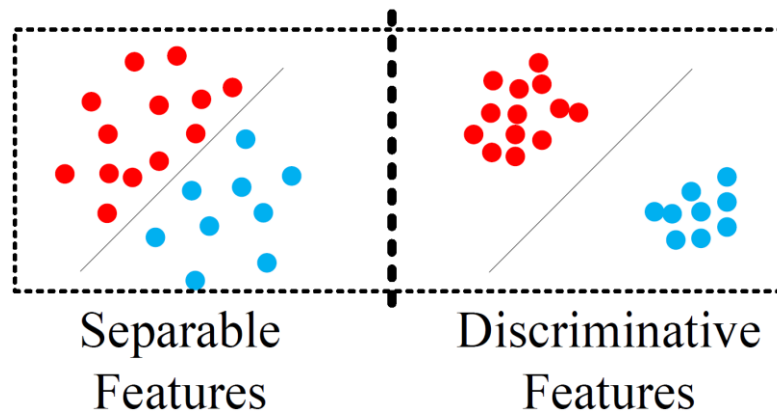
## **2. The proposed method**

- Minkowski Distance-based  
Centre loss (MC loss)**

## 2.1 Softmax Loss and Centre Loss

$$\text{Softmax Loss: } L_S = -\frac{1}{N} \sum_{i=1}^N \log \frac{e^{W_{y_i}^T f_i + b_{y_i}}}{\sum_{j=1}^K e^{W_j^T f_i + b_j}} \quad (1)$$

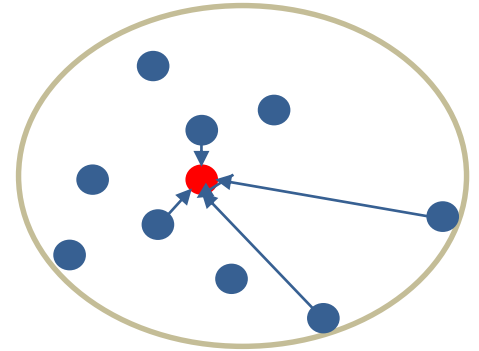
where  $N$  is the batch size,  $K$  is the class number of a batch,  $f_i \in R_d$  denotes the feature of the  $i$ th sample belonging to the  $y_i$ th class,  $W_j \in R_d$  denotes the  $j$ th column of the weight matrix  $W$  in the final fully connected layer and  $b_j$  is the bias term of the  $j$ th class.





## 2.1 Softmax Loss and Centre Loss

$$\text{Centre Loss: } L_C = \frac{1}{2} \sum_{i=1}^N \|f_i - c_{y_i}\|_2^2 \quad (2)$$



where  $c_{y_i}$  denotes the class centre of the  $y_i$ th class

$$\begin{aligned} \text{Total Loss: } L &= L_S + \lambda L_C \\ &= -\frac{1}{N} \sum_{i=1}^N \log \frac{e^{W_{y_i}^T f_i + b_{y_i}}}{\sum_{j=1}^K e^{W_j^T f_i + b_j}} + \frac{\lambda}{2} \sum_{i=1}^N \|f_i - c_{y_i}\|_2^2 \quad (3) \end{aligned}$$

where  $\lambda$  is the hyper-parameter for balancing the two loss functions.

## 2.2 Minkowski Distance-based Centre loss (MC loss)

The Minkowski distance of order  $n$  between two points  $X$  and  $Y$ :

$$D(X, Y) = \left( \sum_{i=1}^k |x_i - y_i|^n \right)^{1/n} \quad (4)$$

where  $X = (x_1, x_2, \dots, x_k)$  and  $Y = (y_1, y_2, \dots, y_k) \in R_k$ . Therefore the  $n$ th power of the Minkowski distance of order  $n$  is:

$$D(X, Y)^n = \sum_{i=1}^k |x_i - y_i|^n \quad (5)$$

## 2.2 Minkowski Distance-based Centre loss (MC loss)

$$\text{MC Loss: } L_M = \frac{1}{n} \sum_{i=1}^N \|f_i - c_{y_i}\|_n^n \quad (6)$$

where  $n \in \mathbb{R}, n > 0$ . Typically,  $n$  is set to be 2, 3, 4, ...

$$\begin{aligned} \text{Total Loss: } L &= L_S + \lambda L_M \quad (7) \\ &= -\frac{1}{N} \sum_{i=1}^N \log \frac{e^{W_{y_i}^T f_i + b_{y_i}}}{\sum_{j=1}^K e^{W_j^T f_i + b_j}} + \frac{\lambda}{n} \sum_{i=1}^N \|f_i - c_{y_i}\|_n^n \end{aligned}$$

where  $\lambda$  is the hyper-parameters for adjusting the impact of MC loss.

## 2.2 Minkowski Distance-based Centre loss (MC loss)

$$\text{Indicator: } \left( \frac{|f_{ik} - c_k|}{|f_{jk} - c_k|} \right)^n,$$

where  $c_k$  is the  $k$ th feature of a class centre,  $f_{ik}$  is the  $k$ th feature of sample  $i$ ,  $f_{jk}$  is the  $k$ th feature of sample  $j$ . Sample  $i$  is on the edge of the class while sample  $j$  is near the class centre, and

$$\frac{|f_{ik} - c_k|}{|f_{jk} - c_k|} > 1.$$

When  $n = 2$ , MC loss deteriorates to Centre loss.

When  $n > 2$ ,  $\left( \frac{|f_{ik} - c_k|}{|f_{jk} - c_k|} \right)^n$  is greater than it was in the Centre loss.

## 2.2 Minkowski Distance-based Centre loss (MC loss)

Algorithm 1 shows the basic learning steps in the CNNs with the proposed **Softmax + MC loss**.

---

**Algorithm 1** Learning algorithm in the CNNs with the proposed Softmax + MC loss.

---

**Input:** Training samples  $\{f_i\}$ , initialised parameters  $\theta_C$  in convolution layers, parameters  $W$  in the final fully connected layer, and initialised class centres  $\{c_j | j = 1, 2, \dots, n\}$ . Learning rate  $\mu^t$ , hyperparameter  $\lambda$ , learning rate of the class centres  $\alpha$  and the number of iteration  $t \leftarrow 1$ .

**Output:** The parameters  $\theta_C$ .

1: **while** not converge **do**

2: Calculate the total loss by  $L^t = L_S^t + L_M^t$ .

3: Calculate the backpropagation error  $\frac{\partial L^t}{\partial f_i^t}$  for each sample  $i$  by  $\frac{\partial L^t}{\partial f_i^t} = \frac{\partial L_S^t}{\partial f_i^t} + \lambda \frac{\partial L_M^t}{\partial f_i^t}$ .

4: Update  $W$  by  $W^{t+1} = W^t - \mu^t \frac{\partial L_S^t}{\partial W^t}$ .

5: Update  $c_j$  for each centre  $j$  by  $c_j^{t+1} = c_j^t - \alpha \Delta c_j^t$ .

6: Update  $\theta_C$  by  $\theta_C^{t+1} = \theta_C^t - \mu^t \sum_i^N \frac{\partial L^t}{\partial f_i^t} \frac{\partial f_i^t}{\partial \theta_C^t}$ .

7:  $t \leftarrow t + 1$ .

8: **end while**

---

## 2.2 Minkowski Distance-based Centre loss (MC loss)

Table 1: Verification performance of state-of-the-art methods on LFW and YTF datasets.

Methods	Source	Images	LFW(%)	YTF(%)
Deep Face [Taigman et al., 2014]	CVPR	4M	97.35	91.4
DeepID2+ [Sun et al., 2015]	CVPR	N/A	99.47	93.2
Fusion [Taigman et al., 2015]	CVPR	500M	98.37	N/A
FaceNet [Schroff et al., 2015]	CVPR	200M	99.63	95.1
Baidu [Liu et al., 2015]	arXiv	1.3M	99.13	N/A
Centre Loss [Wen et al., 2016]	ECCV	0.7M	99.28	94.9
Multibatch [Tadmor et al., 2016]	NIPS	2.6M	98.20	N/A
Aug [Masi et al., 2016]	ECCV	0.5M	98.06	N/A
SphereFace [Liu et al., 2017]	CVPR	0.5M	99.42	95.0
Range Loss [Zhang et al., 2017]	ICCV	1.5M	99.52	93.7
Softmax loss	N/A	3M	99.43	94.9
Softmax loss + Centre loss	N/A	3M	99.50	95.1
Softmax loss + MC loss (Proposed)	N/A	3M	99.57	95.3



## **3. Conclusion and future works**

# Conclusion

- We proposed a Minkowski distance-based generalisation method for improving Centre loss for deep face recognition.
- Experimental results on the LFW image dataset and the YTF video dataset show that the proposed method is highly competitive even compared with the state-of-the-art methods.



# Future works

- Design better loss functions to further enhance the discriminative ability of features.
- Explore the relationship between the network structures and the loss functions, and find a stronger network structure.

# Question and Answer