TBSI 清华-伯克利深圳学院 Tsinghua-Berkeley Shenzhen Institute

Person Recognition with HGR Maximal Correlation on Multimodal data

Yihua Liang(1), Fei Ma(1), Yang Li(1), Shao-Lun Huang(1)

(1) Tsinghua-Berkeley Shenzhen Institute , Tsinghua University

Abstract

- In video analysis and public surveillance, information from multiple modalities are used to jointly determine the identity of a person.
- We propose a correlation-based multimodal person recognition framework that is relatively simple but can efficaciously learn supervised information in multimodal data fusion and resist noise.

Introduction

TBSI 清华-伯克利深圳学院 Tsinghua-Berkeley Shenzhen Institute

Challenges

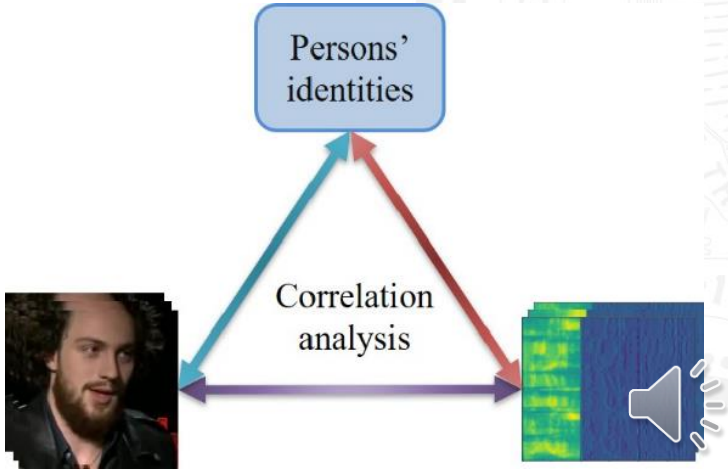
- Learn person's identity while merging multimodal data for person recognition.
- Hold robustness to noise.

Brief introduction

- Analyze correlation among visual and audio input and identities.

Contributions

- Proposed objective merge multimodal data and learn discriminative embeddings more effectively.
- By maximizing the HGR maximal correlation between labels and input, the embedding robustness under noise is improved.

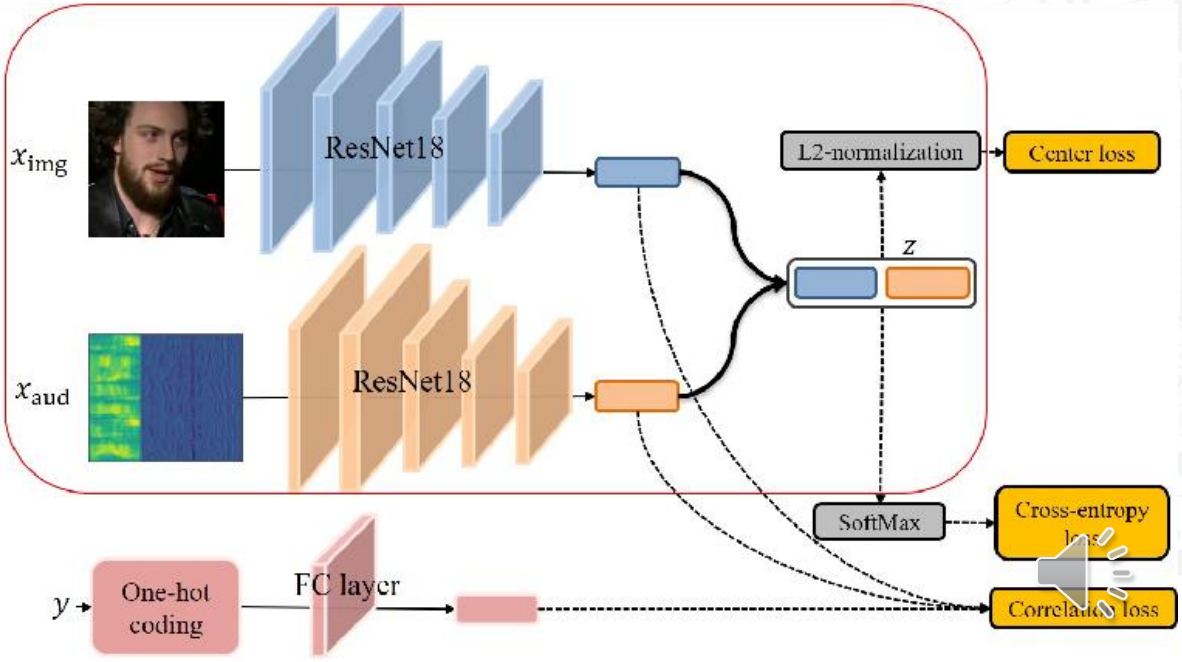


Existing methods

- Uni-modal methods do not fully utilize multimodal information.
- Correlation based methods leave the extraction of multimodal input's relationship with identity information to downstream tasks.
- Multimodal methods does not consider real world noise.

Method

- In training stage, visual feature f(ximg) and audio feature g(xaud) are extracted by ResNet18.
- Embedding z is generated by concatenation; Meanwhile, the identity is converted to an one-hot vector and then mapped to feature h(y) by a fully connecting layer.
- In the end, framework is jointly optimized by three loss functions.
- During validation and test, only ximg and xaud are taken by the framework

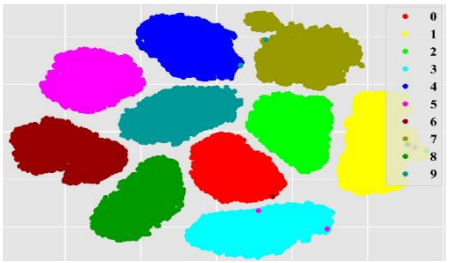


Method

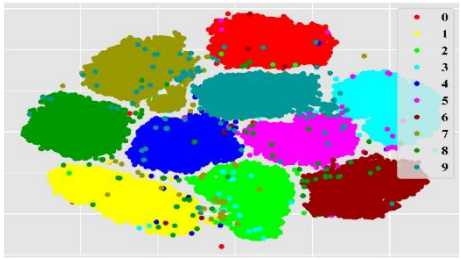
- Cross entropy loss: basic classification.
- Center loss: separates different identities in embedding space.
- Correlation loss:
  - An adoption of HGR maximal correlation which holds good theoretical interpretation.
  - Effective merge multimodal data.
  - Robustness to noise: lead to larger inter-class margin and less falsely classified points.

$$\mathcal{L}_{\text{ctr}} = \frac{1}{2}\sum_{i=1}^{m} \| z^{(i)} - c^{y^{(i)}} \|_2^2$$

$$\mathcal{L}_{\text{corr}} = -\sum_{l \neq k}^{d} (\mathbb{E}[f_l{}^T f_k] - \frac{1}{2}\text{tr}(\text{cov}(f_l)\text{cov}(f_k)))$$



Cross entropy loss



Correlation loss

Experiments & Results

TBSI 清华-伯克利深圳学院 Tsinghua-Berkeley Shenzhen Institute

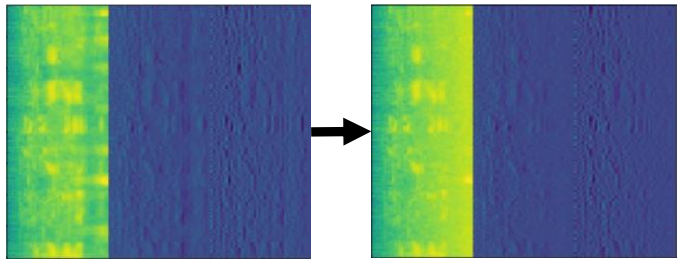
Methods	Accuracy(%)
Product [1]	91.86 ± 0.9
wProduct [1]	90.93 ± 1.7
MMA [2]	91.43 ± 0.7
MSE [3]	90.00 ± 1.0
Imd [4]	91.89 ± 1.3
Ours	**97.56** ± 0.6

Methods	Accuracy(%)
AudioOnly [5]	83.75 ± 1.1
VisualOnly [6]	88.19 ± 1.6
CLF-CTR	89.54 ± 0.3
CLF-ONLY	89.75 ± 0.6
CLF-CORR	**97.84** ± 0.5
CCA [7]	86.37 ± 0.7
Soft HGR [8]	87.74 ± 1.1
Ours	97.56 ± 0.6

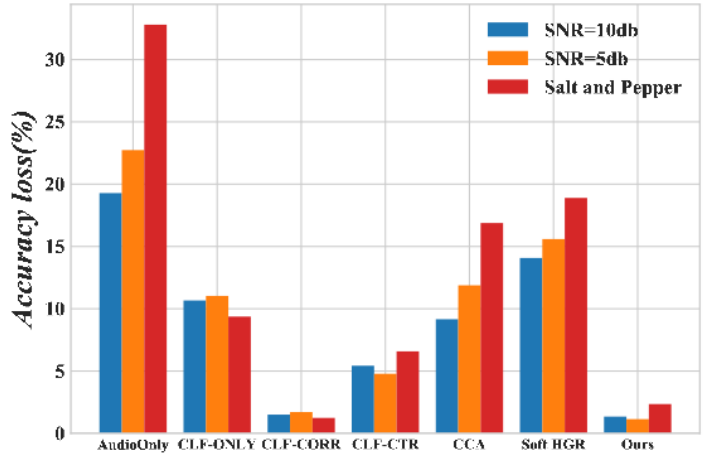
Compared with previous methods , ours methods lead to large improvement in accuracy.

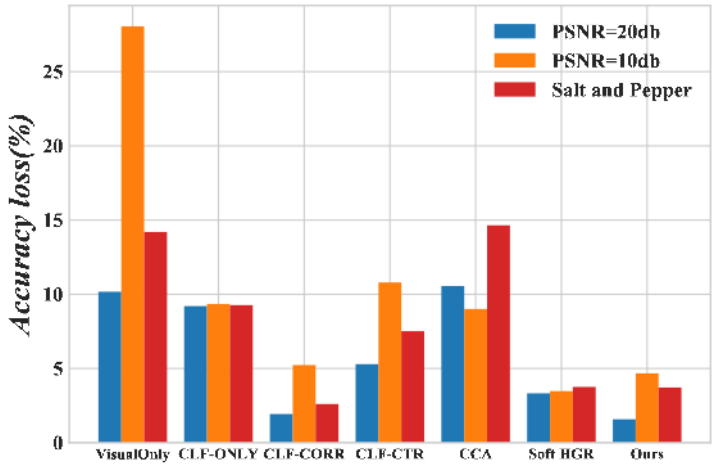
Ablation study shows that this improvement is mainly contributed by our correlation loss.

Experiments & Results



We add noise to test set for testing robustness, and it shows that the correlation loss largely reduces the accuracy loss.





Conclusion

- The proposed objective not only make the framework acquire more sufficient guidance to supervised target in training but improve its robustness to noise. too. Thus the framework effectually solves the challenges about combining multimodal data and resisting different types of noise.

Future Work

- Take more different types of noise into consideration.
- Try to combine attention mechanism with correlation learning.
- Adapt this framework to similar tasks which take multi-modal input and rely on labels.

References

[1] Chowdhury, Y. Atoum, L. Tran, X. Liu, and A. Ross, “Msu-avis dataset: Fusing face and voice modalities for biometric recognition in indoor surveillance videos,” in2018 24th International Conference on Pattern Recognition (ICPR). IEEE, 2018, pp. 3567–3573.

[2] Y. Liu, P. Shi, B. Peng, H. Yan, Y. Zhou, B. Han, Y. Zheng, C. Lin,J. Jiang, Y. Fanet al., “iqiyi-vid: A large dataset for multi-modal person identification,”arXiv preprint arXiv:1811.07548, 20

[3] Chen, S. Wang, and S. Chen, “Deep multimodal network for multi-label classification,” in2017 IEEE International Conference on Multi-media and Expo (ICME). IEEE, 2017, pp. 955–960.

[4] B. Wang, Y. Yang, X. Xu, A. Hanjalic, and H. T. Shen, “Adversarial cross-modal retrieval,” inProceedings of the 25th ACM international conference on Multimedia. ACM, 2017, pp. 154–162

[5] Li, D. Tuo, D. Su, Z. Li, D. Yu, and A. Tencent, “Deep discriminative embeddings for duration robust speaker verification.” in Interspeech,2018, pp. 2262–2266.

[6] Y. Wen, K. Zhang, Z. Li, and Y. Qiao, “A discriminative feature learning approach for deep face recognition,” in ECCV. Springer, 2016, pp.499–515.

[7] X. Chang, T. Xiang, and T. M. Hospedales, “Scalable and effective deepcca via soft decorrelation,” inCVPR, 2018, pp. 1488–1497.

[8] L. Wang, J. Wu, S.-L. Huang, L. Zheng, X. Xu, L. Zhang, and J. Huang,“An efficient approach to informative feature extraction from multimodaldata,” inAAAI, vol. 33, 2019, pp. 5281–5288.