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Efficient Region of Interest Based Metric Learning for Effective Open World Deep Face Recognition Applications

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Abstract

Face Recognition (FR) has recently gained traction as a widely used biometric for security-based applications such as facial recognition payment. The widespread use is due to improvements in deep convolutional neural networks (CNN) and large datasets. However, FR is still an ill-posed problem, especially in an open world scenario. Existing FR methods require finetuning, classifier retraining, or global metric learning to improve the performance for effective domain adaptation. It incurs an undesirable downtime. Open world FR must identify the persons for whom the FR model is not trained. It also produces imbalanced pairs, giving a false sense of high performance. The popular fixed threshold strategies, such as σ values, also lead to sub-optimal performance. This paper proposes a fast and efficient threshold adapter algorithm using an effective Region of Interest (ROI) setting for metric learning . It uses five different ROI schemes to find an adaptive threshold in real-time. The algorithm also determines the FR model quality and usability after new enrolments. To establish the effectiveness, we investigated various threshold finding strategies for five state-of-the-art face recognition algorithms for open world adaptation on different datasets. We also proposed a novel performance evaluation metric for FR algorithms on imbalanced datasets. Experimental results demonstrated that the proposed metric learning is up to 12 times faster than the nearest competitor while reporting higher accuracy and fewer errors. The study suggests that the F1-score is vital as a performance indicator for imbalanced pair evaluation, and accuracy at the highest reported F1-score is the desired metric for benchmarking FR algorithms in open world . © 2013 IEEE.

Author keywords

Adaptive threshold; biometric system; deep metric learning ; distance metric ; face recognition; imbalance binary classification

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