Siamese Graph Convolution Network for Face Sketch Recognition

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Abstract

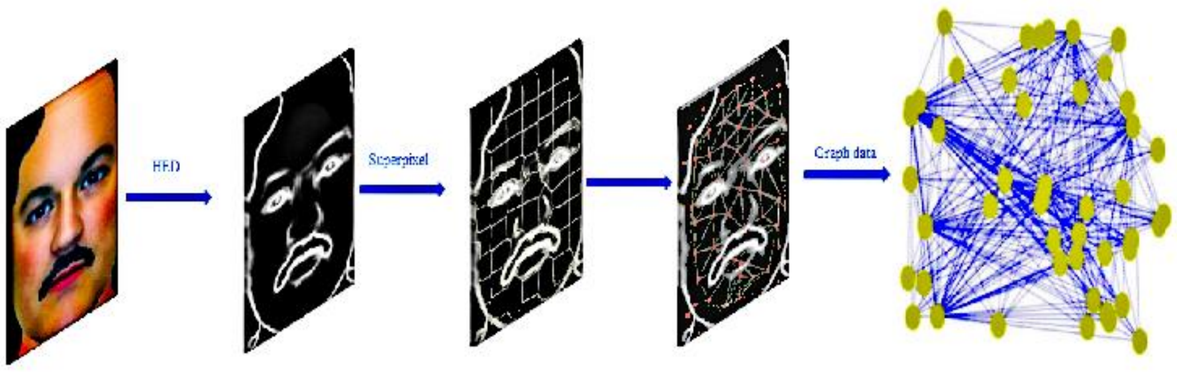
We present a novel Siamese graph convolution network (GCN) for face sketch recognition. To build a graph from an image, we utilize a deep learning method to detect the image edges, and then use a superpixel method to segment the edge image. Each segmented superpixel region is taken as a node, and each pair of adjacent regions forms an edge of the graph. Graphs from both a face sketch and a face photo are input into the Siamese GCN for recognition. A deep graph matching method is used to share messages between cross-modal graphs in the model.

Face photo-sketch Datasets

Hand drawn face photo-sketch Datasets

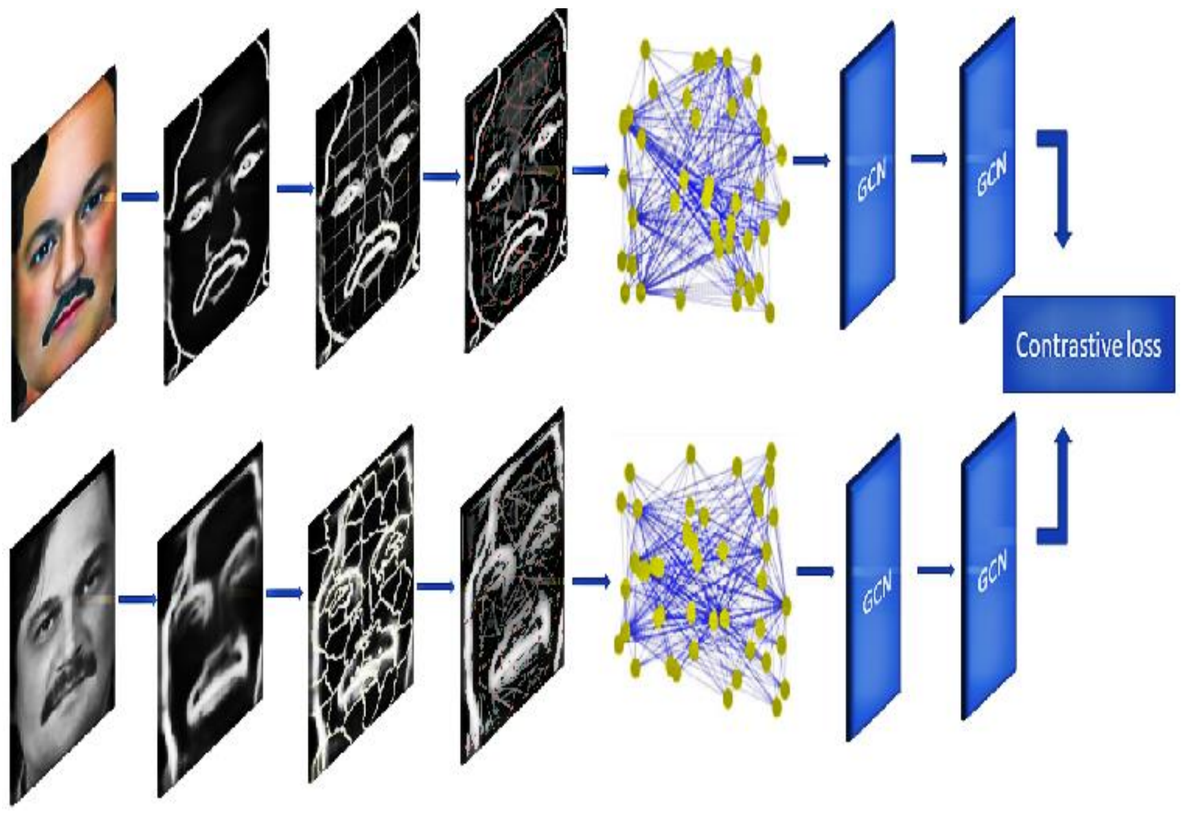
Composited face photo-sketch Datasets

The pipeline of creating graph structure



- The extract image edges using the holistically-nested edge detection method.
- A superpixel segmentation of the edge image is generated.
- An image can be transferred into a 2D matrix as a regulated graph structure *G(V,E)*.
- Elements of the 2D matrix are considered to be nodes $V = \{1,2,\ldots,N\}$ of the regulated graph.
- A region adjacency graph is built based on the superpixel segmentation.

Architecture of the Siamese graph network



- A set of input data which is composed of two graphs, including one from the sketch image and one from the photo image, is input into our Siamese network model.
- Each channel in the Siamese network model consists of two graph convolution layers to extract features from the graph on an embedding space.
- Euclidean distance is used in the contrastive loss function to measure the distance between each reconstructed graph for recognition.

Experiments' result

Method	Top-1 accuracy (UoM-SGFSA)	Top-10 accuracy (UoM-SGFSA)	Top-1 accuracy (UoM-SGFSB)	Top-10 accuracy (UoM-SGFSB)
Siamese GCN (Quickshift)	74.16%	76.66%	65%	80.83%
Siamese MoNet (Quickshift)	64.17%	74.17%	62.5%	80%
Siamese GCN (SLIC)	68.33%	72.25%	60.83%	77.5%
Siamese MoNet (SLIC)	66.65%	73.33%	59.1%	79.17%
DLFace [30]	64.80%	92.13%	72.53%	94.80%
DCNN [33]	31.60%	66.13%	52.17%	82.67%

Experimental results on UoM-SGFSB Dataset

Experimental results on e-PRIP Dataset

e-PRIP (Indntikit)	Top-1 accuracy	Top-10 accuracy
DCNN [33]	54s.90%	80.80%
AADCNN with attributes [34]		76.4%
AADCNN without attributes [34]		69.1%
DAG-HFR [35]		91.73%
Siamese GCN (Quickshift)	55.28%	73.9%
Siamese MoNet (Quickshift)	50.4%	67.48%
Siamese GCN (SLIC)	47.15%	63.4%
Siamese MoNet (SLIC)	48.78%	61.78%

Experimental results on CUFSF Dataset

Methods	Top-10 accuracy
Siamese GCN (Quick shift)	82.25%
Siamese MoNet (Quick shift)	80.25%
Siamese GCN (SLIC)	77.5 %
Siamese MoNet (SLIC)	75.5%
[38]	93.72%

Conclusion

This Siamese network based on graph structural data for facial photo-sketch recognition constructed two graph convolution layers for each channel to learn a set of graphs on an embedding space. In order to reduce the modality gap between the facial photos and sketches, we used a super-pixel method on the contour images obtained from the HED model to extract similar structural graph data from the sketch and the corresponding photo. Experiments showed greater similarity between the graph data of the facial photos and of the sketches if we used the Quickshift method and not SLIC. With the hand-drawn facial photo-sketch datasets, the performance was better than it was with the composite facial photo-sketch datasets.

Reference

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