Order the faces by Manifold Learning for Face dataset

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Introduction

The research topic of face pose estimation is intriguing as it enables us to deduce a person's focus and identify relevant behavior. The objective of this report is to arrange the 33 images of the same individual based on their face orientation, using various manifold learning techniques such as Diffusion map, MDS, ISOMAP, LLE, LSTA, TSNE and UMAP. Our approach involved acquiring the embedding results from the different methods and organizing them based on the size of their first eigenvector. Furthermore, we compared the results of the manifold learning methods used. Finally, we aimed to determine the optimal nearest neighbor number for UMAP.

Dataset

The face dataset contains 33 faces of the same person ($Y \in \mathbb{R}^{112\times92\times33}$) in different angles and has 10304 images in total. The data can be downloaded from the public website link. Figure 1 (a) shows the original data and Figure 1 (b) are ground truth of the original data.

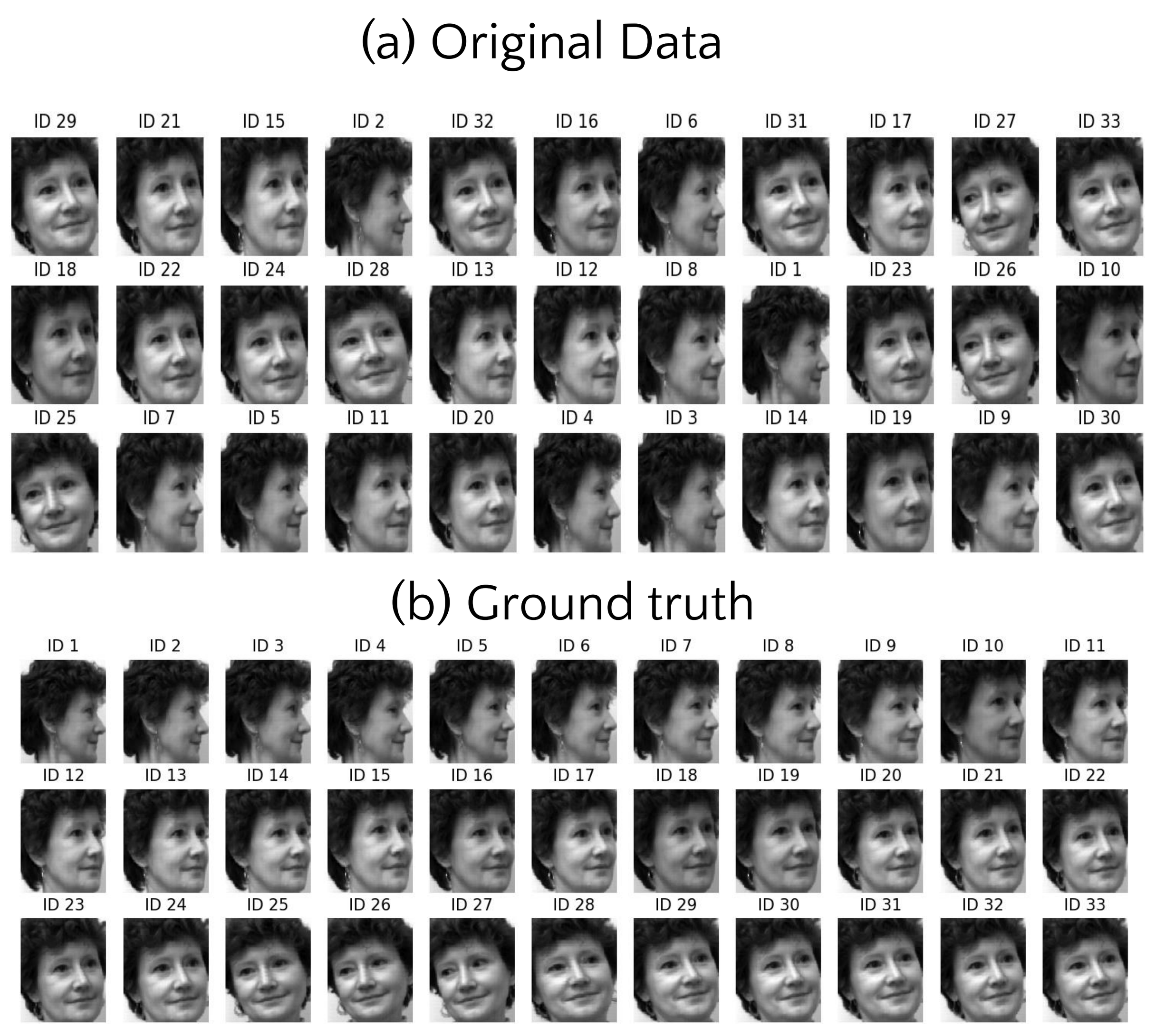

Figure 1 Examples of the data and ground truth

Methodology

We apply seven well-known manifold learning methods (including Diffusion map, MDS, ISOMAP, LLE, LSTA, TSNE, and UMAP) to extract the eigenvectors with the Python package Scikit-learn[1] and use them for ordering.

Diffusion map[2] is a nonlinear dimensionality reduction algorithm that extracts features or reduces dimensionality by computing embeddings of a dataset into Euclidean space based on the eigenvectors and eigenvalues of a diffusion operator. Diffusion maps aim to discover the underlying manifold structure of the data and integrate local similarities at different scales to provide a global dataset description.

MDS[3] is a technique for visualizing the similarity between individual cases in a dataset by creating a low-dimensional space using pairwise dissimilarities based on Euclidean distance. This approach aims to reveal the underlying structure of the data and provide a better understanding of the relationships between individual cases.

ISOMAP[4] is an extension of MDS that incorporates geodesic distances based on a weighted graph. It defines the geodesic distance as the sum of the edge weights along the shortest path between two nodes. By incorporating these geodesic distances, ISOMAP aims to better capture the underlying structure of the data and provide a more accurate low-dimensional representation of the dataset.

LLE[5] focuses on preserving the local linearity of the sample when reducing data dimensionality.

LTSA[6] is a variation of LLE that operates on the premise that all tangent hyperplanes to the manifold will align when a manifold is accurately unfolded.

TSNE[7] is a variation of the SNE algorithm that treats the coordinates in the lower dimension as the t-distribution.

Similar to TSNE, UMAP[8] assumes that the data is uniformly distributed on a locally connected Riemannian manifold and that the Riemannian metric is either locally constant or approximately locally constant.

Evaluation protocol

Kendall's τ is a correlation coefficient that measures the agreement between two rankings. Given two ranking lists X and Y of the same set of elements, Kendall's τ measures the similarity between the two rankings by counting the number of pairwise agreements and disagreements between the rankings. A pair of elements (i,j) is considered to agree if their order is the same in both rankings, and disagree if their order is different. Kendall's tau is defined as: τ = (number of concordant pairs - number of discordant pairs) / (number of pairs) where the number of concordant pairs is the number of pairs (i,j) such that (i,j) is concordant in both X and Y, and the number of discordant pairs is the number of pairs (i,j) such that (i,j) is discordant in both X and Y. The total number of pairs is n(n-1)/2, where n is the number of elements in X and Y.

Kendall's tau ranges from -1 to 1, where a value of 1 indicates perfect agreement, 0 indicates no correlation, and -1 indicates perfect disagreement.

Experimental Results

Table 1 Quantitative Results of different methods.

	Diffusion	MDS	ISOMAP	LLE	LTSA	TSNE	UMAP
τ	0.0114	-0.2689	-0.8939	0.9015	0.8977	0.8977	0.9583

We utilized seven manifold learning methods to analyze the Face dataset, conducting both quantitative and qualitative analyses. The first eigenvector was calculated using each method to represent each image, and Table 1 displays the quantitative results of the seven methods with respect to Kendall's τ and the ground truth. UMAP, TSNE, and LLE showed the best performance, with UMAP having the most similar distribution to the ground truth. We also visualized the eigenvectors generated by these methods using an exemplar, and Figure 2 shows UMAP as having the best performance.

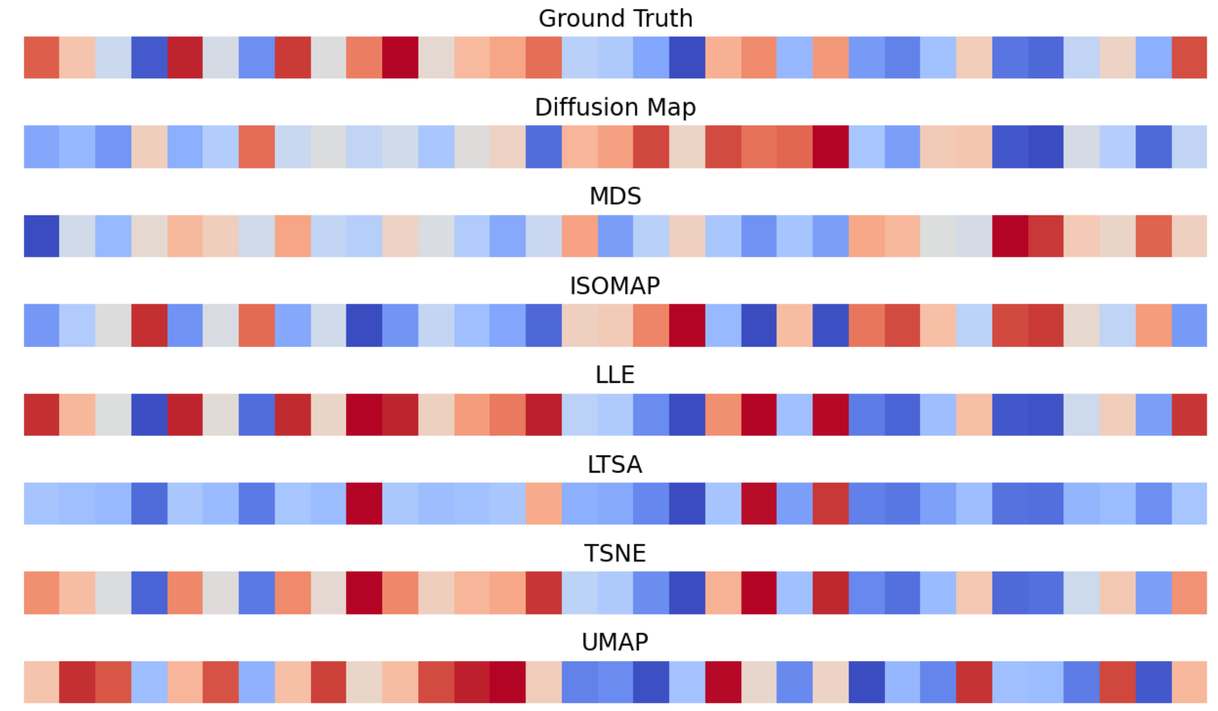

Figure 2 Comparison of eigenvectors for different methods

Conclusion

To summarize, we utilized multiple manifold learning techniques (including Diffusion map, MDS, ISOMAP, LLE, LSTA, t-SNE, and UMAP) to arrange the face orientation from left to right. To measure the sorting performance, we computed the τ between the predicted results and the ground truth ranking labels. Diffusion map, MDS and ISOMAP showed poor performance when ordered by the first eigenvector, while LLE, LSTA, TSNE, and UMAP demonstrated good performance.

References

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