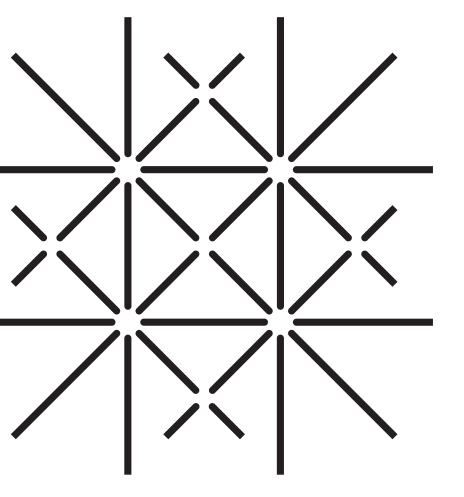


Expression Invariant Face Recognition with a 3DMM

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Contribution

We introduce a method for expression invariant face recognition. A generative 3D Morphable Model (3DMM) is used to separate identity and expression components. The expression removal results in increased recognition performance, even on difficult datasets, without a decrease in performance on expression-less datasets. It is applicable to any kind of input data, and was evaluated here on textureless range scans.

Model

The Model was learnt from 275 subjects. We used one neutral expression scan per identity and 150 expression scans of a subset of the subjects.

The identity model is a linear model build from the neutral scans.

$$\mathbf{f} = \boldsymbol{\mu} + \mathbf{M}_n \boldsymbol{\alpha}_n \quad (1)$$

For each of the 150 expression scans, we calculated an expression vector as the difference between the expression scan and the corresponding neutral scan of that subject. This data is already mode-centered, if we regard the neutral expression as the natural mode of expression data. From these offset vectors an additional expression matrix \mathbf{M}_e was calculated, such that the complete linear Model is

$$\mathbf{f} = \boldsymbol{\mu} + \mathbf{M}_n \boldsymbol{\alpha}_n + \mathbf{M}_e \boldsymbol{\alpha}_e \quad (2)$$

The assumption here is, that the face and expression space are linearly independent, such that each face is represented by a unique set of coefficients.

Fitting

A Robust Nonrigid ICP method was used to fit the model to the data. Robustness was achieved by iteratively reweighting the correspondences and using hard compatibility test for the closest points.

Fitting was initialized by a simple nose detector and proceeded fully automatic.

Distance Measure

The Mahalanobis angle between the identity coefficients $\boldsymbol{\alpha}_n$ was used for classification.

Open Questions

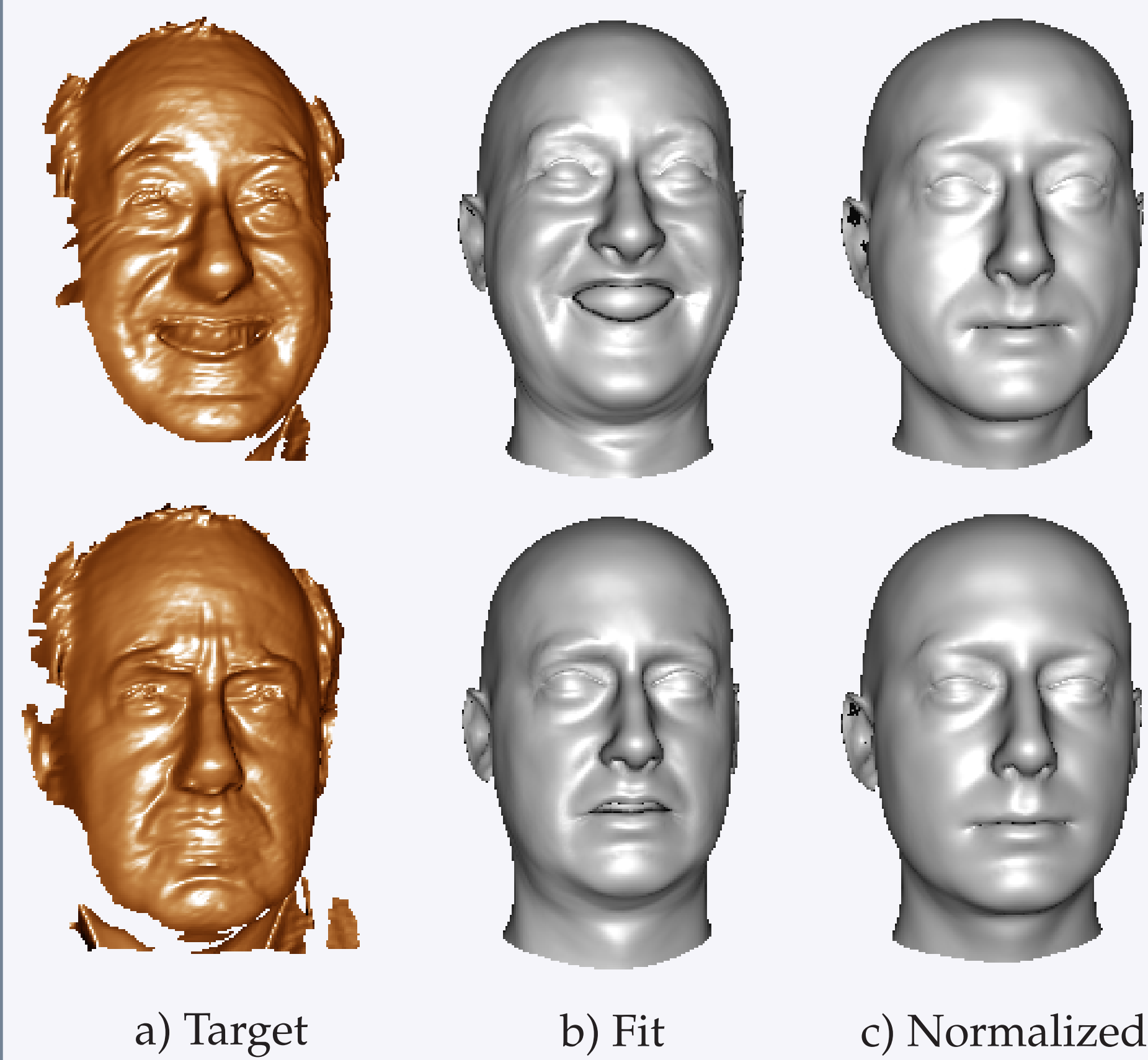
While the expression and identity space are linearly independent, there is some expression left in the identity model. This is because a “neutral” face is interpreted differently by the subjects.

We investigate learning “pure” separated models from our the available “impure” data.

References

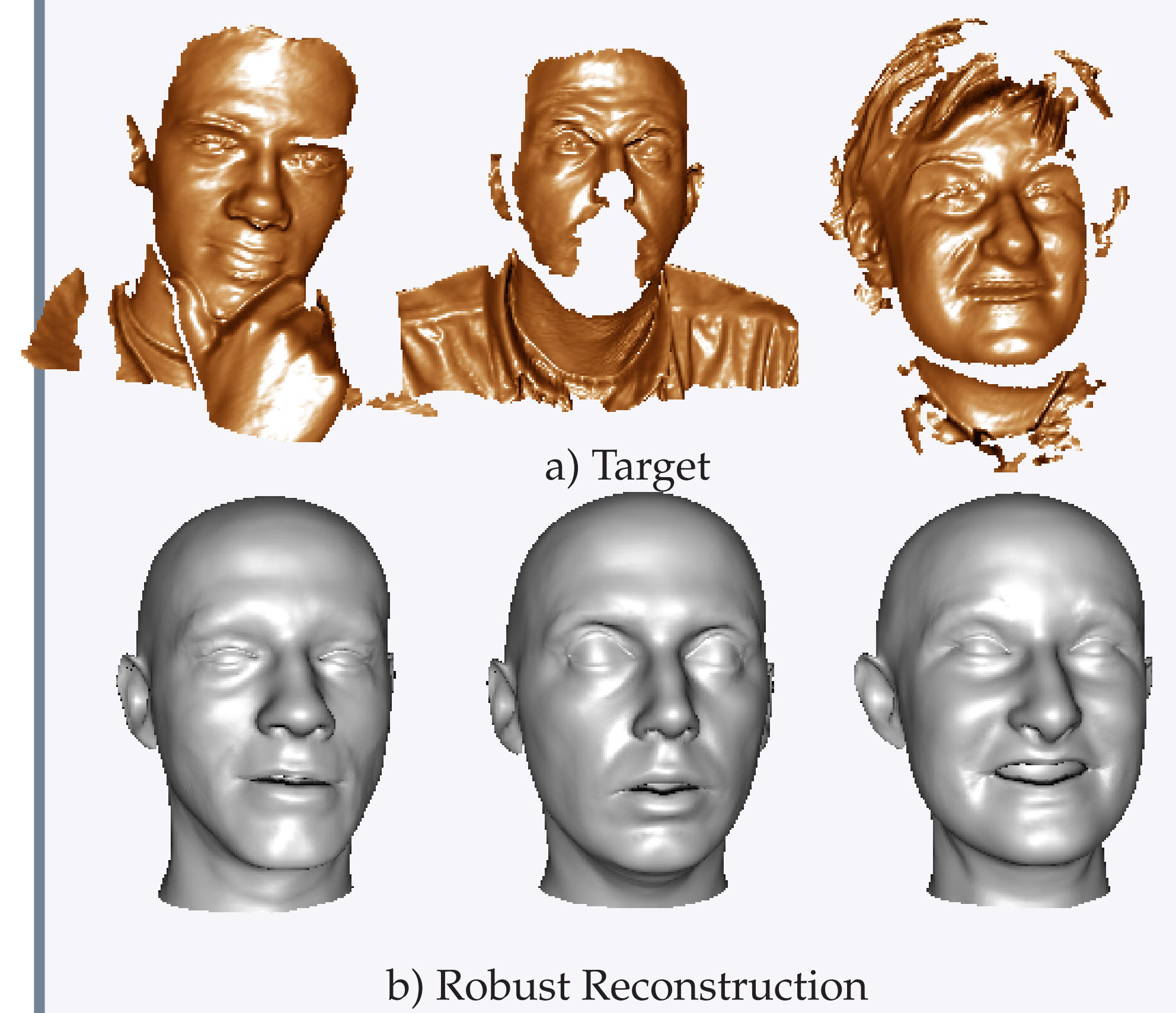
- [1] B. Amberg, S. Romdhani, T. Vetter. Optimal Step Nonrigid ICP Algorithms for Surface Registration In *Computer Vision and Pattern Recognition 2007*
- [2] B. Amberg, R. Knothe, T. Vetter. Expression Invariant Face Recognition with a 3D Morphable Model In *Automated Face and Gesture Recognition 2008*

Expression Neutralization



Expression normalisation for two scans of the same individual. The robust fitting gives a good estimate (b) of the true face surface given the noisy measurement (a). It fills in holes and removes artifacts using prior knowledge from the face model. The pose and expression normalized faces (c) are used for face recognition.

Robustness

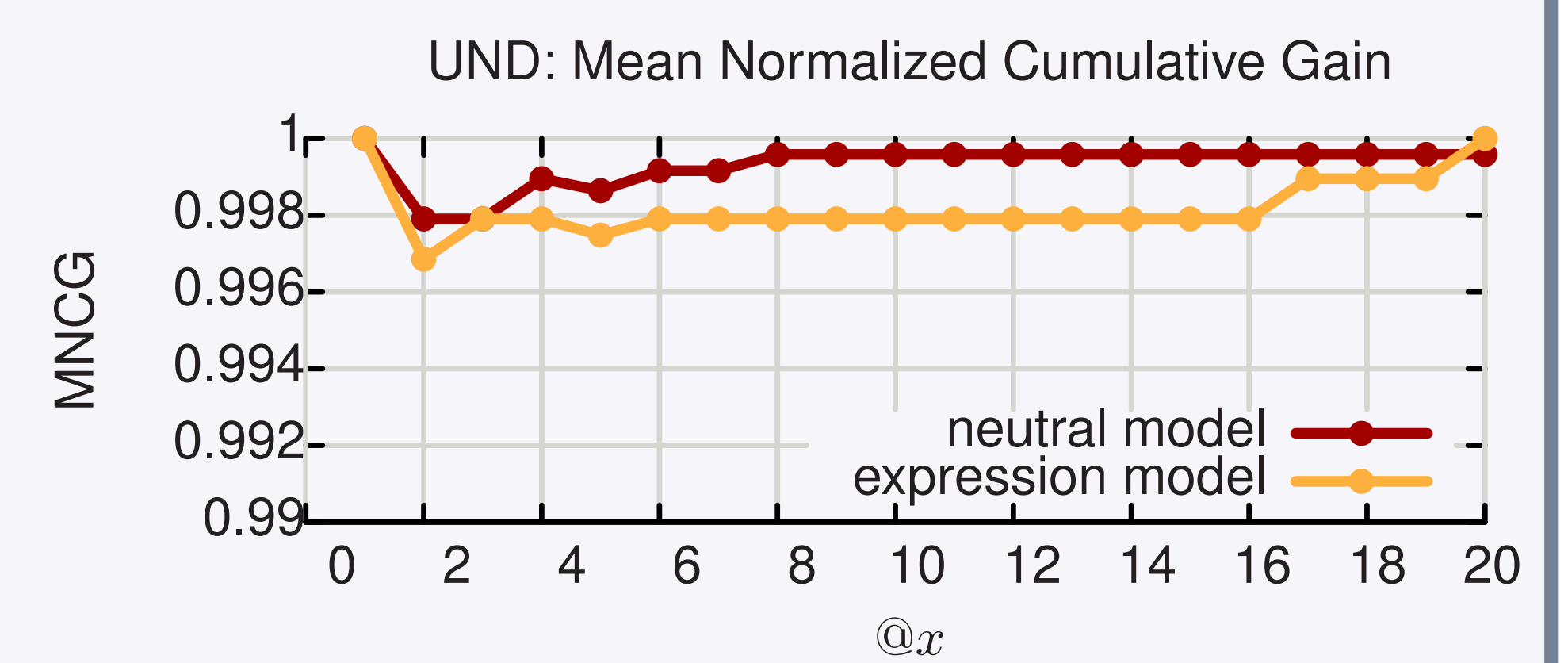
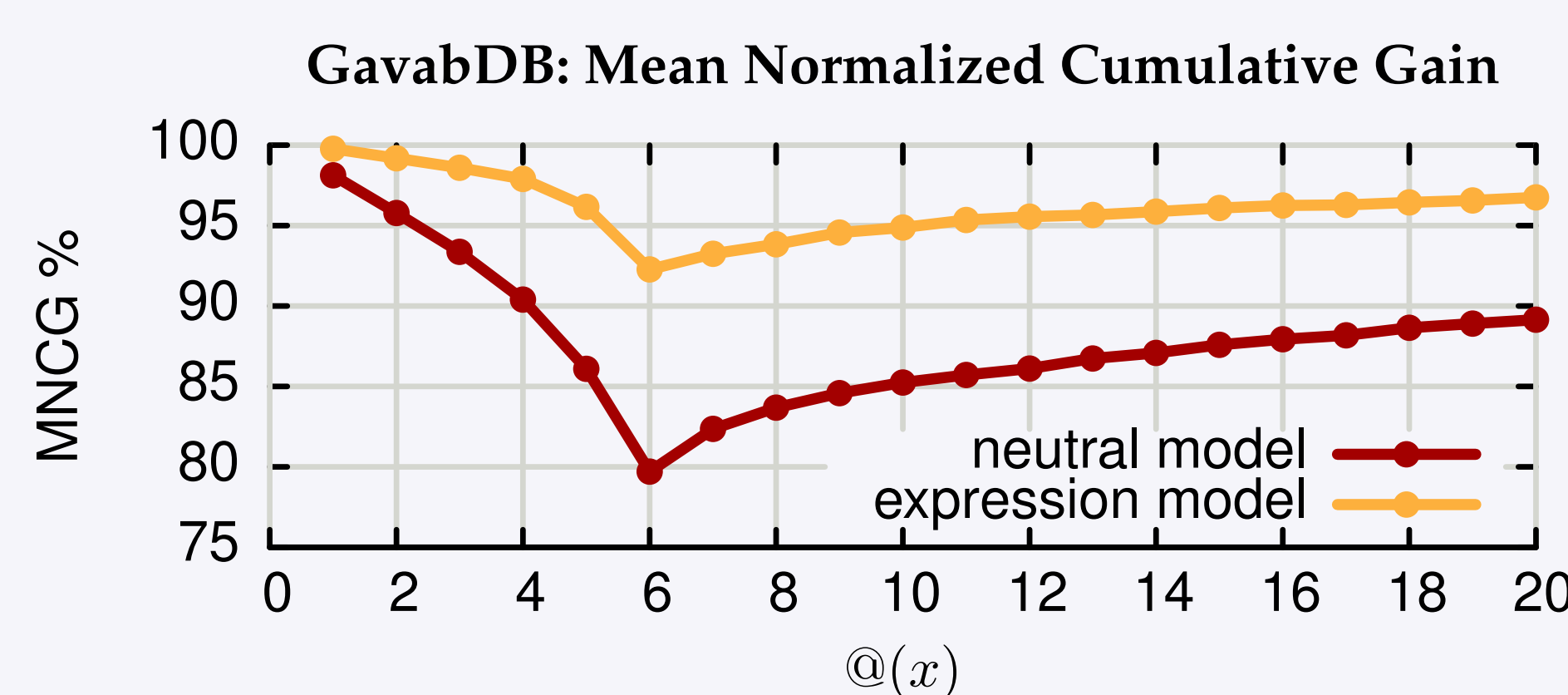


The reconstruction (b) is robust against scans (a) with artifacts, noise, and holes. This is achieved by a robust iteratively reweighted ICP algorithm and outlier rejection based on angle comparisons between corresponding points.

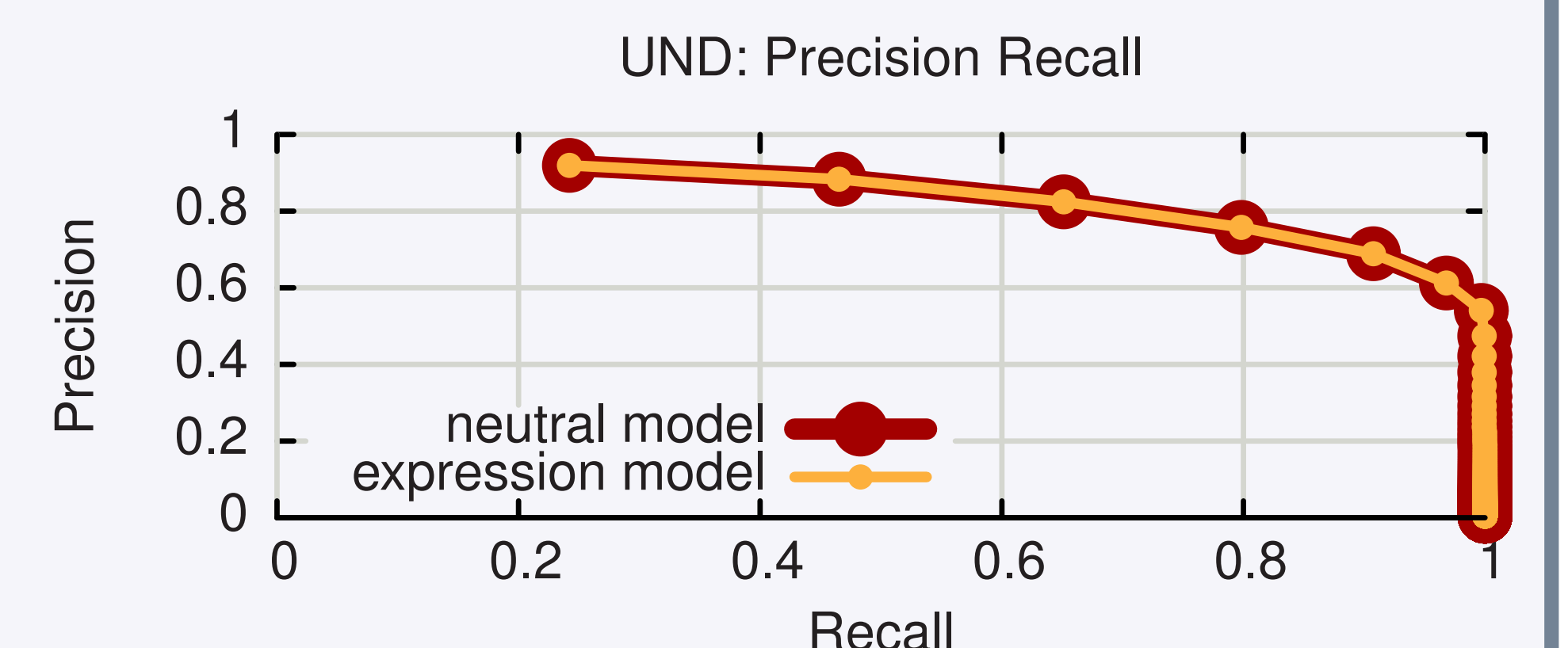
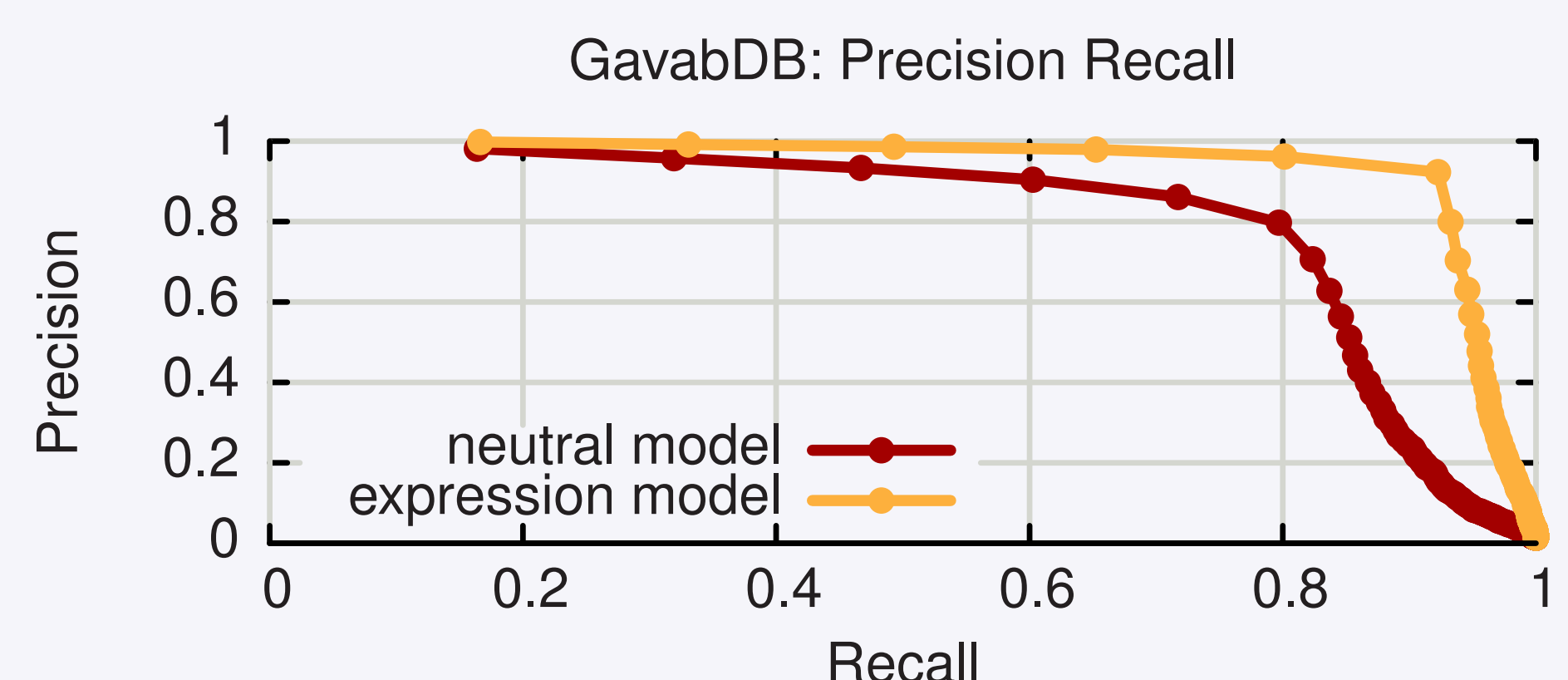
Results

The method was evaluated on the GavabDB expression dataset which contains 427 Scans, with 3 neutral scans and 4 expression scans per ID. To test the impact of expression invariance

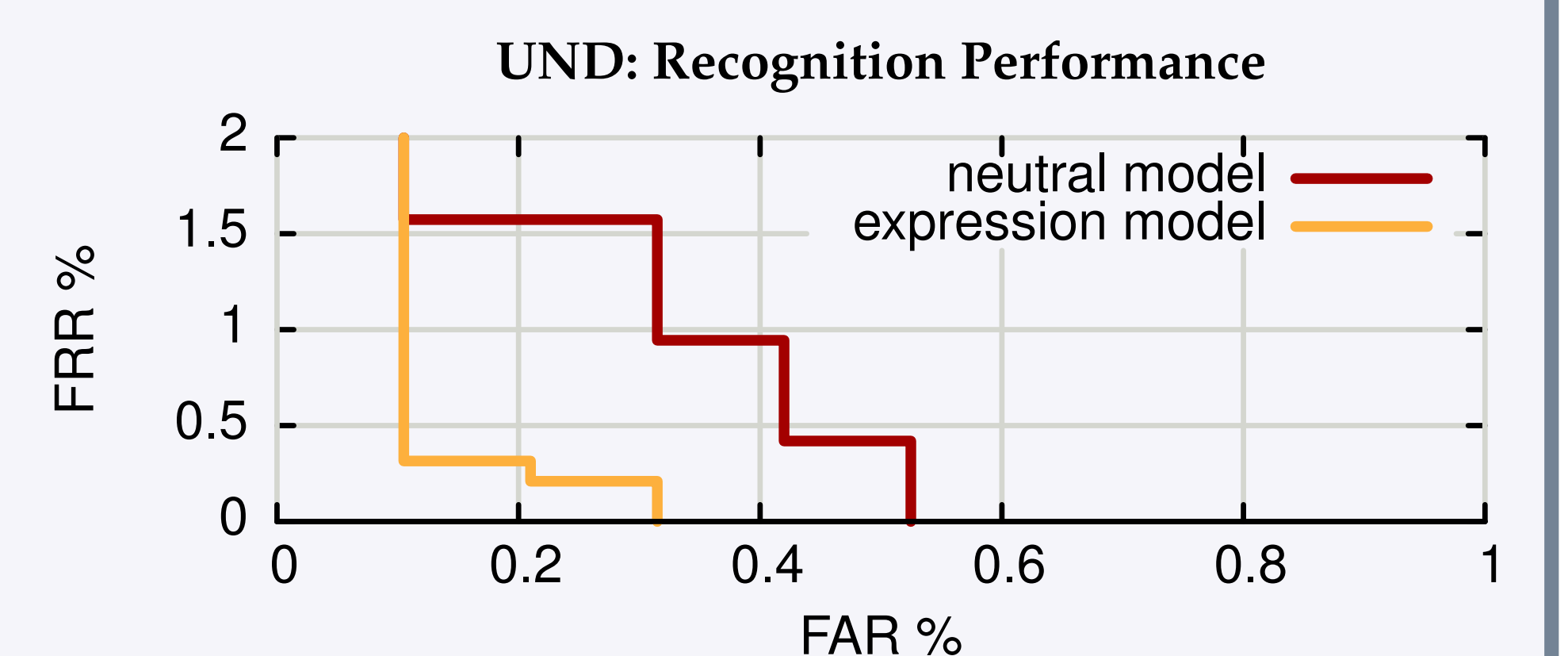
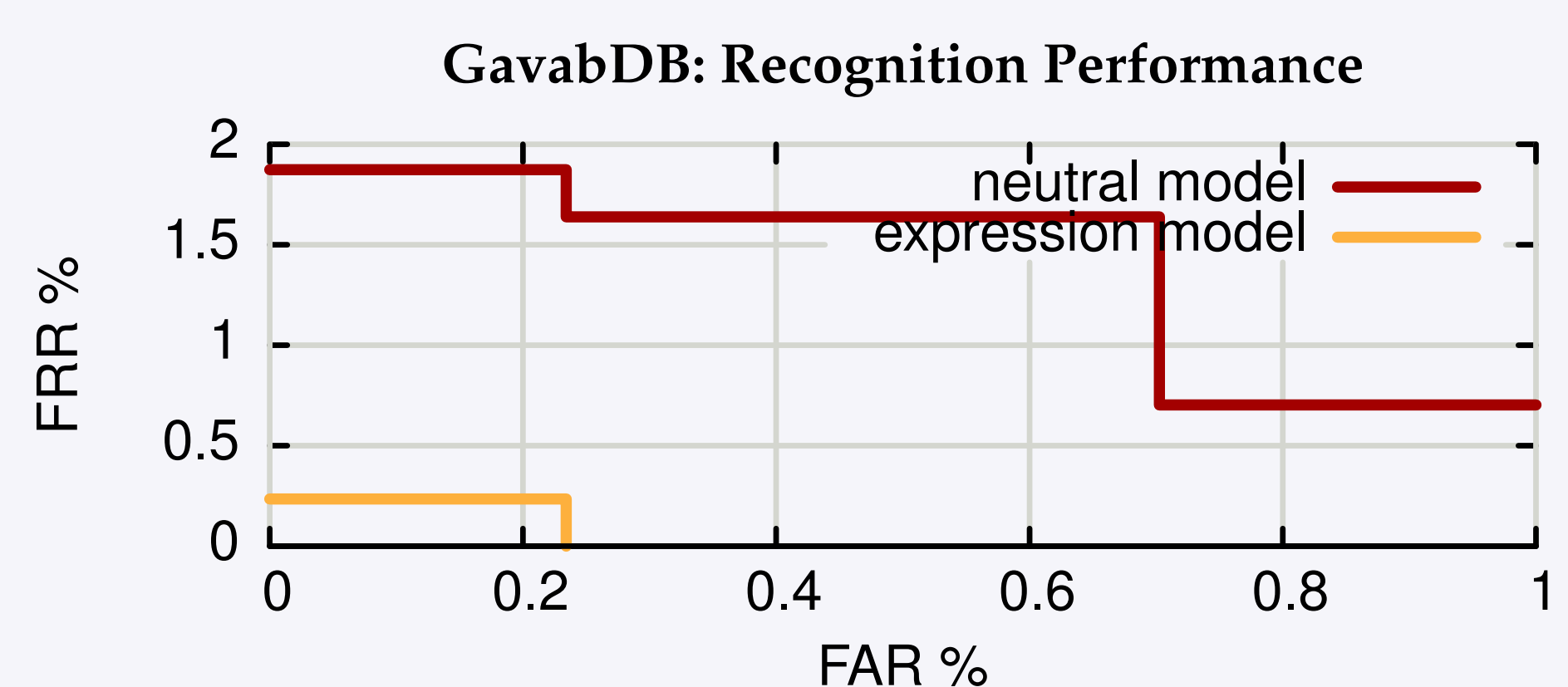
on neutral data we used the UND Dataset from the Face Recognition Great Vendor Test, which contains 953 neutral scans with one to eight scans per subject.



Expression neutralization improves results on the expression dataset without decreasing the accuracy on the neutral testset. Plotted is the ratio of correct answers to the number of possible correct answers.



Plotted are precision and recall for different retrieval depths. The lower precision of the UND database is due to the fact that some queries have no correct answers.



Impostor detection is reliable, as the minimum distance to a match is smaller than the minimum distance to a nonmatch.

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