Supplementary online material for

Developmental processes in face perception

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Classification of the performance for each age group using SVM and linear classification:

In detail, we generated two-dimensional vectors, where the dimensions contained the percentage correct trials in one run of the DMS task (50 random trials) on human or chimpanzee face stimuli, respectively. Together this yielded 468 samples, which we normalized to zero mean and standard deviation 1. Then, each such data point was assigned a class label, whether it belonged to the groups YC or OC. We randomly assigned one tenth of the data to a test set and the rest to the training set. A classification algorithm was trained on the training set and its classification performance was evaluated on the test set. Training and testing was repeated for 10 times on newly generated train and test sets (10-fold cross-validation), in the main text we report the average performances. Chance classification level on our data set is 50%, because the numbers of YC and OC runs are equal. As learning algorithm we employed C-SVM with Gaussian and linear kernels. SVM is a state-of-the-art machine learning technique to classify data by maximizing the margin between the two classes in a possibly high dimensional feature space1. In particular, by implicitly performing a projection into a high-dimensional features space classification can also be done using non-linear classification boundaries. We optimized the parameters of the SVM model (C parameter, regulating the penalty for misclassification when establishing the margin) and the width of the Gaussian kernel (affecting the non-linear shape of the decision boundary). We avoided overfitting by separating train and test set as described above. We found that C = 2.64e+003 and kernel width of 1 provided best results. Simulations showed a stable classification (detection rate: 90.29 % (SEM: 0.01); accuracy: 80.08 % (SEM: 0.02); precision: 75.27 % (SEM: 0.03)). As comparison we also tested standard linear classification when minimizing the mean squared error. In the latter cases, to be able to learn a potential bias of the classification line (i.e. offset from zero), we added a third, constant vector dimension in our sample.

Figure legends:

Figure S1:

Face discrimination modulated by age. a, Proportion of correct responses for pairs of runs of chimpanzee (y-axis) and human stimuli (x-axis). For each participant (colors) pairs of two consecutively performed runs of chimpanzee and human faces are shown. Solid dots indicate the participants' mean performance with standard deviations (whiskers). b, The separation of YC and OC based on pairs of runs using SVM and regression analyses. Markers and colors indicate the proportion of correct responses for pairs of chimpanzee and human runs according to age groups. Data samples are normalized classification performances. The lines indicate a classification boundary of the SVM and regression analyses.

Figure S2:

Similarity estimation between chimpanzee and human faces using Gabor jet filters. a, Gabor Filters of 5 scales and 8 orientations. b, Filters applied to an exemplar of chimpanzee face stimuli. c, Filters applied to an exemplar of human faces stimuli. d, distribution of similarity scores of chimpanzee and human faces. Values increase with increasing similarity. Green lines indicate the range of overlapping similarity scores of the two classes. e, Performance scores in the shared range of similarity scores. Data is split up according to age groups (YC, OC) and stimulus classes (C = chimpanzee, H = human). Boxplots describe the samples of individual runs. The age-related effect occurs independently of the similarity scores.

Figure S3:

Simulation of early and late processes in face perception. a, Feature space. Illustrated are the drawn exemplars of class 1 (blue) and class 2 (red) in a simulation run, which were used for learning the synaptic weights. Dots represent the exemplar with long-term exposure, crosses represent the novel exemplars. Exemplars are plotted for various time steps in years (titles). b, Simulation of the natural scenario of exposure to faces in chimpanzees. Raw data from 200 simulation runs is plotted in light colors, means in solid lines, standard errors in dashed lines.

References:

1 Burges, C. J. C. A tutorial on Support Vector Machines for pattern recognition. Data Min Knowl Disc 2, 121-167 (1998).

Figures

Figure S1:

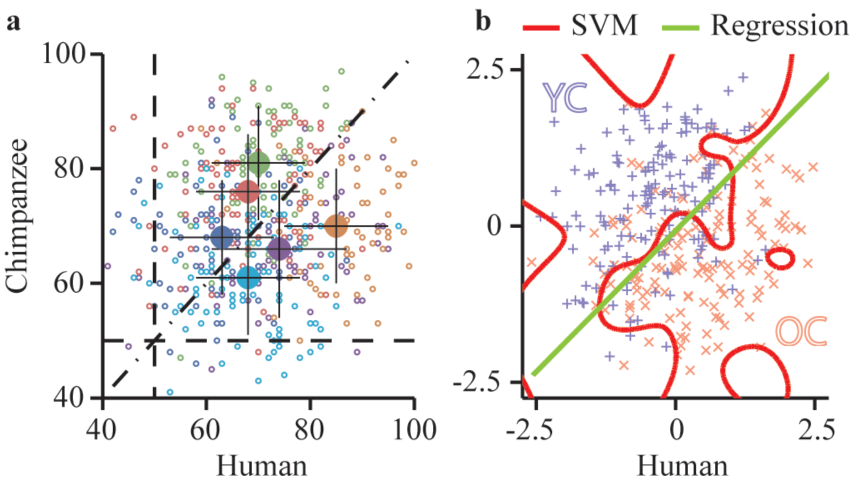


Figure S2:

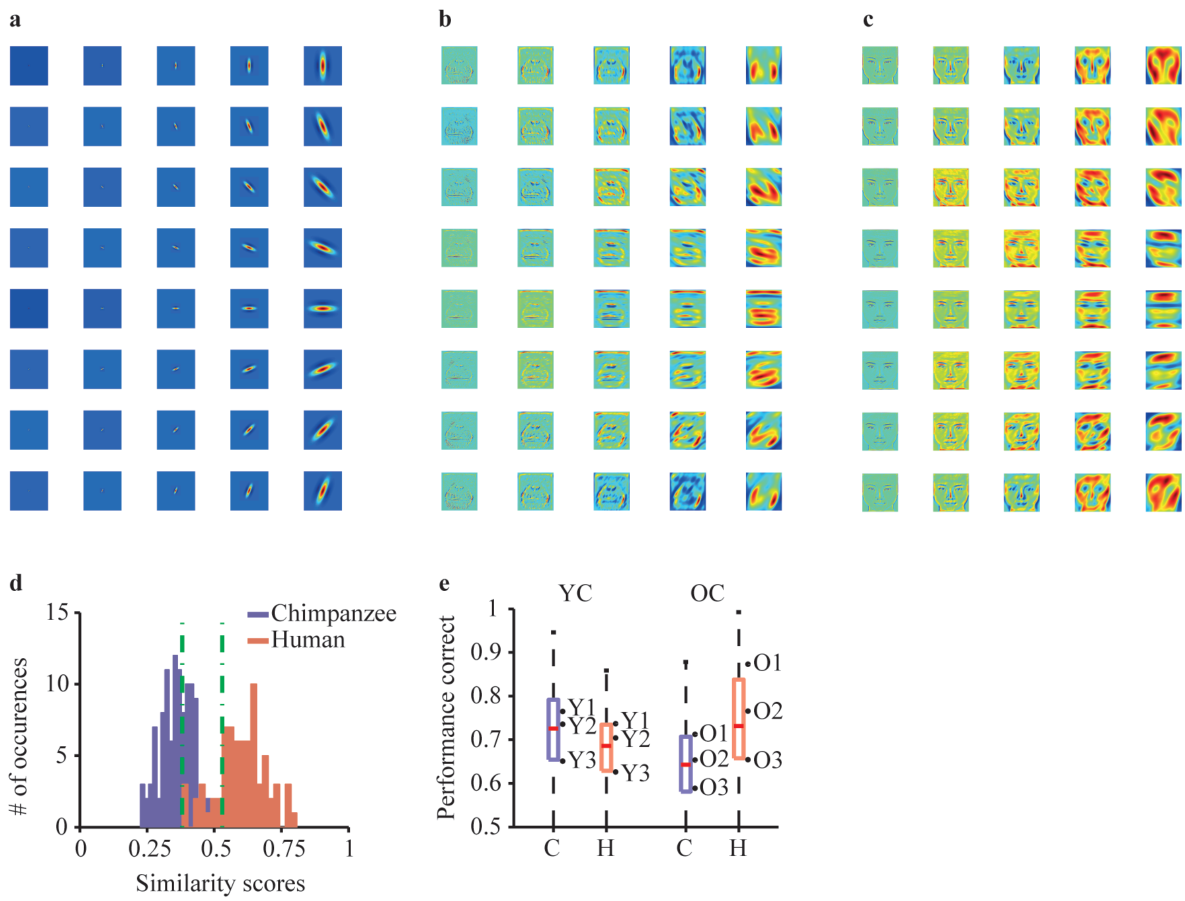
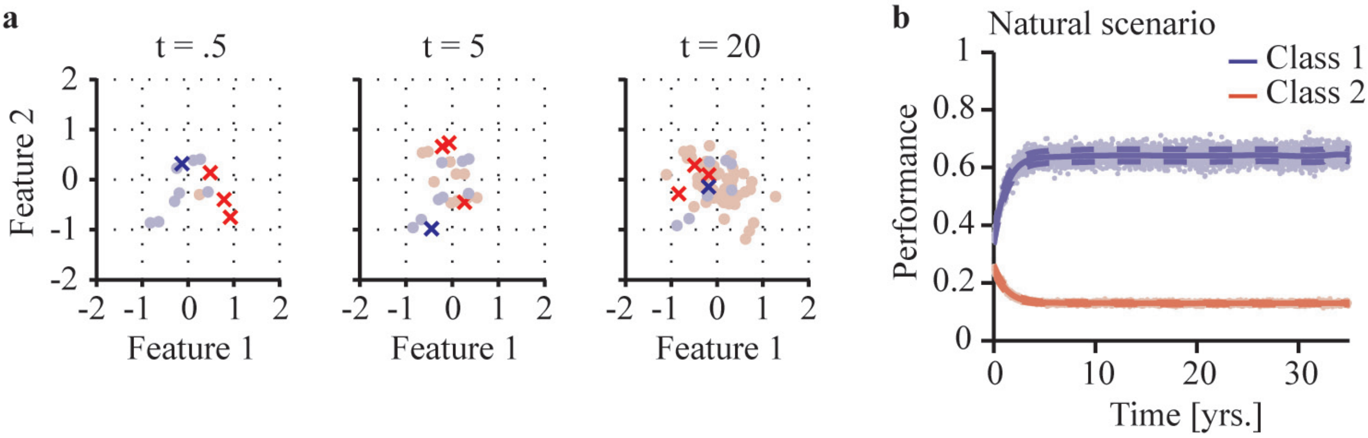


Figure S3:


a
t = .5
t = 5
t = 20
Feature 2
Feature 1
Feature 1
Feature 1
b
Natural scenario
Class 1
Class 2
Performance
Time [yrs.]