

The Determination of an Effective Smile

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Introduction

Background: Facial reanimation surgery restores facial movement and expression ability for individuals suffering from facial paralysis.

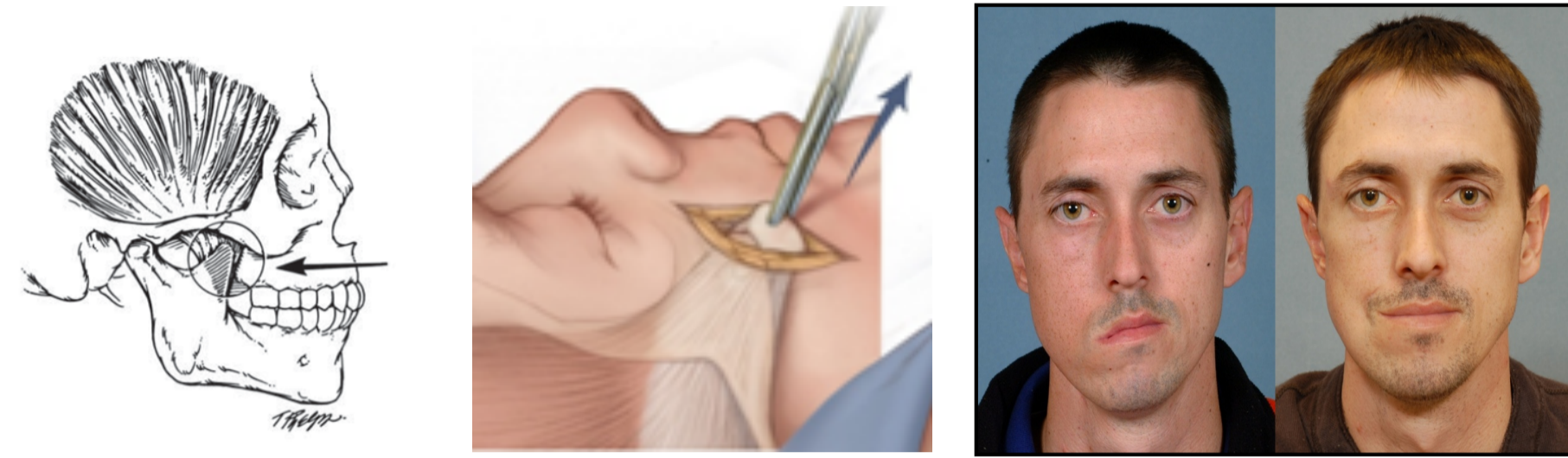


Figure 1: A smile restoration technique: temporalis muscle tendon transfer.

Problem: How can we objectively determine the efficacy of the facial reanimation intervention on expression?

Goal: Determine the characteristics of an effective smile to improve outcomes for patients of facial reanimation surgery.

Computer Animated Facial Model

Computer animations of human facial expressions were created using an interpolative blend shape approach (Pighin et al., 2006).

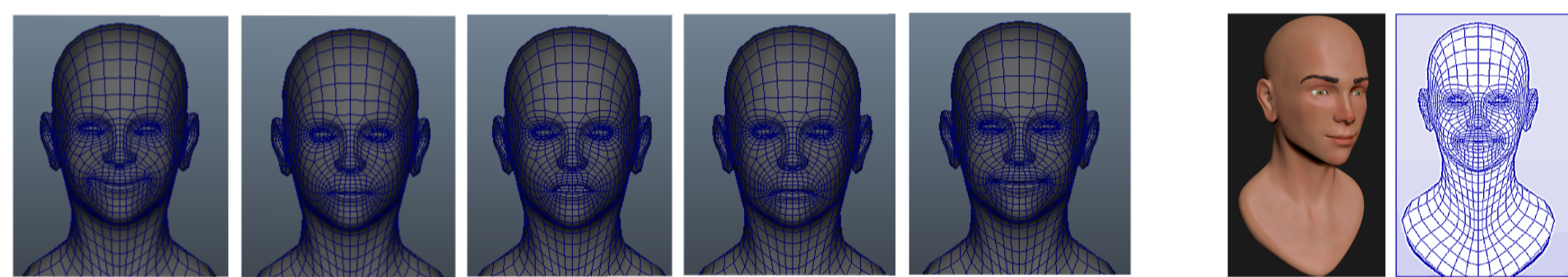


Figure 2: Example of blendshapes used to represent the animations.

We created 27 different smiles that were formed by taking a systematic sweep of three blend shapes.

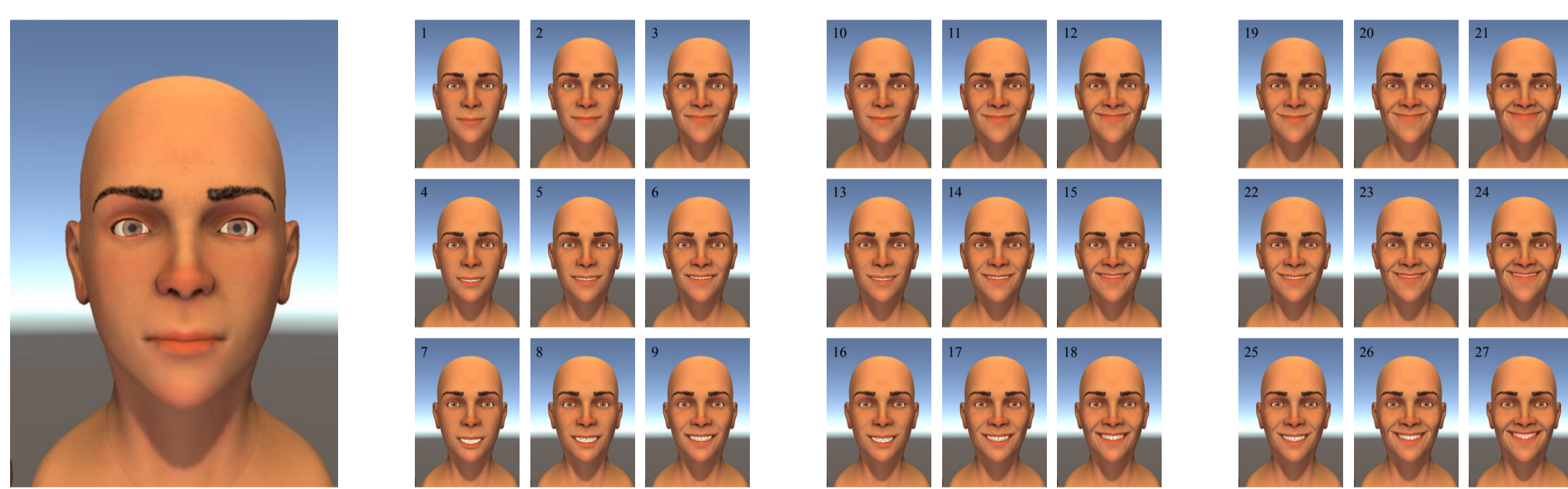


Figure 3: Neutral face used at beginning of all animations (left), and the 27 different smiling faces used in the last frame of the animation.

For each smile we created animations with two timing durations (250 ms and 350 ms).

Facial Rating iPad Application

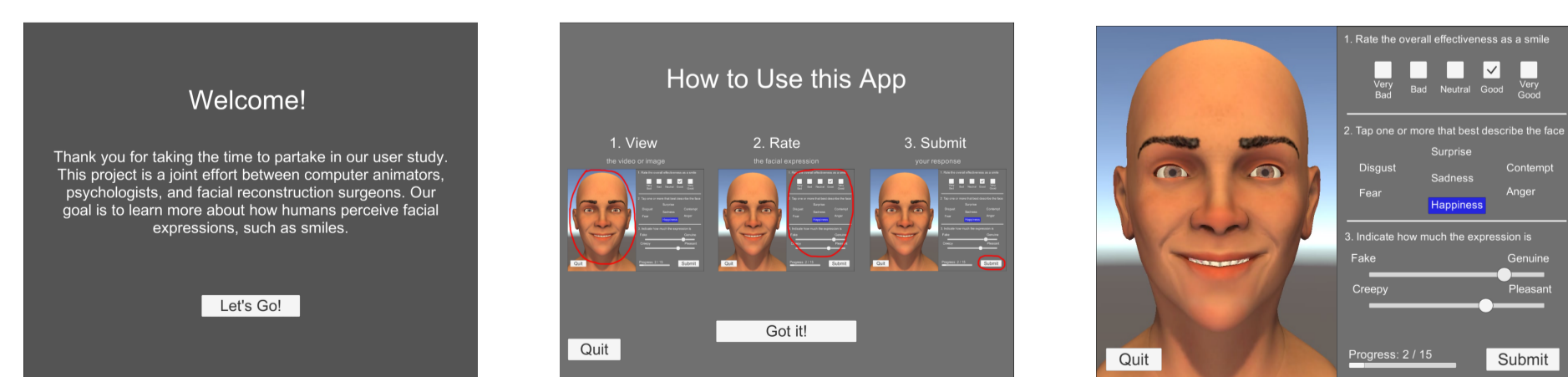


Figure 4: Screenshots from the iPad application used to collect the data.

Data Collection Procedure

Data were collected in the Driven to Discover Building at the 2015 Minnesota State Fair using an iPad application.

Each participant rated a total of 15 animations, which were randomly sampled from a larger set of animations.

Participant characteristics:

- There were a total of 808 participants (64% Female)
- Many younger (ages 18-22) and middle-age (45-55) participants
- Primarily from Minnesota, but zip codes span entire U.S.

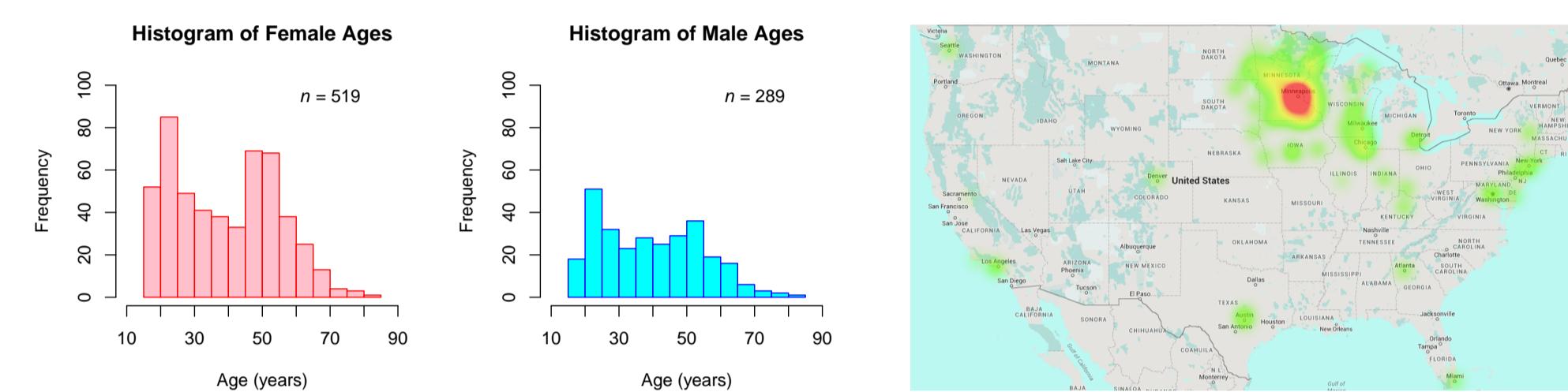


Figure 5: Visualizations of participant ages and zip codes.

Data Analysis Procedure

To model Smile Effectiveness, we use a semiparametric mixed-effects regression model (see Helwig, in press; Gu & Ma, 2005; Wang, 1998a,b; Zhang et al., 1998):

$$y_{ij} = \beta_0 + \beta_1 t_j + \beta_2 m_i + \eta(s_j) + r_i + \epsilon_{ij} \quad (1)$$

where

- y_{ij} is i -th subject's smile effectiveness rating for j -th stimuli
- $t_j = \begin{cases} 1 & \text{if smile is 350 ms} \\ 0 & \text{if smile is 250 ms} \end{cases}$ is the duration of the j -th stimuli
- $m_i = \begin{cases} 1 & \text{if subject is male} \\ 0 & \text{if subject is female} \end{cases}$ is the gender of the i -th subject
- $\eta(s_j)$ is the unknown function that defines the average effectiveness of stimuli for $s_j \in \{1, \dots, 27\}$
- $r_i \stackrel{iid}{\sim} N(0, \theta^2)$ is the latent random intercept for the i -th subject, which allows each subject to have a unique baseline rating
- $\epsilon_{ij} \stackrel{iid}{\sim} N(0, \sigma^2)$ is the error term, which is independent of r_i

Model was fit using the bigsplines (Helwig, 2016) package in the R software environment (R Core Team, 2016).

Model Fit Results

- $R^2 = 0.1$ without the random intercepts included
- Fixed effects portion $\hat{\beta}_0 + \hat{\beta}_1 t_j + \hat{\beta}_2 m_i + \hat{\eta}(s_j)$ accounts for 10% of the variation in smile effectiveness ratings
- $R^2 = 0.4$ with the random intercepts included
- The random (subject specific) baselines account for about 30% of the variation in the smile effectiveness ratings

$\hat{\rho} = \frac{\hat{\theta}^2}{\hat{\theta}^2 + \hat{\sigma}^2} = \frac{0.20}{0.20 + 0.71} = 0.22$ is intraclass correlation coefficient, which is correlation between two ratings from same subject.

Visualization of Results

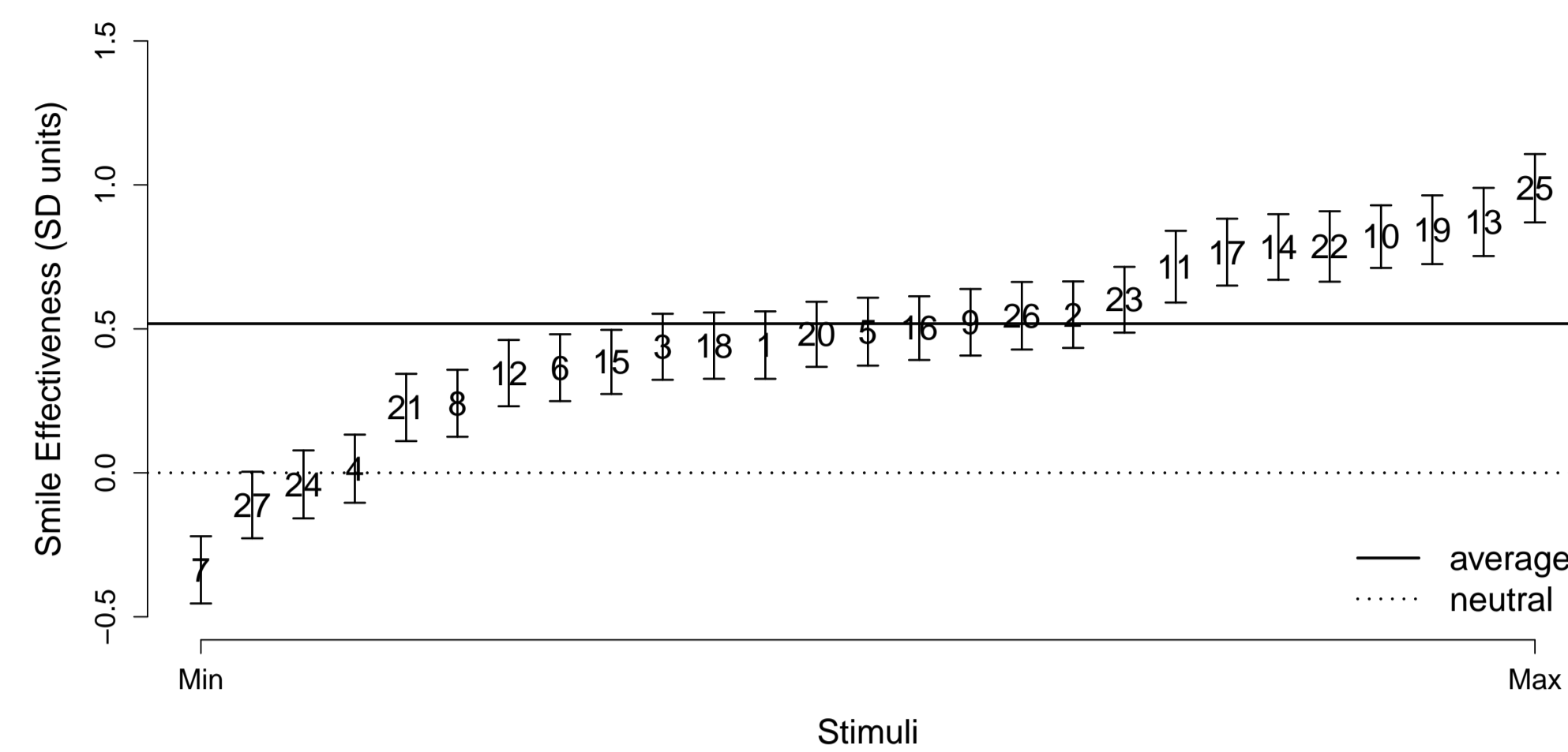


Figure 6: Model predicted effectiveness rating for each smile, along with a 90% confidence interval around each prediction.

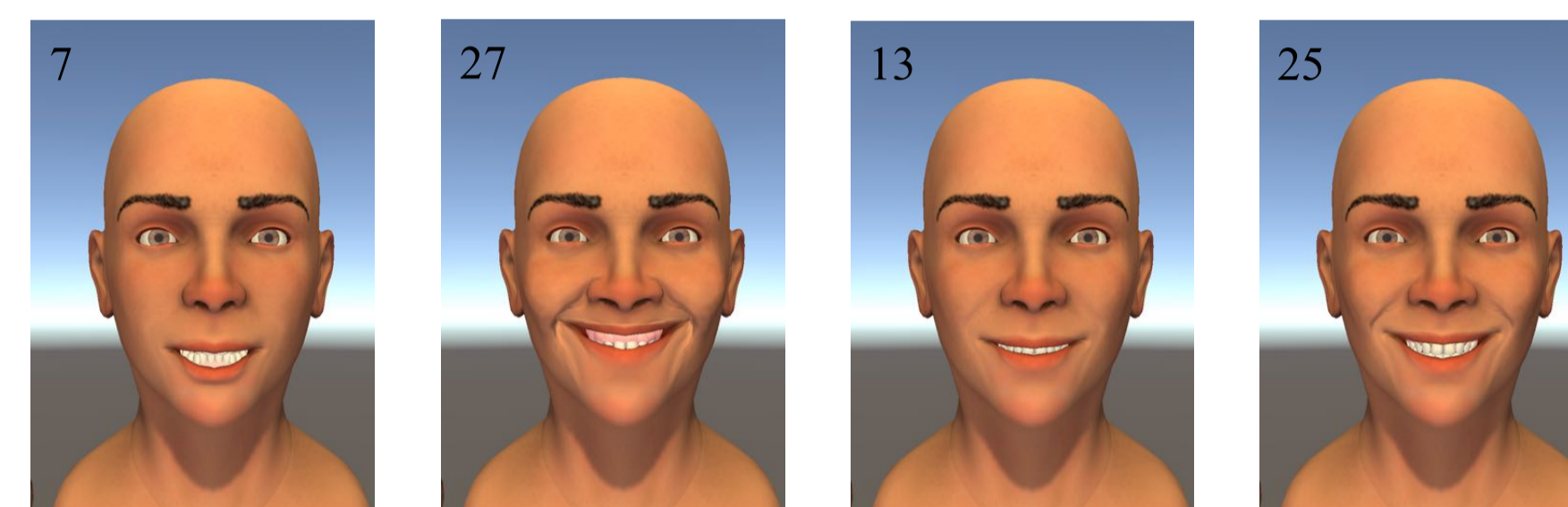


Figure 7: Two least effective smiles (left) and most effective smiles (right).

Angle and Extent of an Effective Smile

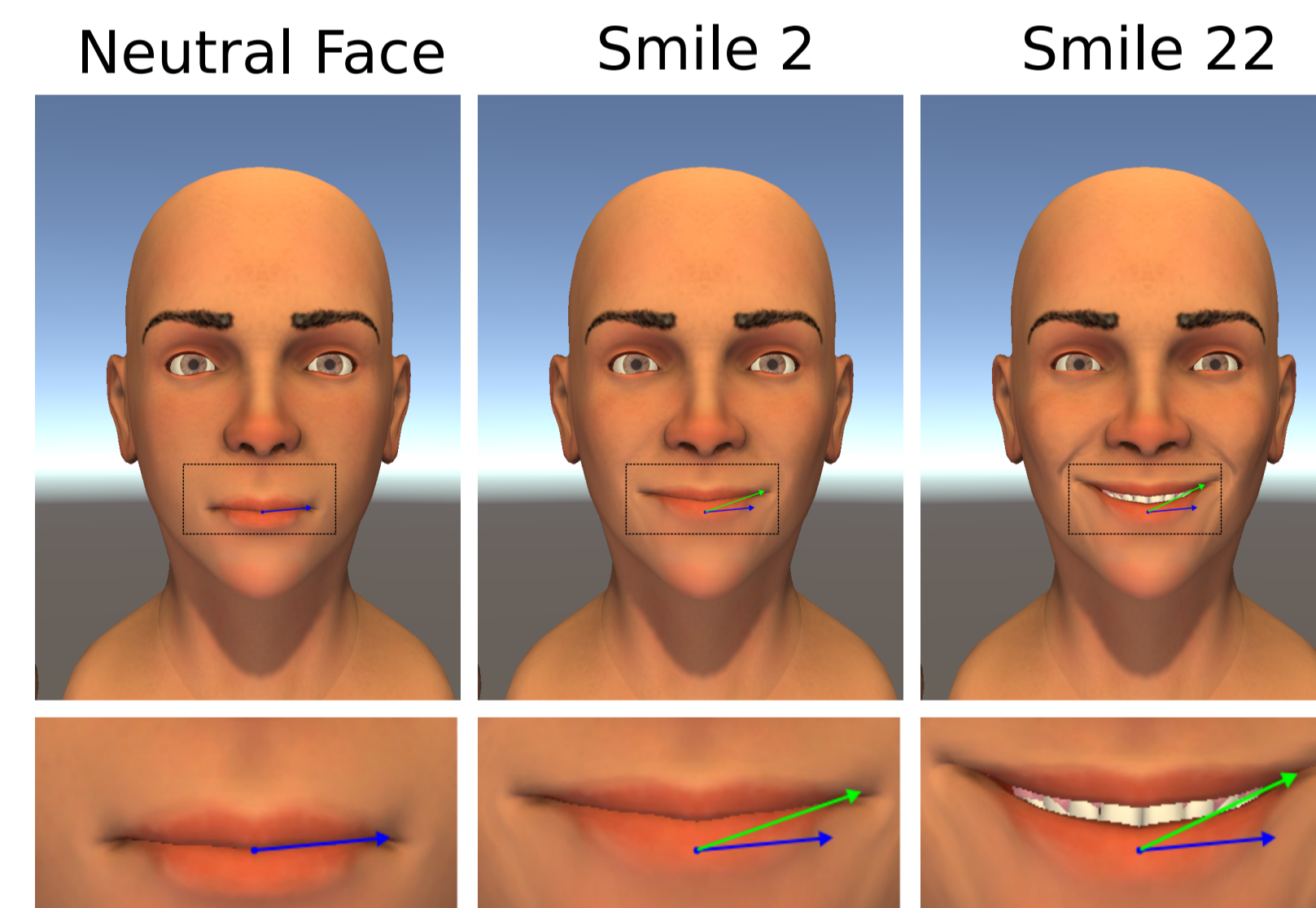


Figure 8: Extent of smile is length of green line, and angle of smile is angle between green and blue lines.

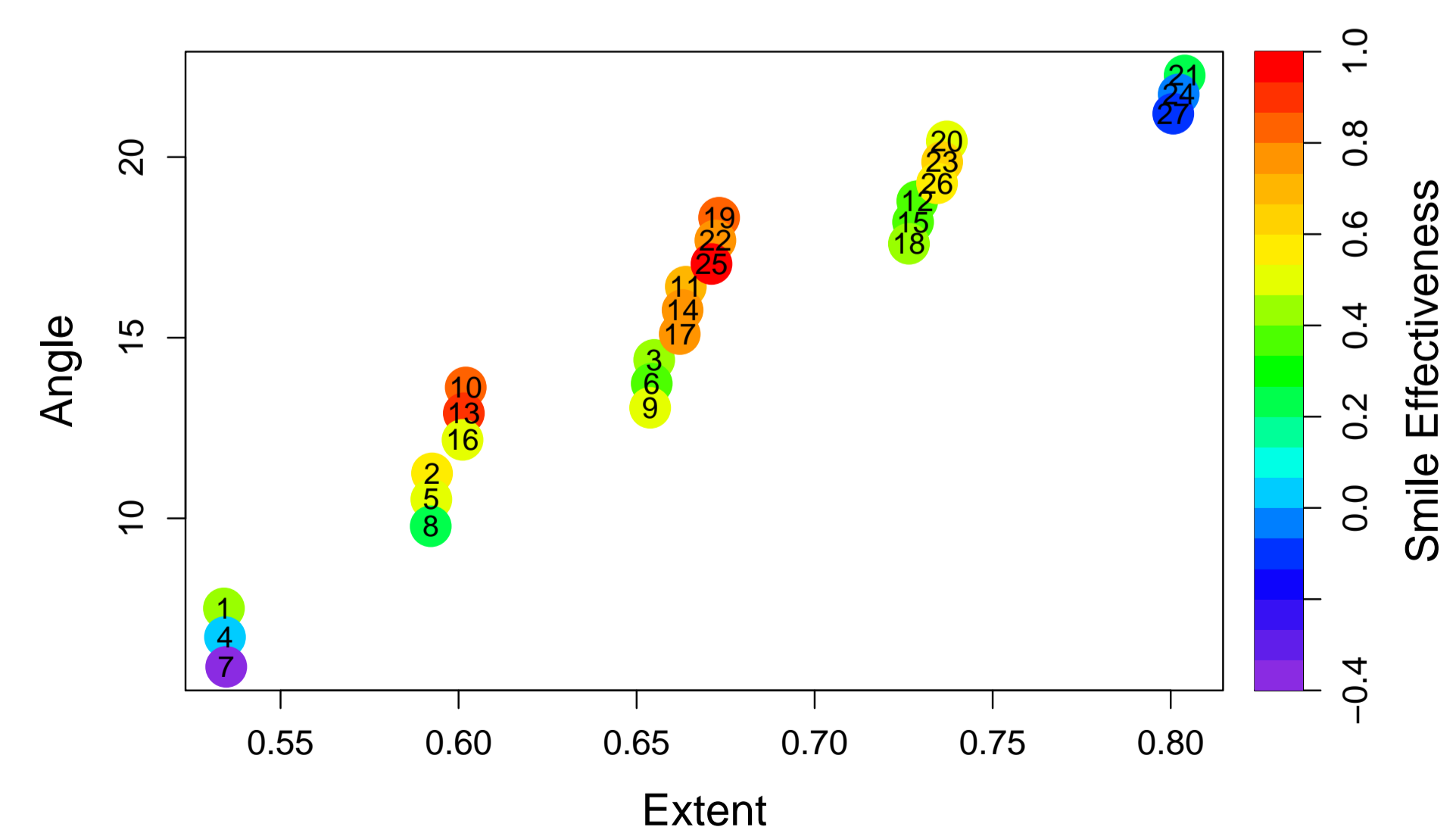


Figure 9: Stimuli plotted by smile extent and angle with smile effectiveness ratings denoted in color.

Conclusions

- (1) Gender and overall timing duration have little to no influence on the perception of an effective smile.
- (2) Smiles with moderate to high dental show (exposed teeth) are rated favorably compared to those with none.
 - Five of the top eight smiles have dental show including the two most effective smiles.
- (3) Too much or too little angle/extent is detrimental to smile effectiveness (see Figure 9).
 - Five least effective smiles include 4 and 7 (low angle/extent) and 21, 24, and 27 (high angle/extent)
- (4) Varying combinations of facial parameters yield effective smiles, and they are diverse in their representations.
 - Comparing the three most effective smiles: Smile 25: high dental show with moderate extent and angle Smile 13: moderate dental show, moderate angle, low extent Smile 19: no dental show with moderate extent and high angle
 - The next five most effective smiles show similar diversity.
- (5) Facial reanimation surgeons should tailor outcomes to effective combinations of angle and extent.
 - Low extent and medium angle, medium extent and medium angle yielded the most effective groups of smiles (see Figure 9).
 - Smile angles around 12–17° are judged as most effective

References

Gu, C. and P. Ma (2005). Generalized nonparametric mixed-effect models: Computation and smoothing parameter selection. *Journal of Computational and Graphical Statistics* 14, 485–504.

Helwig, N. E. (2016). *bigsplines: Smoothing Splines for Large Samples*. R package version 1.0-8.

Helwig, N. E. (in press). Efficient estimation of variance components in nonparametric mixed-effects models with large samples. *Statistics and Computing*.

Pighin, F., J. Hecker, D. Lischinski, R. Szeliski, and D. H. Salesin (2006). Synthesizing realistic facial expressions from photographs. In *ACM SIGGRAPH 2006 Courses*, pp. 19. ACM.

R Core Team (2016). *R: A Language and Environment for Statistical Computing*. Vienna, Austria: R Foundation for Statistical Computing.

Wang, Y. (1998a). Mixed effects smoothing spline analysis of variance. *Journal of the Royal Statistical Society, Series B* 60, 159–174.

Wang, Y. (1998b). Smoothing spline models with correlated random errors. *Journal of the American Statistical Association* 93, 341–348.

Zhang, D., X. Lin, J. Raz, and M. Sowers (1998). Semiparametric stochastic mixed models for longitudinal data. *Journal of the American Statistical Association* 93, 710–719.

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