Computer-generated facial areas of interest in eye tracking research: A simulation study

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21 **Abstract**

22 Advances in eye tracking technology have enabled the development of interactive
23 experimental setups to study social attention. Since these setups differ substantially from the eye
24 tracker manufacturer's test conditions, validation is essential with regard to data quality and other
25 factors potentially threatening data validity.

26 In this study, we evaluated the impact of data accuracy and areas of interest (AOIs) size on
27 the classification of simulated gaze data. We defined AOIs of different sizes using the Limited-
28 Radius Voronoi-Tessellation (LRVT) method, and simulated gaze data for facial target points with
29 varying data accuracy. As hypothesized, we found that data accuracy and AOI size had strong effects
30 on gaze classification. In addition, these effects were not independent and differed for falsely
31 classified gaze inside AOIs (Type I errors) and falsely classified gaze outside the predefined AOIs
32 (Type II errors). The results indicate that smaller AOIs generally minimize false classifications as
33 long as data accuracy is good enough. For studies with lower data accuracy, Type II errors can still
34 be compensated to some extent by using larger AOIs, but at the cost of an increased probability of
35 Type I errors. Proper estimation of data accuracy is therefore essential for making informed decisions
36 regarding the size of AOIs.

37 **Keywords:** eye tracking, areas of interest, accuracy, validity, interactive.

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40 Number of words: 3546

41 Number of figures: 4

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1 Introduction

Eye tracking, especially in its video-based form, has become a standard method for investigating visual attention in many research areas, including social neuroscience (1,2), psychopharmacology (3–5) and virtual reality (6,7). In recent years, several studies have questioned common reporting standards in this field, or the lack of data quality evaluations for the specific setup in use (8,9), e.g., some studies only report the overall accuracy of hardware determined by the manufacturer under ideal test conditions. The issue of data quality and inadequate reporting standards seems to be increasingly relevant as the field advances to develop more naturalistic, interactive or face-to-face eye tracking applications (10–12). Not only do these setups deviate further in design from the manufacturer’s test conditions, but when used in naturalistic interactions, other factors can affect the accuracy of the eye tracking data, such as movements accompanying facial expressions or speech.

AOI-based gaze classification is a popular approach for analyzing eye tracking data (13,14). This approach determines whether a gaze point or a fixation is directed at a predefined region around a target point, e.g., in face perception, the target would be another person's face, while potential AOIs would be the eye region or the mouth. Researchers have taken this approach to study, for example, gaze behavior of participants with (sub-)clinical social anxiety or autism (11,15,16). For these applications in potentially interactive scenarios, automatic procedures to generate AOIs seem beneficial (13), as manual generation can be time-consuming depending on the recording duration. In addition, the uniformity of target stimuli in these setups allow the use of standardized, published procedures (e.g. Limited-Radius Voronoi-Tessellation method, LRVt; (17)), thus ensuring the comparability of research results. In this method, AOI size can be easily regulated by adjusting the limiting radius.

The impact of AOI size on gaze classification has been investigated (13,14). In those studies, suggestions were made that AOIs on sparse stimuli should be large enough to be robust to noise (13), and that oversized AOIs are problematic when considering falsely positive classified gaze data (14). While the problem of inadequate AOI sizes seems to be known, guidelines on how to choose the most appropriate size of AOIs remain vague. In addition, it is conceivable that the choice of AOI sizes depends on the accuracy of eye tracking data. In general, we can assume that low accuracy would require larger AOIs to ensure valid classified gaze points. However, it is unclear how data accuracy and AOI size interact to affect classification performance, and whether false-negatives and false-positives are differentially affected.

With the current study, we aimed to investigate the gaze classification performance as a function of data accuracy and AOI size with simulated gaze data in order to derive guidelines for selecting AOIs and sizing them in interactive (face-to-face) eye tracking applications. Thereby, we focus on classification performance with respect to false-positives (falsely classified inside a specific AOI; Type I error) and false-negatives (falsely classified outside a specific AOI; Type II error) to derive recommendations for choosing AOI size depending on data quality. Specifically, we expected gaze data accuracy and AOI size to independently influence classification performance and for the two factors to interact such that AOI size has a greater impact on classification performance when data accuracy is low. Along with these recommendations, we present a software tool that allows gaze data to be generated with a given accuracy, the visualization of gaze data on AOIs of different sizes, and the evaluation of the resulting classification of gaze data.

89 2 **Method**

90 2.1 **Stimuli**

91 Facial stimuli from the Face Research Lab London (version 3; DeBruine and Jones, 2017)
 92 served as the basis for this simulation. The following four stimuli were selected to represent different
 93 ethnic groups: 005 (male, Asian, 28 years old), 012 (male, Caucasian, 24 years old), 025 (female,
 94 African American, 21 years old) and 134 (female, Caucasian, 21 years old). A picture with a neutral
 95 facial expression and direct gaze was chosen for each stimulus. Stimuli were resized and rescaled to
 96 480 x 480px resembling the size of a real person sitting at a viewing distance of approx. 130cm
 97 recorded at 1920 x 1080px resolution. After rescaling, the facial stimuli covered an average area of
 98 2.8 by 1.9°, which corresponds to the size of a real face in a face-to-face conversation at the
 99 aforementioned viewing distance.

100 2.2 **Gaze data simulation**

101 The goal for our data simulation was to mimic a standard test procedure with multiple
 102 participants and several runs of a gaze validation on facial features, i.e. the instructed sequential
 103 fixation of specific targets points on a facial stimulus. For each target, fixations lasting one second
 104 each were simulated at a recording frequency of 120 Hz. The coordinates of five facial features (left
 105 eye, right eye, nose, mouth & forehead) were chosen as targets. Each target point corresponded to an
 106 AOI center point, except for the forehead point, no AOI was generated. Both target points and AOI
 107 center points were determined using OpenFace landmarks (see Fig 1B; (19)).

108 To simulate a realistic set of gaze data for a group of (simulated) participants, the fixation
 109 points around the facial targets were determined in several steps. First, a fixed number of virtual
 110 participants was generated: Each participant was assigned a random offset angle and a base accuracy
 111 derived from a generalized gamma distribution around the intended mean accuracy. The standard

deviation was set to 0.5 times the mean accuracy and the skewness to 0.6. Second, for each simulated participant, a fixed number of offsets per target was created by varying the individual base accuracy according to normal distribution with a standard deviation of 0.15 times the base accuracy, recalculating all outliers that fell outside three standard deviations. This procedure allowed us to account for within- and between-subjects variance. We applied the above-mentioned method to simulate data with mean accuracy values of 0.5° , 1.0° and 1.5° . The distribution of the simulated data for the three accuracy levels can be found in Fig 1A.

A total of 100 virtual participants were simulated with 30 runs of face validation for each mean accuracy value and stimulus, resulting in 36000 data sets. Data was simulated with an in-house tool written in Python 3.7. The tool can be downloaded here:
https://osf.io/ytrh8/?view_only=bedda3995dba447bb58f81c2f8c27880.

2.3 Definition of AOIs

We used the LRV method (13) with varying radii for facial features and a face ellipse to automatically define AOIs. In the first step, facial landmarks (eyes, nose & mouth) were obtained using OpenFace (19) – Fig 1B. Second, AOI centers were either derived directly from the facial landmarks (nose & mouth) or by calculating the midpoint between two landmarks (left & right eye). The center of the face ellipse is created by calculating the midpoint between the left and right eye corners (x-coordinate) and 1.5 times the distance between facial landmark 8 and 33 (y-coordinate) – Fig 1B. In the final step, AOIs were defined by applying the LRV method with three different radii (1.0° , 1.5° & 2.0°) for the facial features and OpenFace landmarks were used to define the face ellipse. The horizontal radius of the ellipse is the smaller distance between the face's center point and facial landmark 0 or 16 (x-coordinate). The vertical radius is the distance between the face center and facial landmark 8 (y-coordinate). To assess the effect of data quality and AOI size on gaze classification

performance, the AOI radius of 4° proposed in the literature (17) was adjusted to a 131cm viewing distance, resulting in a radius of approx. 2.0° ($\sim 4.6\text{cm}$). Additionally, the radius was further reduced twice (1.0° [$\sim 3.4\text{cm}$] & 1.5° [$\sim 2.3\text{cm}$]) to test the effect of different AOI sizes on classification performance.

a) Data simulation

b) Automatic AOI construction process

Fig 1. Visualization of gaze data simulation and areas of interest (AOI) definition.

(A) Visualization of the three gamma functions used to generate gaze data with three levels of accuracy (0.5° , 1.0° & 1.5°) and examples of the simulated data for the left eye of a facial stimulus as the fixation target ($n = 100$ data sets, averaged over 30 simulated fixations each). (B) Visualization of the three steps of the automatic AOI construction process. 1. Facial landmarks from OpenFace. 2.

145 *AOI center points derived from the facial landmarks. 3. Resulting AOIs using the Limited-Radius*
 146 *Voronoi-Tessellation (LRVT) method (example with 2.0° radius). Note OF = OpenFace (19).*

147 **2.4 Data analyses**

148 As a prerequisite for aggregating the data across stimuli, we performed a two-way analysis of
 149 variance (ANOVA) with the between-subject factors stimulus (005, 012, 025 & 134) and accuracy
 150 (0.5°, 1.0° & 1.5°), to test whether the percentage of correctly classified fixation points differed as a
 151 function of facial stimulus used for the simulation.

152 To investigate the influence of data quality and AOI size on false-negatives (Type II error), we
 153 analyzed the number of fixation points directed to one of the four facial AOIs that were misclassified
 154 as belonging to a different AOI, or to no AOI at all (*rest of face & surrounding*). We chose to
 155 visualize the effect using confusion matrices and bar plots, and analyzed the data descriptively.

156 The effect of data quality and AOI size on false-positives (Type I error) was tested by
 157 simulating fixation points on the forehead of the facial stimuli for which no AOI had been defined.
 158 Classification was correct when no AOI was detected, whereas false-positives occurred when
 159 fixations points were misclassified as belonging to one of the AOIs. Again, bar plots were created to
 160 visualize the effect of the independent variables, and analyses were performed at the descriptive
 161 level.

162 Last, the effect of data quality on false-negatives was further tested by simulating fixation
 163 points directed towards the face and analyzing the percentage of points classified as being directed
 164 away from the face.

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3 Results

The two-way ANOVA for the percentage of correctly classified fixation points revealed a non-significant main effect of facial stimulus, $F(3, 1188) = 1.62, p = .182, \eta^2_G < .01$, a significant main effect of condition, $F(2, 1188) = 408.01, p < .001, \eta^2_G = .41$ and a non-significant interaction effect, $F(6, 1188) = 0.55, p = .768, \eta^2_G < .01$, resulting in the aggregation of classification data across stimuli.

3.1 Classification of fixations on facial feature AOIs

Fixations simulated on eyes, nose, and mouth with high data quality, e.g., accuracy values of 0.5° , were correctly classified in 82.3 to 97.2 percent of cases. Misclassification and non-classification of fixations (false-negatives; Type II error), in turn, occurred in only 0 to 10.8 percent of cases. In this condition, the classification performance was largely independent of AOI size (Fig 2 right column along the vertical axis). With reduced data quality, we noted that differences emerged in the classification performance as a function of AOI size (Fig 2 left and middle column along the vertical axis). Fixations with an accuracy of 1.5° were on average correctly classified in 22.0 to 60.7 percent of the cases. Large AOIs with a radius of 2.0° resulted in correct classification above chance level for most AOIs (left eye, right eye & mouth), whereas classification of fixation points on the nose AOI were evenly distributed across all other AOIs, resulting in the highest percentages of false-negatives (19.2 to 27.8%). Reducing AOI size, on the other hand, is associated with fewer misclassified fixation points, at the expense of an increase in false-negatives in terms of non-classification (*rest of face & surrounding*: 4.3 to 43.7%).

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188 **Fig 2. Confusion matrices of the fixation classification performance as a function of gaze data**
 189 **accuracy and AOI size.**

190 *The percentages in the diagonal represent correctly classified fixation points, while the percentages*
 191 *outside the diagonal represent misclassified fixation points. The percentages in the last two rows*
 192 *correspond to the number of unclassified fixation points (rest of face & surrounding).*

193 In a second step we averaged classification performance over all facial target points (see Fig
194 3B). Concerning false-negative classifications, the AOI size seems irrelevant for accuracy values
195 below or equal to 0.5° . For scenarios with accuracy values over 1.0° , larger AOIs result in more
196 correctly classified fixation points at the expense of a slightly increased percentage of misclassified
197 fixation points. Smaller AOIs, on the other hand, lead to fewer misclassified fixation points, but also
198 to a reduction of correctly classified fixation points due to up to 50% unclassified data-quality-
199 dependent fixation points.

200 3.2 Classification of fixations outside AOIs

201 To investigate the effect of data quality and AOI size on false-positives (Type I error), data
202 were simulated on a target point for which no AOI had been defined. In this particular case, we
203 simulated data on the forehead of the facial stimuli to recreate a situation in which someone is trying
204 to avoid eye contact and hides their behavior by fixating on the forehead. Fig 3D shows that large
205 AOIs in combination with good data quality (0.5° accuracy) result in over 90% misclassified fixation
206 points (inflation of Type I error). As expected, most fixation points were falsely classified as
207 belonging to the left or right eye. Smaller AOIs in combination with good data quality, on the other
208 hand, lower numbers of false-positives drastically with over 80% of fixation points being correctly
209 classified outside any specific AOI. The effect of data quality is inverse, while smaller AOIs profit
210 from better accuracy in terms of Type I error, the error increases with better accuracy for larger
211 AOIs.

Classification for gaze inside AOIs

Classification for gaze on forehead

212

213 **Fig 3. Effect of gaze data accuracy and AOI size on classification performance of simulated**
 214 **fixations (on eyes, nose & mouth) averaged over all facial AOIs.**

215 (A) Visualization of the AOI sizes 1.0° and 2.0° drawn around the blue center points and the
 216 simulated fixation points in red ($n = 100$, averaged over 30 simulated fixations; accuracy 0.5°). (B)
 217 Green indicates correct classification within the corresponding AOI, orange and gray indicate
 218 misclassifications as fixations within the other AOIs, or no AOI at all. Effect of gaze data accuracy
 219 and AOI size on classification performance of simulated fixations (on the forehead). (C)
 220 Visualization of AOIs with 1.0° and 2.0° radius and the simulated fixation points on the forehead in
 221 red ($n = 100$, averaged over 30 simulated fixations; accuracy 0.5°). (D) Green indicates the correct
 222 classification outside any AOI, orange and gray indicate misclassifications as fixations within the
 223 AOIs of the eye region or within the other AOIs.

224 **3.3 Classification of fixations on the face**

225 The largest meaningful AOI for facial stimuli can be assumed to be the whole face, represented
 226 by an ellipse drawn around the entire face with no specific facial features discriminated. To
 227 investigate the effect of data accuracy on false-negatives, data was simulated on four facial targets
 228 points (left eye, right eye, nose & mouth) and classified as being directed towards or away from the
 229 face. Accuracy values up to a 1° degree visual angle allow nearly error-free classification of fixation
 230 points (0.5° accuracy: approx. 99% correct classification; 1.0° accuracy: approx. 97% correct
 231 classification), but even accuracy values of a 1.5° degree visual angle reduce the classification
 232 performance by only about 10% (approx. 89% correct classification) (see Fig 4B).

233
 234 **Fig 4. Effect of gaze data accuracy on classification performance of simulated fixations (on**
 235 **eyes, nose & mouth) within the face ellipse.**

236 *(A) Visualization of the face ellipse and the simulated fixation points with an accuracy of 1.5° (n =*
 237 *100, averaged over 30 simulated fixations) in red. (B) Green indicates correct classification within*
 238 *the face ellipse compared to orange for misclassification outside the face ellipse.*

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240

241 **4 Discussion**

242 In the present simulation study, we investigated the effect of data accuracy and AOI size on
 243 gaze data classification for facial stimuli in a (simulated) interactive eye tracking setup. As
 244 hypothesized, we found that the AOI size's effect on classification performance is strongly dependent
 245 on gaze data accuracy. Differentiating this effect in terms of Type I and Type II errors, we found that
 246 AOI size is irrelevant concerning Type II error (falsely classified outside predefined AOIs) for data
 247 accuracy better than 1.0°. The picture changed when data accuracy exceeded the threshold of 1.0°
 248 within the present setup: larger AOIs increased classification accuracy leading to lower Type II
 249 errors. On the other hand, if we consider the Type I error (falsely classified inside a predefined AOI),
 250 the definition of smaller AOIs seems appropriate for all levels of data accuracy simulated here.
 251 However, the advantages of smaller AOIs decline with a data accuracy worse than 1.0°. Here the
 252 probability of misclassification or Type I errors increases.

253 Our findings regarding Type II error are consistent with previous accounts of the interaction
 254 between data accuracy and AOI size on gaze data classification performance (20,21). Moreover, a
 255 systematic observation of gaze data classification performance on facial stimuli using the same AOI
 256 definition as in the present study concluded that larger AOIs are a noise-robust solution (13).
 257 Therefore, larger AOIs might be a better choice with data accuracy worse than 1.0°, but larger AOIs
 258 are also associated with higher Type I error when data accuracy is low.

259 This distinction seems particularly relevant when examining clinical disorders such as social
 260 phobia or autism with such interactive eye tracking setups, for which small spatial differences in
 261 attention allocation are characteristic (22,23). We simulated such a scenario by including fixations
 262 directed at a target point on the forehead of the facial stimuli for which no AOI had been defined. We
 263 chose this scenario because people suffering from social interaction disorders often report employing

264 strategies to normalize their gaze behavior in social interactions, such as looking between the eyes or
265 at their interaction partner's forehead. Our simulation results are in line with another publication that
266 recommended smaller AOIs to prevent inflated Type I errors (14). However, by examining a wide
267 range of data accuracy in the current study, we additionally observed that the superiority of smaller
268 AOIs decreases in conjunction with reduced data accuracy.

269 Given the differential effects on Type I and Type II errors, medium-sized AOIs would
270 represent a compromise, but when we consider the data accuracy for values worse than 1.0° , only
271 about 40% of fixations were correctly classified in both simulations. Therefore, we included a
272 simulation designed for scenarios with low data accuracy that sacrifices facial feature distinction in
273 favor of classification performance. While 1.5° data accuracy resulted in a classification performance
274 below the chance level when differentiating facial features, the face ellipse as the largest meaningful
275 AOI in face perception resulted in almost 90% of the fixations being classified correctly even with
276 data accuracy as low as 1.5° .

277 Based on the present simulation study, the recommendations for the choice of facial AOI size
278 in interactive eye tracking setups can be summarized as follows:

- 279 • Inflation of Type I error (falsely classified gaze points inside an AOI) can be prevented by
280 using small AOIs, such as radii of 1.0° , regardless of the data accuracy
- 281 • As previously published and recommended, the use of larger AOIs prevents the inflation of
282 the Type II error (falsely classified gaze points outside an AOI), especially for data accuracy
283 above 1.0°
- 284 • If both error types (Type I & Type II errors) are to be compensated for in a setup with data
285 accuracy of 1.0° or better, smaller AOIs appear to be the better choice

- If both error types (Type I & Type II errors) are to be compensated for in a setup with data accuracy worse than 1.0° , we suggest not using AOIs to distinguish facial features, but instead a face ellipse as an indicator of facial gaze

While the AOI size can be freely chosen by the investigator, the limiting factor is the data accuracy. Hence, it seems crucial not only to maximize the data accuracy as far as possible, but furthermore to estimate data accuracy based on the data set under the specific recording conditions. Ideally, distinct trials instructing the participants to fixate predefined points in the tracking area are included in the study protocol that allow the proper calculation of data accuracy. If this is not possible, attempts should be made to estimate the data accuracy from data recorded under the specific conditions, which are often imperfect and often not comparable to the conditions on which the manufacturers base their specifications.

One potential limitation might be that the present simulation was based on the assumption that gaze data follows a unique distribution for all generated data sets. Although, the overall parameters (deviation and skewness) are largely in accordance with data recorded in the real setup underlying the present simulation (12), it is possible that other recording conditions, populations or interaction paradigms will lead to different data distributions. Therefore, we make the gaze data simulation tool used in the present study freely available and encourage repeating or modifying the simulation process.

Furthermore, one might question the use of AOIs in general due to their subjective nature and the fact that the definition can be very time-consuming especially with moving AOIs in interactive setups (24). We tried to minimize these practical disadvantages by using a validated automatic AOI-definition method that takes a Voronoi-Tessellation approach to avoid subjectivity, and the OpenFace tool to save time. Nevertheless, data-driven approaches based on neural networks (25,26) could be an

309 alternative approach when data quality is uncertain or difficult to estimate, an approach that could be
310 evaluated in future studies when used in interactive eye tracking setups.

311 It should be noted that visual angle values used in the present study need to be adjusted to
312 differing viewing distances for meaningful comparison between studies. Thus, lower data accuracy
313 can be in part compensated by using shorter viewing distances, as long as the setup allows shorter
314 viewing distances. In turn, longer viewing distances or situations with stimuli which are observed at
315 varying viewing distances should be treated with caution. However, future studies can apply the
316 general recommendations proposed in the present paper to justify the choice of AOI size depending
317 on data accuracy and viewing distance in the given setup and environment.

318 The present study thus might help to further improve reporting standards in eye tracking
319 research (20,21,27). Furthermore, the freely available simulation tool used in the present study can be
320 used to support the validation process of novel eye tracking setups.

321 Eye tracking during real social interactions is a powerful tool to examine social attention and
322 behavior in both healthy and clinical populations. Data accuracy in these setups can be compromised
323 by movements caused by speech, facial expressions, or head rotations. It is thus essential to validate
324 novel interactive eye tracking setups carefully. The proper estimation of data accuracy is an essential
325 prerequisite for informed decisions regarding the size of AOIs used for data analysis. The results of
326 the present simulation study indicate that smaller AOIs minimize false classifications (both Type I
327 and Type II errors) as long as data accuracy is good enough. For studies with lower data accuracy,
328 Type II errors can still be compensated to some extent by using larger AOIs, but at the cost of
329 increasing the probability of Type I errors. When data accuracy is low, facial feature discrimination
330 should better be omitted and larger AOIs, such as a face ellipse, should be preferred to allow valid
331 AOI classification.

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6 Competing interest statement

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

7 Funding

The study was in part supported by grants from the German Research Foundation (DO1312/5-1) and Trier University Research Priority Program “Psychobiology of Stress”, funded by the State Rhineland-Palatinate.

8 Data Availability Statement

The datasets generated and analyzed in this study can be reproduced using the described software tool, which can be downloaded from the following website:
https://osf.io/ytrh8/?view_only=bedda3995dba447bb58f81c2f8c27880