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Information accrual from the period preceding racket-ball contact for tennis ground strokes: Inferences from stochastic masking

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31   Abstract

32   Previous research suggests the existence of an expert anticipatory advantage, whereby skilled

33   sportspeople are able to predict an upcoming action by utilising cues contained in their opponent's

34   body kinematics. This ability is often inferred from "occlusion" experiments: Information is

35   systematically removed from first-person videos of an opponent, for example by stopping a tennis

36   video at the point of racket-ball contact, yet performance, such as discrimination of shot direction,

37   remains above chance. In this study, we assessed the expert anticipatory advantage for tennis

38   ground strokes via a modified approach, known as "bubbles", in which information is randomly

39   removed from videos at in each trial. The bubbles profile is then weighted by trial outcome (i.e. a

40   correct vs. incorrect discrimination) and combined across trials into a classification array, revealing

41   the potential cues informing the decision. In two experiments (both with N = 34 skilled tennis

42   players) we utilised either temporal or spatial bubbles, applying them to videos running from 0.8 s to

43   0 s before the point of racket-ball contact (cf. Jalali et al., 2018). Results from the spatial experiment

44   were somewhat suggestive of accrual from the torso region of the body, but were not compelling.

45   Results from the temporal experiment, on the other hand, were clear: information was accrued

46   mainly during the period immediately prior to racket-ball contact. This result is broadly consistent

47   with prior work using non-stochastic approaches to video manipulation, and cannot be an artifact of

48   temporal smear from information accrued after racket-ball contact, because no such information

49   was present.

50

51 Elite athletes demonstrate extraordinary ability in their sport of choice. While their sporting acumen

52 may seem like a fundamentally physical attribute, it is in fact scaffolded by a range of cognitive skills

53 that span the sensorimotor pipeline, from perception to action execution (Yarrow, Brown, &

54 Krakauer, 2009). One such skill that has received considerable attention from experimental

55 psychologists is the expert anticipatory advantage.

56

57 The expert anticipatory advantage in sports describes a domain-specific benefit that sportspeople

58 exhibit when predicting what is about to happen based on their opponent's current bodily

59 kinematics (as opposed to their opponent's previous action history, which provides a separate cue

60 for predicting current behaviour; Mann, Schaefers, & Cañal-Bruland, 2014). This advantage has been

61 demonstrated in experiments simulating a variety of sports, most commonly via temporal and

62 spatial occlusion methodologies (e.g. Abernethy, 1988; Jones & Miles, 1978). Hence the advantage is

63 widely exhibited, although the extent to which it benefits actual competitive performance remains

64 uncertain (van Maarseveen, Mariëtte, Oudejans, Mann, & Savelsbergh, 2018).

65

66 A typical occlusion experiment runs as follows. A sporting scenario is selected, for example a football

67 (soccer) goalkeeper attempting to save penalties (e.g. Dicks, Button, & Davids, 2010; Smeeton &

68 Williams, 2012). Videos are shot from the sportsperson's (here the goalkeeper's) perspective,

69 capturing various instances of two or more categories of outcome (for example penalties struck to

70 the left or right of the goalkeeper). In the actual experiment, participants, often varying in sports

71 expertise (e.g. novice vs. expert goalkeepers) view these videos, attempting to discriminate which

72 outcome will occur on each trial. Critically, the videos are manipulated to exclude some of their

73 visual information. In temporal occlusion, the video is usually terminated early (for example at or

74 before ball contact) so that only particular sequences of body kinematics are available to guide the

75 response. In spatial occlusion, particular features at constrained spatial locations (for example the

76 striker's hips) are also removed from the video.

77

78   The logic of these experiments is that participants will only be able to perform at above-chance

79   levels if there is information in the video to guide their decision, with performance declining towards

80   chance as this information is systematically removed. Certain sports, such as cricket, have been long-

81   running favourites in the occlusion literature (e.g. Abernethy, & Russell, 1984; Müller & Abernethy,

82   2006; Müller, Abernethy, & Farrow, 2006), but occlusion approaches have been applied to sports as

83   diverse as volleyball (e.g. Loffing, Hagemann, Schorer, & Baker, 2015) and karate (Mori, Ohtani, &

84   Imanaka, 2002).

85

86   Racket sports (e.g. badminton and squash; Abernethy, 1990; Abernethy, Bruce & Russell, 1987) have

87   been particularly well studied via occlusion techniques. The focus of the current study is the sport of

88   tennis. This sport was amongst the first to provide evidence of an expert anticipatory advantage,

89   with Jones and Miles (1978) showing that experts were above chance (and better than intermediate

90   or novice players) at guessing the landing position of a serve when the video was stopped 0.042 s

91   before ball contact. Subsequent work has found, for example, that experts extract information from

92   the time when the ball's toss is at its apex onwards when predicting spin (Goulet, Bard, & Fleury,

93   1989). The temporal occlusion method has also been adjusted slightly to present one of several

94   possible windows of visibility (0.3 seconds in duration) during service, with above-chance

95   performance for experts when viewing the video for only the 0.3 s immediately before ball contact

96   (Farrow, Abernethy, & Jackson, 2005). These temporal occlusion results are supplemented by spatial

97   occlusion studies, showing for example that experts can still discriminate the direction of tennis

98   serves at above-chance levels following removal of body regions such as the entire lower body, but

99   not when the ball's toss was occluded (Jackson & Mogan, 2007). Experts were also impaired (but to a

100   lesser extent) by removal of the arm and racket.

101

102 While the tennis serve is the most straightforward scenario to investigate, ground strokes have also

103 been probed via occlusion methods. With temporal occlusion at ball contact, experts were above

104 chance to discriminate between left/right lobs and passing shots when shutter goggles were used to

105 block vision in situ on a tennis court (Shim, Carlton, Chow, & Chae, 2005). More traditional video-

106 based studies have shown that unlike novices, experts could already predict shot direction above

107 chance at -0.12 s relative to ball contact, with further improvements for occlusion occurring at -0.08

108 and -0.04 s (Rowe, Horswill, Kronvall-Parkinson, Poulter, & McKenna, 2009). Spatial occlusion work

109 suggests that the arm/racket regions are critical when predicting ground-shot direction (Shim,

110 Carlton, & Kwon, 2006).

111

112 Video-based occlusion methods are not perfect, and our knowledge about the expert anticipatory

113 advantage has been supplemented by a variety of techniques. Such techniques include eye tracking

114 to provide information about where sportspeople attend, and animating/manipulating the opponent

115 (e.g. Cañal-Bruland, van Ginneken, van der Meer, Bart, & Williams, 2011; Ida, Fukuhara, Ishii, &

116 Inoue, 2013) including via virtual reality (Vignais, Kulpa, Brault, Presse, & Bideau, 2015). For example,

117 Ida et al. (2013) manipulated the arm/racket angles of computer-generated opponents to

118 successfully influence experts' analogue estimates of the direction, speed, and spin of a tennis serve.

119 In another study, swapping the arm/racket of stick-man representations of an opponent to that of a

120 different shot confused experts trying to predict the direction of ground strokes (Cañal-Bruland et

121 al., 2011). However, here we stay closer to the traditional occlusion approach, but attempt to

122 remedy a possible weakness of the method: Its dependency on experimenter decisions regarding

123 exactly what to occlude.

124

125 To this end, we utilise a stochastic method of video occlusion borrowed from the psychophysical

126 literature (Ahumada Jr & Lovell, 1971), specifically a form of classification-image analysis (sometimes

127 called reverse correlation) known as bubbles (Gosselin & Schyns, 2001). Bubbles are Gaussian-

profiled windows of visibility that reveal the information from an otherwise masked (e.g. uniform

grey) display. In the temporal domain, they are rather like the occlusion approach of Farrow et al.

(2005) who displayed only a 0.3 second window of information from a video at a time. However,

unlike in that study, which utilised a discrete set of non-overlapping windows as separate conditions,

in a bubbles experiment several bubbles typically appear on each trial and the midpoint of each

bubble is chosen at random. Furthermore, their Gaussian profiles remove transients and give the

impression of the underlying display being smoothly revealed and subsequently re-masked (see

Figure 1 for illustration). At the analysis stage, the random bubbles profiles from the different trials

are binned by correctness of response and combined to produce a classification sequence. This

classification can then be used to highlight the regions from which information must have been

utilised to generate correct discriminations.
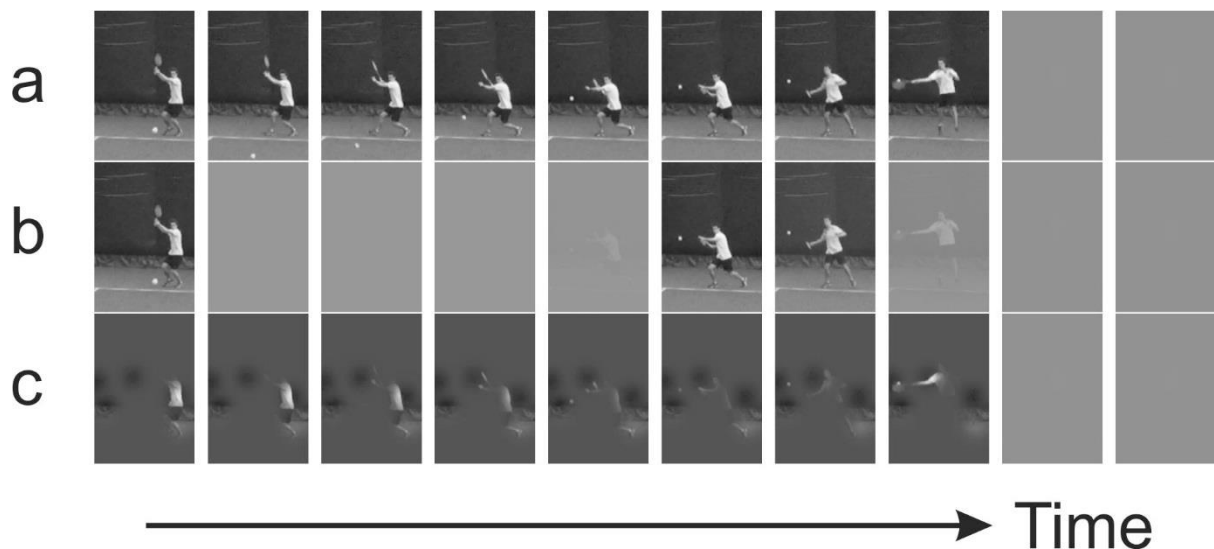
*Figure 1. Example stimuli, shown as snapshots from video every 100 ms. **A.** Video occluded at point of racket-ball contact but with no bubbles manipulation (equivalent to pre-test trials here). **B.** Temporal bubbles permit viewing of entire image, but only at certain times. **C.** Spatial bubbles permit viewing of only certain regions of the image, but across all (pre-contact) frames.*

146 Although bubbles are typically applied to sparse, tightly controlled psychophysical stimuli, their

147 applicability to a complex real-word scenario like tennis anticipation has been demonstrated

148 recently (Jalali, Martin, Murphy, Solomon, & Yarrow, 2018). In that study, we had both novice and

149 competent tennis players view opponents in both service and forehand-groundstroke scenarios. We

150 did not stop the video at racket-ball contact, but the structure of the experiment encouraged

151 participants to respond as fast as possible while maintaining an acceptable level of accuracy. The

152 bubbles technique proved effective in both the temporal and spatial domains but it suggested that

153 our participants were primarily utilising information from the beginning of the ball's trajectory off

154 the racket face rather than their opponent's pre-contact kinematics. However, the temporal

155 classification sequence did imply possible information accrual just prior to racket-ball contact as

156 well, but this interpretation remained speculative. The reason is that the bubbles technique yields a

157 classification sequence in which very discrete information sources can become smeared (i.e.

158 exaggerated in extent), such that an information source at or just after racket-ball contact might

159 spread back to appear significant in the immediately preceding frames.

160

161 Here, we again use bubbles to attempt to find evidence of an expert anticipatory advantage in

162 tennis. Our aim is to quantify the extent of the temporal and spatial regions, prior to ball contact,

163 from which skilled tennis players are able to extract useful information about shot direction, but

164 using a stochastic masking technique (i.e. bubbles). The implementation of the bubbles method does

165 not require any intuitions about information sources which need to be designed as separate

166 conditions, but rather allows any region of information to emerge in a bottom-up manner. As such,

167 we believe it provides a useful form of methodological triangulation relative to traditional occlusion

168 approaches. However, we made an important change relative to our previous study: We stopped the

169 video at racket-ball contact, with bubbles appearing at random up to that point but no information

170 ever provided afterwards. This change guarantees that any information sources we identify, even if

171 near the point of racket-ball contact, are not the result of the aforementioned temporal smear

172   arising at the analytic stage. We also focus on ground strokes only, without considering services. To

173   presage our results, we find unequivocal evidence for the utilisation of kinematic information by

174   competent tennis players, but only for the period immediately prior to ball contact.

175

176   Methods

177

178   Participants

179   We utilised a smorgasbord[1] sampling method, attempting to recruit participants with experience

180   playing competitive tennis by various means. Where possible, we recorded their years of experience,

181   current competitive tennis matches per year, and International Tennis Number (ITN), which is an index

182   of their standard of play and ranges from ITN 1 (a player with extensive professional tournament

183   experience and who currently holds or is capable of holding an ATP/WTA ranking) to ITN 10 (a player

184   that is just starting to play competitively). Eleven participants (8 male, 3 female, mean age 30, mean

185   years of tennis experience 13, mean matches per year 48, mean ITN 2.8) were recruited via adverts at

186   London tennis clubs and by word of mouth, and travelled to City, University of London to participate.

187   All completed both temporal and spatial bubbles sessions (see design, below).[2] We also took the

188   opportunistic step of developing a portable setup and taking it to the National UK University

189   championships, where we recruited participants in their down time between matches (or after they

190   had been eliminated). We tested 22 such participants in total, with 13 completing a spatial bubbles

191   session (8 male, 5 female, mean age 22, mean years' experience 11, mean matches per year 37, mean

192   ITN 2.1) and 13 completing a temporal bubbles session (8 male, 5 female, mean age 22, mean years'

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[1] This is our own dubious terminology. We originally intended to recruit several separate samples and address additional questions, but recruitment proved more challenging than expected, leading us to form a composite sample.

[2] Most of these participants also completed sessions in which they attempted to guess the direction of serves, but our service stimuli proved extremely difficult to discriminate, thus yielding no conclusive results, and are omitted from our report for concision.

193   experience 10, mean matches per year 44, mean ITN 2.1).[3] We subsequently took our portable setup

194   to a second lab (at Technische Universität Kaiserslautern) in order to exploit its proximity to an elite

195   school for sport (Heinrich Heine Gymnasium) attended by promising young tennis players and their

196   coaches. We tested 10 such participants (8 male, 2 female, median age 16) who completed both

197   spatial and temporal bubbles sessions.[4] For the German participants we recorded their

198   "Leistungsklassen" or performance class abbreviated as LK. According to the German Tennis

199   Federation (DTB) the lowest class is LK23 and the highest LK1 consisting of top ranked players in

200   Germany. The German pool had three LK1 players, one LK23 and average of LK 10 (std 8.5). They

201   averaged 7.7 years of experience and 26 competitive matches per year. Finally, from the resulting

202   complete samples of 34 (temporal bubbles) / 34 (spatial bubbles) participants, we rejected

203   participants who were unable to perform the task significantly above chance during bubbles blocks

204   (<55%, yielding binomial $p > 0.05$ that they were simply guessing), but only for our mean classification-

205   array analysis (one of several analyses we ran; see below). We did this because an inability to perform

206   the task makes it impossible for the bubbles technique to retrieve meaningful sources of information.

207   This left final samples of 24 (spatial) and 27 (temporal) participants for mean classification-array

208   analysis. Informed consent was obtained from all participants, who were paid £10 per hour (London)

209   and €10 per hour (Germany) for their time. Ethical approval was granted by the relevant local Ethics

210   Committees at City, University of London, and Technische Universität Kaiserslautern.

211

212   *Apparatus & Stimuli*

213   We used the ground-stroke subset of video stimuli from those previously described by Jalali

214   et al. (2018). They were recorded at a tennis club using a tripod-mounted camera (frame rate 120 Hz,

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[3] Nine from each group completed just a single block, and four competed both. Some participants failed to report some measures of experience, particularly ITN, so the means are based only on those who responded. Three participants from this group also completed a block using service stimuli, not reported here (see footnote 2).

[4] These participants completed two further blocks with a modified presentation sequence (a fixed rather than random ordering of opponents, to see if experiencing the same opponent repeatedly made them easier to predict) but this change did not generate any clear trend, and these blocks are not analysed here.

215   frame size 1280x720 pixels). Four club coaches/hitters of a good but not elite standard acted as models

216   and were instructed to "hit winners" without attempting explicit deception. They were situated near

217   the baseline and recorded against a largely uniform blue backdrop. They were recorded playing

218   forehand ground strokes (running rightwards from a central position to return near the singles side

219   line), directing their shots towards an imaginary receiver's forehand or backhand. To increase image

220   resolution, the camera was positioned at the net, on a line projecting from the filmed player to the

221   imaginary receiver at the opposite baseline (height = 1.6 m, left of centre line by 1.25 m).

222   Videos were first transformed to eight-bit greyscale. Two authors picked a subset of videos

223   that were unambiguous (regarding the direction of the shot – line/cross), relatively homogeneous in

224   terms of the position of the players at the time of ball contact, and lacking in artefactual cues that

225   might allow the videos to be easily remembered for future classification (e.g. an unusual delivery

226   trajectory). In each video, the frame corresponding to ball contact and the position at which the ball

227   struck the racket head on this frame were manually identified for use in the subsequent presentation

228   and analysis (see below).

229   The experiment was controlled by computers running scripts written in Matlab® (The

230   Mathworks, Natick, U.S.A.) using the Psychophysics Toolbox (Brainard, 1997; Kleiner et al., 2007;

231   Pelli, 1997). Video stimuli were presented via either a CRT monitor (for sessions at City, University of

232   London), a short-throw gaming projector (Optoma® GT760; for sessions at Kaiserslautern and

233   temporal sessions at UK university championships), or a MacBook® Pro (spatial sessions at UK

234   university championships). The former two displays had a vertical refresh rate of 120 Hz, while the

235   latter refreshed at 60 Hz, playing a down-sampled video. Only a central 600 x 400 pixel region of

236   each video that excluded irrelevant peripheral information was presented. Displays were presented

237   at around eye level and viewed at an appropriate distance in order to present the opposing tennis

238   player with a height subtending ~4° visual angle (approximating their size as seen from the baseline

239   during actual play). Participants responded by either stepping rightward or leftward, thus lifting the

240   corresponding foot from one of two digital pedals, monitored at 100,000 Hz via a 16 bit A/D card

241 (National Instruments X-series PCIe-6323; for sessions at City) or by pressing an appropriate arrow

242 key on a computer keyboard (all other sessions).

243

244 *Design & Procedure*

245   There were two types of session incorporating either temporal or spatial bubbles blocks with

246 participants completing one or both of these sessions, and in some cases up to two additional sessions

247 not reported here (see footnotes 2-4). Each session took around an hour, and consisted of three

248 blocks: One practice, one pre-test, and one bubbles block (in that order). During practice, participants

249 viewed a small number of videos (between 10 and 24 depending on the experimental location; 50%

250 to forehand, 50% to backhand) containing any of four players (8 possible videos per player) but with

251 a preponderance of videos (70%) from one player and fewer videos (10% each) from the remaining

252 three players, who were saved mainly for the experimental trials (see below). Videos were randomised

253 with replacement.

254   Videos presentations began at −0.8 s relative to racket-ball contact. The practice block

255 constituted a warm-up in which trials terminated at +0.2 s relative to racket-ball contact to provide

256 clear information about the trajectory of the ball off the racket head. By contrast, in pre-test and

257 bubbles blocks, videos terminated at racket-ball contact (replaced with a uniform grey screen) or at

258 the time of response if earlier than this.

259   For these pre-test and bubbles blocks, 24 new videos (8 per player, 50% to forehand and 50%

260 to backhand) were selected from the three players seen less often during practice. For the pre-test,

261 the videos were presented between one and four times each in a random order, yielding a block of

262 either 24 trials (City and Kaiserslautern) or 96 trials (UK university championships). These differences

263 reflected the fact that City and Kaiserslautern participants typically performed multiple sessions, so

264 could have their pre-test data combined across them. For the critical bubbles block, these videos were

265 presented a further 16 times each in a random order, yielding a block of 384 trials. Participants

266 responded without any deadline. Trials with presentation glitches, i.e. where one or more frames were

267 dropped after the −0.2 s time point, were re-randomised and repeated at the end of the block.

268 Feedback about correctness was provided after every trial.

269 Importantly, during bubbles trials only, the videos were subjected to random masking via

270 the application of bubbles (see Figure 1; for videos showing examples of temporal and spatial

271 bubbles, see videos 1 and 2 respectively from Jalali et al. (2018), available at

272 https://www.frontiersin.org/articles/10.3389/fpsyg.2018.02229/full#supplementary-material).

273 Individual bubbles were combined to generate bubbles profiles in one (temporal) or two (spatial)

274 dimensions. The number of bubbles presented began at 8 or 20 for temporal and spatial sessions

275 respectively. In principle, this (maximum) number could then be adjusted downwards via a QUEST

276 staircase (Watson & Pelli, 1983) varying the number of bubbles in order to try and maintain

277 participants' performance at around 75% correct (i.e. lowering the number of bubbles if the task was

278 too easy). However, as discussed further below, this was never required as the task was very hard

279 even in the absence of any masking. The profile of each individual bubble was that of a 1, or 2-

280 dimensional Gaussian density function, scaled to have unit height. In the temporal sessions its width

281 (σ) was 3 frames; in the spatial sessions its width was 12 pixels (vertically and horizontally).[5]

282
283 Bubble mean positions were selected at random within a domain extending throughout the

284 relevant space of the video. Bubbles profiles were determined by combining the individual bubbles

285 together. This was achieved by first reflecting bubble magnitudes around 0.5, then multiplying them

286 together, and finally re-reflecting:

287

288 (1) $\text{Bubbles} = 1 - \prod_{b=1}^{B}(1 - \text{bubble}_b)$

289

290 Pixel intensities were then calculated for display as the mean pixel intensity plus the difference

291 between original and mean intensities multiplied by the Bubbles profile at each point. Expressed in

---

[5] To speed calculations, each bubble was rounded to zero beyond 4 (temporal) or 3 (spatial) σ from its centre.

292   terms of Weber contrasts, pixels were displayed at their original Weber contrasts multiplied by the

293   Bubbles profile.

294

295   *Data Analysis*

296   The saved Bubbles profiles from each trial formed the starting point in generating

297   classification sequences (temporal conditions) or images (spatial conditions), which reveal the regions

298   from which information supporting a correct response has been extracted. We calculated these

299   classification arrays as per our previous report (Jalali et al., 2018). First, for the spatial condition only,

300   Bubbles were re-centred so that the profile (saved in video coordinates) was translated to a new

301   coordinate frame, centred on the ball at the time of racket-ball contact. Next, for each participant, a

302   weighted sum of (re-centred) Bubbles profiles yielded the raw classification array. The sum weights

303   profiles from correct trials positively and profiles from incorrect trials negatively:

304

305   (2) $\text{RCA} = \sum_{c=1}^{C} \text{Bubbles}_c - \sum_{i=1}^{I} \text{Bubbles}_i$

306

307   However, in order to provide more intuitive values for visualising and combining data across

308   participants, raw classification arrays were normalised to a z-like format. This was achieved via a

309   permutation approach. For each of 2000 iterations, correct/incorrect labels were randomly re-

310   assigned (without replacement) to individual trials. The means and standard deviations at each point

311   (i.e. each frame and/or pixel) calculated over these 2000 permutations were used to z-score the

312   classification array. This yielded an array varying around zero with positive values indicating regions

313   of possible information accrual.

314   In order to draw statistical inferences across large arrays while controlling familywise type 1 error

315   appropriately, data from all participants who were able to perform the task at significantly above-

316   chance levels during bubbles blocks were combined and assessed via both cluster and t_{max} (also known

317   as pixel or single-threshold) corrected permutation tests. These methods, derived from the

318   neuroimaging literature (Blair & Karniski, 1993; Nichols & Holmes, 2002) are standard approaches for

319   solving the multiple comparison problem with large sets of potentially correlated and non-normal

320   data. Our particular implementation is more fully described in Jalali et al. (2018).

321   We also addressed a prediction particular to the data collected in these experiments, which, unlike

322   typical bubbles experiments, were derived from participants who rarely achieved 75% correct in a

323   two-choice discrimination. We reasoned that the variability in performance across participants might

324   be utilised in statistical inference. Bubbles are most efficient with 75% correct performance (Gosselin

325   & Schyns, 2001) and would be expected to become less efficient, and thus produce classification arrays

326   more dominated by random noise, with lower levels of discrimination performance. We would

327   therefore expect that for an information-carrying region, there should be a positive correlation across

328   participants between the magnitude of the classification array at that point and discrimination

329   performance. We tested this prediction in a manner exactly analogous to the cluster / t_{max} approach,

330   but using Pearson's r-statistic in place of Student's t-statistic in order to formulate cluster and r_{max}

331   corrected permutation correlations. Where t-based tests reveal significant regions of information, r-

332   based tests reveal regions more successfully exploited by better participants. All reported p values are

333   two-tailed, unless otherwise noted.

334

335

336   Results

337

338   *Pre-tests*

339

340   In pre-test trials, participants saw the videos without degradation, but terminating at the point of

341   racket-ball contact. Pre-tests were identical in spatial and temporal sessions, and our samples were

342   not fully overlapping between these experiments, so data were collated across all 43 unique

343   participants. Participants showed some ability to discriminate the direction of tennis ground strokes

344   in the absence of information about the ball's trajectory off the racket head (mean proportion

345   correct = 0.632, SD = 0.093) and they did so on average at a level significantly above chance:

346   Modelling these binomial data in the most appropriate way (i.e. with a general linear mixed model

347   (GLMM) with logistic link function, incorporating a random term for the intercept) revealed a fixed

348   intercept term of 0.55, which differed significantly from zero, i.e. the null hypothesis of scoring 50%

349   correct ($t_{[42]}$ = 9.25, p < 10^{-10}). For the subsets of U.K. participants reporting ITNs (N = 18), years of

350   playing experience (N = 31), or matches per year (N = 27), these variables were each entered as lone

351   predictors in separate GLMMs but failed to significantly correlate with discrimination performance

352   (all p > 0.29). However, matches per year did become a significant positive predictor of performance

353   (odds ratio = 1.011, 95% CI 1.004-1.18, $t_{[24]}$ = 3.28, p = 0.003) when an outlying participant (claiming

354   150 competitive matches per year) was excluded.

355

356   *Temporal Bubbles*

357

358   In temporal bubbles trials, videos ran to the point of racket-ball contact, but only those periods

359   revealed by randomly placed temporal bubbles were visible (Figure 1b). The Bubbles profiles from

360   each trial were combined with accuracy data to create classification sequences for each participant.

361   The mean z-scored classification sequence across participants is shown in Figure 2a, with positive

362   values denoting regions from which information may have been extracted. No frames were

363   significant after t_{max} correction, but a subset of frames (from 86 onwards, i.e. from around 0.083s

364   before racket-ball contact) contribute to a significant cluster (p = 0.013). Cluster-based testing

365   corrects for familywise error on the overall inference that the classification image differs reliably

366   from zero, but does not imply that every point within the cluster is significant (Groppe, Urbach, &

367   Kutas, 2011), particularly in combination with the smoothing effects of bubbles (see Jalali et al.,

368   2018, for further discussion). However, it is clear that some information was successfully extracted

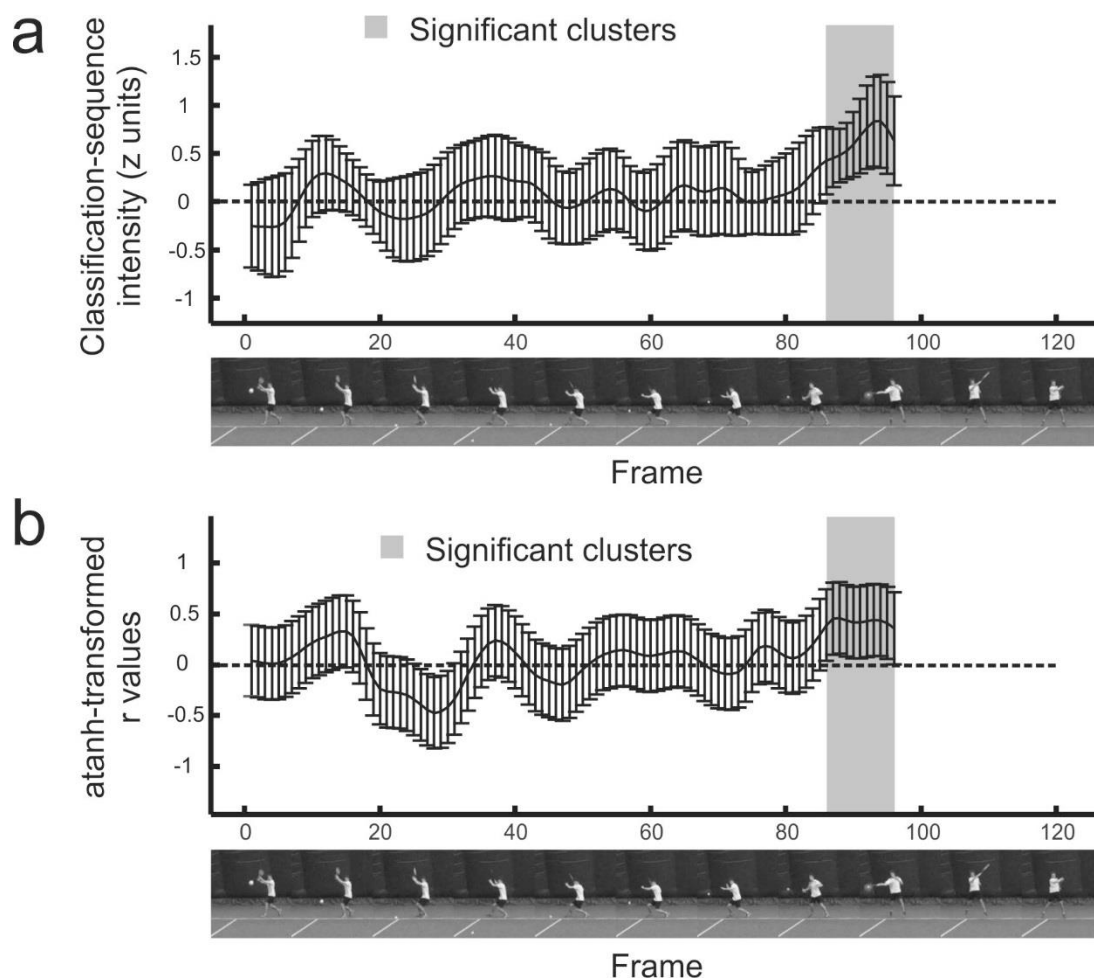369   from the moment just before racket-ball contact.

370

371

372

373   *Figure 2. Results from temporal bubbles experiment. Error bars denote 95% confidence intervals.*

374   *Shaded regions denote significant clusters. **A.** Mean z-scored classification sequence. **B.** Correlations*

375   *between classification sequences and classification performance across participants.*

376

377   Figure 2b shows additional results from a second statistical analysis. Here, instead of assessing the

378   mean classification sequence for just those participants who were still able to perform above chance

379   even during bubbles blocks, we assessed the correlation (for the entire sample of participants)

380   between individual classification sequences and discrimination success. The raw r values have been

381   transformed to permit the creation of a constant confidence interval which clarifies where possible

382   clusters emerge. This happens wherever the confidence interval does not include zero, i.e. for r

383   values that are significant without any familywise correction. However, these transformed r values

384   retain their basic meaning, in the sense that positive values represent frames where more successful

385   participants (in terms of their ability to do the task) showed more positive classification sequence

386   magnitudes. Our participants varied considerably in their ability to perform the task (between 50

387   and 75% correct). Because bubbles should be most effective (revealing pronounced peaks at points

388   where useful information is extracted) for participants who approach 75% performance, and much

389   less effective (reflecting mainly noise) for participants who are just guessing, these correlations are

390   informative. Interestingly, the correlation analysis reveals a cluster with the exact same temporal

391   extent as that found in the mean classification image (p = 0.029). Of course, these two analyses

392   cannot be considered as independent tests. However, we believe they can sometimes be

393   complementary to one another, as will become clearer in our spatial results.

394

395   *Spatial Bubbles*

396

397   In the spatial bubbles task, only particular areas of the video image were visible at random on each

398   trial (Figure 1b). Data from our spatial bubbles experiment are shown in Figures 3 and 4. Figure 3

399   shows the mean classification image, along with associated statistical inferences, for participants

400   able to perform the bubbles task above chance. The top part of the figure shows the classification

401   image itself, while in the bottom part of the figure statistical thresholding has been applied to reveal

402   a single large significant cluster (p = 0.0005). This cluster also incorporates two smaller regions that

403   additionally survive t_{max} correction. This contrast *should* illustrate spatial areas from which visual

404   information was accrued. However, the result is unconvincing. Although the cluster does include a

405   region over the position of the opposing player's body at the time of ball contact, this region only

406   appears within the cluster by virtue of a slim connection to a larger and more pronounced region.

407   The larger region might, at best, be considered to have overlaid parts of the opponent's body at the

408   beginning of the video, when they started their run to intercept the ball. However, this larger region

409   would be inconsistent with the results of the temporal experiment, which suggested that useful

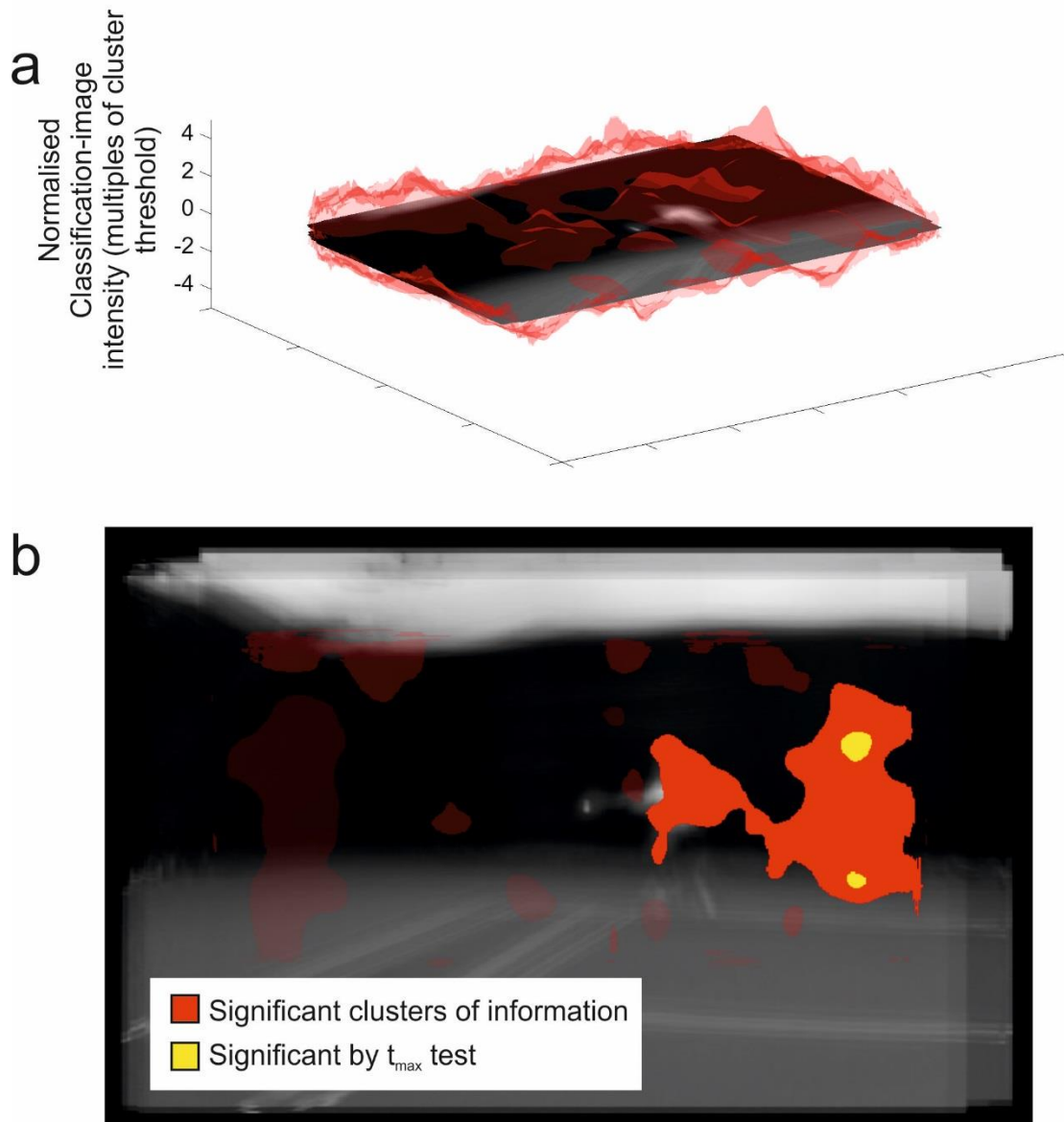410   information guiding the decision was not extracted until near the time of racket-ball contact.

411

412

413

414   *Figure 3. Classification image results from the spatial bubbles experiment. Results are overlaid on an*

415   *image of the mean of all presented videos for the frames capturing racket-ball contact, centred on*

416   *the point of racket-ball contact (hence constituent images do not perfectly align). However, the*

417   *results of the spatial analysis are not specific to any one time point. **A.** Transparent red peaks denote*

418   *mean classification-image intensity normalized to the cluster threshold value used in permutation*

*testing (i.e., values more extreme than ±1 formed potential clusters). **B.** Solid coloured regions were*

420 *significant in cluster/t_{max} permutation testing, suggesting information might have been extracted*

421 *from this part of the video. Transparent red regions denote non-significant clusters.*

422

423 Our complementary correlation-based analysis is shown in Figure 4, which in this case appears

424 somewhat instructive. The format is the same as for the mean classification image shown in Figure 3

425 with the raw correlations shown at the top, and statistical thresholding applied at the bottom.

426 However, in this case it is normalised correlation (r) values that are being illustrated and assessed for

427 cluster or r_{max} based significance. No significant clusters were observed, but there is one non-

428 significant cluster worthy of mention (one-tailed $p = 0.096$; all other clusters one-tailed $p > 0.36$)

429 which sits over the position of the opponent's body at the time of ball contact. This suggests a trend

430 for those participants better able to discriminate shot duration during spatial bubbles sessions to

431 have classification images that show stronger peaks in this region. In combination with the data from

432 our analysis of the mean classification image (Figure 3), this result suggests that much (or all) of the

433 cluster revealed there may represent a false positive, as it was no more likely to emerge in

434 participants for whom bubbles had a good chance of actually working than it was for participants for

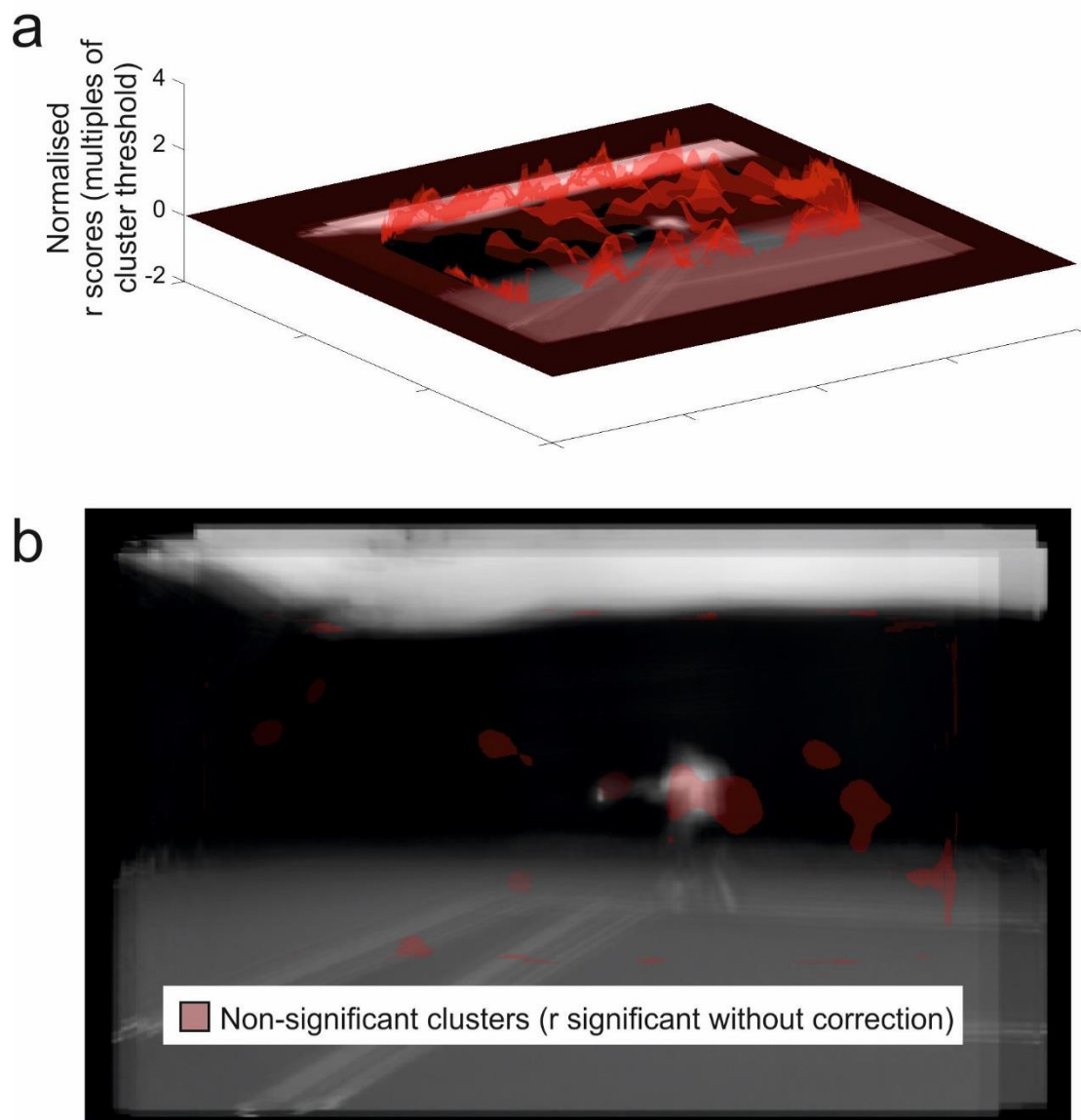435 whom bubbles could reveal only noise.

436

439   *Figure 4. Correlation results from the spatial bubbles experiment. Results are overlaid on an image of*

440   *the mean of all presented videos for the frames capturing racket-ball contact, centred on the point of*

441   *racket-ball contact (hence constituent images do not perfectly align). However, the results of the*

442   *spatial analysis are not specific to any one time point. **A.** Transparent red peaks denote correlations*

443   *between classification-image intensities and discrimination performance, normalized to the cluster*

444   *threshold value used in permutation testing (i.e., values more extreme than ±1 formed potential*

445   *clusters). **B.** Transparent red regions denote points where the cluster threshold (representing a*

446   *significant correlation in the absence of familywise correction) was exceeded, but resulted in only*

447   *non-significant clusters.*

448

449

450   Discussion

451

452   In our experiments, competent but non-elite tennis players first attempted to discriminate the

453   direction of upcoming forehand ground strokes from videos of a tennis opponent, based only on

454   information available prior to the point of racket-ball contact. On average, they were able to do so,

455   in line with previous reports (Rowe et al., 2009; Shim et al., 2006). Unlike previous reports, we went

456   on to remove additional information using a stochastic approach to video manipulation, by

457   introducing bubbles rather than by applying systematic masking or image manipulation in a

458   particular set of planned conditions. Our main finding was that participants used information from

459   the period immediately before racket-ball contact, specifically within a window reaching back

460   approximately 0.083s, to perform the direction-discrimination task. Because this information source

461   precedes racket-ball contact, it cannot include the trajectory of the ball off the racket head.

462

463   Our temporal results seem fairly consistent with previous reports. For example, Rowe et al. (2009)

464   had tennis experts (broadly comparable to ours in competence, with ITNs of 2-4) judge forehand and

465   backhand ground strokes (going to either the right or left) from videos which could be occluded at

466   between -0.12 and +0.04s relative to racket-ball contact. They found that experts could predict

467   undisguised shot direction at approaching 75% correct when the video stopped at racket-ball

468   contact, falling to around 60% when models were attempting disguise (c.f. 63% mean performance

469   during pre-test here; note that our models were instructed only to "hit winners", but were

470   presented to participants with smaller spatial extents than those of Rowe et al., to be more

471   consistent with typical match viewing). Rowe et al. (2009) also found that experts could still

472   discriminate the direction of ground strokes significantly above chance when the video stopped at

473   either 0.12 or 0.08s before racket-ball contact, but performed better with occlusion at 0 s. These

474   results imply some accrual from roughly the temporal window we obtained here (in order to show

475   improvement) but also some additional accrual from earlier frames (in order to still be performing

476   above chance). Indeed, a similar study utilising stick-man graphics in place of videos even found

477   above-chance performance with occlusion at -0.24s, although performance actually then trended

478   worse with occlusion at -0.16, -0.08 or 0 ms (Cañal-Bruland et al., 2011).

479

480   Our method was in principal well-suited to find the locus of any such early periods of information

481   accrual, because bubbles could appear at any point back to 0.8s before ball contact. Several

482   possibilities should be considered regarding why we failed to find any such loci, reflecting the

483   various limitations of our approach. The first relates to statistical power. Bubbles is a trial-hungry

484   technique, with typical psychophysical applications using fairly simple stimuli and also very large

485   numbers of trials (Gosselin & Schyns, 2001). This limitation is exacerbated when performance is only

486   a little above chance even in the absence of any bubbles, as was the case here. Indeed, pre-test

487   performance suggests that our stimuli were very challenging to discriminate for most participants, so

488   perhaps our stimuli simply didn't contain usable information as early as the videos used in other

489   studies, or perhaps it was sufficiently subtle that bubbles could not reveal it.

490

491   A second possibility is that information must be integrated over a protracted period, or combined

492   from both of two temporally distinct epochs, during early shot preparation, in order to be usable.

493   Such temporally complex cues would still be present in standard temporal occlusion approaches

494   where videos run continuously until a single occlusion point. However, while classification arrays can

495   in principle reveal these kinds of features with enough trials, the bubbles approach is most efficient

496   when the temporal extent of a cue is approximately matched to the temporal extent of an individual

497   bubble (see for example the simulations presented by Jalali et al., 2018). Note that various

498   suggestions have been made within the bubbles literature to address this issue (Blais, Roy, Fiset,

499   Arguin, & Gosselin, 2012; Chauvin, Worsley, Schyns, Arguin, & Gosselin, 2005) and might be

500   considered in future research on sports.

501

502   Regardless of whether there were any earlier information sources that went undetected in our

503   experiment, we can at least assert with confidence that useful information was extracted from our

504   videos immediately prior to racket-ball contact (although, as noted in the methods, we cannot assert

505   that every individual frame highlighted by our cluster test was important). This ability may be learnt

506   through regular match play, generalizing immediately to the particular opponents encountered here.

507   It is also possible that the ability to anticipate was actually learnt entirely during the experiment,

508   given that each stimulus was encountered multiple times. The correlation between pre-test

509   performance and matches per year suggests that more regular players are at least quicker to learn

510   their new opponent's kinematic "gives" (or perhaps they are quicker to learn other spurious cues in

511   our videos, although we took steps to minimise these). However, this result must be considered

512   tentative, as it was both exploratory, and relied on the exclusion of an outlying participant.

513

514   Our results from spatial bubbles sessions were not compelling and can at best be considered

515   suggestive that our participants may have extracted some information from the torso region of their

516   opponents. This would presumably be during the temporal window revealed by the temporal

517   bubbles sessions, but the experiments are independent so this need not necessarily be the case. The

518   need to apply statistical control across a much larger 2D space, relative to our temporal

519   experiments, may have left our spatial experiment underpowered. We have previously shown that

520   spatial bubbles can be effective with a setup and sample size similar to this one (Jalali et al., 2018),

521   but in that case performance was nearer to 75% correct for all participants. Previous spatial

522   occlusion work with video stimuli has been more conclusive. Shim et al. (2006) used a four-choice

523   task (ground strokes or lobs to forehand or backhand), and found that removing the racket/arm

524 impaired discrimination of videos when viewing was stopped at racket-ball contact. This suggests

525 that these distal regions, which did not emerge in our analysis despite the fact that we centred our

526 co-ordinate frame (and thus maximised power) at the racket head, are in fact important. However,

527 they also observed performance which was still well above chance after these regions had been

528 occluded. Therefore, participants must also have extracted information from other parts of the

529 video, presumably proximal body segments, although the pattern of data was inconclusive in this

530 regard. Indeed, some results from more recent studies using computer graphics in place of real

531 videos suggest primacy for the proximal body: Fukuhara, Ida, Ogata, Ishii, and Higuchi (2017) found

532 that an opponent rendered with a realistic body (but only point-light information for their arm and

533 racket) was better predicted than one with a realistic arm and racket but only a point-light body.

534

535 In conclusion, we have replicated classic research showing that skilled tennis players can anticipate

536 upcoming shots based on their opponent's body kinematics. We also used a novel stochastic

537 masking approach in order to highlight the role of the period immediately preceding racket-ball

538 contact in supporting this ability. Although our bubbles approach could in principal have revealed a

539 wider range of information sources relative to traditional occlusion studies (where a limited set of

540 masking conditions must be selected in advance) in practice we have revealed, if anything, fewer

541 such loci. The approach may still have merit, but primarily as a means of methodological

542 triangulation, making an inference based on multiple complementary approaches, such as the

543 temporal result observed here, more secure.

544

545

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549

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