Demand-based dynamic distribution of attention and monitoring of velocities during multiple-object tracking

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20The ability to track multiple moving objects with attention has been the focus of much research. However, the literature is relatively inconclusive regarding two key aspects of this ability, (1) whether the distribution of attention among the tracked 2122targets is fixed during a period of tracking or is dynamically adjusted, and (2) whether motion information (direction and/or speed) is used to anticipate target locations even when velocities constantly change due to inter-object collisions. These 23 questions were addressed by analyzing target-localization errors. Targets in crowded situations (i.e., those in danger of 2425being lost) were localized more precisely than were uncrowded targets. Furthermore, the response vector (pointing from the 26target location to the reported location) was tuned to the direction of target motion, and observers with stronger direction tuning localized targets more precisely. Overall, our results provide evidence that multiple-object tracking mechanisms 2728dynamically adjust the spatial distribution of attention in a demand-based manner (allocating more resources to targets in crowded situations) and utilize motion information (especially direction information) to anticipate target locations. 29

30 Keywords: attention, direction, localization, motion, multiple-object tracking, representational momentum, speed

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Introduction

37 The ability to track multiple moving objects (multipleobject tracking) is crucial in daily life. For example, while 38driving a car, one may need to simultaneously keep track 39of a running dog and child who might suddenly dash into 40 traffic, a nearby car that might unexpectedly swerve, and 41 42oncoming traffic that might suddenly turn. Several hypotheses have been proposed to explain the mechanisms 43underlying this ability. For example, the visual system 44 might use multiple "attention indices¹" that can be 4546 assigned to a limited number of to-be-tracked objects 47(for reviews, see Cavanagh & Alvarez, 2005; Pylyshyn, 2001; Scholl, 2001). Although the prevalent explanations 48 of multiple-object tracking have postulated the involve-49ment of up to five discrete attention indices, a recent study 50has suggested that there may be a trade-off between the 5152number of attention indices deployed and the spatial 53resolution of each attention index (Alvarez & Franconeri, 2007). For example, the visual system might deploy many 54

low-resolution indices or a few high-resolution indices, 55 being constrained by resource limits rather than by a strict 56number limit. Alternatively, the visual system might 57rapidly shift a single focus of attention among tracked 58objects to continually update their locations (e.g., Oksama 59 & Hyönä, 2008). The visual system might also utilize 60 global-pattern processing to track multiple objects as a 61coherent group, such as tracking target objects as vertices 62 of a deforming polygon (e.g., Yantis, 1992). It is possible 63 that multiple-object tracking is mediated by some combi-64nation of these mechanisms. 65

We used a novel experimental paradigm to address two 66 fundamental questions that were not decisively answered 67 in previous research regarding how the targets are tracked 68 during multiple-object tracking. Answers to these ques-69 tions will provide important constraints on current models 70of multiple-object tracking. The first question is whether 71multiple-object tracking mechanisms dynamically adapt to 72changing demands. Specifically, we investigated whether 73attention resources (e.g., spatial resolution of attention 74 indices or frequency of attentional fixation) were shifted 75

on-line from targets in uncrowded situations (where low
spatial resolution or infrequent attentional fixations would
be sufficient to track targets) to targets in crowded
situations (where high spatial resolution or frequent
attentional fixations would be necessary to avoid losing a
target).

The second question is whether multiple-object tracking 82 mechanisms monitor the velocities (as well as the loca-83 tions) of tracked objects. It is clear that motion information 84 85is utilized (and pursuit eye-movements are engaged) when only one object is tracked and the trajectory of its motion is 86 relatively constant (e.g., when playing tennis). In fact, 87 many studies have provided evidence suggesting that the 88 89 visual system utilizes motion information to anticipate 90 target locations when one or two targets are tracked and the target velocities are constant, nearly constant, or 91 predictably varied (e.g., Fencsik, Klieger, & Horowitz, 922007; Müsseler, Stork, & Kerzel, 2002; Verfaillie & 93 d'Ydewalle, 1991; for a review, see Thornton & Hubbard, 94 2002). The question we addressed was whether multiple-95object tracking mechanisms could utilize motion (direction 96 and/or speed) information even when multiple targets were 97 simultaneously tracked, the trajectories of the tracked 98targets intermingled with those of multiple moving dis-99 tractors, and when the velocities of the targets frequently 100 changed due to inter-object collisions. 101

These questions are difficult to investigate using the 102conventional multiple-object tracking paradigm where 103performance is measured in terms of the number of 104 objects that are successfully tracked. Instead, we meas-105ured the precision of tracking of individual objects. Our 106 observers tracked three initially flashed target circles 107moving among seven distractor circles as in a typical 108multiple-object tracking task. The three targets, however, 109were labeled with distinct colors, red, green, and yellow 110 111 (see Figure 1). Because the distractors shared these colors, the colors did not distinguish the targets from distractors, 112 and thus targets had to be attentionally tracked. At the end 113 of a tracking period (6 sec in Experiment 1 and variable in 114 Experiment 2) all circles disappeared, simultaneously with 115the auditory presentation of a color name. Observers were 116117instructed to precisely indicate with a mouse-click the last-known location of the tracked target of the named 118 color. Because observers did not know in advance which 119of the three targets would be cued to be localized, they 120had to track all three targets. We were thus able to 121 122measure the localization error (the distance from the final 123location of the target to the location of the mouse-click) for a randomly selected target while observers tracked all 124three targets (see the Methods section). This procedure 125allowed us to evaluate the dynamic distribution of 126 127attention resources and the use of motion information 128during multiple-object tracking.

Regarding the distribution of attention resources, if more resources were dynamically allocated to targets in crowded situations, target-localization error should be inversely related to the degree of crowding (measured as



Figure 1. The rectangular tracking region contained ten colored circles that moved independently, bouncing off of one another and the border walls. The three to-be-tracked circles (labeled "T" here) were assigned different colors. The target labels and the arrows were not present in the actual display.

the distance from the target to its nearest distractor) at the 133time of the display offset. We thus predicted that if the 134cued target happened to be relatively far from its nearest 135distractor, multiple-object tracking mechanisms would 136have allocated a relatively small amount of attention 137resources (e.g., a low-resolution attention index or non-138 prioritized allocation of attention), so that it should be 139localized with a relatively large error. In contrast, if the 140cued target happened to be close to a distractor, multiple-141 object tracking mechanisms would have allocated a 142relatively large amount of attention resources (e.g., a 143 high-resolution attention index or prioritized allocation of 144attention), so that it should be localized with a relatively 145small error. 146

Regarding the use of motion information, in order to 147 intercept a moving target, one must aim ahead of the 148current location of the target along its motion trajectory. 149We thus hypothesized that if the targets' motion directions 150were monitored during multiple-object tracking, observers 151would systematically mouse-click ahead of the target's 152actual location at the time of its disappearance along its 153motion trajectory; that is, the response vector (pointing 154from the location of the target disappearance to the 155location of the mouse-click) should be directionally tuned 156to the target's motion. In addition, if the targets' speeds 157were also monitored during multiple-object tracking, the 158amplitudes of forward-location clicking should be pos-159itively correlated with the target's speed. Finally, if 160motion direction and/or speed were not merely monitored 161 but were actually utilized by multiple-object tracking 162mechanisms, stronger direction tuning (indicative of more 163 reliable encoding of motion direction) and/or stronger 164

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165 correlation between the target's speed and the amplitude
166 of forward-location clicking (indicative of more reliable
167 encoding of speed) should be associated with more precise
168 target localization.

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Method for Experiment 1

172 **Observers**

Twenty undergraduate students at Northwestern University gave informed consent to participate for partial course credit. They all had normal or corrected-to-normal visual acuity and normal color vision and were tested individually in a dimly lit room.

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179 Stimuli

The tracking display contained ten moving circles 180181 (diameter = 0.69°), including the three targets and seven distractors. The moving circles were confined within an 182 11.8° (horizontal) by 8.9° (vertical) rectangular region. 183The circles were colored red (CIE = [.623, .347], 19.7 cd/ 184 m^2), green (CIE = [.295, .588], 20.6 cd/m²), and yellow 185 $(CIE = [.402, .443], 66.3 \text{ cd/m}^2)$ and were presented 186against a black (0.14 cd/m^2) background. Each of the three 187 targets had a different color, while the distractors were 188 assigned one of the three colors with the constraint that at 189least two distractors had the same color as each target. All 190circles initially moved at the same speed (2.43°/sec), but 191192 their initial locations and motion directions were randomly determined on each trial. Vertical and horizontal 193directions were not used as initial directions because 194motions in these cardinal directions are salient. The circles 195bounced against one another and against the walls of the 196197rectangular tracking region according to the principle of 198 perfect elastic collision (i.e., conserving both momentum and kinetic energy). Both motion directions and speeds 199frequently changed due to collisions. At the end of the 200tracking period, the speeds of the circles had a unimodal 201distribution with a range of $0.12-6.15^{\circ}/\text{sec.}^2$ 202

The stimuli were displayed on a color CRT monitor (1024 \times 768) at 75 Hz, and the experiment was controlled by a Macintosh PowerPC 8600 using Vision Shell software (micro ML, Inc.). A chin rest was used to stabilize the viewing distance at 68 cm.

209 **Procedure**

210 Observers initiated each trial with a button press. The 211 three to-be-tracked targets initially flashed for 1.8 sec. 212 Observers maintained eye fixation at a central cross (0.51°) 213 by 0.51° , 31.4 cd/m^2) while attentionally tracking the 214 three target circles for the remaining 4.2 sec. To ensure central eye fixation, a small digit $(0.17^{\circ} \text{ by } 0.42^{\circ})$ 215randomly selected between 0 and 9 (inclusive) was flashed 216for 134 ms replacing the fixation cross at a randomly 217chosen time on each trial (between 1.6 and 4.6 sec from 218the trial beginning), and the observer verbally reported the 219digit when it appeared. The few trials (1.4%) in which the 220digit was not correctly reported were excluded from the 221analyses. Although central eye fixation was not required in 222most prior studies of multiple-object tracking, we 223enforced it here so that we could measure distributions 224of attention during tracking without potential confounds 225from eye movements. 226

Following the 6-sec tracking period, the display turned 227blank (except for the central fixation cross), simultane-228ously with an auditory presentation of a color name. 229Observers were instructed to mouse-click the location of 230the target of the indicated color as precisely as possible 231(the initial location of the mouse cursor was at the fixation 232cross). Note that mouse-click responses have been shown 233to be sensitive for revealing encoding of motion informa-234tion in a localization task, especially for smoothly moving 235stimuli (e.g., Kerzel, 2003a). When observers lost track of 236the target, they were instructed to mouse-click a location 237outside of the rectangular tracking region. The overall 238probability of losing a target was 9.8% (SEM = 1.7%). 239Note that this probability of target loss would have been 240much higher if observers adopted the strategy of tracking 241only one target (with an expected probability of loss = 24267%) or two targets (with an expected probability of loss = 24333%). It might be the case that observers failed to indicate 244that they lost the target when they actually did and instead 245mouse-clicked an arbitrary location. However, this possi-246bility is unlikely as the target localization was overall 247quite precise for the trials on which observers mouse-248clicked within the tracking region; the magnitude of 249target-localization errors had a unimodal distribution with 250the mode less than 0.5° and most errors less than 1.0° 251(Figure 2). These results indicate that observers success-252fully tracked all three targets on most trials. Each observer 253



Figure 2. The distributions of target-localization errors (for Experiments 1 and 2) for the trials in which observers did not indicate that they lost the target. Note that most errors were small (less than 1.0°).

performed four blocks of 20 trials; 5 practice trials weregiven prior to these experimental trials.

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257 Data analyses

Target-localization error was measured as the vector pointing from the location of the center of the target when it disappeared to the location of the mouse-click. Unusually large errors (beyond the 99th percentile in amplitude) were excluded from the analyses because those most likely represented targets that were lost without the observers' knowledge.

The degree of crowding around each target was 265measured as the distance from the target to its nearest 266distractor, D_{nearest}. The crowding region was truncated 267near the borders of the tracking display because distractors 268could not appear outside of the tracking region. Due to 269270this border effect, targets near the edges of the display would of necessity have been relatively uncrowded, and 271those uncrowded targets may have produced large local-272ization errors due to their high eccentricity. To resolve this 273274confound, when we analyzed the effect of crowding on the 275precision of tracking, we recursively removed high-276eccentricity targets from the analyses until the average target eccentricity was equivalent across the targets associated with different ranges of D_{nearest} .

Results from Experiment 1

Demand-based dynamic distribution of attention resources

We first discuss evidence indicating that multiple-object 285tracking mechanisms dynamically allocate attention 286resources to targets in crowded situations where the chance 287of losing the targets increases. We used the distance from 288each target to its nearest distractor (at the time of target 289disappearance), D_{nearest} , as the measure of crowding, with 290smaller D_{nearest} values indicating greater crowding. To 291determine how target-localization error depended on 292 D_{nearest} , we plotted average target-localization error as a 293cumulative function of D_{nearest} (Figure 3A). Each point 294shows the average localization error for the targets 295associated with D_{nearest} equal to or less than the indicated 296value. An advantage of plotting average localization error 297 as a *cumulative* function of D_{nearest} is that a continuous 298function could be obtained without dividing D_{nearest} values 299into artificial bins while preserving the general pattern of 300 dependence of target localization on D_{nearest} (though with 301 progressively greater data smoothing for larger values 302 of D_{nearest}). The target-localization error clearly reduced 303 for smaller values of D_{nearest} , with a significant linear 304trend, F(1,19) = 5.762, p < 0.027, $\eta_p = 0.233$ (all of our 305



Figure 3. Target-localization error (for Experiments 1 and 2) plotted as a function of the distance between the target and its nearest distractor, D_{nearest} . (A) A cumulative plot where each point shows the average localization error for all D_{nearest} up to the indicated value. (B) A non-cumulative plot where different values of D_{nearest} are divided into six intervals, and the average error for each interval of D_{nearest} is plotted against the average D_{nearest} for that interval. The error bars indicate ± 1 SEM (with observers as the random effect; the variance due to overall individual differences in localization errors was removed before computing SEM).

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Figure 4. The spatial distribution of mouse-click locations (+ symbols) for Experiment 1 (A) and Experiment 2 (B). The mouse-click locations are normalized with respect to the axis and scale defined by the target (indicated with a circle), its nearest distractor (indicated with a triangle), and the distance between them. The accompanying histograms show the distributions of the normalized X and Y coordinates of mouse-clicks.

linear-contrast analyses are based on a conservative 306 method using a contrast-specific error term). This indicates 307that the targets were more precisely localized when they 308 were more crowded by the distractors. The same effect is 309 also apparent in the non-cumulative plot (Figure 3B) in 310 which the D_{nearest} values were divided into six nearly even 311intervals with the constraint that at least five of the six 312 intervals included ten or more data points from each 313 observer. The linear trend was again significant, F(1, 19) =3147.807, p < 0.012, $\eta_p = 0.291$. 315

These results are consistent with the idea that greater 316 attention resources are dynamically allocated to crowded 317 targets. Furthermore, this dynamic demand-based alloca-318 tion of attention did not engage until a distractor closely 319 approached a tracked target as localization error did not 320 begin to improve until D_{nearest} became less than $\sim 3^{\circ}$ 321 (Figure 3). 322

One might argue that the improved target-localization 323 accuracy with close distractors may partially reflect a 324tendency for observers to group targets with their 325 proximate distractors. Such target-distractor grouping 326 would have been uncommon during the course of tracking 327 because such a strategy would increase the chance of 328 confusing targets and distractors. Nevertheless, it is still 329 possible that at the time of localization the mouse-click 330 response might have been attracted to the center of gravity 331 between the target and its proximate distractor. We 332 evaluated this possibility by plotting all mouse-click 333 locations relative to the axis and scale defined by the 334 target and its nearest distractor. If observers tended to 335 mouse-click the center of gravity between the target and 336 its nearest distractor, the mouse-clicks should be clustered 337 around the mid point between the target and its nearest 338 distractor. In contrast, if observers aimed at the target 339 irrespective of the proximate distractor, the mouse-clicks 340 should be clustered around the target. The data clearly 341support the latter (Figure 4A). 342

Taken together, these results demonstrate that the 343 precision of multiple-object tracking increases when a 344 distractor moves close to a tracked target (within $\sim 3^{\circ}$ 345 radius), suggesting that multiple-object tracking mecha-346 nisms dynamically and adaptively distribute attention 347 resources to targets in more crowded situations where 348 more precise tracking is necessary. 349

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The use of motion information

To determine whether multiple-object tracking mechanisms monitor motion direction information, we examined 355 the direction tuning of the response vector (which points 356 from the location of the target disappearance to the 357 location of the mouse-click). For each trial, we computed 358 the direction of the response vector relative to the 359 direction of the target motion (at the time of its 360



Figure 5. The direction tuning of multiple-object tracking (for Experiments 1 and 2). The distribution of the directions of response vectors (pointing from the target locations to the mouse-click locations) is plotted relative to the direction of target motion (shown as 0°).

disappearance) in terms of angular deviation. We col-361362 lapsed over the clockwise and counterclockwise deviations while averaging across all directions of target 363 motion. The response vector is clearly tuned to the 364 direction of target motion (Figure 5; the mirror reflection 365 of the data has been added as negative errors to aid 366 visualization of the direction tuning). The flanking troughs 367 368 around $\pm 90^{\circ}$ indicate that the directions orthogonal to target motions are inhibited by multiple-object tracking 369 mechanisms. 370

To statistically verify this tuning, we computed a direction-tuning index for each observer, defined as,

Direction-tuning index

$$=\frac{[\# \text{ of absolute angular deviations between } 90^{\circ} \text{ and } 180^{\circ}]}{[\# \text{ of absolute angular deviations between } 0^{\circ} \text{ and } 90^{\circ}].}$$
(1)

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A value of zero indicates consistent direction tuning (i.e., all response vectors project positively to targetmotion vectors), whereas a value of 1 would indicate no direction tuning (i.e., response vectors project positively and negatively to target-motion vectors with equal probability). The mean direction-tuning index for the 380 20 observers was significantly below 1 (see Figure 6 for 381the distribution), verifying that observers tended to click 382 ahead along the target's anticipated motion trajectory; 383 t(19) = 3.424, p < 0.003, d = 0.766 (the ratio-based 384direction-tuning indices were log-transformed prior to 385 *t*-test). This provides evidence that the directions of targets' 386 motions were monitored during multiple-object tracking. 387

Successful monitoring of motion direction information, 388 however, does not necessarily mean that it contributes to 389 tracking performance. If multiple-object tracking mecha-390 nisms utilize motion-direction information to increase the 391 precision of tracking, smaller direction-tuning indices 392 (indicative of stronger direction tuning) should be asso-393 ciated with smaller localization errors. This was indeed 394the case (Figure 6), r = 0.521, t(18) = 2.591, p < 0.02. 395

We next examined whether the targets' speeds (in 396 addition to directions) were monitored during multiple-397 object tracking. If speeds were monitored, anticipatory 398 forward shifting of mouse-clicks should be greater when 399 targets were moving faster. To evaluate this relationship, we 400quantified the amplitude of forward shifting of the mouse-401click as the scalar product between the response vector and 402 the unit vector along the target's motion direction; a larger 403 positive value would indicate a greater forward shift, a zero 404 would indicate no shift, and a larger negative value would 405indicate a greater backward shift. We then computed the 406 linear correlation between this measure of forward shift and 407 the target speed for each observer (outliers outside the 95% 408



Figure 6. A scatter plot showing the correlation between the direction-tuning index (smaller values indicating stronger direction tuning) and average target-localization error, for Experiments 1 and 2. Each point represents one observer. The solid and dashed lines indicate the linear fits for Experiments 1 and 2, respectively.

409 confidence ellipse were eliminated before computing each 410 correlation). A larger positive value of the correlation 411 coefficient, r_{speed} , would indicate a more consistent linear 412 relationship between the target's speed and the amplitude 413 of the forward shift of the mouse-click, implying more 414 reliable monitoring of the targets' speeds. Thus, r_{speed} 415 provided an index of speed monitoring.

Although r_{speed} was small (M = 0.115 with SEM =416 0.025), it was significantly larger than zero, t(19) = 4.600, 417p < 0.0002, d = 1.029, suggesting that the targets' speeds 418 (in addition to directions) were monitored during multi-419ple-object tracking. The speed monitoring index, r_{speed}, 420 was uncorrelated with the direction-tuning index $(r^2 =$ 421422 0.002), suggesting that the targets' speeds and directions 423are monitored as separate parameters during tracking. Although the direction-tuning index was strongly corre-424lated with the precision of target localization (Figure 6), 425the speed-monitoring index, r_{speed} , was not ($r^2 = 0.000$ for 426 $r_{\rm speed}$ -vs.-localization-error correlation), suggesting that 427 speed information (though monitored) does not substan-428tially contribute to multiple-object tracking. This lack of 429correlation cannot be due to the possibility that the speed-430related forward mouse-clicking substantially contributed 431as localization errors and canceled out the beneficial effect 432of speed monitoring. The r_{speed} -vs.-localization-error 433 correlation was still insignificant ($r^2 = 0.020$) even when 434we removed the systematic speed-related forward shifting 435of mouse-clicks (explained by the regression lines) from 436each response vector prior to computing the correlation. 437 We also note that the amplitude of the speed-related 438439forward shifting was overall very small (i.e., the mean regression slope for the speed-vs.-forward-shifting corre-440lation was 0.074° shift per degrees/sec, indicating that 441 forward shifting increased by only 0.074° per 1°/sec 442 increase in target speed); thus forward shifting minimally 443 444 contributed to target-localization errors. A null result on the usefulness of speed information, however, must be 445interpreted with caution. For example, it is possible that, 446 although r_{speed} was an adequate measure to demonstrate 447 that speed information was monitored during multiple-448 449object tracking, it might not have been a sensitive enough 450measure of the "goodness of speed monitoring" to reveal the contributions of speed information to the precision of 451target localization. Nevertheless, we have provided clear 452evidence that (1) the targets' velocities (i.e., both 453454directions and speeds) are monitored during multipleobject tracking, and that (2) at least the motion direction 455information substantially contributes to the precision of 456457multiple-object tracking.

There were several methodological concerns about the 458459design of Experiment 1. First, the trial duration was always 460 6 sec, so that observers could have potentially adopted the strategy of only loosely tracking the targets most of the 461 time and focusing attention on the targets only at the end of 462each trial when they had to report the location of one of the 463targets. If this were the case, our results would not imply 464465that attention resources are dynamically shifted to crowded targets in the course of continuous tracking. To address 466 this concern, in Experiment 2 we randomly varied the trial 467 duration so that observers did not know when they had to 468localize a target. A second concern regarded the method 469we used to ensure central eye fixation. Although the 470unpredictably flashed probe digits were identified with 471high accuracy (only 1.4% errors), we cannot definitively 472rule out eye movements as a factor. Enforcing central eye 473fixation is crucial in our paradigm so that more precise 474target localization in crowded situations can be attributable 475to demand-based allocations of attention resources rather 476 than to eye movements. A third concern was that our 477results could be specific to the situation where observers 478 479 perform a concurrent secondary task. In Experiment 2, we thus eliminated the secondary fixation task and monitored 480eye movements using an eye tracker to ensure central 481 fixation. Finally, because our paradigm is novel, it was 482important to replicate our original results. 483

Method for Experiment 2

Observers

Thirty-six undergraduate students at Northwestern Uni-488 versity gave informed consent to participate for partial 489course credit. They all had normal or corrected-to-normal 490visual acuity and normal color vision and were tested 491individually in a dimly lit room. Thirteen of them did not 492complete the experiment because they were unable to 493maintain central eye fixation on most trials. This may 494indicate that it is difficult to maintain central eye fixation 495during multiple-object tracking without a concurrent 496 fixation task, or that many observers in Experiment 1 497actually made numerous eye movements. Nevertheless, as 498shown below, we replicated all of the primary results from 499Experiment 1 with strict enforcement of central eye 500 fixation, suggesting that our primary results are applicable 501whether or not central eye fixation is strictly maintained. 502Of the 23 observers who completed the experiment, the 503data from one observer was removed from the analyses 504because of a relatively large number of eye movements 505(greater than 2.5 SD from the group mean). The remaining 50622 observers maintained central eye fixation within 1° 507from the center on 93.8% of the trials (SD = 4.3%), and 508the few trials in which their fixation deviated more than 1° 509 were removed from the analyses. Eye movements were 510monitored using an EyeLink 1000 eye tracker (SR 511research, with 0.15° resolution). 512

Stimuli

These were the same as in Experiment 1 except that no 515 digits were flashed at the center, and the trial duration was 516

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randomly varied between 4 sec and 8 sec (matched to
Experiment 1 in terms of the mean duration of 6 sec); 80
evenly spaced durations were generated within this
range, and those durations were randomly assigned to
the 80 trials for each observer.

523 **Procedure and data analyses**

524 These were the same as in Experiment 1, except that 525 observers did not perform the secondary task of digit 526 identification.

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Results from Experiment 2

The proportion of target loss 3.0% (*SEM* = 0.6%) in this experiment was significantly reduced compared to 9.8% (*SEM* = 1.7%) in Experiment 1, t(40) = 3.891, p < 0.00037, d = 1.20. This improvement is not surprising because observers in this experiment did not perform the concurrent secondary task of digit identification.

As shown in Figures 2, 3, 4, 5, and 6, we replicated all 537of the primary results from Experiment 1, while we 538randomly varied trial duration, eliminated the secondary 539540task, and enforced central eye fixation. The overall distribution of target-localization error was nearly identi-541cal in the two experiments (Figure 2). Importantly, the 542target-localization error clearly reduced as the distance to 543544the nearest distractor, D_{nearest} , diminished, with significant linear trends obtained for both the cumulative analysis 545546(Figure 3A), F(1,21) = 13.687, p < 0.0013, $\eta_p = 0.395$, and the non-cumulative (binned) analysis (Figure 3B), 547 $F(1,21) = 13.392, p < 0.0015, \eta_p = 0.389$. Note that the 548dependence of target-localization error on D_{nearest} was 549similar (Figure 3) and statistically indistinguishable 550551between the two experiments, with all relevant F's (involving experiment as a factor) being less than 1. The 552normalized spatial distribution of mouse-clicks was also 553similar for the two experiments (Figure 4). 554

555With regard to the use of motion information, observers in Experiment 2 also tended to click slightly ahead in the 556direction of the target's motion, yielding a direction tuning 557 similar to that obtained in Experiment 1 (Figure 5). The 558only difference was that the overall mean direction-tuning 559index was not as robustly less than 1 in this experiment, 560561t(21) = 2.020, p < 0.056, d = 0.463. This occurred because a few observers yielded direction-tuning indices that were 562relatively substantially deviated from 1 in the positive 563direction (indicative of backward clicking), but note that 564those observers were also poor at localizing targets (see 565open circles in Figure 6). Importantly, greater direction 566567 tuning (i.e., a smaller value of the direction-tuning index indicating a greater tendency for forward clicking) was 568strongly associated with more precise target localization 569

(i.e., a smaller value of target-localization error), r =570 0.630, t(20) = 3.632, p < 0.0017, replicating Experiment 1 571 with a larger effect size. Thus, anticipating the targets' 572locations based on their motions increases the precision of 573multiple-object tracking, whereas the precision suffers 574when tracking mechanisms fail to anticipate or fall 575behind. This confirms that motion direction information 576is utilized by multiple-object tracking mechanisms to 577 increase the precision of target tracking. 578

The correlation between the amount of forward shifting 579 of mouse-clicks and target speed, r_{speed} , was small (M =5800.052 with SEM = 0.024) but significant, t(22) = 2.167, 581p < 0.042, d = 0.462. This replicates Experiment 1 and 582confirms that target speeds (as well as directions) were 583encoded during multiple-object tracking. Furthermore, 584observers who tended to encode targets' speeds with 585greater reliability (i.e., those with larger positive values of 586 $r_{\rm speed}$) tended to localize targets more precisely, as 587 reflected in the significant negative correlation between 588 r_{speed} and target-localization error, r = -0.41, t(20) =5892.115, p < 0.048. Note that this correlation was not 590significant in Experiment 1. It is possible that having no 591concurrent secondary task and/or the enforcement of 592central eye fixation in this experiment facilitated the use 593of speed information. 594

Finally, as in Experiment 1, the degree to which targets' 595speeds were monitored (measured by r_{speed}) was not 596significantly correlated with the degree to which targets' 597motion directions were monitored (measured by the 598direction-tuning index), r = -0.27, t(20) = 1.330, *n.s.*, 599suggesting that the targets' speeds and directions were 600 monitored as separate parameters during multiple-object 601 tracking. It is, however, possible that a significant 602 correlation might have been obtained had we devised 603 more precise measures of how observers monitored the 604 speeds and directions of target motion, so that this null 605 correlation must be interpreted with caution (although 606 both measures were robust enough to reveal significant 607 correlations with target-localization error). 608

Overall, the combined results from Experiments 1 and 2 609 suggest that (1) attention resources are dynamically 610 allocated in a demand-based manner, preferentially to 611 targets in more crowded situations, and that (2) both 612 targets' motion directions and speeds are monitored 613 during multiple-object tracking, with at least the motion 614 direction information substantially contributing to the 615 precision of target localization. 616

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Discussion

People have the ability to simultaneously track multiple moving objects with attention and this ability has 621 been extensively studied. Using a novel paradigm to 622 measure target-localization errors, we investigated two 623 624 fundamental questions that were not conclusively addressed in previous research. The first question was 625 how attention is distributed among the tracked targets, and 626 627 the second question was whether motion information (direction and/or speed) is utilized by multiple-object 628 tracking mechanisms. Our results provide important con-629 630straints for the current models of multiple-object tracking. Broadly, there are two classes of models of multiple-631 object tracking, one postulating that a fixed number of 632633 attention indices are available for assignment to tracked objects-"multiple-index" models (for reviews, see 634 Cavanagh & Alvarez, 2005; Pylyshyn, 2001; Scholl, 635 2001), and the other postulating that a single focus of 636 637 attention rapidly switches among the tracked objects to update their changing positions-"rapid-switching" mod-638 els (for a review, see Oksama & Hyönä, 2008). Currently 639no decisive evidence favors either class of models. 640

Our primary finding is that the precision of tracking 641 increases for targets in more crowded situations (measured 642 as reduced localization errors for targets in more crowded 643 situations). For the multiple-index type models, this result 644would suggest that the spatial resolution of an attention 645 index is increased when its assigned target gets more 646 647 crowded by distractors. This view is consistent with a recent result, suggesting that the resolutions of attention 648 indices are adjustable under the constraint of limited 649capacity (Alvarez & Franconeri, 2007); for example, 650 many indices might be deployed with coarse spatial 651resolution, or a few indices might be deployed with fine 652 spatial resolution. Our result would extend this idea in 653 suggesting that even while tracking a fixed number of 654 objects, the spatial resolutions of attention indices can be 655adaptively adjusted to provide finer resolutions for targets 656 in more crowded situations. 657

For the rapid-switching type models, our result would 658659 suggest that the mechanism that controls the shifting of attention among the tracked targets prioritizes updating of 660 targets in more crowded situations. For either model, our 661 result suggests that increased attention resources (in the 662 form of finer resolution or prioritized updating) are 663 allocated to a target when distractors approach within 664665 $\sim 3^{\circ}$.

Our second major finding is that the motion directions 666and speeds of the tracked targets are encoded during 667 multiple-object tracking, and that the direction informa-668 tion contributes to the precision of tracking. For the 669 670 multiple-index type models, this would suggest that the mechanisms by which attention indices follow the targets 671 utilize motion as well as location information. In the 672 rapid-shifting type models, it is postulated that the targets' 673 674 locations are temporarily stored in visual short-term 675 memory (VSTM) while other targets are being visited and updated; thus, the major source of tracking error 676 according to these models is the discrepancy between the 677 stored location and the actual location of a target when it 678 is re-visited for updating (e.g., Oksama & Hyönä, 2008). 679 680 Our result would suggest that this discrepancy is reduced by storing the motion (in addition to the location) 681 information in VSTM for each target so that the motion 682 information can be used to appropriately extrapolate a 683 target's location before shifting attention to it (to 684 compensate for its movement while other targets were 685 updated). Note that a recent study suggests that multiple-686 object tracking mechanisms utilize brief sensory memory 687 (lasting a few hundred milliseconds) of motion trajectories 688 (Narasimhan, Tripathy, & Barrett, 2009). Thus, the 689 motion and location information used for target updating 690 may be extracted from the persisting sensory memory of 691 target trajectories without the use of VSTM. 692

In summary, any model of multiple-object tracking 693 needs to accommodate our two key findings: 694

- attention resources are dynamically and adaptively 695 distributed among the tracked targets so that those in 696 more crowded situations receive more resources 697 than those in less crowded situations, and 698
- motion directions (and perhaps also speeds) of the 699 tracked targets are monitored and utilized during 700 multiple-object tracking. 701

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Relation to previous studies 78

Many prior studies pertain to our finding on the use of 706 motion information during multiple-object tracking. For 707 example, a recent study by Howard and Holcombe (2008) 708 reported a seemingly opposite result; their observers 709 tended to localize a tracked target in its earlier (rather 710 than extrapolated) location. As in our study, Howard and 711 Holcombe measured target-localization errors, but the 712 tracking display they used was somewhat atypical. A 713 square-shaped tracking region was divided into eight 714 sectors of an equal area with each sector containing only 715one moving item. A subset of these eight items was 716 designated as the targets to be tracked. At the end of each 717 trial, one of the sectors was cued and observers mouse-718 clicked the last seen location of the target that moved 719about in the cued sector. Because the targets were always 720 confined within their respective sectors (which were 721distinct from the sectors that contained the distractors), 722 there was no danger of losing a target as long as observers 723 remembered the target-containing sectors. Thus, rigorous 724 tracking of targets using motion information would not be 725necessary in their task at least for the purpose of not 726 losing a target. Their observers therefore might have used 727 a less effortful strategy of serially monitoring the target-728 containing sectors. Such a strategy could result in local-729 ization of the target in the cued sector based on its earlier 730 location remembered from the most recent attentional visit 731 to that sector. In contrast, in typical multiple-object 732 tracking tasks (including ours), continuous tracking of all 733 734 targets is necessary in order not to lose a target because 735 the trajectories of the targets and distractors closely intermingle. In such a demanding case of tracking, 736 737 encoding the targets' motions to anticipate their future locations would be especially useful. We thus consider the 738 seeming discrepancy between Howard and Holcombe's 739 740 (2008) results and ours as a reflection of the strategic flexibility of multiple-object tracking mechanisms; a 741relatively less resource-demanding strategy such as serially 742743 monitoring the target-containing regions would be used when such a strategy is sufficient for not losing a target, but 744 all targets are rigorously tracked utilizing most available 745 information (including motion information) when the 746 747 targets and distractors closely intermingle and the danger 748 of losing a target is high.

In general, prior results on target localization are 749 consistent with the interpretation that the visual system 750anticipates future locations of objects based on motion-751based extrapolation. Notably, the extensive literature on 752the phenomenon known as representational momentum 753has demonstrated that when a moving object is suddenly 754extinguished observers tend to locate it ahead of where it 755 actually disappeared—termed forward displacement, sug-756 gesting that the visual system tends to anticipate future 757 locations of moving objects based on their motion 758trajectories (e.g., Freyd & Finke, 1984; Freyd & Johnson, 7591987; Finke & Shyi, 1988; for a review, see Thornton & 760 Hubbard, 2002). The phenomenon of forward displace-761ment has been demonstrated for linear as well as non-762 linear motion trajectories such as those with periodic 763 764changes in direction and/or speed (e.g., Müsseler et al., 2002; Verfaillie & d'Ydewalle, 1991). 765

Broadly speaking, forward displacements have been 766 shown to ubiquitously occur when relatively few items are 767 present (typically one or two) in the display, so long as 768 769 attention is not strongly captured by a distractor at the time of target localization (e.g., Kerzel, 2003b). Forward 770 displacements, however, had not been examined in the 771context of multiple-object tracking where multiple mov-772 ing targets are simultaneously tracked in the presence of 773 multiple moving distractors, the targets' and distractors' 774 775 trajectories intermingle, and when the targets' motions frequently change due to inter-object collisions. We have 776 clearly demonstrated forward-displacement effects in 777 multiple-object tracking, suggesting that the mechanisms 778 underlying the phenomenon of representational momen-779 780 tum are also operational during multiple-object tracking.

781 The question of whether motion information is utilized by multiple-object tracking mechanisms was previously 782 investigated, but the results were mixed. For example, 783 tracking performance was unaffected whether or not a 784 785 temporarily occluded target reappeared at the location predicted by the motion trajectory prior to occlusion. 786 Instead, tracking performance was primarily determined 787 by the distance between the points of target disappearance 788 and reappearance (e.g., Franconeri, Pylyshyn, & Scholl, 789 790 2006; Keane & Pylyshyn, 2006), suggesting that multipleobject tracking mechanisms relied on proximity rather 791 than motion. In contrast, a recent study showed that, when 792 motion trajectories were nearly constant (except for 793 bouncing at the region boundaries) and only one or two 794targets were tracked, re-capturing of tracked targets 795 following a 300-ms blank interruption in the tracking 796 display was improved by the presence of motion informa-797 tion prior to the interruption (Fencsik et al., 2007). 798

Our results strongly support the use of motion informa-799 tion during multiple-object tracking. The consistent for-800 ward displacements of mouse-clicks that were positively 801 correlated with the targets' speeds indicated that the 802 targets' motion directions and speeds were both monitored 803 during tracking. The fact that the direction tuning of the 804 response vector robustly correlated with target-localization 805 error in both Experiments 1 and 2 (and r_{speed} correlated 806 with target-localization error in Experiment 2) suggested 807 that multiple-object tracking mechanisms certainly utilize 808 motion direction information (but perhaps also speed 809 information) to increase the precision of tracking. It is 810 possible that this motion-based anticipation of target 811 locations operates only within a short range, both in space 812 and time, shorter than the spatiotemporal dimensions of 813 occluders used in Franconeri et al. (2006) and Keane and 814 Pylyshyn (2006), unless targets' motions are nearly 815 constant as in Fencsik et al. (2007). 816

Finally, a study investigating how well people detect 817 deviant motion trajectories suggests that the magnitude of 818 deviation that can be detected depends on how many 819 trajectories are simultaneously monitored. It was found 820 that the detectable magnitude of angular deviation was 821 about $\pm 19^\circ$, $\pm 38^\circ$, or $\pm 76^\circ$ when the effective number of 822 trajectories tracked by observers was one, two, or four, 823 respectively (Tripathy, Narasimhan, & Barrett, 2007). Our 824 observers tracked three targets, so the expected degree of 825 direction tuning based on Tripathy et al.'s result would be 826 somewhere between $\pm 38^{\circ}$ and $\pm 76^{\circ}$. The tuning of the 827 response vector we obtained was about $\pm 70^{\circ}$ (Experiment 1) 828 and $\pm 45^{\circ}$ (Experiment 2) based on the angular deviations at 829 half amplitude (measured from peak to trough) of the 830 direction-tuning functions shown in Figure 5. Thus, our 831 direction-tuning results are broadly consistent with the 832 result of Tripathy et al. (2007) despite the fact that the two 833 studies used very different experimental paradigms and 834 measures. 835

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Conclusions

We used a novel experimental method to measure 839 target-localization errors while observers tracked multiple 840 targets that independently moved among and collided with 841 distractors. Our results provide evidence that multipleobject tracking mechanisms (1) dynamically distribute 843 attention resources among the tracked targets in a 844 demand-based manner, preferentially allocating resources to targets in more crowded situations (when distractors approach within $\sim 3^{\circ}$ of a tracked target), and (2) utilize motion direction (and perhaps also speed) information to anticipate target locations to increase the precision of tracking.

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Footnotes

¹According to Pylyshyn and colleagues' original theory 865 (e.g., Pylyshyn, 2003; Pylyshyn & Storm, 1988), these 866 867 indices that follow their assigned targets operate independently of attention, and they serve as pointers for 868 attention processes to rapidly but serially access the 869 tracked targets. In this sense, their theory is a hybrid 870 between those postulating multiple foci of attention and 871 872 those postulating rapid switching of a single focus of attention (for reviews of the various models of multiple-873 object tracking, see Oksama & Hyönä, 2004, 2008, and 874 Cavanagh & Alvarez, 2005). 875

²This range of speed was somewhat slow compared to 876 877 typical studies examining multiple-object tracking. In most prior studies, the number of successfully tracked 878 targets was the dependent measure, so that the motion 879 needed to be fast enough for most observers to lose track 880 of at least some of the targets. In contrast, our dependent 881 882 measure was the precision of tracking, so that the motion needed to be slow enough for most observers to success-883 fully track all three targets in most trials. Although this 884 might be considered a potential limitation of our techni-885 que, we argue that the speed range we used is relevant on 886 the basis of ecological and neurophysiological consider-887 ations. For example, in a typical driving situation (while 888 moving at 35 mi/hr), the stopping distance (under normal 889 road conditions) is about 52 ft. Suppose a driver tracks 890 oncoming traffic (also moving at 35 mi/hr) for potentially 891dangerous swerves from about twice the stopping dis-892 893 tance, 104 (= 52 \times 2) ft, to avoid collision. At this distance, the oncoming traffic (assuming a typical 2-lane 894

road) would move toward the retinal periphery at $\sim 7^{\circ}/\text{sec}$ 895 (assuming the driver is looking forward). The retinal 896 speeds of the cars that the driver is following would 897 typically be in a slower range. A stationary object such as 898 a pedestrian would move toward the periphery at $\sim 3.3^{\circ}/$ 899 sec. If a pedestrian was walking ($\sim 2.5 \text{ mi/hr}$) or running 900 (~6.3 mi/hr), that would add about $\pm 0^{\circ}$ to 2° /sec (if 901 walking) or $\pm 0^{\circ}$ to 5°/sec (if running) of retinal speed 902 depending on the direction in which the pedestrian is 903 moving. As can be seen from this example, the range of 904 speeds that we used in our study $(0.12-6.15^{\circ}/\text{sec})$ covers 905 much of this typical range of retinal speeds of objects that 906 need to be tracked while driving. Furthermore, the average 907 speed tunings of visual neurons in areas V1 and MT are 908 4.47°/sec and 7.52°/sec, respectively (Priebe, Cassanello, 909 & Lisberger, 2003; Priebe, Lisberger, & Movshon, 2006), 910 within or near the range of speeds included in this study. 911 The speed range we used is thus representative of normal 912 experience on the basis of both ecological and neuro-913 physiological considerations. 914

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