

## **The Efficiency of Vision and Action**

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We sit in a garden with no particular goal in mind. Something moves in the corner of our eye and—based on low-resolution peripheral information—we move our eyes to better view it. Once it is imaged in the high-resolution fovea of each eye we recognize it: a misplaced kitten. Based on this visual information, we decide what to do next. We can inspect it further to determine whose kitten it might be or we can engage in visual search and look for a mother cat. Using coordinated eye and hand movements we can try to capture the kitten. Once we have it, we can admire it, occasionally returning to monitoring the scene visually with no particular goal in mind.

Eye movements serve multiple roles: gathering information about a scene and guiding actions within the scene. These future actions can be further eye movements or other movements, for example, reaching or grasping toward visible objects. Visual input can also serve to guide these movements as well. The articles in this Special Issue address the ways in which we use the eyes to

gather information, how we use that information to guide visual search and to guide hand movements.

In the past decade researchers have compared visually guided movement to models based on Bayesian decision theory (Maloney & Zhang, 2010; Trommershäuser, Maloney & Landy, 2009; Wolpert & Landy, 2012). In the decision-theoretic framework, the outcome of any movement entails a specified gain or loss to the subject and the subject's goal is to select movements that maximize expected gain. Decision-theoretic models allow us to characterize the best performance possible in a particular task and express human performance as a percentage of ideal performance, i.e., as *efficiency*.

The decision-theoretic framework applies equally to any movement task where there are explicit gains and losses. Two extensively studied areas are planning of speeded reaching and pointing movements and planning of saccadic eye movements. Measures of efficiency in reaching tasks are typically high (80-100%) and often indistinguishable from 100% (e.g., Trommershäuser, Maloney & Landy, 2003). Subjects do exhibit patterned deviations from model predictions (e.g., Wu et al., 2009) but these are typically small with little impact in terms of efficiency.

In contrast, evaluations of human performance in planning saccades are decidedly mixed with reports of near-optimal performance in some visual-search

tasks (Najemnik & Geisler, 2005) but reports of large and patterned failures in others (Araujo, Kowler & Pavel, 2001; Morvan & Maloney, 2012; Verghese, 2012). The articles in this special issue examine human performance in planning movement and the efficiency—or inefficiency—of the movements planned. One theme common to several of the contributions concerns the time needed to plan movements.

### ***Time constraints***

One plausible explanation for observed differences in efficiency in reaching and oculomotor tasks may simply be that eye movements are executed over a very short time-scale. There may simply not be enough time to plan the first eye movement or, in the case of saccades, to include information gained from one saccade into the planning of later saccades. If so, then we would expect that performance in eye-movement tasks would improve with available planning time.

Several articles in this issue examine how the time course of decision affects movement planning. Early manual and oculomotor responses are more susceptible to distracting influences (Moher & Song, 2015; van Zoest & Kerzel, 2015) and may not reflect task demands (Ghahghaei & Verghese, 2015; Paoletti, Weaver, Braun & van Zoest, 2015; Schütz, Lossin & Gegenfurtner, 2015), but longer latency eye movements and manual choice responses are often goal-directed. Saccades with latency less than 250 ms tend to select a more salient distractor (Paoletti et al., 2015; van Zoest & Kerzel, 2015). In their study, Van

Zoest & Kerzel (2015) also showed that short-latency reaching movements select the more salient distractor. Even when the final reach endpoint lands on the target, the path of the reach trajectory curves towards the distractor with the degree of curvature increasing with the salience of the distractor (Moher & Song, 2015). Schütz and colleagues (2015) pitted salience versus reward in a task that required smooth pursuit of one of two motion directions and showed that pursuit was determined primarily by salience for the first 300-400 ms after motion onset and then gradually shifted towards the rewarded direction. This echoes an earlier study that pitted salience against value for saccades and showed that early saccades were determined by salience, and later saccades by value (Schütz, Trommershäuser & Gegenfurtner, 2012). Indeed, observers make saccades to more informative locations when asked to withhold saccades for 200 ms after display onset (Ghahghaei & Verghese, 2015).

For a manual task in which observers are required to tap as many targets as they can in two minutes, they make reasonable (if not optimal) choices that take their motor variability and the ease of hitting targets into account (Brenner & Smeets, 2015). This result might be due to the fact that a tap has a longer latency (~400 ms) than the initiation of an eye or hand movement, and therefore has more time to reflect the accumulation of evidence towards a decision.

The results of these studies suggest that the maximization of expected value for reaches reported by researchers beginning with Trommershäuser and

colleagues (2003) is due to the fact that manual trajectories are typically slower than eye movements and therefore have more time to incorporate neural population activity that is evolving towards a decision. Indeed, the time course of these movements may provide a continuous readout of this accumulation towards a decision (Bonnen et al., 2015; Resulaj, Kiani, Wolpert & Shadlen, 2009; Roitman & Shadlen, 2002; Selen, Shadlen & Wolpert, 2012).

### ***Task complexity***

Arguably the visual displays used in laboratory reaching tasks are simpler than those used in saccadic-planning tasks such as visual search. All of the manual tasks in this Special Issue required a binary choice between suprathreshold, visually distinct stimuli that were far apart. In some tasks (Moher & Song, 2015; van Zoest & Kerzel, 2015), the targets were large ( $> 2^\circ$ ) or the acceptance window of the touch endpoint was bigger than the target. In other cases (Brenner & Smeets, 2015) observers had to choose between spatially separate small and large targets to maximize the number of targets tapped within a fixed interval. Even in cases where the two choices are spatially overlapping (Trommershauser et al., 2003), the choices are visually distinct, and the challenge is to plan a movement that takes intrinsic motor error and reward into account. In contrast, in many of the eye-movement planning tasks, the stimuli are noisy and there is not a single unique eye-movement target. Furthermore, the eye movements are typically made up of a series of saccades directed toward gathering information for a subsequent decision (Ackermann & Landy, 2013; Eckstein et al., 2015;

Ghahghaei & Verghese, 2015; Najemnik & Geisler, 2005; Renninger, Verghese & Coughlan, 2007; Verghese, 2012). Given the internal noise of the observer, and the time required to incorporate information into a saccade plan, it is not surprising that saccadic choices deviate from an ideal-observer model that maximizes the information gained with each fixation.

### ***Task familiarity***

The kinds of simplified tasks used in laboratory studies may differ in familiarity from typical everyday tasks. If so, lack of familiarity with the task may play a role in reducing efficiency. For example, Ghahghaei & Verghese (2015) asked subjects to search a visual array for an unknown number of targets under time pressure and found that performance by any measure was far from optimal. In contrast, when the choices are clearer or fewer, such as the pursuit of one rewarded target of two options (Schütz et al., 2015), subjects planned movements efficiently. If task familiarity is a factor, then we might expect that even in unfamiliar tasks, with extensive training or experience, performance will move toward optimal. This might account for the fact that the most practiced observers are closest to optimal (Ghahghaei & Verghese, 2015).

### ***Other factors that impact efficiency***

Even if they deviate from optimality, saccadic eye movements do adapt to ambient conditions. Paulun and colleagues (2015) show that under scotopic illumination eye movements incorporate the scotopic visibility profile, which

includes poor visibility at the rod-free fovea. Humans make fewer saccades under scotopic viewing conditions when they search for a single target in  $1/f$  noise. In addition, dwell times are 200 ms longer for scotopic compared to photopic conditions, consistent with the longer integration time of the rod system. Thus, the eye-movement system is able to make appropriate adjustments for the prevailing context.

Studies that compare eye movement targets to optimal strategies show considerable deviations in the spatial distribution of eye movements relative to ideal predictions (Ackermann & Landy, 2013; Paulun et al., 2015; Eckstein et al., 2015). However, Eckstein and colleagues (2015) show that when observers are given a brief interval to gather visual information for a subsequent rewarded decision, their reward is close to that predicted for the ideal observer, even though the choice of saccade locations deviates from the ideal observer. The clearest deviation of saccade landing position from the prediction of the ideal observer is that humans rarely make saccades to locations that lie between potential target locations as predicted by information-maximizing models (Najemnik & Geisler, 2005; Renninger et al., 2007), but direct their saccades directly towards potential target locations. Thus, it is clear that observers can use a non-ideal strategy that nevertheless achieves a close-to-ideal outcome (although, for non-ideal outcomes, see Morvan & Maloney, 2012; Verghese, 2012).

At one extreme we might have found that eye-movement planning, like the planning of reaching and touching movements, adapts to explicit rewards in tasks and comes close to optimizing a measure of expected gain. At the other extreme we might have found large qualitative differences between eye-movement planning and the planning of other movements. Eye movements, unlike hand movements, might not have been sensitive to explicit rewards associated with tasks. We could describe them as “stereotyped”, insensitive to the task at hand. There are evident reasons why this might be so, including the rapid pace of eye-movement planning and its computational complexity. If there is no time to plan strategically then we expect stereotypical eye movement patterns not well matched to the task at hand.

What we found corresponds to a continuum between these two extremes. Saccadic planning under time pressure deviates markedly from the predictions of an ideal-observer model that maximizes the information gained with each saccade. But with more available time, planning conformed more and more to the predictions of an ideal planner maximizing expected gain. We cannot exclude the possibility that saccadic planning in a sufficiently slow and simple task would resemble planning of reaching and grasping movements in every respect. Future research is needed to explore the effects of task complexity and task familiarity on all kinds of movement planning.



## References

Ackermann, J. F. & Landy, M. S. (2013). Choice of saccade endpoint under risk. *Journal of Vision*, 13(3):27, 1-20.

Araujo C, Kowler E, & Pavel M. (2001). Eye movements during visual search: the costs of choosing the optimal path. *Vision Research*, 41, 3613-3625.

Bonnen, K. L., Burge, J. D., Yates, J. L., Pillow, J. W. & Cormack, L. K. (2015). Continuous psychophysics: Target-tracking to measure visual sensitivity. *Journal of Vision*, 15(3):14, 1-XXX.

Brenner, E. & Smeets, J. B. J. (2015). Quickly making the correct choice. *Vision Research*, 112, XXX-XXX.

Eckstein, M., Schoonveld, W., Zhang, S., Mack, S. & Akbas, E. (2015). Optimal and human eye movements to clustered low value cues to increase decision rewards during search. *Vision Research*, 112, XXX-XXX.

Ghahghaei, S. & Verghese, P. (2015). Efficient saccade planning requires time and clear choices. *Vision Research*, 112, XXX-XXX.

Maloney, L. T. & Zhang, H. (2010), Decision-theoretic models of visual perception and action. *Vision Research*, 50, 2362-2374.

Moher, J. & Song, J.-H. (2015). Goal-directed action is automatically biased towards looming motion. *Vision Research*, 112, XXX-XXX.

Morvan, C. & Maloney, L. T. (2012), Human visual search does not maximize the post-saccadic probability of identifying targets. *PLoS Computational Biology*, 8(2), e1002342, 1-11.

Najemnik, J. & Geisler, W. S. (2005). Optimal eye movement strategies in visual search. *Nature*, 434, 387–391.

Paoletti, D., Weaver, M. D., Braun, C. & van Zoest, W. (2014). Trading off stimulus salience for identity: a cueing approach to disentangle visual selection strategies. *Vision Research*, 112, XXX-XXX.

Paulun, V. C., Schütz, A. C., Michel, M. M., Geisler, W. S. & Gegenfurtner, K. R. (2015). Visual search under scotopic lighting conditions. *Vision Research*, 112, XXX-XXX.

Renninger, L. W., Verghese, P. & Coughlan, J. (2007). Where to look next? Eye movements reduce local uncertainty. *Journal of Vision*, 7(3):6, 1-17.

Resulaj, A., Kiani, R., Wolpert, D. M. & Shadlen, M. N. (2009). Changes of mind in decision-making. *Nature*, 461, 263-266.

Roitman, J. D. & Shadlen, M. N. (2002). Response of neurons in the lateral intraparietal area during a combined visual discrimination reaction time task. *Journal of Neuroscience*, 22, 9475-9489.

Schütz, A. C., Lossin, F. & Gegenfurtner, K. R. (2015). Dynamic integration of information about salience and value for smooth pursuit eye movements. *Vision Research*, 112, XXX-XXX.

Schütz, A. C., Trommershäuser, J., Gegenfurtner, K. R. (2012). Dynamic integration of information about salience and value for saccadic eye movements. *Proc Natl Acad Sci U S A*, 109, 7547-52.

Selen, L. P., Shadlen, M. N. & Wolpert, D. M. (2012). Deliberation in the motor system: reflex gains track evolving evidence leading to a decision. *Journal of Neuroscience*, 32, 2276-2286.

Trommershäuser, J., Maloney, L. T. & Landy, M. S. (2003). Statistical decision theory and trade-offs in the control of motor response. *Spatial Vision*, 16, 255-275.

Trommershäuser, J., Maloney, L. T. & Landy, M. S. (2009). The expected utility of movement. In Glimcher, P. W., Camerer, C. F., Fehr, E. & Poldrack, R. A. (Eds.), *Neuroeconomics: Decision Making and the Brain* (pp. 95-111). New York: Academic Press.

Van Zoest, W. & Kerzel, D. (2015). The effects of saliency on manual reach trajectories and reach target selection. *Vision Research*, 112, XXX-XXX.

Verghese, P. (2012). Active search for multiple targets is inefficient. *Vision Research*, 74, 61-71.

Wolpert, D.M., & Landy, M.S. (2012). Motor control is decision-making. *Current Opinion in Neurobiology*, 22, 996-1003.

Wu, S.-W., Dal Martello, M. F. & Maloney, L.T. (2009). Sub-optimal allocation of time in sequential movements. *PLoS ONE*, 4(12):e8228.

Zhang, H., Morvan, C., Etezzad-Heydari, L.-A., Maloney, L. T. (2012), Very slow search and reach: eye-hand coordination in finding and touching a target among distractors. *PLoS Computational Biology*, 8(10), e1002718, 1-12.