Title

Foraging in the Virtual Himalayas: Intrinsic and Extrinsic Factors in Search

Permalink

https://escholarship.org/uc/item/7pg923kz

Journal

Proceedings of the Annual Meeting of the Cognitive Science Society, 42(0)

Authors

Garg, Ketika
Kello, Christopher

Publication Date

2020

Peer reviewed

Foraging in the Virtual Himalayas: Intrinsic and Extrinsic Factors in Search

Ketika Garg (kgarg@ucmerced.edu)

Christopher Kello (ckello@ucmerced.edu)

Abstract

Foraging over land for resources was central to the evolution of search processes and decision-making for many organisms, including humans. The processes underlying natural foraging behaviors are foundational to cognition. However, in the field, it is difficult to collect detailed and accurate measures of search behaviors and hard to manipulate search conditions. We used Google Earth and the Unity 3D platform to recreate a patch of the Himalayan foothills with ancient temples used as way-points for travelers on foot. Two hundred players recruited via MTurk moved over the landscape with realistic speed, energy usage, and perceptual conditions to find as many temples as possible given a limited energy budget. Half were constrained by the need to return to a home base to report found temples, and half were not. When search paths were analyzed in terms of segment distributions, players who found relatively more temples (high scorers) more closely followed the theoretically optimal Lévy walk that balances exploration and exploitation, regardless of the home base. This intrinsic pattern was also found in perceptual search intervals, with high scorers leaning more towards exploration. By contrast, when search paths were analyzed as wholes, an extrinsic pattern was found in that players ranged farther without a home base, and this difference was more pronounced for high scorers. We conclude that Lévy-like patterns are intrinsic and effective in terms of path segments and perceptual intervals, but overall search behavior adapts to extrinsic factors and constraints.

Keywords: Human Foraging; Search; Lévy walks; Diffusion; Virtual Environment

Introduction

Foraging is fundamental to the survival of all mobile species, from bacteria to humans. It is also the quintessential search process under conditions of uncertainty, where the location of resources is mostly unknown (Todd, Hills, & Robbins, 2012). Foraging processes, therefore, are engaged not only to find food and other physical resources but also information as in as memory search (Kerster, Rhodes, & Kello, 2016) and perceptual search (Rhodes, Kello, & Kerster, 2014). Foraging is widespread in many types cognitive functions and is hypothesized to play a foundational role in the evolution of human and biological intelligence (Rosati, 2017).

Given the fundamental and widespread nature of foraging, researchers have suggested a common basis to search behaviors that may have evolved across species and environments. One candidate that has been studied extensively is *Lévy search* (Viswanathan et al., 2011). Lévy search processes are comprised of frequent short movements interspersed with increasingly rarer, longer movements, where the probability of observing a given path length is inversely proportional to the length(l_j), $P(l) \sim l_j^{-\mu}$; $1 < \mu \leq 3$ and paths refer to the distances traveled between consecutive pauses or turns. Many studies across species in various domains have found foraging path length distributions to follow those predicted by Lévy search (Reynolds, 2018) including human foraging (Brown, Liebovitch, & Glendon, 2007; Raichien et al., 2014; Reynolds et al., 2018) and in abstract spaces like memory (Kerster et al., 2016) and visual scenes (Rhodes et al., 2014).

Widespread evidence for Lévy search suggests that it might reflect a basic property of search that is *intrinsic* when resources are scarce and uncertain, and the searcher has little or no memory to devote their search history (Sims et al., 2019). When searchers do have memory and decision-making capabilities, they still exhibit Lévy-like search paths, but search patterns are also adaptable to *extrinsic* factors that are informative of successful search behaviors. For instance, the exponent μ has been observed to increase when resources are plentiful (Nurzaman et al., 2010), and to adjust for whether resources or destructive or non-destructive (da Luz, Raposo, & Viswanathan, 2015). Lévy search patterns are local to the sizes of individual path segments (Viswanathan et al., 2011), whereas, from a broader perspective, goal-directed search behaviors depend on decision processes that span spatial and temporal scales in which local choices integrate over short timescales and interact with broader, non-local decision processes (Purcell & Kiani, 2016).

Figure 1: Example player view near the start point of the virtual foraging game, with the landmark tower in the background.

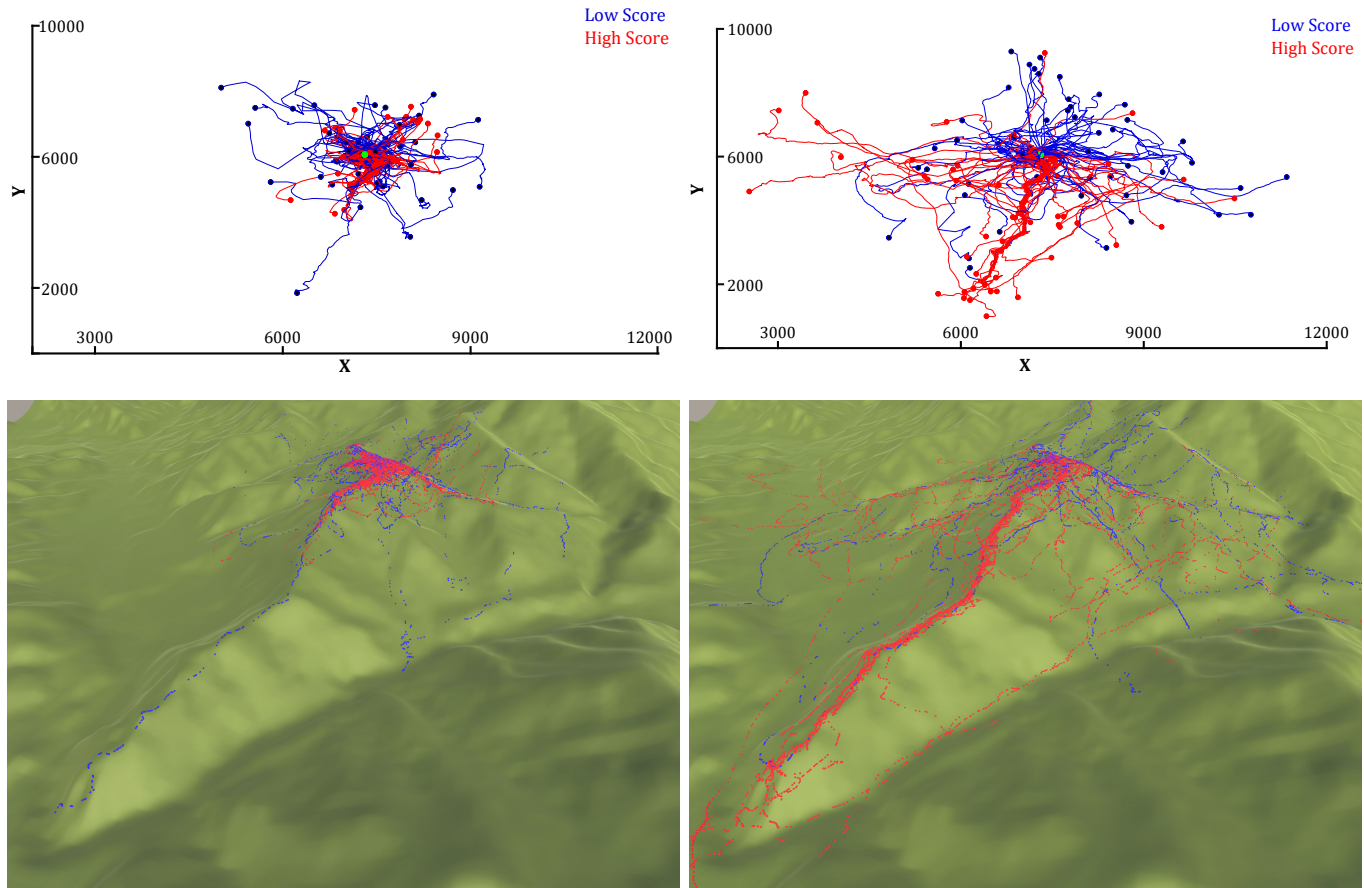In the present study, we examine human foraging in an eco-

Figure 2: Trajectories of Home-Base players (Left) versus No-Home players (Right). Colors indicate trajectories for low-scorers (blue) and high-scorers (red) for each condition.

logically natural search task designed to test for both intrinsic and extrinsic factors at play in search processes over multiple scales. Given the role of foraging in human evolutionary history as hunter-gatherers, we designed a 3D game environment based on an actual terrain space and resource distribution in the Himalayas (Fig 1). Items to be foraged are existing temples that are spatially distributed according to human on-foot movement patterns–historically, some of them served as waypoints for journeys of nomadic tribes of the region (Kaushal, 2001), and they are non-randomly distributed due to various environmental and human behavioral and cultural factors (Hill, 2006). Our design decisions focused more on the way the game is played, and we included two ecologically valid modes of play. All players started on top of the same hill where a tower landmark stood, and in one condition they only needed to see and click on temples to find them. In another "home base" condition, players had to see and click on temples and then report them back to home base by clicking on the tower landmark. Therefore, home base was an extrinsic constraint on search trajectories that introduced a broader layer of decision-making to the more local level of decisions to find new temples, and the even more local level

of decisions about individual movements.

Our game is modeled on human hunter-gatherer foraging, and previous studies have shown that foraging humans exhibit Lévy-distributed movements (Raichien et al., 2014). We expect to replicate these previous studies, but with the added benefit of precise and fairly complete measures of foraging behaviors, including perceptual actions (looking around) and search efficiency (temples found given a fixed energy budget, c.f. (Wilson, Quintana, & Hobson, 2012). Given the energetic cost of movement over the landscape, versus no energetic cost for scanning, we also predict costly movements to be exploited by "free" perceptual exploration at intermittent stops along the way–the difference in costs should be reflected in different patterns of perceptual versus locomotive search. We also predict effects of the home base manipulation given previous studies showing influences of memory and learning on search strategies (Namboodiri et al., 2016) that make them more efficient (Méndez, Campos, & Bartumeus, 2014). Specifically, it should be more efficient and less taxing on memory to constrict excursions closer to the home base.

Methods

The foraging game was implemented in Unity® 3D and primarily scripted in C#. The game was modeled on a five km-square area in the Himalayas (Top-Left - 32.6548, 76.056530, Bottom-Right - 32.54895, 76.194889). The relief of the terrain was downloaded from Google Earth and rendered in the Unity environment using Infinity Code. Forty-nine temples were identified in the chosen area based on location data from Google Maps. The coordinates of the temples were marked in the Unity landscape, and a model temple was placed at each location. Trees were distributed uniformly across the landscape with a medium level sparsity, which served as visual distractors that made temple detection more effortful. The game start point was a hilltop location near the center of the landscape, and each player was given an energy budget that roughly enabled them to traverse 10 kilometers of a flat plane. Movement was only forward and backward with turns to change direction, and movement speed was set to be 6m/s, which is a fast but realistic human 5K race. A visible energy bar was depleted as a function of the slope approximated from prior studies on human energy expenditure (Minetti et al., 2002). Specifically, a constant minimum was set per meter for flat and downhill surfaces, and energy expenditure increased by 35% for each angular degree of increase in grade.
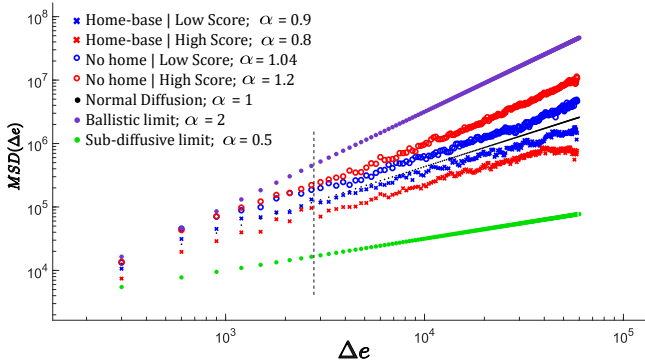

Figure 3: Coarse-graining of MSD as a function of energy expended for ensemble trajectories in each condition, separated by low (blue) and high (red) scorers. Displacement are also divided into local (left) and non-local (right) scales by the vertical dashed black line.

Players used six keys to control movement and perspective ('w,' 'a,' 's,' 'd,' 'up arrow,' 'down arrow'), the latter two tilting their line of sight up and down to adjust for sloping terrain. Mouse movements were used for clicking on temples in view when found, and auditory feedback was available with steps to indicate movement, and clicks to indicate successful temple identification. Players were given a guided practice trial to acclimate to the game and its rules and controls. They were instructed to find as many temples as possible before depleting their energy, with the number of temples displayed in the corner of the screen. In the home base condition, the number found and number reported back to base were both

displayed, where players clicked on the home base to report temples found. Player scores were only based number reported, and to calibrate, players were told that 49 temples existed in the game.

The game was hosted on Amazon's Mechanical Turk, and 100 unique participants played in the home-base condition and another 100 in the no-home condition. Each player was paid a base amount of 50 cents for completing the game, and an additional bonus of 20 cents was awarded for every temple successfully recorded in no-home condition, but for home-base, the bonus was awarded for every temple reported back to the home base. The game was played for 12 minutes on average, and the average number of temples recorded or reported in the two conditions was 7.

Results

All individual search trajectories are plotted in Fig 2 separated by the home base condition. The plots show that players generally ranged farther away from the starting point when there was no need to report back to home base, even though the environment, energy budget, and other search conditions remained constant.

The degree of spatial dispersion of search trajectories was quantified by diffusion analysis via mean squared displacement (MSD). MSD was computed as a function of energy expended (similar to time passed) to characterize the type of diffusion, where a random Brownian walk generates a displacement slope (α) of 1. Subdiffusive ($\alpha < 1$) and superdiffusive ($\alpha > 1$) MSD functions indicate more or less locomotively constrained search processes than expected by a chance random walk. To examine the relationship between MSD functions and search efficiency, trajectories were further classified by a median split (4 temples found) of low and high scorers, which had means of 1 versus 13 temples found, respectively.

MSD was calculated as

$$MSD = \frac{1}{n} \sum_{j=1}^{n} < [r(e+\Delta e) - r(e)]^2 >_j \qquad (1)$$

where $r(e)$ is the position vector of the player at energy e, Δe is the energy expended, n is the total number of players. MSD values were computed over an ensemble average of all trajectories in the four conditions. MSD is usually calculated as a function of time, but our study afforded the opportunity to measure displacement in terms of energy expenditure which was more relevant to game play and arguably more relevant to organisms in natural foraging environments compared with time.

MSD functions were similar at local scales (see path segment analyses below) but diverged at longer scales, so we focus our MSD analyses on the longer scales. We fit regression lines to MSD functions in logarithmic coordinates to estimate the degrees to which players ranged farther or less far compared with the random walk baseline of 1 (Fig 3).

We found that players were significantly superdiffusive in the no-home condition, with a mean diffusion of exponent of 1.12 ± 0.5, and significantly subdiffusive in the
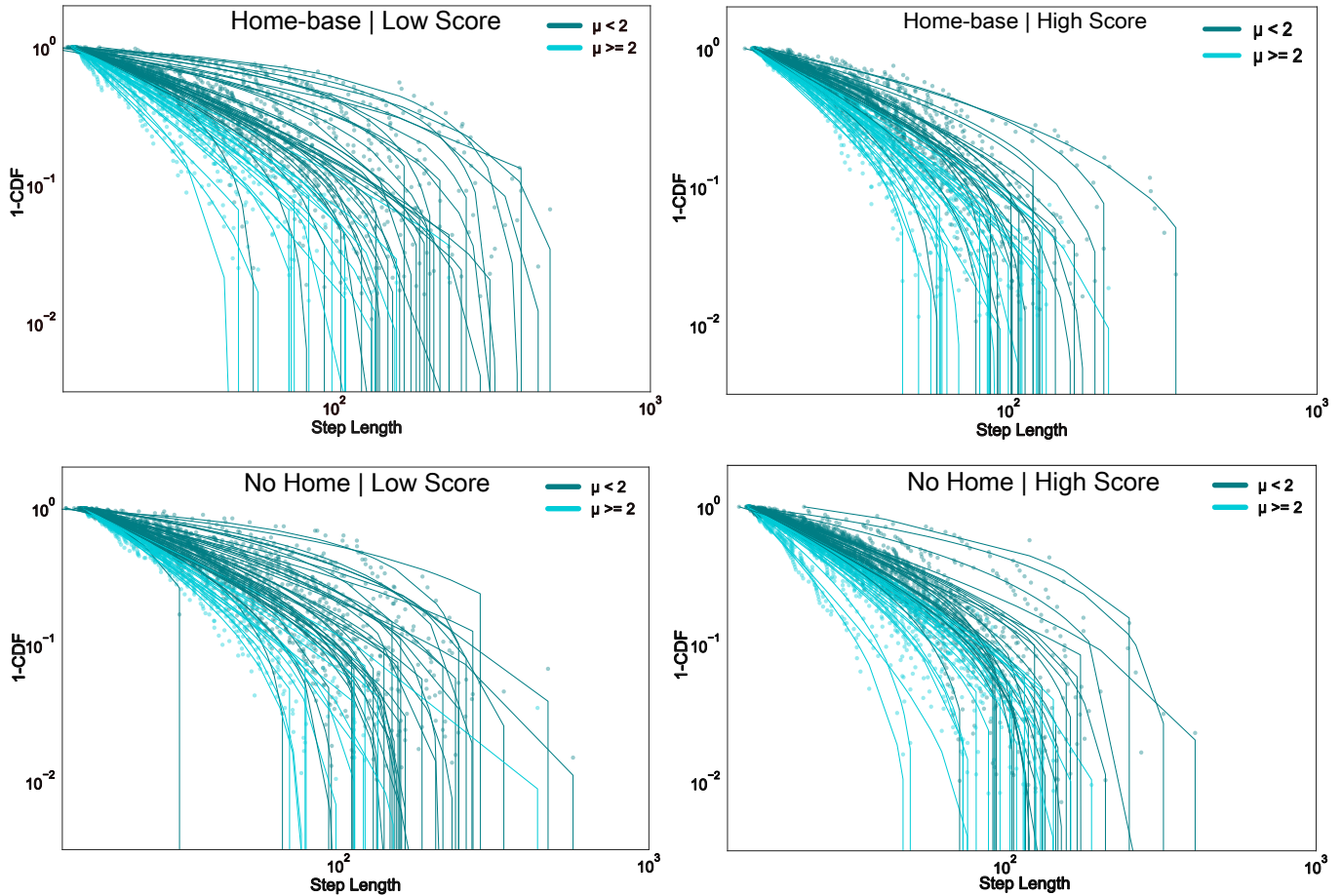
Figure 4: Raw Complementary Cumulative Distribution Function (CCDF a.k.a. 1 - CDF) for movement step sizes aggregated across all subjects in each condition (circles). A truncated power-law distribution was fit to the distribution of movement segments or each player (solid lines), and distributions with power-law exponents under the Lévy optimum $\mu < 2$ are shaded more darkly compared with those at or above $\mu >= 2$.
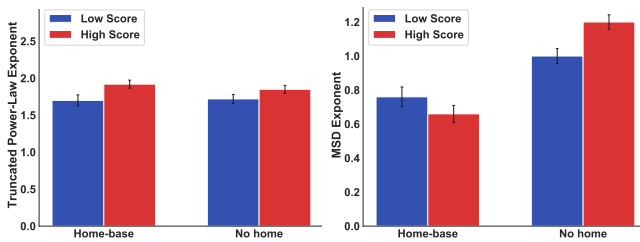

Figure 5: Mean μ (left) and mean α (right) of the four conditions.

home-base condition with a mean exponent of 0.7 ± 0.5, $F(1, 196) = 4.96, p = 0.02$. Moreover, the effect of home base was exaggerated for high versus low scores as evidenced by an interaction between home base condition and score, $F(1, 196) = 3.07, p = 0.08$. Fig 5 shows the mean diffusion exponents for each condition separated by low versus high scorers.

The MSD results show that players adapted their over-

all search trajectories to range farther when there was not a home-base constraint, and this adaptation was greater for high scorers. We further analyzed search behaviors by dividing paths into movement segments and scan segments. Movement segments were defined as time intervals of continuous straight movement, with each one demarcated by stop points or turn points. Scan segments were defined as time intervals during which players turned or stood still but did not move. We assume that players were mostly acquiring visual information during these periods.

We analyzed each type of segment distribution by estimating model parameters using maximum-likelihood estimation (MLE). The best-fitting model was determined on the basis of relative likelihoods using Akaike Information Criteria (AIC) and the Kolmogorov-Smirnov D goodness-of-fit metric. We tested the model distributions commonly examined in behavioral and foraging studies: Truncated Power-Law, Pareto, Lognormal, Exponential, and Bi-Exponential distributions.

AIC results showed the truncated power-law model was most commonly the most likely model for movement seg-

ments (84% of trajectories). Bi-exponential and lognormal models were also likely, but were not favored because additional parameters or lack of fit, respectively. Therefore we analyzed the best fitting truncated power-law parameters for all trajectories as common measure to compare shapes across conditions. The power-law exponent, μ, was closer to the theoretical optimum of 2 for high scorers ($M_{\text{home-base}} = 1.92 \pm 0.05, M_{\text{no-home}} = 1.85 \pm 0.05$) compared with low scorers ($M_{\text{home-base}} = 1.70 \pm 0.08, M_{\text{no-home}} = 1.72 \pm 0.06$), $F(1,196) = 12.03, p < 0.05$), and there was no reliable effect of home base, $F(1,196) = 0.15, p = 0.7$. This pattern of results adds to the large body of evidence for an intrinsically optimal Lévy-like distribution of movement path lengths.

Finally, the same analysis of scan segments yielded results that were consistent with movement segments in one respect, but different in another. But first, we establish that scan segments did, in fact, provide us with a gauge of perceptual search. Fig 6 plots the sum of perceptual intervals for each trajectory against the score obtained for that trajectory, separated by the home base condition. It shows a reliable positive correlation in both conditions, $r_{\text{home-base}} = 0.45, p < 0.001; r_{\text{no-home}} = 0.60, p < 0.001$. This implies that visual search was indeed engaged during scan segments. AIC results showed that truncated power-law distributions were again the most likely and showed a dependence on score $F(1,179) = 3.8, p < 0.05$. And again, home base had no reliable effect on mean power-law exponents μ, $F(1,179) = 0.51, p = 0.5$. However, μ estimates for perceptual segment distributions were closer to 1 whereas those movement segments were closer to 2 (see above). Moreover, μ estimates for low scorers ($M_{\text{home-base}} = 1.30 \pm 0.05, M_{\text{no-home}} = 1.26 \pm 0.05$) were larger than those for high scorers ($M_{\text{home-base}} = 1.18 \pm 0.05, M_{\text{no-home}} = 1.17 \pm 0.05$). The direction of this effect was opposite that for movement segments. This difference between segment types may be explained by the fact that scan segments cost no energy, which led better players to spend proportionally longer times on visual search, resulting in heavier-tailed distributions and lower μ estimates.

Discussion

The foothills of the Himalayas provided a heterogeneous landscape populated with temples located by humans, for human navigation and shelter. Locomotive and perceptual conditions were at the human scale, and the foraging game was designed to examine intrinsic and extrinsic factors at multiple levels of analysis. At the level of movement segments, players exhibited Lévy-like search paths with estimated exponents closer to the theoretical optimum of 2 corresponding with more efficient search trajectories, regardless of the home base manipulation. The optimum represents a mix of longer, extensive segments interspersed with shorter, intensive segments that exploit the new territory found by longer movements. This mix is theorized to balance the more en-
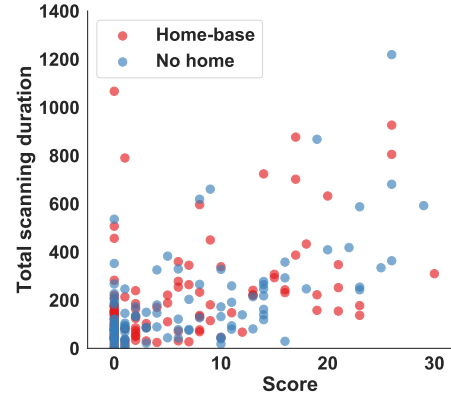

Figure 6: Correlation between the total duration of perceptual events and score, separated by home-base (red) and no-home (blue) players.

ergetically costly (and time consuming) long segments with less costly shorter ones. By contrast, at the scale of perceptual search, μ estimates for scan segments were far from the optimal two and instead appeared to improve as they approached 1. This difference implies that Lévy-like search patterns depend on the type of search behavior engaged. In the absence of energetic costs (and lower time costs), longer perceptual scans have greater utility and hence shift the optimal μ towards 1.

At the level of whole search trajectories, efficient search depended on the constraint of reporting temples back to the home base. MSD analyses yielded far-ranging, super-diffusive trajectories without a home base constraint, versus tighter, sub-diffusive trajectories with home base. Thus, the home base had an effect on the whole trajectories that was not present at the level of path segments. The home base served as a resource akin to a temple, i.e. a structure to be located. However, unlike temples, the home base was a resource that players could return to repeatedly as they found temples, reported them back to base, and then embarked on another excursion to find more temples. The function of the home base introduced a broader level of constraint on the non-local search, but not on the local path segments. The emergence of home range in home-base condition is a direct spatial expression (Börger, Dalziel, & Fryxell, 2008) of the multi-scale nature of efficient foraging strategy. An efficient foraging strategy should involve an adequate exploration of the environment, which should be balanced by energetically-optimal exploitation. This trade-off operates on multiple scales; on one scale, it manifests as a balance between many short-step sizes and a few long-step sizes, while, on a larger scale, it may lead to the emergence of a home range (Kazimierski, Abramson, & Kuperman, 2015), (Sakiyama & Gunji, 2016).

Our results call for theories of foraging that explain search patterns at multiple levels, with both intrinsic properties as well as extrinsic effects and constraints. In terms of intrinsic properties, Lévy-like segment distributions may reflect simple heuristics, such as priority-based queuing (Barabási,

2005) or temporal discounting (Namboodiri et al., 2016). These heuristics operate by giving more or less priority to extensive (exploration) versus intensive (exploitation) search patterns (Reynolds et al., 2015). Our results indicate that the balance of these priorities can be controlled separately for different levels of search (movement versus perceptual), and for different scales (local for non-local). Our results also indicate that varying extrinsic constraints can affect diffusive properties of whole search trajectories while keeping the local balance of intensive versus extensive search patterns intact. The findings resemble previous studies that have found a similar distinction between extrinsic and intrinsic factors of search, and suggest how externally influenced search may build upon inherent Lévy-like patterns that increase the chances of random encounters (Salvador et al., 2014; Bartumeus & Levin, 2008; Bartumeus, 2007). The role of cognitive processes underlying such multi-scale patterns and the constraints that shape them need further examination.

Finally, our virtual game environment allowed us to examine foraging as a function of energy expenditure that varied naturally with the terrain. Most notably, maintaining high ground was both energetically and perceptually advantageous, and search trajectories were clearly constrained to maintain this advantage, as can be seen in 2–players tended to move along ridges rather than go down to lower elevations. Considerations of energy and viewpoint affected search trajectories, but further studies and analyses are needed to investigate the nature of these effects. We can also expect trade-offs to occur between intrinsic costs of time and mental effort, and extrinsic costs of energy expenditure, e.g. in making decisions to expend energy to walk up closer to the temples or spending more time to visually scan and plan.

In conclusion, our virtual foraging environment is a platform for studying search processes in conditions that mimic our hunter-gatherer history, yet afford complete control over the environment and measurements of all aspects of search behaviors. Our long-term aim is to use the virtual environment to study human foraging as a quintessential expression of intelligence.

References

Barabási, A. L. (2005, may). The origin of bursts and heavy tails in human dynamics. *Nature*, *435*(7039), 207–211. doi: 10.1038/nature03459

Bartumeus, F. (2007, jun). Lévy processes in animal movement: An evolutionary hypothesis. *Fractals*, *15*(2), 151–162. doi: 10.1142/S0218348X07003460

Bartumeus, F., & Levin, S. A. (2008). *Fractal reorientation clocks: Linking animal behavior to statistical patterns of search* (Vol. 105; Tech. Rep. No. 49). doi: 10.1073/pnas.0801926105

Börger, L., Dalziel, B. D., & Fryxell, J. M. (2008, jun). Are there general mechanisms of animal home range behaviour? A review and prospects for future research. *Ecol-

ogy Letters*, *11*(6), 637–650. doi: 10.1111/j.1461-0248.2008.01182.x

Brown, C. T., Liebovitch, L. S., & Glendon, R. (2007). Lévy flights in dobe Ju/'hoansi foraging patterns. *Human Ecology*, *35*(1), 129–138. doi: 10.1007/s10745-006-9083-4

da Luz, M. G., Raposo, E. P., & Viswanathan, G. M. (2015). And yet it optimizes. Comment on "Liberating Lévy walk research from the shackles of optimal foraging" by A.M. Reynolds. *Physics of Life Reviews*, *14*, 94–98. doi: 10.1016/j.plrev.2015.07.007

Hill, R. A. (2006, feb). Thermal constraints on activity scheduling and habitat choice in baboons. *American Journal of Physical Anthropology*, *129*(2), 242–249. doi: 10.1002/ajpa.20264

Kaushal, M. (2001). Divining the Landscape—the Gaddi and his land. *India International Centre Quarterly*, *27*, 31–40.

Kazimierski, L. D., Abramson, G., & Kuperman, M. N. (2015). Random-walk model to study cycles emerging from the exploration-exploitation trade-off. *PHYSICAL REVIEW E*, *91*(1), 12124. doi: 10.1103/PhysRevE.91.012124

Kerster, B. E., Rhodes, T., & Kello, C. T. (2016). Spatial memory in foraging games. *Cognition*, *148*, 85–96. doi: 10.1016/j.cognition.2015.12.015

Méndez, V., Campos, D., & Bartumeus, F. (2014). Stochastic Foundations in Movement Ecology. *Stochastic Foundations in Movement Ecology*, 321. doi: 10.1007/978-3-642-39010-4

Minetti, A. E., Moia, C., Roi, G. S., Susta, D., & Ferretti, G. (2002, sep). Energy cost of walking and running at extreme uphill and downhill slopes. *Journal of Applied Physiology*, *93*(3), 1039–1046. doi: 10.1152/japplphysiol.01177.2001

Namboodiri, V. M. K., Levy, J. M., Mihalas, S., Sims, D. W., Shuler, M. G., & Hussain Shuler, M. G. (2016, aug). Rationalizing spatial exploration patterns of wild animals and humans through a temporal discounting framework. *Proceedings of the National Academy of Sciences*, *113*(31), 8747–8752. doi: 10.1073/pnas.1601664113

Nurzaman, S. G., Matsumoto, Y., Nakamura, Y., Shirai, K., Koizumi, S., & Ishiguro, H. (2010, oct). An adaptive switching behavior between levy and brownian random search in a mobile robot based on biological fluctuation. In *Ieee/rsj 2010 international conference on intelligent robots and systems, iros 2010 - conference proceedings* (pp. 1927–1934). IEEE. doi: 10.1109/IROS.2010.5651671

Purcell, B. A., & Kiani, R. (2016, aug). Hierarchical decision processes that operate over distinct timescales underlie choice and changes in strategy. *Proceedings of the National Academy of Sciences of the United States of America*, *113*(31), E4531–E4540. doi: 10.1073/pnas.1524685113

Raichien, D. A., Wood, B. M., Gordon, A. D., Mabuiia, A. Z., Marlowe, F. W., & Pontzer, H. (2014, jan). Evidence of Lévy walk foraging patterns in human hunter-gatherers. *Proceedings of the National Academy of Sciences of the United States of America*, *111*(2), 728–733. doi: 10.1073/pnas.1318616111

Reynolds, A. M. (2018, jan). Current status and future directions of Levy walk research. *Biology Open*, *7*(1), bio030106. doi: 10.1242/bio.030106

Reynolds, A. M., Ceccon, E., Baldauf, C., Medeiros, T. K., & Miramontes, O. (2018, jun). Lévy foraging patterns of rural humans. *PLoS ONE*, *13*(6), e0199099. doi: 10.1371/journal.pone.0199099

Reynolds, A. M., Ropert-Coudert, Y., Kato, A., Chiaradia, A., & MacIntosh, A. J. (2015, oct). A priority-based queuing process explanation for scale-free foraging behaviours. *Animal Behaviour*, *108*, 67–71. doi: 10.1016/j.anbehav.2015.07.022

Rhodes, T., Kello, C. T., & Kerster, B. (2014, jul). Intrinsic and extrinsic contributions to heavy tails in visual foraging. *Visual Cognition*, *22*(6), 809–842. doi: 10.1080/13506285.2014.918070

Rosati, A. G. (2017, sep). Foraging Cognition: Reviving the Ecological Intelligence Hypothesis. *Trends in Cognitive Sciences*, *21*(9), 691–702. doi: 10.1016/j.tics.2017.05.011

Sakiyama, T., & Gunji, Y. P. (2016). Emergent weak home-range behaviour without spatial memory. *Royal Society Open Science*, *3*(6). doi: 10.1098/rsos.160214

Salvador, L. C., Bartumeus, F., Levin, S. A., & Ryu, W. S. (2014). Mechanistic analysis of the search behaviour of Caenorhabditis elegans. *Journal of the Royal Society Interface*, *11*(92). doi: 10.1098/rsif.2013.1092

Sims, D. W., Humphries, N. E., Hu, N., Medan, V., & Berni, J. (2019). Optimal searching behaviour generated intrinsically by the central pattern generator for locomotion. *eLife*, *8*, 1–31. doi: 10.7554/eLife.50316

Todd, P. M., Hills, T. T., & Robbins, T. W. (2012). *Cognitive search: Evolution, algorithms, and the brain* (Vol. 9). MIT press.

Viswanathan, G. M., Da Luz, M. G., Raposo, E. P., & Stanley, H. E. (2011). *The physics of foraging: An introduction to random searches and biological encounters* (Vol. 9781107006). Cambridge: Cambridge University Press. doi: 10.1017/CBO9780511902680

Wilson, R. P., Quintana, F., & Hobson, V. J. (2012, mar). Construction of energy landscapes can clarify the movement and distribution of foraging animals. *Proceedings of the Royal Society B: Biological Sciences*, *279*(1730), 975–980. doi: 10.1098/rspb.2011.1544