

# Movement and spatial specificity support scaling in ant colonies and immune systems: Application to national biosurveillance

Tatiana Flanagan<sup>1,2</sup> Walt Beyeler<sup>2</sup> Drew Levin<sup>2</sup> Patrick Finley<sup>2</sup> Melanie Moses<sup>1</sup>

1. Department of Computer Science, University of New Mexico, Albuquerque, New Mexico
2. Sandia National Laboratories, Albuquerque, New Mexico

Corresponding author: Tatiana Flanagan, [tpflana@sandia.gov](mailto:tpflana@sandia.gov)

Data obtained from biosurveillance can be used by public health systems to detect and respond to disease outbreaks, and save lives. However, existing data is distributed across large geographic areas, and both the quality and type of data vary in space and time. We discuss a framework for analyzing biosurveillance information to minimize detection time and maximize detection accuracy while scaling the analysis over large regions. We propose that strategies used by canonical biological complex systems, which are adapted to diverse environments, provide good models for the design of a robust, adaptive and scalable biosurveillance system. Drawing from knowledge of the adaptive immune system, and ant colonies, we examine strategies that support the scaling of detection in order to search and respond in large areas with dynamic distributions of data. Based on this research, we discuss a bio-inspired approach for a distributed, adaptive, and scalable biosurveillance system.

## Introduction

Analyzing and responding to biosurveillance information is fundamental for the health of modern societies. Strategies for the detection of disease outbreaks have received considerable attention from researchers and policymakers, but making the development of a detection and actionable analysis approach scalable over large areas, and applicable to diverse populations, environments and social contexts, remains a formidable challenge. Disease outbreaks are inevitable, and early detection is necessary for adequate containment. However, more data exist than can effectively be analyzed, and those data are distributed across large geographic areas. Further, data sources are diverse (Gajewski et. al 2014, Althouse et al. 2015), noisy, variable in space and time, and have locally distinct contexts that can affect their interpretation. Therefore, intelligent, distributed and adaptive sampling, detection and response is required. Sampling and analyzing data with the goals of reducing detection time and maximizing accuracy is challenging. Additionally, scaling results to large and diverse areas is not feasible without a distributed approach. Current biosurveillance architectures that enable both local and global data analysis could also benefit from a scalable approach with decentralized authority to detect and respond.

44  
45 How effectively strategies used by biological systems perceive information depends on how it is  
46 distributed in time and space. Biological systems respond to distributions of information across  
47 time by bet-hedging on uncertain information (Donaldson-Matasci 2001), and evolve rules (aka  
48 algorithms) that produce behaviors, or structures, shaped in response to the dynamics of the  
49 environment (Gordon 2016). Distributed and parallel solutions adapted to the distribution of  
50 resources or information in a system's environment provide efficient strategies and structures  
51 adapted to the distribution of information. Marzen and Dedeo (2017) provide a theoretical  
52 framework for achieving optimal information perception under competing constraints on  
53 accuracy and misclassification. This approach involves the evolution of a perceptual mapping  
54 operating on environmental information where the environment is defined by a stationary  
55 probability distribution as well as by a penalty function that imposes costs for misclassification  
56 by the perceptual mapping. Mapping accuracy is constrained by a cost proportional to the  
57 sophistication of the mapping as measured by the mutual information between the perceived  
58 state and the environment that induces the perception. This work highlights tradeoffs in the  
59 coupling between perception and environment, but focuses on a unitary rather than a distributed  
60 perceptual system.

61  
62 Complex systems in nature have evolved solutions adapted to distributed search and response.  
63 Immune systems and ant colonies scale search and automated response in dynamic environments  
64 using a distributed approach (Banerjee and Moses 2011) in which many agents can sample  
65 information from different locations. Ant colonies and immune systems have evolved solutions  
66 that rely on distributed local sensing to perceive their environment, establish an appropriate  
67 response, and dynamically adapt their response over time according to the spatial distribution of  
68 resources and varying complexity of the environment. The robust, adaptive and scalable  
69 computation realized by biological systems makes them suitable models for addressing problems  
70 that require distributed computation that is adaptive and scalable (Moses et al. 2013).

71  
72 Five RADAR principles proposed by Banerjee and Moses (2011) are common in complex  
73 systems and relevant to all systems that seek to adapt to information from dynamic  
74 environments. These principles are (1) Robustness, achieved by redundancy, flexible diversity  
75 and probabilistic response to partial information, (2) Aadaptation to environment signals, (3)  
76 Decentralized control for search, (4) an Automated Response that is as distributed as the search,  
77 and (5) are scalable to millions of agents, conferring the ability to act in parallel. In previous  
78 work (Banerjee and Moses 2011, Moses et al. 2013), we discussed how each of these principles  
79 is evident in ant colonies and immune systems. Extending this work here, we consider how the  
80 principle of decentralized control and search adapts to a dynamic distribution of resources, and  
81 scales to territory or body size increases. We start by describing biological distributed detection  
82 and search systems. Drawing from the immune system and ant colonies, we discuss the strategies  
83 that support the scaling of search and detection to large areas, and to dynamic distributions of  
84 resources by three adaptations: trafficking, or movement of agents through space; functional  
85 specificity or spatial memory; and hubs or temporary resident structures. Finally, we discuss the  
86 application of these concepts to a bio-inspired approach for a distributed, adaptive and scalable  
87 biosurveillance system.

88  
89

90 **Biological systems**

91  
92 Immune systems and ant colonies use a distributed approach that adapts to dynamic distributions  
93 of pathogens or resources. Millions of ants in a colony, and trillions of cells in the immune  
94 system detect food or pathogens locally and scale efficiently with increase in size. Scale  
95 invariance is relevant to any problem where distributed detection can positively affect the  
96 efficiency of the system. Although ants and immune systems are spatially constrained, with  
97 behavior clearly adapted to their environment and the use of movement, memory, and local and  
98 global information balance, these systems accomplish their tasks efficiently regardless of  
99 organism or territory size (Banerjee and Moses 2011).

100

101 *The immune system*

102

103 It is unusual for biological systems to be scale invariant. Metabolic scaling theory proposes that  
104 most biological rates systematically slow as a function of body size due to the overhead of  
105 centralized transport and energy (West et al. 1997, Banavar et al. 2010). Whether immune  
106 response times systematically slow with body size is an important theoretical question (Weigel  
107 and Perelson 2004, 2009; Althaus 2015). There is some evidence of differences in immune cost,  
108 replication rates, and resulting duration of infectivity due to body size (Blaze et al 2017, Althaus  
109 2015, Banerjee, Perelson and Moses 2017). However scaling theory would predict that humans  
110 (10,000 times larger than mice) would have immune response times 10 times slower than mice;  
111 this has not been observed. We hypothesize that the apparent scale invariance of immune  
112 response is due to RADAR principle 3, decentralized search, an example of decentralized  
113 processing of information. We propose that scalability is achieved in the immune search for  
114 pathogens through three factors, trafficking, memory or functional specificity, and  
115 communication.

116

117 Mammals rely on their immune system to detect and react to invading pathogens whose  
118 distribution in the body varies over time and space. Despite this dynamic environment, and  
119 widely varying body sizes, immune response times are nearly scale invariant (Banerjee and  
120 Moses 2011). When communication and actions are executed locally, each cell can respond  
121 quickly regardless of the size of the system. Distributed processing and the absence of central  
122 control lead to immune system computation that is highly scalable, through a combination of  
123 strategies such as T cell trafficking, functional specificity, and a balance of local and global  
124 communication. Trafficking and specificity allow for better homing to a particular tissue (Wong  
125 et al. 2016), thus enabling search strategies to adapt to local context and larger areas. All these  
126 strategies are all supported by dynamic structures in the immune system that support the  
127 adaptations of search to local context, and larger areas.

128

129 Immune cells *traffic* through the body via a partially decentralized infrastructure: the lymphatic  
130 network transports immune cells to local regions where they either identify pathogens in lymph  
131 nodes or kill pathogens in tissue. In contrast to the systemic, centralized movement of cells  
132 through the cardiovascular network, immune cells traffic to particular tissues and recirculate  
133 between tissues and the local lymph nodes, through the lymphatic network in a way that balances

134 local and global movement of immune cells (Moses 2011, Banerjee & Moses 2011). The  
135 trafficking of T cells is a dynamic process. Following their development in the thymus, naïve T  
136 cells continually circulate throughout the body until they encounter foreign pathogens. When  
137 naïve T cells recognize a pathogen, they divide and express molecules that help fight infection.  
138 Of this new population, 90–95% undergoes apoptosis, the rest remain close to the site of  
139 infection.

140  
141 As immune cells circulate, some stay close to the tissues where a pathogen is likely to reside.  
142 Human T cells have unique phenotypes with different degrees of tissue *specificity* (Wong et al.  
143 2016). Surviving T cells give rise to long-lived memory populations (Nolz et al. 2011). Resident  
144 memory T cells mediate immune memory, which generates long-lived non-recirculating cells  
145 that reside within the originally infected tissue. These cells are superior to circulating T cells at  
146 providing rapid long-term protection against re-infection in specific tissues (Jiang et al. 2012).  
147 In contrast to re-circulating T cells, resident T cells are positioned for rapid detection and  
148 response. Once a virus is detected, resident T cells respond to an infection by using the local  
149 tissue environment to recruit immune cells (Rosato et al. 2016). To ensure *communication* of  
150 learned pathogens throughout the body, a proportion of memory T cells, like naïve cells,  
151 circulate throughout the body until they are needed (Omilusik and Goldrath 2017). Memory T  
152 cells are maintained by continual recruitment of new cells from the circulation, suggesting a  
153 dynamic memory in the immune system that depends on a systemic source (Ely et al. 2006).

154  
155 *Local and dynamic structures* throughout the body support efficient search and response  
156 strategies. Search is focused in small lymph nodes where antigen-bearing cells are concentrated.  
157 Immune cells conduct efficient parallel search in lymph nodes where immune cells are  
158 introduced to potential pathogens in a small search space. Immune cell movement is evolved to  
159 sample multiple pathogens quickly (Fricke et al. 2016). Immune cells are guided by chemokines  
160 (Banerjee et al. 2011, Levin 2016) and structural cues (Mrass et al. 2017) in tissues. Guidance to  
161 sites of infection particularly speeds up search in large animals more than in small animals,  
162 decreasing time to clear infection in humans by orders of magnitude more than in mice (Banerjee  
163 et al. 2010).

164  
165 To support dynamic specificity of local search and response strategies, the immune system  
166 evolved temporary resident structures that allow the immune system to dynamically adapt to its  
167 environment. One such structure is the inducible bronchus-associated lymphoid tissue (iBALT),  
168 an immune system structure that develops in lung tissue in response to tissue inflammation.  
169 Present in larger numbers when local inflammation is chronic, iBALTs provide a local site for T  
170 cell priming and B-cell education to clear future infections in nearby tissue and enhance  
171 protective immunity against future respiratory pathogens (Foo et al. 2010).

172  
173 An efficient and proportionate response derives from having distributed memory realized  
174 through circulating and resident memory T cells. Antibodies are produced faster and more  
175 efficiently where the body experiences the same disease in the same general location. Thus a  
176 memory and movement dependent efficiency of response and proportionate response (not  
177 overreacting to the threat) are essential features of well-trained immune systems.

178

179 Distributed processing and the absence of central control in the immune system lead to scalable  
180 processing and response. Scalability is realized through a combination of T cell trafficking,  
181 functional specificity, and a balance of local and global communication. All of these factors,  
182 which make the immune system scalable, are possible because the immune system uses  
183 decentralized recognition of self from others that may be potential pathogens, and remembers  
184 previously encountered pathogens (Von Boehmer 1990) so that, for example, T cells are able to  
185 kill cells in tissue without any centralized input: negative selection ensures that T cells attack  
186 only non-self cells. Negative selection is the hallmark of the adaptive immune system enabling  
187 encoding of self and other. In scaling, these strategies, supported by dynamic structures, adapt  
188 search to local context, and larger areas.

189

190

### 191 *Ant colonies*

192

193 Ant colonies rely on individual foragers to search for food sources and bring them back to the  
194 colony. The distribution of these resources varies in space and time, so ant colonies use diverse  
195 foraging strategies (Lanan 2014) that emerge in response to direct and indirect social cues  
196 (Gordon 2010). Distributed foraging and lack of central control in ant colonies lead to scalable  
197 foraging and response. Scalability in ant foraging is achieved through a combination of foraging  
198 behaviors that involve distributed movement of individual ants, learning, remembering, and  
199 communicating the location of food resources. These foraging strategies are all supported by  
200 dynamic colony structures, nests and trails, and adapt to local context and territory size. We  
201 hypothesize that scalability of foraging in ant colonies, like the immune system, is due to  
202 RADAR principle 3, decentralized search, a means to process distributed information. This is  
203 possible through three strategies, autonomous movement of individual ants, memory, and  
204 communication that allows the colony to learn from individual sampling of information.

205

206 The *movement* of individual ants in a colony reflects different strategies to retrieve food for the  
207 colony. The repertoire of foraging behaviors reflects the distribution of resources (Levin 2015).  
208 In prior modeling work we demonstrated that ant colonies effectively use different collective  
209 foraging strategies that respond to these distributions by combining a small set of simple  
210 behaviors tuned for a particular environment (Letendre et al. 2013, Hecker et al. 2015). These  
211 combined strategies make for effective search among large numbers of individuals connected by  
212 a distributed communication network. The resulting behaviors are not directed by any individual  
213 ant but, rather, emerge from interactions among individuals and from the interaction of the  
214 individuals with its local environment, where ants perceive information about the distribution of  
215 resources in their territory using only local sensing. An individual ant can learn and *memorize*  
216 information about the location of resources only from a small portion of its environment and  
217 respond to local conditions. However, the sampling of environmental information by ants  
218 through their movement, individual sensing, and *communication* among them through local  
219 interactions tends to overcome individual errors, improving collective function on average. The  
220 combination of movement, memory and local perception paired with communication increases  
221 the repertoire of responses to varying quality of foraging sites.

222

223 As colonies and their territories grow, search and communication strategies must vary  
224 accordingly. Ant colonies use additional behaviors and *dynamic structures* that allow them to

225 retain efficiency when searching. In large ant colonies, energy constraints prevent moving  
226 resources to one central nest. In response, ant colonies choose to deploy temporary structures  
227 (nests or trails) closer to locations where resources are more likely to occur. In a strategy  
228 analogous to the immune system, ant colonies distribute their nests, making their foraging  
229 spatially specific to a smaller area and allowing them to use behaviors adapted to the local  
230 environment. This is the case in polydomous ant colonies, which have evolved strategies to deal  
231 with the diminishing returns of central place foraging by establishing multiple interconnected  
232 nests with decentralized foraging. Argentine ants support distributed, adaptive foraging through  
233 dynamic foraging structures (nests and trails) that exist only when needed. Ephemeral trails  
234 connect to persistent trails, providing efficient routing, just as with virtual networks like cell  
235 phone towers (Flanagan et al. 2013).

236  
237 The ability of ant colonies to scale foraging to large territories using distributed, dynamic and  
238 adaptive structures leads to scalable processing and response. Like the immune system, ant  
239 colonies can efficiently scale to large territories through a combination of movement, local  
240 foraging, and a balance of local and global communication; they support these strategies by  
241 establishing dynamic support structures, temporary nests and ephemeral trails.

242  
243

#### 244 **Scale invariant biosurveillance**

245  
246 From these principles and scaling strategies used by biological systems we posit that memory  
247 and movement are fundamental properties of adaptive biosurveillance. To maximize  
248 representation accuracy and minimize detection time, a combination of trafficking and spatial  
249 specificity is necessary. This can be achieved by sampling adaptively and locally, matching the  
250 dynamic distribution of information in space and time, through deployment of distributed motile  
251 sensors, which can become specific and reside in the local environment, and through structures  
252 that create, and allow sensors to learn and respond in close proximity. The number, spatial  
253 distribution, functionality, and behavior of sensors will depend on the distribution of information  
254 and local context. To *maximize representation accuracy*, trafficking sensors are necessary to  
255 detect information that is randomly distributed in space or time. Once information clusters are  
256 found, more communication between sensors can lead to an efficient response. To *minimize*  
257 *detection time*, the use of individual memory, resident detectors, and physical structures  
258 analogous to temporary ant colony structures, memory cells, and iBALT can quickly respond to  
259 localized events or information, regardless of scale.

260  
261 Ants and immune systems have evolved strategies that solve distributed search and  
262 communication problems (Prabhakar 2012, Dorigo 2006). Some of these strategies mirror or  
263 inspire engineered approaches. The multi-place foraging algorithm for robot swarm by Lu et al.  
264 (2017) is an example of the efficiency provided by dynamic structures in an engineered system  
265 inspired by ant colony behaviors. The study demonstrates how using robotic depots that  
266 dynamically adapt to local information in their environment generates more flexible and scalable  
267 swarms.

268  
269 Due to the expansive size, anticipated growth rate and extent of modern biosurveillance data  
270 feeds, any potential approach must lend itself well to distributed computation. A balance

271 between local and global information processing can achieve detection that is appropriate  
272 geographically and produces optimal response times. Scale invariance in decentralized  
273 information processing systems is a must for information systems that operate over a large  
274 geographical extent, such as national biosurveillance. As with a partially decentralized immune  
275 system, we propose that a scalable design should follow RADAR principles with the addition of  
276 memory and movement for scalability, a system that thinks locally, but can act globally.  
277 Following these principles will result in a system that is:

- 278
- 279 (1) robust, redundant, flexible, and stochastic responses to partial information by using  
280 sensors that utilize stochastic and inferential change detection able to predict, rather than  
281 only statistically describe;
- 282 (2) adaptive to dynamic environmental information through sensors that are capable of  
283 processing multi modal information;
- 284 (3) decentralized through local sampling and detecting, aggregating and analyzing  
285 information locally, using temporary or permanent local nodes as support structures, and  
286 increasing the spatial extent for aggregation of data according to the severity of the  
287 signal;
- 288 (4) automated for efficient responses, distributed according to local detection; and
- 289 (5) scalable to millions of agents through the use of a balance of autonomous trafficking  
290 through space to search for distributed information and to distribute information  
291 remembered locally, utilizing specificity, and resident structures to minimize detection  
292 and response time in a dynamic environment.

293

294 A biosurveillance system consists of detection and analysis of harvested information. Detectors  
295 that are motile, able to learn from local context, use diverse information streams, along with  
296 temporary resident nodes that provide local aggregation can support scalability in a  
297 biosurveillance system. In previous work (Levin 2017), we described the implementation of an  
298 anomaly detector for health data based on the human immune system. Our negative selection  
299 algorithm detects anomalies in the large, complex data from modern health monitoring data  
300 feeds. The parallelized version of the algorithm demonstrates the potential for implementation on  
301 a scalable distributed architecture. Using strategies analogous to distributing search into lymph  
302 nodes of the immune system, these anomaly detectors have the potential to be motile, to be able  
303 to distinguish self and remember encounters with non-self, and to act as trafficking or resident T  
304 cells, making them the perfect detector for a robust, adaptive, and scalable national  
305 biosurveillance system. Figure 1 illustrates our concept of a National Immune Network.  
306 Information nodes can form dynamically according to local information gathered by detectors.  
307 By varying cluster size and number of connections, we achieve an optimal global detection time  
308 and immediate local detection  $O(\log(n/c))$ , where  $n$  is the number of nodes, and  $c$  is the number  
309 of nodes in a cluster. This ‘densification’ is an emergent property of technological networks  
310 (Kleiberg 2004).

311

312 There are a number of biosurveillance scenarios that would improve using dynamic, adaptive  
313 detection, local training and residence, and global sharing of information. Biosurveillance efforts  
314 need to balance memory of events that occur in a specific spatial context while recognizing the  
315 motility of both people and pathogens that require the motility of detectors. For example, as a

316 result of sporadic cases, New Mexico hospitals are trained to detect bubonic plague in patients,  
317 while most other hospitals in the nation are not. This resulted in the death of a person from New  
318 Mexico when a hospital in South Carolina was not able to make a timely detection (Valentine  
319 1983). In a more recent incident (DePalma 2013), a case of bubonic plague was initially  
320 suspected of being a bio-terrorist attack because it was discovered in New York, a location with  
321 a different epidemiological context than New Mexico, the location where the infection occurred.  
322 Although the spatial incidence of disease may be more likely in some locations than others,  
323 human motility can cause disease spread to span large areas. While local biosurveillance nodes  
324 can develop specialized detectors, ensure the presence of locally trained detectors that work in  
325 combination with specialized nodes, detector motility provides a powerful tool to share detected  
326 information on a global scale. In contrast, Zika is an example of a local outbreak of a virus  
327 endemic to specific regions and recently detected in Florida. The Zika outbreak spurred a  
328 national effort to expand our detection ability. In this case, detectors informed by the local  
329 context can improve the efficiency of biosurveillance by acting locally and communicating  
330 globally only when needed, following the spatial patterns of the spread from the center of an  
331 outbreak to unexpected locations.

332  
333 Using a distributed, adaptive biosurveillance system we can also address questions about health  
334 behaviors such as opioid abuse. How does opioid abuse manifest itself in different regions of the  
335 country? Regional detectors can adapt to the regional context and behavior indicators specific to  
336 patterns of opioid abuse and spread. We can detect behaviors within those regions, and compare  
337 rural versus urban behaviors. A detector for one region may not work as well as a detector for  
338 another, but motile detectors would be a way to combine local context with global  
339 communication and eventually adapt to different regional contexts.

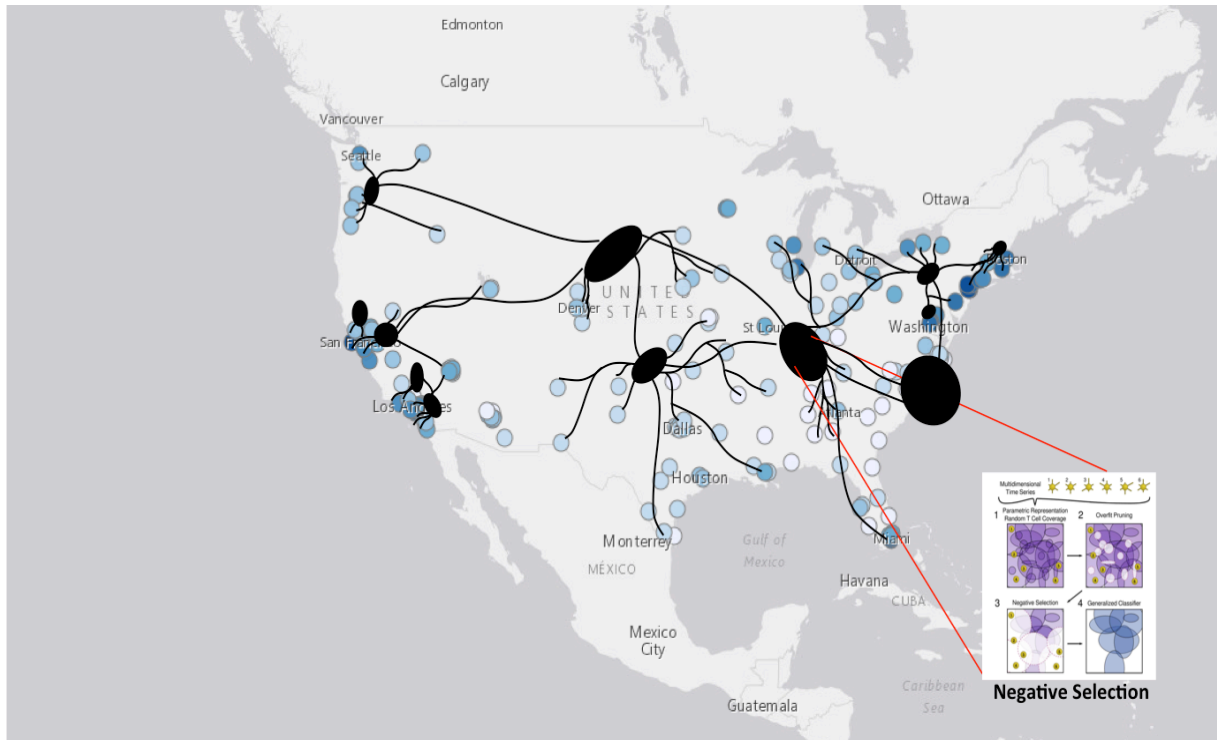
340  
341 The application of RADAR principles is not limited to the implementation of detection and  
342 analysis, it can be used to complement organizational practices in national agencies invested in  
343 biosurveillance. Managing biosurveillance data requires discriminating access to information, for  
344 example due to privacy, national security and other data sharing limitations, but requires  
345 transparency at the same time. RADAR suggests that information sharing can be effective when  
346 information is communicated locally. Regionalization, benchmarking, and sharing best practices  
347 can be seen as organizational analogies for keeping institutional memory/modeling robust in  
348 biosurveillance initiatives.

349  
350 Further studies would benefit from an extended mathematical framework for distributed  
351 perception. To characterize perception accuracy, an approach that perceives environmental  
352 information conditional on the position of perceptual nodes and detectors, and introduces inter-  
353 agent communication with the quantification of associated costs and contributions to accuracy.  
354 This elaboration could be used to understand the relationship between information variability and  
355 distribution/specialization as an optimal detector design, as a function of relevant costs and  
356 communication designs. Immune systems and public health networks reward early detection of  
357 non-stationary processes. To characterize perception delays, penalties associated with delayed  
358 response may be captured as misclassification of stationary processes. Longer-term non-  
359 stationarity is also of interest. We are interested not only in the optimal organization of  
360 perceptual networks, but also in the ability of that organization to efficiently track dynamics of  
361 the environmental signal over time. Studying the properties of optimal solutions will be helpful,



362 however attention to the processes driving structural dynamics will be needed for a design  
363 approach that utilizes different perspectives.

364  
365  
366  
367  
368



369  
370  
371 **Figure 1. A bio-inspired disease surveillance system** with distributed information processing in information nodes  
372 (lymph nodes). shown as black ovals. The flow of information towards and between nodes is shown as black lines.  
373 Blue circles represent population density according to shade; darker shades of blue are more densely populated than  
374 lighter shades. Each node concentrates and processes information.

375  
376

### 377 **Acknowledgements**

378  
379 We gratefully acknowledge funding from a Sandia National Laboratories Academic Alliance  
380 LDRD Award. TPF and MEM also acknowledge funding from the McDonnell Foundation  
381 Complex Systems Scholar Award. We also thank Judy Cannon for her insightful guidance on  
382 immune system memory cells, Stephanie Forrest for insightful discussions about negative  
383 selection and its relevance to biosurveillance, and Louise Maffitt for helpful editing suggestions.

384  
385 Sandia National Laboratories is a multimission laboratory managed and operated by National  
386 Technology & Engineering Solutions of Sandia, LLC, a wholly owned subsidiary of Honeywell  
387 International Inc., for the U.S. Department of Energy's National Nuclear Security Administration

388 under contract DE-NA0003525. The views expressed in the article do not necessarily represent  
389 the views of the U.S. Department of Energy or the United States Government.

390

391

392 **Literature cited**

393

394 Althaus, Christian L. "Of mice, macaques and men: scaling of virus dynamics and immune  
395 responses." *Frontiers in microbiology* 6 (2015): 355.

396

397 Banavar, Jayanth R., Melanie E. Moses, James H. Brown, John Damuth, Andrea Rinaldo,  
398 Richard M. Sibly, and Amos Maritan. "A general basis for quarter-power scaling in animals."  
399 *Proceedings of the National Academy of Sciences* 107, no. 36 (2010): 15816-15820.

400

401 Banerjee, Soumya, and Melanie E. Moses. "Scale invariance of immune system response rates  
402 and times: perspectives on immune system architecture and implications for artificial immune  
403 systems." *Swarm Intelligence* 4, no. 4 (2010): 301-318.

404

405 Banerjee, Soumya, Alan S. Perelson, and Melanie Moses. "Modelling the effects of phylogeny  
406 and body size on within-host pathogen replication and immune response." *Journal of The Royal  
407 Society Interface* 14, no. 136 (2017): 20170479.

408

409 Banerjee, Soumya, Drew Levin, Melanie Moses, Frederick Koster, and Stephanie Forrest. "The  
410 value of inflammatory signals in adaptive immune responses." In *International Conference on  
411 Artificial Immune Systems*, pp. 1-14. Springer, Berlin, Heidelberg, 2011.

412

413 Brace, Amber J., Marc J. Lajeunesse, Daniel R. Ardia, Dana M. Hawley, James S. Adelman,  
414 Katherine L. Buchanan, Jeanne M. Fair, Jennifer L. Grindstaff, Kevin D. Matson, and Lynn B.  
415 Martin. "Costs of immune responses are related to host body size and lifespan." *Journal of  
416 Experimental Zoology Part A: Ecological and Integrative Physiology* 327, no. 5 (2017): 254-  
417 261.

418

419 DePalma Anthony. "Reliving the nightmare of plague, 10 years on". *The New York Times,  
420 Health*, January 7, 2013. URL: [https://www.nytimes.com/2013/01/08/health/when-the-plague-  
421 came-to-new-york.html](https://www.nytimes.com/2013/01/08/health/when-the-plague-came-to-new-york.html). Accessed on 3/26/2018. A version of this article appears in print on  
422 January 8, 2013, on Page D5 of the New York edition with the headline: Reliving Nightmare Of  
423 Plague, 10 Years On.

424

425 Donaldson□Matasci, Matina C., Carl T. Bergstrom, and Michael Lachmann. "The fitness value  
426 of information." *Oikos* 119, no. 2 (2010): 219-230.

427

428 Dorigo Marco, Gambardella L, Birattari M, Martinoli A, Poli R, et al.. (2006) Ant Colony  
429 Optimization and Swarm Intelligence: 5th International Workshop, ANTS 2006, Brussels,  
430 Belgium, September 4–7, 2006, Proceedings: Springer.

431

432 Ely, Kenneth H., Tres Cookenham, Alan D. Roberts, and David L. Woodland. "Memory T cell  
433 populations in the lung airways are maintained by continual recruitment." *The Journal of*  
434 *Immunology* 176, no. 1 (2006): 537-543.  
435

436 Flanagan, Tatiana P., Noa M. Pinter-Wollman, Melanie E. Moses, and Deborah M. Gordon.  
437 "Fast and flexible: Argentine ants recruit from nearby trails." *PloS one* 8, no. 8 (2013): e70888.  
438

439 Foo, S. Y., and S. Phipps. "Regulation of inducible BALT formation and contribution to  
440 immunity and pathology." *Mucosal immunology* 3, no. 6 (2010): 537.  
441

442 Fricke, G. Matthew, Kenneth A. Letendre, Melanie E. Moses, and Judy L. Cannon. "Persistence  
443 and adaptation in immunity: T cells balance the extent and thoroughness of search." *PLoS*  
444 *computational biology* 12, no. 3 (2016): e1004818.  
445

446 Gajewski, Kimberly N., Amy E. Peterson, Rohit A. Chitale, Julie A. Pavlin, Kevin L. Russell,  
447 and Jean-Paul Chretien. "A review of evaluations of electronic event-based biosurveillance  
448 systems." *PloS one* 9, no. 10 (2014): e111222.  
449

450 Gordon, Deborah M. *Ant encounters: interaction networks and colony behavior*. Princeton  
451 University Press, 2010.  
452

453 Gordon, Deborah M. "The evolution of the algorithms for collective behavior." *Cell systems* 3,  
454 no. 6 (2016): 514-520.  
455

456 Hecker, Joshua P., and Melanie E. Moses. "Beyond pheromones: evolving error-tolerant,  
457 flexible, and scalable ant-inspired robot swarms." *Swarm Intelligence* 9, no. 1 (2015): 43-70.  
458

459 Jiang, Xiaodong, Rachael A. Clark, Luzheng Liu, Amy J. Wagers, Robert C. Fuhlbrigge, and  
460 Thomas S. Kupper. "Skin infection generates non-migratory memory CD8+ T RM cells  
461 providing global skin immunity." *Nature* 483, no. 7388 (2012): 227.  
462

463 Kleinberg, Jon. "The small-world phenomenon and decentralized search." *SIAM News* 37, no. 3  
464 (2004): 1-2.  
465

466 Lanan, Michele. "Spatiotemporal resource distribution and foraging strategies of ants  
467 (Hymenoptera: Formicidae)." *Myrmecological news/Osterreichische Gesellschaft fur*  
468 *Entomofaunistik* 20 (2014): 53.  
469

470 Letendre, Kenneth, and Melanie E. Moses. "Synergy in ant foraging strategies: memory and  
471 communication alone and in combination." In *Proceedings of the 15th annual conference on*  
472 *Genetic and evolutionary computation*, pp. 41-48. ACM, 2013.  
473

474 Levin, Drew, Joshua P. Hecker, Melanie E. Moses, Stephanie Forrest, G. Matthew Fricke, Sarah  
475 R. Black, Judy L. Cannon et al. "Volatility and spatial distribution of resources determine ant  
476 foraging strategies." In *Proceedings of the European Conference on Artificial Life (ECAL)*.  
477 (2015).

478  
479 Levin, Drew, Stephanie Forrest, Soumya Banerjee, Candice Clay, Judy Cannon, Melanie Moses,  
480 and Frederick Koster. "A spatial model of the efficiency of T cell search in the influenza-infected  
481 lung." *Journal of theoretical biology* 398 (2016): 52-63.  
482  
483 Levin, Drew, Melanie E. Moses, Tatiana P. Flanagan, Stephanie Forrest, and Patrick D. Finley.  
484 "Negative selection based anomaly detector for multimodal health data." *IEEE Symposium*  
485 *Series on Computational Intelligence (SSCI)* (2017).  
486  
487 Lu, Qi, Joshua P. Hecker, and Melanie E. Moses. "Multiple-place swarm foraging with dynamic  
488 depots." *Autonomous Robots* (2018): 1-18.  
489  
490 Marzen, Sarah E., and Simon DeDeo. "The evolution of lossy compression." *Journal of The*  
491 *Royal Society Interface* 14, no. 130 (2017): 20170166.  
492  
493 Moses, Melanie, and Soumya Banerjee. "Biologically inspired design principles for scalable,  
494 robust, adaptive, decentralized search and automated response (radar)." In *Artificial Life*  
495 *(ALIFE), 2011 IEEE Symposium on*, pp. 30-37. IEEE, 2011.  
496  
497 Moses, Melanie, Tatiana Flanagan, Kenneth Letendre, and Matthew Fricke. "Ant colonies as a  
498 model of human computation." In *Handbook of human computation*, pp. 25-37. Springer, New  
499 York, NY, 2013.  
500  
501 Mrass, Paulus, Sreenivasa Rao Oruganti, G. Matthew Fricke, Justyna Tafoya, Janie R. Byrum,  
502 Lihua Yang, Samantha L. Hamilton, Mark J. Miller, Melanie E. Moses, and Judy L. Cannon.  
503 "ROCK regulates the intermittent mode of interstitial T cell migration in inflamed lungs." *Nature*  
504 *communications* 8, no. 1 (2017): 1010.  
505  
506 Nolz, Jeffrey C., Gabriel R. Starbeck-Miller, and John T. Harty. "Naive, effector and memory  
507 CD8 T-cell trafficking: parallels and distinctions." *Immunotherapy* 3, no. 10 (2011): 1223-1233.  
508  
509 Omilusik, Kyla D., and Ananda W. Goldrath. "The origins of memory T cells." *Nature* 552, no.  
510 7685 (2017): 337-339.  
511  
512 Perelson, Alan S., and Frederik W. Wiegel. "Scaling aspects of lymphocyte trafficking." *Journal*  
513 *of theoretical biology* 257, no. 1 (2009): 9-16.  
514  
515 Prabhakar, Balaji, Katherine N. Dektar, and Deborah M. Gordon. "The regulation of ant colony  
516 foraging activity without spatial information." *PLoS computational biology* 8, no. 8 (2012):  
517 e1002670.  
518  
519 Rosato, Pamela C., Lalit K. Beura, and David Masopust. "Tissue resident memory T cells and  
520 viral immunity." *Current opinion in virology* 22 (2017): 44-50.  
521  
522 von Boehmer, Harold. "Developmental biology of T cells in T cell-receptor transgenic mice."  
523 *Annual review of immunology*, no. 1 (1990): 531-556.

524  
525 West, Geoffrey B., James H. Brown, and Brian J. Enquist. "A general model for the origin of  
526 allometric scaling laws in biology." *Science* 276, no. 5309 (1997): 122-126.  
527  
528 Wiegel, Frederik W., and Alan S. Perelson. "Some scaling principles for the immune  
529 system." *Immunology and cell biology* 82, no. 2 (2004): 127.  
530  
531 Wong, Michael Thomas, David Eng Hui Ong, Frances Sheau Huei Lim, Karen Wei Weng Teng,  
532 Naomi McGovern, Sriram Narayanan, Wen Qi Ho et al. "A high-dimensional atlas of human T  
533 cell diversity reveals tissue-specific trafficking and cytokine signatures." *Immunity* 45, no. 2  
534 (2016): 442-456.  
535  
536 Valentine, Paul. "Bubonic Plague Feared in Death Of Girl in S.C.". *The Washington Post*,  
537 August 4th, 1983. URL: <http://www.washingtonpost.com> Accessed on 3/6/2018.