

## Autonomous search by robots and animals: A survey

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### Abstract

This paper is a survey of research on autonomous search strategies which originate in engineering and biology. Our motivation is to identify methods of search in an essentially two-dimensional Euclidean space, which can be applied to the area of demining. Such search strategies are based on spatio-temporal distributions. These distributions may be known in advance, because of prior intelligence or through the use of remote sensing, or they may be the result of on-line gathering of information as the search progresses, or of both. We first review the literature on search and coordination which emanates from the field of robotics, we then summarize significant research in the field of animal search, and also discuss relevant results in robotics which are inspired by animal behavior.

*Keywords:* Natural search; Optimized search strategies; Robotics; Search for explosive mines

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### 1. Introduction

This paper is a survey of research on autonomous search strategies which originate in engineering and biology. Our motivation is to identify methods of search in an essentially two-dimensional Euclidean space, which can be used in the area of demining. Such search strategies are based on spatio-temporal distributions. These distributions may be known in advance, because of prior intelligence or through the use of remote sensing, or they may be the result of on-line gathering of information as the search progresses, or both. Indeed, the spatial distribution of mines, whether known beforehand, or learned in the process of detection, or based on both kinds of information, will have a major impact on how the mine sensors and detectors must be deployed and moved

in the minefield. Spatial distributions of the mines, or more generally of the objects being searched for, can be regular, totally random, patchy or graded. Search strategies are affected by these distributions and need to be optimized for various environments.

When the distribution is patchy, encountering one object should raise the estimate of finding other objects in the vicinity. An efficient strategy in patchy environments from behavioral biology is to increase the rate of turning when the rate of object encounter increases. For graded distributions, it can be shown that the optimal strategy is to travel up the gradient to reduce turning rate while the gradient slope is positive. Thus in the sequel we will survey work on navigation and search which may be relevant both from the field of robotics, and from research on animal foraging and behavior.

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## 2. Autonomous navigation of robots and agents

According to an early discussion [30], autonomous navigation in a multi-dimensional environment raises two main questions: (1) what is an adequate representation of the world, and (2) what should be the location of the robot(s) in this map at any given time. Given an initial location, the robot must find a continuous path in an environment through obstacles whose spatial locations are known or are being discovered. This continuous path cannot always be predetermined because information about the path and the obstacles is often only available *on-line*. In the specific context of demining, the autonomous agent has to sense the contents of the terrain where it currently resides as well as of its immediate neighborhood, and it must make decisions about the “*next step*” as it collects information. In [30] comparisons are made between robotic navigation and three great sailors of the past: Magellan, Columbus, and Ulysses. Magellan knows where all the obstacles are located, and has to come up with a map of the world by navigating around the obstacles. Columbus does not know anything, and has to discover all the environment and the obstacles and, like Magellan, Columbus must create a map. Ulysses has a complete global map, but the environment changes often due to the will of the Gods against Ulysses’ travels; in his case we could consider that the map is composed of static and dynamic areas.

In another study [37] *Clustering by discovery* is discussed. Landmarks are present in the environment considered; They can be detected by the sensors of the robot during the exploration. We define a logical road (*LR*) is a straight line between two landmarks. The physical road (*PR*) considers the real shapes of the obstacles. During motion, the symbolic mobile “builds” a map with the landmarks already defined. There are two kinds of maps: Topological maps describe the pattern of landmarks and their connections with the *LR*, while metric maps give the position of each landmark in a Cartesian space. The knowledge of these two maps permits the partitioning of space into clusters which depend on the scale and the environment. Clustering by discovery is then the technique for identifying clusters in a map being learned by exploration. The clustering problem consists in finding the optimized partition of a given set of points called landmarks in clusters. Clusters may change during the motion of the robot

in the environment. There are different types of partitions: *edge based* and *vertex based*, characterized by clusters of edges linked by *border sets* and by clusters of vertices connected by *bridge sets*. Clustering defines a new topology of the environment which can be used for optimized navigation.

Another approach, the *artificial potential field* method was first developed in [32] and subsequently in [1,2,12,15,50,65] to solve robotic motion planning problems. In the path finding problem, the mobile agent must find a collision-free path starting from a given initial position to a given goal, avoiding a set of obstacles. This problem is a typical application of the artificial potential field method, where each obstacle exerts a repulsive force on while the goal exerts an attractive one. As an example, in [28], an algorithm based on an artificial potential field and a *hierarchical cell decomposition technique* is given. A hexagon is labeled *passable* or *impassable*. The advantages of using this partitioning is that each hexagon can be recursively divided into a set of smaller ones and they each have six immediate neighbors whose distance between centers are equal. That is not the case for a decomposition into squares. As we begin the search, the robot will be at the center of a hexagon. From this place it has to move towards the goal. The search algorithm will examine the neighboring hexagons. It computes the potential of the hexagons that are *passable*. It selects the best one, according to the algorithm, and the robot moves towards it. If there are obstacles on the selected hexagon, it is labeled *mixed*, then decomposed, and the search step is decreased. If there are no obstacles, the step is unchanged or even increased. This method insures that, in the worst case, the mobile agent will not take a direction opposite to its goal, but will instead try to go around the obstacle. This approach is thus a permanent progression around the optimal direction, namely the straight line, from the starting point to the goal.

One difficulty of the artificial potential field method is that the mobile agent may be caught in local minima (e.g., a “trap”) rather than a global minima (i.e., the goal position). Methods to avoid this problem and to insure convergence to global minimum include the use of special potential functions and methods to escape local minima [33,35].

An approach to autonomous navigation is discussed in [67], with the example of HERMIES-IIB

(hostile-environment robotic machine intelligence experiment series) which has been built to perform complex navigations and manipulations in a hostile environment with imprecise sensory information. Algorithms have been implemented to search an optimum path to the goal, considering the size and the shape of the robot, combining the knowledge of the environment with the data from different sensors. A network of nodes and node-connections is given to the robot as an initial navigation map. The different locations where work has to be performed are also known, and this knowledge specifies the areas where HERMIES-IIB has to perform predetermined tasks. Each work location is associated with a time allowed to complete the task. For each mission, the robot examines the different times and paths for an optimized motion. If during the navigation on the selected path an obstacle is detected, the robot goes back to the previous node and checks a new path from this new origin. If this subgoal is reachable with the new time constraint, it goes forward. If not, it goes back to the first starting point, and tries to find another location to perform work. HERMIES-IIB is a powerful research tool, but is rather limited as a complete autonomous robot.

Learning models that are capable of forming a cognitive map to be used in search and navigation are discussed in [53] using either discrete elements of topographic information, or continuously available and updated information gathered during the search process.

Another recent direction of research is the relation between artificial evolutionary paradigms (known under the term “Genetic Programming”) and the search strategies of animals. In [34] a genetic programming paradigm that genetically breeds a population of computer programs to solve problems is applied to finding an optimal food-foraging strategy for the Caribbean Anolis lizard. Simulation of the adaptive behavior of the lizard is required to evaluate each possible adaptive control strategy considered for the lizard. It is suggested that artificial intelligence, including artificial life studies, may provide metaphors (e.g., an animal may instinctually possess a simple decision rule whose repeated application leads to optimal behavior) for how animals behave adaptively.

An important general issue is the coordination of multiple robots carrying out a joint task. In the search

for mines, both human and robotic teams with identical or dissimilar sensors may be deployed and will then need to be coordinated. Current robotic technologies make it possible to use robots instead of human beings to perform demining by sending many robots to a mine field. In order to demine effectively, the robots are required to avoid interfering with each other, cover the terrain effectively, share the workload, help each other by providing complementary information via different sensors, and be capable of dynamic redistribution in case of robot fatality. Together the robots should patrol their “territory”, detecting and neutralizing mines. Traditional robotic motion planning approaches do not apply here. Besides the intractable computational complexity, we do not have the necessary prior knowledge of the field for planning. The drawbacks of traditional centralized control are high computational and communication complexity, lack of flexibility and of robustness. Therefore a distributed control approach is more suitable for the control of systems of a large number of robots [6,7,11,25,36,38,47,58,64] as well as for systems where information about the environment is being collected or sensed by the robots themselves. In such a distributed-control framework, each robot determines its movement by observing the environment at that moment and applying some pre-defined *control laws*. The main idea is to design control laws such that the robot system as a whole will achieve the given goals, such as collision-free navigation, moving an object, or forming a spatial structure.

Social potential fields [49], where a global controller defines (possibly distinct) pairwise potential laws for ordered pairs of components (i.e., robots, obstacles and objectives) of the system, have also been proposed as a tool to organize collaboration or, at least, non-interference between agents. Social potential fields are more general than the artificial potential field methods used in robotics mentioned above, where in most situations, there is only one dynamic robot among other static components in the system (such as obstacles), so one robot’s behavior will not change the environment. The force laws used in robot motion planning are either attractive force laws assigned to goals or repulsion force laws assigned to obstacles but not both in combination. In the social potential fields method, each robot senses the resultant potential field from all other components (or from neighboring components as an approximation) and acts under the

resultant force. Once the force laws are defined, force calculation can be carried out by individual robots in a distributed manner: thus the control is completely distributed. The force laws are inverse power laws of distances incorporating both attraction and repulsion, and are chosen to reflect the relations of robots, e.g. that they should stay close together or far apart. For example, we can define a force law where attraction dominates for far distance and repulsion dominates for close distance. Such force laws are similar to those found in molecular dynamics, plasma gases, and fluids. It is known that molecules and plasma gases, while obeying simple force laws, form interesting and complex structures and arrangements and exhibit a wide variety of dynamics. These force laws are, however, more general than the usual molecular force laws; in fact the parameters of the force laws, i.e. the constants and the exponents, are chosen arbitrarily by the global controller. Social potential fields allow for the behavioral control of systems of large numbers of robots. Although the basic control model is quite simple, the system can display quite complex and interesting “social” behaviors, in addition to beyond collision free movement. Simulations described in [49] successfully showed the behavior of clustering, guarding and defending against invaders, and they can also display behaviors such as escorting and patrolling. One generally can employ a potential law that is the summation of two terms which are both inverse power functions of distance (with different coefficients and exponents). The negative term, which indicates a repulsive force, dominates when the distance is small (i.e., when the two robots are close), while the positive term, which indicates an attractive force, dominates when the distance is large. Using such a potential law, the robots will converge to a uniform distribution and the neighboring distance is controlled by the parameters of the potential law. A *dispersion law* is one with the coefficients and the exponents set such that the robot will converge to a uniform distribution over a given area. Social potential fields can be applied to the demining task in several different phases: in the migrating phase when a new minefield is discovered and the robots have to move to the newly discovered field, in the dispersing or self-organizing phase when a group of tightly clustered robots spread out and are more or less evenly distributed over the search area, in the demining phase, involving territorial patrol and possi-

ble dynamic redistribution, and in the final gathering phase when the robots, after finishing the job, gather together to be transferred to other places. During different phases, different sets of potential laws are used. A centralized controller can detect the transitions between different phases and broadcast this information to all the robots, so that the robots can learn which set of potential laws to use.

In the demining phase, since the robots are already distributed evenly, the dispersion law will have a lesser effect. On the other hand, individual robots may execute a random walk in order to patrol for and destroy mines within their territory. Moreover, adaptive clustering around a discovered high-density mine area might be achieved with an attractive term between robots and mines. If we set the parameters such that the neighboring distance is small, we obtain a *gathering law*, which will enable the robots gather tightly together but without colliding with each other. In migrating phase, the central controller can designate a single or a few robots as leaders and control their motions explicitly. The rest of the robots, whose motion are governed by a *following law*, will follow the leaders to the new mining field. In a following law, the rest of the robots may feel a stronger potential from the leaders, but a weaker ones from the peers. In the demining phase, since the robots are already distributed evenly, the dispersion law should have a less effect. On the other hand, individual robot may execute a random walk in order to find and destroy mines.

The social potential fields method offers the advantage of being very robust. In contrast to many of the motion planning algorithms, the method does not require precise sensors or precise actuators and inaccuracies can be tolerated.

Related techniques have been used by computer scientists to model and simulate animal behavior for quite unrelated applications such as computer graphics.

### 3. Autonomous search and animal foraging

Nature has many examples of autonomous search, and some of the instances which have been studied most extensively cover the behavior of animals foraging for food. Relevant research on foraging covers a variety of topics:

- Studies that test whether animals forage so as to optimize some currency, such as energy intake per unit time.
- Studies that look at refinements of the currency – taking into account the variance as well as the mean of the intake distribution over time, or looking at the probability of a fatal gap in feeding.
- Research that studies how animals balance conflicting demands – to forage and to mate or scan for predators.
- Studies that look at particular foraging mechanisms (algorithms), usually in the context of optimization: how well does the rule do in comparison with some optimality criterion.
- Research that uses a laboratory analog or model of foraging to explore either empirical variables or theoretical ideas about how foraging works.

Much work has been published on this subject in a variety of sources in psychology and animal behavior. We have selected to survey a number of relatively recent references in order to summarize the flavor of this work, and also to indicate potential sources of ideas and paradigms for artificial organized search strategies.

A typical example of work on a mathematical modeling approach to the study of animal foraging is presented in [45]. Here, a simple instrumental model of the behavior of an animal selecting a diet, exploiting continuous sources of food distributed in patches that are depleted as it feeds, and of animals feeding together, distributing themselves among patches of regenerating food, is compared with variational models, and the appropriateness of such models for the description of the behavior of animals is discussed. This paper is a good example of how an engineering and modeling approach can be used in this area.

Some of the research on animal behavior indicates that the *time cost* incurred during individual foraging trips is much more important than energy cost in terms of maximizing reward over time. This observation is supported by the work described in [31] which investigated the behavior of five blue jays hunting for dispersed, cryptic prey in an operant simulation in which the birds were trained to search projected images for noctuid moths. Each image contained either a single moth or no moth. Each trial was structured so as to simulate traveling between patches, search-

ing within patches, and attacking and handling each moth that was detected. In two experiments in which the travel time between patches was manipulated, increases in travel time produced increased persistence within patches. Although this qualitative effect was predicted by the marginal value theorem, quantitative analyses revealed that the birds were using a strategy that was more sophisticated and more efficient than the simple time-in-patch rule implied by the marginal value theorem.

In [26] a computer model of the searching activity of an ant species, based on quantitative data obtained in the field about search for individual items of food in the open on flat ground on which search paths mapped, is presented. Actual behavior was well described by the model in which individuals went out for the first time to search in a direction determined at random. Individual ants searched in restricted areas, commonly sectors centered on the nest. This behavior was reproduced in the model, as were quantitative aspects of the nest behavior. Communication between ants was not required in the model. In [62] an experiment is designed to distinguish between two models of risk-sensitive feeding behavior: the variance discounting model, which assumes that mean reward levels do not affect preferences over reward variability, and the z-score model which assumes that mean reward levels do affect preferences over variability. Two choices were presented to feeding rufus hummingbirds (*Selasphorus rufus*). One alternative had a higher mean and a higher variance than the other. After measuring preference, the mean of both alternatives was increased by adding the same amount to all possible outcomes. The variance discounting model predicts that such a general shift should not change preferences, but the z-score model predicts that preferences will change. Results support the z-score model. Observational data imply that foraging paths of bumblebees may be determined, in part, by a tendency to visit nearest inflorescences [59]. The angular distributions from the field data were similar to those derived from a computer model in which consumers visited the nearest inflorescences provided that they revisited few flowers. There was no evidence of area-restricted foraging.

In [41] a model was developed for daily patterns of singing and foraging in a small male bird singing for a mate. The bird must balance singing to attract a

mate with the need to forage. Energy expenditure and reserves were used to calculate the optimal pattern by dynamic programming. The cost of energy consumed in singing is not constant throughout the day, being greater in the morning and less in the evening when the birds build up energy reserves for the night. A peak in singing at dawn can come from variability in overnight use of energy. The model is robust to changes in a wide range of parameters and shows that there can be great differences in song level produced at different times in relation to energy and foraging.

Another interesting aspect is the switching in search dynamics for a given population of foragers [46]. Field mark recapture studies and analysis of the behavior of wild female pipevine swallowtail butterflies of different ages were used to distinguish between the alternative mechanisms for the shift in the populations' leaf-shape search mode. Results support the hypothesis that the seasonal shift in searching behavior was due to (1) the successive emergence of naïve females that learn to prefer host species with different leaf shapes and (2) the synchronous switching by experienced foragers from one learned preference to another. A simple model of an environment in which prey are distributed in patches is considered in [40]. Each patch contains at most one item, but items can vary in the ease with which they can be found. The time spent in unsuccessful search on a patch gives information about whether a patch contains an item, and if it does, how difficult that item is to find. Ways in which this information can be used to find the policy that maximizes the mean rate of reward for the environment are outlined, with two examples of studies of blue jays and crows. The examples suggest that the reward rate on the patch must be based on what is expected to happen in the *immediate* future.

Research reported in [14,29] also sheds light on the issue of optimizing behavior during animal foraging. In [29] four male rats were housed in a laboratory environment that simulated foraging costs with barpressing requirements. The rats encountered sequential opportunities to eat meals in two food patches that differed in the size and/or "cost" of food pellets, and accepted more opportunities and ate larger meals in the patch offering the more "profitable food", whether the larger or the lower cost pellets. Despite widely varying patterns of intake between the patches, total daily intake was constant across most conditions. The

degree of difference in the feeding measures between patches was strongly correlated with the relative unit cost of food, and more strongly with the relative rate of food intake, at the feeders. Results contradict a simple, effort-minimization model of optimal foraging, but support the notion that the cost of suboptimal behavior will influence its occurrence.

In [14], patch-use behavior of small bluegill sunfish foraging for chironomid larvae in artificial macrophyte patches is investigated, to examine search patterns and to determine the decision rule used to leave a patch. The subjects were exposed to a sequence of habitats which differed in quality (i.e., total prey density); however, within a habitat all patches were of equal quality. Results show that when foraging in a single patch, the fish encountered prey randomly. Agreement was observed between fish behavior and predictions of a rate decision rule indicated that the decision to leave a patch was based on some estimate of capture rate in the patch. The sunfish generally stayed longer and captured more prey than predicted by a model based on an exponential distribution of intercapture intervals, using "giving-up" times that were longer than optimal. The relationship between rate of prey capture for the habitat and giving-up times was such that it appeared that the sunfish minimized the cost, in terms of a decrease in capture rate, by overestimating the optimal giving-up time.

The work in [68] observed the influence of prey distribution and capture on the search path configuration of the beetle *Gyrinus picipes*. All paths were analyzed before and after prey capture. Prey distribution had little impact on search configuration. However, prey capture caused significant reductions in step length, linear displacement, and path straightness. Thoroughness and turning angle increased significantly after prey capture. A simulation model was developed to analyze influences of search parameters on search efficiency. Simulated search paths did not differ from actual search paths, indicating that the model accurately describes gyrid search behavior. Actual search paths were compared to a simulated Brownian (random) search. Results indicate that gyrid searches are not random. However, search behavior after prey capture was similar to that derived from the Brownian model.

In [56] the problem of how animals keep track of unpredictable changes in the profitability of foraging

sites is studied. An optimality model was used to predict the frequency with which a forager should sample a foraging site in which the probability of reward fluctuates randomly between high and low and an alternative site that offers an intermediate probability of reward. The model was tested with pigeons in a shuttlebox in which the two ends represented the foraging sites. The pigeons succeeded in tracking the changes in the fluctuating site, and the payoff attained was close to the optimum. Another detailed study of pigeon behavior is reported in [27]. Studies of “optimal” search plans in animals seems to indicate that time cost incurred during individual foraging trips is much more important than energy cost, in terms of maximizing net resource intake over time [66]. In [68] the influence of prey distribution and capture on the search path configuration of the beetle *Gyrinus picipes*, was observed. All paths were analyzed before and after prey capture. Prey distribution had little impact on search configuration. However, prey capture caused significant reductions in step length, linear displacement, and path straightness. Thoroughness and turning angle increased significantly after prey capture. A simulation model was developed to analyze influences of search parameters on search efficiency. Simulated search paths did not differ from actual search paths, indicating that the model accurately describes gyridid search behavior. Actual search paths were compared to a simulated Brownian (random) search. Results indicate that gyridid searches are not random. However, search behavior after prey capture was similar to that derived from the Brownian model. Bovet and Benhamou [8] examined the case of a hypothetical forager searching for immobile, randomly distributed prey items from a central place and homing straight back to determine the optimal sinuosity of the search path. The optimal policy consists of minimizing the expected total path length required to survey a given area, depending on the number of prey items the subject is able to carry, its search path width, and the prey density. An “optimal sinuosity” formula was derived using computer simulations. For a given prey density, the formula predicts a logarithmic decrease with the number of prey items the central place forager was searching for. The formula was also extended to deal with patchy environments. Applicability of this formula and its robustness to errors in the subjects’ estimate of the prey density are discussed. In [3]

two spatial memory-based searching mechanisms are modeled by combining elementary orientation mechanisms with a path-integration process. These mechanisms make it possible to account for the behavior of many animals that locally increase their search effort in the vicinity of a given memorized location to discover with maximal efficiency a small target that is likely to be close to this location. The efficiency of a predator searching for clustered prey items with a mechanism of this type was computed in four habitat types with differing grains and/or heterogeneity levels. A predator exhibiting optimal spatial memory-based area-concentrated searching behavior was able to harvest about 1.6 times more prey items than if it exhibited optimal area-concentrated searching behavior without referring to a spatial memory. In [13] it was noticed that during the dry season, collembolans ants aggregate in wet patches randomly scattered in the dry litter. The authors simulated this situation and observed that the ants seemed able to use the humidity gradient direction to efficiently orient themselves toward a wet patch. Once the patch had been reached, they exhibited area-concentrated searching. After capturing a collembolan, they returned to their nest along nearly straight paths. This ability may rely on a spatial memory of nest location by means of a path-integration process. In the absence of prey, various behaviors were observed after an unsuccessful search. Comparison with results obtained with a homogeneously wet environment, simulating the rainy season, showed that the ants are also sensitive to degree of patchiness in the environment. Cassini [10] tested the qualitative predictions on patch use for two searching strategies, random forager and systematic forager, for four adult armadillos. Results on patch use suggest that *Ss* developed a systematic search strategy, and the observed tendency toward a spiral route seemed to be their searching strategy for minimizing revisits. Sheehan et al. [55] examined the role of both visual and olfactory cues in discriminating previously searched sites by *M. croceipes* females foraging freely in an experimental patch. Sites contained a natural host kairomone but no host. Wasps spent less time searching frass sites previously searched by themselves or by conspecifics than unsearched frass sites. In addition to chemical marking, spatial memory of visual cues was implicated as a mechanism for discriminating against self-visited, host-free sites.

The interaction of multiple animals is examined in several papers. In [60] the effect of perch height on the allocation of search and pursuit foraging behavior in hawk owls was studied. 178 artificial perches of three different heights were mounted in a 20-ha clear cut area, and data on nine hawk owls were collected. Results indicate that increasing perching height increases search area and increasing search area increases perching time. Also, hawk owls seldom start searching at perch base and progress outward. The probability of capturing prey declines with its distance from the predator; if no prey is detected, the hawk owls move to another perch that would minimize travel time and overlap between search areas of successive perches. McMahon and Evans [39] examined foraging strategies of the American white pelican, and classified them along a continuum based on degree of coordination, ranging from mobile individuals, then uncoordinated aggregations, through increasing degrees of coordination in following, nuclei, and semi-circles. Prey size and capture rates were greatest for the more highly coordinated strategies, while less coordinated strategies appeared to be involved primarily in searching. Switching among strategies appeared to fit along the same continuum, with a tendency to switch from less to more coordinated when prey was located and to return to less coordinated search when capture rates declined. Search in a coordinated group benefited from the presence of others. Thus, the American white pelican has an effective group foraging system for harvesting mobile clumped fish prey.

In [13] the problem of spatial components of foraging was examined, both at the colony and at the individual level, in a generalist predatory species of the African stink ant. Colony fragments consisting of a queen, 75 workers, 100 larvae, and several eggs were installed in two adjacent test tubes. Foragers were tested as to whether they foraged individually or as members of a group of workers, and whether they specialized on particular zones to ensure the simultaneous coverage of a wide foraging area. Also tested was whether workers can increase their rate of net energy delivery to the nest by shortening their homing trips. Solitary worker hunting-zone specialization was found as well as different prey-searching path characteristics.

Noda et al. [44] examined patterns of searching behavior in a local population of stout-body chromis (Ss) feeding on zooplankton in mobile foraging

aggregations. Although Ss tended to wander independently of each other, their foraging ranges overlapped. The local population had a more or less common home range within which there were three foraging regions. Within these regions, each identified S usually stayed for more than 1 h, irrespective of the presence or absence of prey, and searched in a tortuous pattern with reduced velocity. In contrast, movements between regions tended to be rapid with almost no feeding. Ss employed a local search strategy involving spatial memory and expectation. This searching pattern probably enables foraging to be concentrated at the front of zooplankton-supply routes associated with tidal currents, thus resulting in relatively high capture rates per unit effort. In [43] a behavior-based, analytical model that finds the ideal free distribution of predators searching for food in a patchy environment, incorporates the effects of the degree of interference and the total prey density on such distributions. An over-representation of predators in the best patch is always predicted. This effect is enhanced by increasing prey abundance.

#### 4. Conclusions

Much of the work we have surveyed on robotic search parallels the ideas concerning animal search strategies. Studies of “optimal” search plans in animals seems to indicate that time cost incurred during individual foraging trips is much more important than energy cost, in terms of maximizing net resource intake over time [66]. Many other studies show that animals do indeed optimize.

The volume edited by Meyer et al. [42] presents ideas about how to use the inspiration from animal cooperation and social interaction in the design of robotic systems. “Designing Emergent Behaviors: From Local Interactions to Collective Intelligence” by Maja J. Mataric describes a research program for studying social interactions leading to group behavior (tested on a herd of physical mobile robots). “Adaptive Action Selection for Cooperative Agent Teams” by Lynne E. Parker discusses two types of animal societies – differentiating and integrative – and their parallels to cooperative mobile robot work. “From Tom Thumb to the Dockers: Some Experiments with Foraging Robots” by Alexis Drogoul and Jacques



Ferber experiments with different implementations of the “explorer robots application”; these are “Tom Thumb” robots whose behavior is based on the foraging behavior of ants, and chain-making robots, the “dockers”, governed by local perceptions and interactions. “Collective Robotic Intelligence” by C. Ronald Kube and Hong Zhang examine the problem of controlling multiple behavior-based autonomous robots. “Collective Choice of Strategic Type” by Chisato Nu-maoka and Akikazu Takeuchi proposes a computational model for an emergent collective behavior that collectively changes strategy, such as from attack to defence (and describes the result of an experimental simulation with multiple autonomous robots). “An Adaptive Communication Protocol for Cooperating Mobile Robots” by Holly Yanco and Lynn Andrea Stein describe mobile robots engaged in a cooperative task that requires communication by adapting an initial fixed but uninterpreted vocabulary. “Dimensions of Communication and Social Organization in Multi-Agent Robotic Systems” by Ronald C. Arkin and J. David Hobbs present extensions of schema-based reactive navigation as a basis for constructing multi-robot societies. “Evolution of Trading Strategies Among Heterogeneous Artificial Economic Agents” by Andrea Beltratti and Sergio Margarita consider an artificial stock market populated by three types of neural network based agents (trying to outperform each other by improving their ability to forecast the forecasts of others). Gerard Weiss’ “Action Selection and Learning in Multi-Agent Environments” discusses how several artificial agents can collectively adapt to their environment by learning to generate a sequence of action sets that solves an environmental task.

As a whole, the work we have surveyed indicates parallels between robotic and animal search. Indeed, animal foraging appears to follow optimization rules which can be represented formally and sometimes described mathematically as decision rules under uncertainty. They also indicate that animals appear to use local optimization heuristics more systematically than global rules. Also, the importance of map formation is apparent in many studies; this points to interesting links between purely local strategies and global optimization rules. A companion paper will discuss search strategies with local and global optimizing rules in a randomly characterized environment [22].

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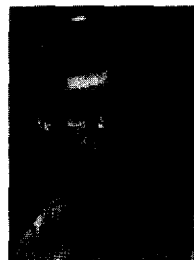
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