Spatiotemporal Braitenberg Vehicles

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ABSTRACT

How does complex spatiotemporal behavior arise from, and from which, spatiotemporal knowledge? In an attempt to answer this question, we extend Valentino Braitenberg's thought experiment [3] by describing and implementing vehicles with explicit, and increasingly sophisticated, spatiotemporal knowledge. We then observe the corresponding spatiotemporal behavior that can result. These spatiotemporal vehicles are able to move about their environment. The paper shows how vehicles can be incrementally equipped with three fundamental spatial constructs: knowledge of places, of neighborhoods, and the ability to communicate with other nearby vehicles. In turn we demonstrate, using agent-based simulations, how the fundamental spatial concepts of fields, networks, objects, and reference frames can emerge from these basic constructs. Our approach contributes to ongoing efforts of identifying the core concepts of spatial information [11] and of understanding the relationships between interaction with space and spatial computation [6].

Categories and Subject Descriptors

I.2. [**Knowledge representation and reasoning**]: Spatial and physical reasoning; I.6. [**Simulation types and techniques**]: Agent / discrete models

General Terms

Theory

Keywords

Braitenberg vehicles, spatial information, decentralized spatial computing

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1. INTRODUCTION

Is there a "natural" ordering of spatial knowledge, independent of its representation? Spatial information theory, and in particular geographic information science, tend to focus on representational aspects: what knowledge representation paradigms, techniques, and tools best support certain computations. Here, we take a different approach and ask whether spatial knowledge can be ordered from simple to complex in terms of the questions it answers. We approach this issue by seeking a generative procedure to construct increasingly sophisticated spatial knowledge from sensor data acquired by moving and communicating agents. In this way, we test a complexity ordering of spatial information by computing increasingly complex information from sensor inputs.

While this approach demonstrates a single way knowledge construction could occur, the ordering it exhibits has implications for the foundation of a more generalized artificial intelligence model of spatiotemporal learning. Thus, human developmental studies along the lines of Piaget and his colleagues [18] and newer research [14] are informing us about choices of concepts and ontogenetically motivated orderings, but they are neither constraining our findings nor are we contributing insights on human spatial cognition.

The idea that complexity results from (and can be explained in terms of) layered simplicity is long-standing and prominent in artificial intelligence, cognitive sciences, biology, economics, and other fields. For example, a variety of work in the area of embodied intelligence is attempting to understand the spatial cognitive or computational processes of agents in terms of the space with which they interact (e.g., [6, 16, 17]). Valentino Braitenberg has applied it in his famous little book on "Vehicles" [3], in order to demonstrate how sophisticated behavior results from the combination of simple stimulus-response patterns. These vehicles are situated and moving in space, but Braitenberg does not focus on their spatial knowledge and keeps its representation fairly generic (as a simple 2d array).

Inspired by Braitenberg's seminal work, we propose a new small set of vehicles focusing on spatiotemporal knowledge and behavior. These vehicles also move around and sense their environment, which we chose to be geographic space (though there may be little difference between geographic and table-top spaces for our purposes). We make the spatial information held by the vehicles explicit, through the sequence of spatial information concepts proposed in [11]. Furthermore, we go beyond single vehicles and consider swarms of communicating vehicles. Each vehicle has a memory in which we make the spatial information concepts explicit.

Spatial concepts	Information concepts
Location: where is ... ?	
Neighborhood: what is nearby?	*Granularity*: how precise is it?
Field: what is the value of attribute z at location x?	*Accuracy*: how accurate is it?
Object: what are the properties and relations of object o?	*Meaning*: what is meant by?
Event: what did/could happen?	*Value*: what roles does this play?
Network: what are the connections between objects?	

Table 1: Spatial concepts (left) and information concepts (right) after [11]

The exact form these representations of space and time take is irrelevant and only optimized for simplicity and ease of computations. What matters is that the vehicles can answer questions in terms of particular concepts (such as location or neighborhood). Thereby, we make Braitenberg's notions of space and time explicit, without adding fundamentally new ideas to them.

In parallel with spatiotemporal knowledge per se, our vehicles shall also eventually obtain the capacity to assess the granularity, accuracy, meaning, and value of spatiotemporal information. This will be a step beyond Braitenberg, but it can only begin to be sketched in this paper. These four meta-concepts are also part of the core concepts of spatial information that structure our design.

In some senses, our vehicles are simpler than Braitenberg's: they have no emotions, no free will, no dreams and the like. Perhaps it is more adequate to state that we remain silent about such interpretations of behavioral patterns. Our goal is to test a complexity ordering of core concepts of spatial information, by computing increasingly complex information from sensor inputs.

The remainder of this paper begins by providing background on both the core concepts of spatial information (first introduced in [11]) and the role of space and time in Braitenberg's vehicles (section 2). From this basis, section 3 extends Braitenberg's vehicles with three key spatial constructs: place recognition, neighborhood recognition, and spatially-mediated communication. Section 4 then designs and tests experimentally four "spatiotemporal" Braitenberg vehicles (SBVs) that rely on one or more of these three spatial constructs. The behaviors of those SBVs are discussed and reviewed in section 5, with the conclusions in section 6 identifying future work to extend this initial paper.

2. BACKGROUND

The ten core concepts of spatial information, as defined in [11], are meant to provide a common-sense vocabulary for asking and answering questions about phenomena occurring in space and time. They focus on geographic space, motivated by the extensive ranges of experiences with, and applications for coping with moving in and observing outdoor environments. However, any limitations to only a subset of scales in the spectrum of human experiences have been carefully avoided. Braitenberg does not seem to make a distinction between table-top and geographic spaces, nor do the core concepts.

The concepts have previously been introduced and discussed in an ordered list, but without any explicit claims about an inherent ordering. Here, such a claim will be made and tested: the six spatial concepts can be organized into a "natural" order of complexity, in the sense that each spatial concept builds on some or all previous ones. This order is based on their acquisition from sensor observations or manipulation and computation with other concepts. For example, neighborhood knowledge builds on the capacity to recognize places; network knowledge in turn builds on neighborhood information.

The testing of this claim uses the idea, advanced in [11], that each core concept has some core questions associated with it. Spatial information is then defined as answers to these questions. For example, a question associated with the concept of location is "where is ... ?" Our spatial Braitenberg vehicles are equipped incrementally with the concepts and have to answer questions about their environments. The list of ten concepts and associated questions is given in Table 1.

These concepts, while nominally intended for aiding in discussion for people, are also of use when discussing simulated agents. Braitenberg's vehicles, while not explicitly answering questions about space and time, do have a priori (built in) notions of space and time, starting from his vehicle 8. However, they are intentionally limited to stimulus-response devices, without long-term memory. Consequently, they cannot have information concepts, i.e., there is no explicit modeling of accuracy and precision or meaning and value. They appear to have a notion of objects with identity (names), but again without memory.

The a priori category of space in Braitenberg's vehicles is a two-dimensional array of a predetermined (and low) resolution, capturing what a vehicle "sees," like a digital camera, but not remembering anything beyond short (unspecified) time frames. It is only used to guide momentary inference and action in view of a sensed environment. One could label this idea a "field," yet it is not only transitory, but also local. This applies also to the extensions into three dimensions and other sensory modalities. The notion of "neighborhood" in Braitenberg's vehicles is also transitory. Networks are touched upon, but as wirings of parts and devices, not as representations of space and connected objects in it. Events are patterns of stimuli, but the vehicles have no model or memory for them either.

Yet, Braitenberg clearly foresees the extensions we are proposing here, both toward communicating vehicles and toward more interesting spatial concepts. For example, he says on page 47: "we are no longer working on individuals taken by themselves but on the members of a community in which there are complicated interactions between vehicles of the same or of different kinds"; and before on page 40: "This gives you the freedom to mimic all sorts of spaces, including spaces that a human mind cannot imagine." Further, on page 49: "We built very simple homogeneous networks and then discovered that they contain implicit definitions of such concepts as 3-dimensional space, continuous movement, reality of objects, multitude of objects, and personal relation." On the whole, Braitenberg targets more powerful world models, as expressed on page 72: "We were careful to reproduce inside the vehicles' brains many rules and regularities that govern the world. This way we could speak of the vehicles' brains as models of the world, as miniature editions of external, public space."

Our contribution in this paper is to explore a simple route to building such world models by generating concepts of spatial information in devices which communicate and have memory.

3. SPATIAL CONSTRUCTS FOR VEHICLES

We argue that three fundamental spatial constructs are sufficient to augment Braitenberg Vehicles (BVs) with a wide variety of spatial capabilities. These additions are *place recognition*, *neighborhood recognition*, and *communication*, and are defined more precisely in the following subsections. Together, these constructs can give rise to what we refer to in this paper as *spatiotemporal Braitenberg vehicles* (SBVs).

3.1 Sensing

Before discussing spatial constructs, we must first assume the ability of an SBV to sense information about the place at which it is located. As already alluded to in section 2, sensing ability is already assumed in [3] for any BV, and is not explicitly regarded as a spatial construct (although what can potentially be sensed by a vehicle is surely dependent on its location). The ability of a vehicle to sense information about its immediate environment at any point in time can be represented as a sensor function:

$$s : T \to D$$

where T is a set of discrete time instants and D is the codomain of the sensed information. For example, BVs equipped with temperature sensors and humidity sensors could be represented using $D = \mathbb{R} \times [0, 100]$ (i.e., temperature/percentage humidity pairs).

3.2 Place recognition

The most basic spatial knowledge provided to an SBV is the ability to recognize *places*. We use the term "place" here in a narrow sense, to mean simply sets of locations identifiable by an intelligent agent which are broadly similar and spatially contiguous (cf. [2]). The selection of what set of locations makes up a particular place is based on a collection of sensed values from the vehicles' various sensors. Thus, in this paper our use of the term "place" lies somewhere between its narrowest sense of named granular spatial regions, for example as used in [9, 20, 22]; and its broadest connotations with an evolving "sense of place" (e.g., [1, 4, 13]). However, in common with this broader sense, our recognized places "do not necessarily mean the same thing to everybody" [13]—we assume places known to one vehicle may have different names and extents to those known to another vehicle.

More precisely, we model place recognition as a *place knowledge* function:

$$k_p : S \to P$$

where P is some arbitrary set of names for places, and S is some set of locations in space, such as sets of points, regions, vertices or edges in a network, or so forth. In short, place recognition for an SBV involves the identification of a name with some set of known locations in space. Thus, places in this context are simply a granulation of space: sets of contiguous and similar locations that are collectively known to the agent by the same name.

We can further represent an SBV's capability to associate *sensed values* with places (i.e., to "recognize" places based on what can be sensed there) as a function:

$$k_s : P \to D$$

We refer to k_s as the *sensor knowledge* function.

3.3 Neighborhood recognition

The next level of spatial knowledge is the ability to recognize neighborhoods of known places. We model neighborhood as a relation N on the set of places:

$$N \subseteq P \times P$$

where $(p_1, p_2) \in N$ indicates that places p_1 and p_2 are neighbors. For simplicity we assume a symmetric relation N—$(p_1, p_2) \in N$ implies $(p_2, p_1) \in N$. Clearly, it would also be possible to represent asymmetry in neighborhoods.

While the terms "place" and "neighborhood" are used here in a more restrictive sense than in the spatial cognition literature, there exists a clear and deliberate analogy between the definitions of place and neighborhood above and those found in studies of human spatial learning and knowledge (cf. [7, 12]).

3.4 Spatially mediated communication

The third and final spatial construct concerns communication between nearby vehicles. The capability for communication can be represented as a time-varying graph:

$$C(t) = (V, E(t))$$

where the set of vehicles is given by V and the set of direct communication links at some time instant $t \in T$ is given by $E(t)$. Thus, $\{v_1, v_2\} \in E(t)$ at a some time t represents the potential for direct communication between the two vehicles v_1 and v_2. We assume bidirected communication (an undirected graph), but again generalizations to unidirectional communication are clearly possible (and may be desirable in some contexts, such as geosensor networks [5]).

Note the implicit assumption that in order to communicate, two nodes must be in close spatiotemporal proximity (i.e., $\{v_1, v_2\} \in E(t)$ only if nodes v_1 and v_2 are spatially close at time t). In other words, communication is mediated by space. Today's digital communications network, which allow near-instantaneous communication over large geographical distances, can sometimes obscure this fundamentally spatial nature of communication. Unaided by digital communications technology, communication between intelligent agents can only occur when in spatial and temporal proximity. Thus, we include communication as a spatial construct.

4. SPATIAL BRAITENBERG VEHICLES

Building on the basic spatial constructs from the previous section, this section explores a series of spatial Braitenberg vehicles (SBVs) that exhibit increasingly complex spatial behaviors.

- SBV1: The series begins with SBV1, which is able to build up its knowledge of a sensed spatial field using its sensor knowledge function in combination with place recognition.

- SBV2: SBV2 is able to construct knowledge of routes between places, by additionally building up knowledge about the neighborhoods that connect known places, as it moves around the space.

- SBV3: Using the same knowledge as SBV2, SBV3 is able to identify objects, in the form of spatial regions.

- SBV4: SBV4 is additionally able to communicate with other nearby vehicles, enabling it to collaborate and more efficiently complete each of the tasks of the other SBVs, constructing fields, routes, and objects, as well as construct a shared reference system for the places and neighborhoods in the space.

Before launching into an exploration of SBVs, it is necessary to first review in more detail a few features of Braitenberg's own vehicles.

4.1 Preliminaries

Braitenberg vehicles are mobile agents that respond to their immediate environment. Vehicle type-2, amongst the simplest of Braitenberg's vehicles, is equipped with two sensors (at the front left and front right) and two motors (at the back left and right). The intensity of sensed information can be used to excite or inhibit the actions of either or both of the motors. Depending on the exact wiring used, different behaviors are achieved. For example, if the sensors are wired only to the motors on the same side, vehicles will tend to veer away from regions of high intensity (vehicle type-2a, termed by Braitenberg "fearful" behavior); crossing the wires over, left to right and right to left, will lead to the opposite movements towards regions of high intensity (vehicle type-2b, termed by Braitenberg "aggressive" behavior).

A natural step is to implement these types of behaviors in an agent-based simulation. For this paper we used the NetLogo agent-based simulation system [23], as it is well-suited to simulating both the behavior of intelligent agents and the spatial environments with which they interact. Rather than physically wiring vehicles, our simulated vehicles are equipped with the ability to sense information directly in front of them and to either side (see Figure 1). The vehicle's direction of movement is then determined based on the gradient between the sensed information ahead: "fearful" vehicles veer away from the highest intensity sensed reading; "aggressive" vehicles veer towards the same signal. In this way, vehicles were capable of selecting any direction between their left and right sensors (i.e., between $-45°$ and $45°$). For each timestep of the simulation, the vehicle would move the width of one grid cell in this direction before refreshing its sensed readings and selecting a new direction of movement. To ensure that there were no edge effects, the simulation world was wrapped both horizontally and vertically (i.e., homeomorphic to a torus).

4.2 SBV1: Field memory

Our first SBV requires only the sensor functions s and k_s and the place recognition function k_p in order to incrementally construct memory of a spatial field. Algorithm 1 provides a basic SBV, which extends Braitenberg's vehicle type-2, capable of moving around a space and constructing knowledge about a sensed field in that space. The behavior of the SBVs are based on the place recognition function, where known locations serve as attractors for type-2b ("aggressive") vehicles and detractors for type-2a ("fearful") vehicles. This, somewhat counter-intuitively causes the "fearful" vehicles to avoid known places and the "aggressive" vehicles to move towards known places.

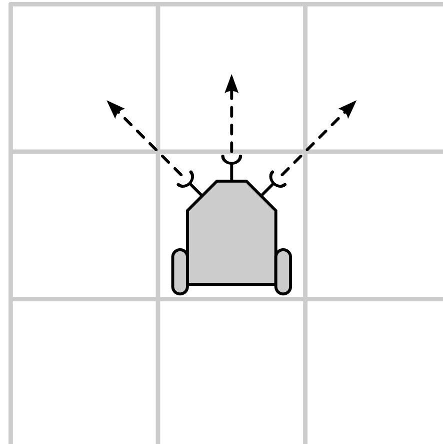


Figure 1: Implementing sensing in Braitenberg vehicles with NetLogo.

The distributed algorithm specification style used in Algorithm 1 is based on that developed by Santoro [19] and extended in [5]. In summary:

- States are indicated with uppercase names. In Algorithm 1 vehicles may be in one of two states, either FEAR (Braitenberg vehicle type-2a, who fear known locations) or AGGR (Braitenenberg vehicle type-2b, who are attracted to known locations, see section 4.1).

- Vehicles respond to system events, such as triggers (indicated with the *When* keyword). In Algorithm 1, two triggers are defined: when a vehicle is deciding where to move next; and when a vehicle detects it has arrived at a new location.

- Actions are atomic sequences of operations that a vehicle performs in response to system events. For example, when a vehicle detects it has encountered a new place, it will learn to recognize that place and store a sensed value for that place.

The behavior in Algorithm 1 was simulated on top of the basic Braitenberg vehicles simulator described in section 4.1. Figure 2 shows the results of a simulation of 100 FEAR (type-2a) and 100 AGGR (type-2b) vehicles exploring a geographic space. The figure shows the percentage of the simulation space (a grid of 40 by 40 locations, with each location mapped to a unique place) known to the vehicles as simulation time elapses, averaged over all 100 vehicles. Each response curve's 95% confidence interval is depicted using a dotted line. As might be expected, the figure illustrates that FEAR vehicles tend to explore more of the space than the AGGR vehicles. This is because the FEAR vehicles tend to avoid places they know whereas the AGGR vehicles

Algorithm 1 SBV1: Field memory

1: Local variables: place knowledge function $k_p : S \to P$; sensor function $s : T \to \mathbb{R}$; sensed knowledge function $k_s : P \to \mathbb{R}$
2: Initialization: $k_p(l) \mapsto$ *'unknown'* for all $l \in S$; all nodes either in state FEAR or AGGR.

FEAR
3: *When* vehicle deciding to move
4: Adopt Braitenberg vehicle type-2a behavior, being repulsed by locations $l \in S$ such that $k_p(l) =$ *'unknown'* (see section 4.1).

AGGR
5: *When* vehicle deciding to move
6: Adopt Braitenberg vehicle type-2b behavior, being attracted by locations $l \in S$ such that $k_p(l) \neq$ *'unknown'* (see section 4.1).

FEAR, AGGR
7: *When* vehicle moved to location *here* from location *there*
8: **if** $k_p(here) =$ *'unknown'* **then**
9: Find a new place name $p \in P$ such that $p \notin \mathrm{Im}(k_p)$, where $\mathrm{Im}(k_p)$ is the *image* of the function k_p
10: Store $k_p(here) \mapsto p$
11: Store $k_s(p) \mapsto s(now)$ where $now \in T$ is the current time

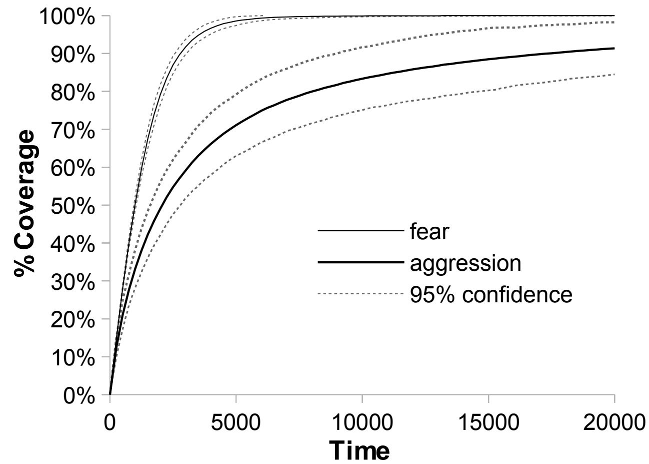
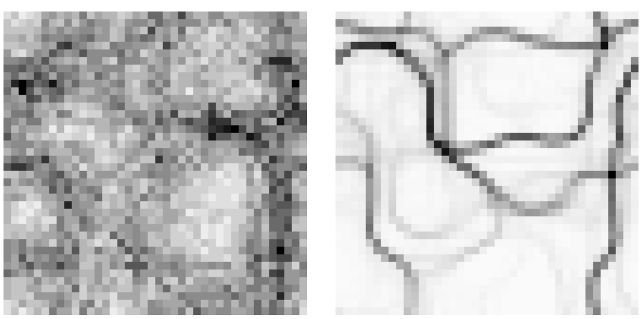


Figure 2: Memory (percentage coverage) of a spatial field over simulation time, averaged across 100 vehicles exhibiting either Braitenberg type-2a ("fear") or Braitenberg type-2b ("aggressive") behavior.

are attracted to known places. These FEAR vehicles more rapidly reach 100% knowledge of the space, and do so more reliably (shown by the tighter 95% confidence interval).

Additionally, Figure 3 illustrates the way in which the two vehicles explore the space differs using a heatmap. From the figure we can see that the FEAR vehicles explore the area fairly evenly whereas the AGGR vehicles tend to constrain their movement to a network of paths. While we may infer from Figure 2 that the FEAR vehicles are better explorers, Figure 3 demonstrates that by making paths between places, the AGGR vehicles are more constrained in their movements.



Braitenberg type-2a ("fear") behavior.

Braitenberg type-2b ("aggressive") behavior.

Figure 3: Heatmap of an individual experimental run for both fear and aggr vehicles. Darker colors indicate locations visited more frequently.

4.3 SBV2: Network memory

Our second SBV extends SBV1 with knowledge about the neighborhoods between known places. SBV2 can be achieved with two simple extensions of Algorithm 1. For conciseness, we specify only the differences from SBV1 for SBV2:

- First, the local data on line 1, Algorithm 1, must be extended with a data structure for storing additional neighborhood information. We use a graph, $G = (P, N)$, where P is the set of places and N is the neighborhood relation on places. N is initialized to the empty set, $N = \varnothing$.
- Second, an additional operation must be added after line 11, Algorithm 1, to populate the neighborhood information as a vehicle moves to a new location *here* from *there*: Store $N := N \cup \{(p_1, p_2), (p_2, p_1)\}$, where $p_1 = k_p(here)$ and $p_2 = k_p(there)$.

Together, these two extensions enable the vehicle incrementally to build up memory of neighborhood between places it has moved between. Our notion of neighborhood is in this sense akin to the approach introduced in [10], where a boathouse might be considered "near" a water body if one can carry a boat between the two. Similarly, a vehicle may memorize two places as neighbors of each other if it can move directly between those places.

In turn, neighborhood memory may be used by a vehicle as the basis for answering higher-level questions about a network of known places. For example, Figure 4 summarizes the results of an experiment that tests the vehicle's network memory, by examining the route knowledge of 100 FEAR and 100 AGGR vehicles exploring the simulation space. The figure shows over time the efficiency of known vehicle paths, measured as the average length of the shortest known path in vehicles' networks, compared with the actual length of the shortest path through the space.

The specific origin and destination tested for each vehicle is randomly chosen. To ensure comparability across different vehicles, the response curves are normalized to the time at which a vehicle has encountered 10% of the simulation space. After that point, the simulation tests the length of the shortest path between some arbitrarily chosen known place in the vehicle's memory and some arbitrarily chosen and initially unknown place.

Because the destination is initially unknown to the vehicle, no path between origin and destination will be identified until the destination is also encountered. Beyond that time, a vehicle will possess enough information to determine a path between origin and destination, although it is unlikely that

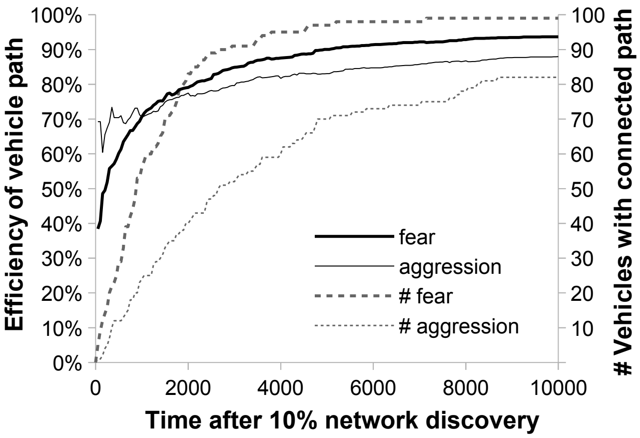


Figure 4: Ratio of known to actual shortest path length over simulation time, averaged across 100 vehicles exhibiting Braitenberg type-2a ("fear") and 100 vehicles exhibiting Braitenberg type-2b ("aggressive") behavior. The auxiliary axis and associated dashed lines show the number of vehicles contributing to the average.

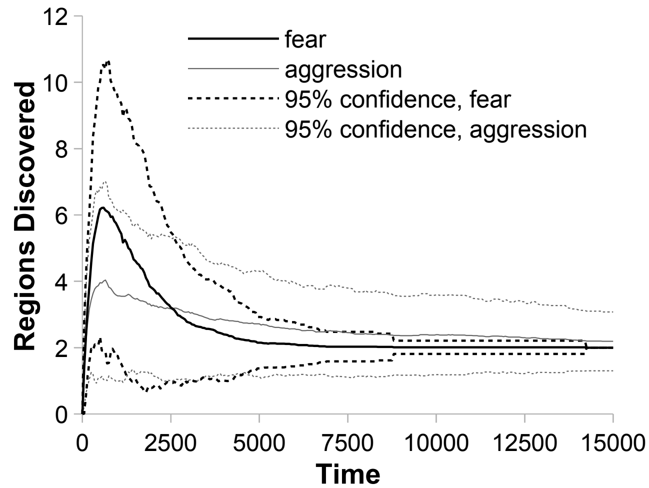


Figure 5: Average number of region objects known to vehicles over simulation time, for total 200 vehicles (100 "fear" type-2a and 100 "aggression" type-2b). The actual number of region objects embedded in the environment is 2 for these experiments.

the vehicle's network knowledge of the space will provide an especially efficient path. Over time, new neighborhood memory acquired by the vehicle will incrementally enable it to identify progressively shorter paths. Thus, the auxiliary y-axis in Figure 4, and associated dashed lines, show the number of vehicles contributing to the average path efficiency (and so provides some indication of the confidence of the efficiency curve).

The results demonstrate that the vehicles do indeed form increasingly detailed and complete network knowledge, and are capable of increasingly efficient routing between known places. As might be expected, the type-2b vehicles tend initially to know more efficient routes (since they tend to form a more linear network of known places, as shown in Figure 3.b). Conversely, type-2b vehicles do not improve their network memory as quickly as the more exploratory 2a vehicles.

4.4 SBV3: Object memory

We can relatively easily extend SBV2 to identify "objects" in the environment: aggregates of places. In our experiments with SBV3 we use connectivity between places, derived from a vehicle's network memory (cf. SBV2), as the mechanism for aggregating places into objects.

To test vehicles' object memory, a specific experiment was designed where two distinct spatial regions (objects) were embedded in the simulation space. Vehicles' sensing capabilities were extended to enable vehicles to additionally sense when it is inside an object. Formally, this can be achieved by extending a vehicle's sensor knowledge function with a Boolean codomain $\{0, 1\}$, i.e., $k_s : P \to \mathbb{R} \times \{0, 1\}$, indicating whether the vehicle can sense part of the region at a particular time t (i.e., $k_s(p) = (x, 1)$) or whether it can not (i.e., $k_s(p) = (x, 0)$).

Vehicle SBV3 now possesses enough information to deduce the number of objects it has detected in its environment. Formally, the graph $G' = (P', N')$, where $P' = \{p \in P | k_s(p) = (x, 1)\}$ and $N' = \{(n, n') \in N | n, n' \in P'\}$, is the subgraph of G (see section 4.3) induced by the vehicle's sensor knowledge function k_s. Vehicle SBV3 can simply count the number of connected components in G' to decide how many objects it has detected in its environment.

Figure 5 shows the results of an experiment to test the SBV's knowledge of two spatial regions embedded in the environment. The response curves in Figure 5 are averaged over 100 type-2a and 100 type-2b SBVs. The figure also shows the 95% confidence interval for both response curves.

The results show that, at the beginning of the experiment, vehicles have no knowledge of any region objects. As they explore the space, encountering parts of the regions, their estimate of the total number of regions increases rapidly to more than the actual number of regions in the space (an average of six regions for vehicle type-2a compared with two regions in actuality). However, as vehicles increase their knowledge of places and neighborhoods, apparently distinct regions begin to coalesce, as new discoveries connect previously disconnected parts of regions. In time, both vehicle types tend towards accurate knowledge of the number of regions in the environment (in the case of Figure 5, two regions).

Comparing vehicles 2a (fear) and 2b (aggression), more exploratory type-2a vehicles tend to perform worse than type-2b earlier in the simulation, dramatically overestimating the number of regions and with much lower reliability (wider confidence interval). However, given time to explore the space more fully, this result is reversed with type 2a vehicles outperforming type 2b vehicles after about 2500 simulation timesteps both in terms of accuracy (i.e., closeness of the number of regions discovered to the correct answer of two) and reliability (i.e., small size of the 95% confidence interval). On average, both vehicle types 2a and 2b also tend to slightly overestimate the number of regions, since occasional encounters with previously undiscovered parts of known regions will initially be assumed to be new distinct regions. On average, vehicle type 2a tends to be less affected by this overestimate bias.

4.5 SBV4: Spatial reference frames

As already argued, communication is at root a *spatial* process, mediated by distance. Even with today's wide area networks, the importance of the spatial constraints to the movement of information remain evident in the latest technologies, such as geosensor networks (e.g., [5, 15]). Thus, a core constraint to communication assumed for SBV4 is spatiotemporal: vehicles may only communicate if in close spatial and temporal proximity.

However, the ability to communicate messages does not necessarily imply that those messages will be understood. More specifically, there is no reason to expect that the place name used by one vehicle to refer to a set of locations will be the same name as that used by another vehicle. Indeed, different vehicles may of course identify different but overlapping sets of locations as places.

Thus, a fundamental task for communication is to provide a mechanism by which vehicles may agree on a shared reference frame for places and neighborhoods. Algorithm 2 extends SBV2 with the capability for communication between nearby nodes. The objective of Algorithm 2 is to generate a shared reference frame, such that all vehicles ultimately arrive at the same set of place names to refer to the same locations.

Algorithm 2 SBV4: Communication and place reference frames

1: Extends SBV2 (see Algorithm 1 and section 4.3)
FEAR, AGGR
2: *When* vehicle comes within communication range of another vehicle
3:   **broadcast** (`hand`, *here*, $k_p(here)$)
4: *Receiving* (`hand`, l, p)
5:   **if** $l = here$ and $p \neq k_p(here)$ **then**
6:     Store $p_k(here) \mapsto \min(p, k_p(here))$
7:   **if** $l \cap here \neq here$ **then**
8:     Store $k_p(here) \mapsto$ *'unknown'* {"Forget" previous place name for *here*}
9:     Store $k_p(here - l) \mapsto p'$ where $p' \in P$ is new place name such that $p \notin \mathrm{Im}(k_p)$
10:     **if** $l - here = \varnothing$ **then**
11:       Store $k_p(l) \mapsto p$ {Case: *here* contains l}
12:     **else**
13:       **broadcast** (`hand`, $here - l$, $k_p(here - l)$) {Case: *here* and l overlap}

To assist in understanding Algorithm 2, it is worth summarizing a number of key points:

- By "extending" SBV2 (line 1), we assume SBV4 inherits all the local variables, initialization, events, and actions of SBV2 (detailed in Algorithm 1 and section 4.3).
- Two vehicles v_1 and v_2 come within communication range of each other (line 2) when they are spatially close enough to "talk" to each other, i.e., at any time t when $\{v_1, v_2\} \in E(t)$ (see section 3.4).
- The shorthand *here* (lines 3 and 5–13) is used to refer to a description of the extents of the place at which a vehicle is currently situated. This description can be thought of as a vehicle "pointing out" the locations that are included in its current place. The broadcast `hand` ("handshake") message contains this description and the vehicle's place name itself.
- When receiving a broadcast `hand` message, a vehicle compares its interlocutor's place name (p) and place extents (l, line 4) with its own current place name and extents. Two possibilities need to be dealt with:
  1. The two extents, l and *here* are the same, but different names are used to refer to that place ($p \neq k_p(here)$, line 5). In such cases, a convention is required for both vehicles to agree on a shared name for that place (Figure 6.a). In Algorithm 2, it is assumed that place names can be totally ordered, and so first (min) name is adopted by both vehicles (line 6).
  2. The two extents l and *here* overlap (Figure 6.b) or l is contained within *here* (Figure 6.c) (i.e., $l \cap here \neq here$ line 7, disjoint locations $l \cap here = \varnothing$ are disallowed by the requirement that vehicles must be in close spatial proximity to communicate). In these cases, a vehicle updates its place recognition to accommodate the additional detail provided by its interlocutor (lines 8–9). If l is contained within *here*, the vehicle receiving the message must choose a new and unique place name to identify the extent $l - here$ (line 11). If instead the two place extents overlap, then both vehicles must agree on a name for the place created by the intersection of those extents (line 13).

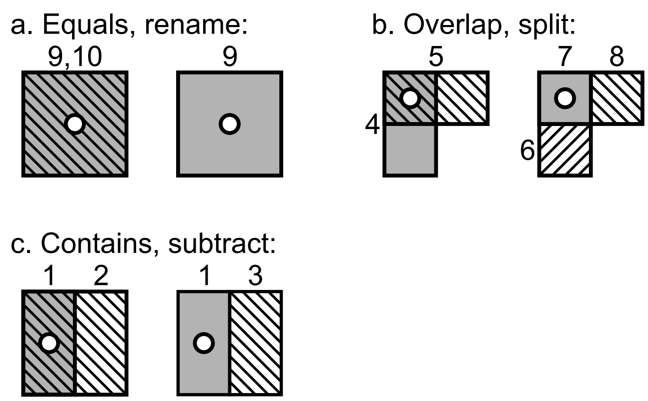


Figure 6: Possible topological relations between two places which share at least some of their locations. Actions taken by vehicles receiving a `hand` message differ based on these relations. Numbers represent the place names and white dots represent the meeting point of the two vehicles.

Over time, it is expected that SBV4s will eventually agree on a common reference system set in terms of a shared set of place names and associated extents. Having arrived at shared place names and extents, adapting SBV4 to additionally arrive at shared neighborhood relations is straightforward.

To test the expectation that SBV4s will indeed converge upon a shared reference frame, Figure 7 shows the results of a simulation with a 50/50 mix of type-2a and type-2b SBV4 vehicles. The graph measures the total number of place names used by all vehicles, as a proportion of the total number of distinct locations in our discrete simulation environment (400 locations in these experiments). The graph

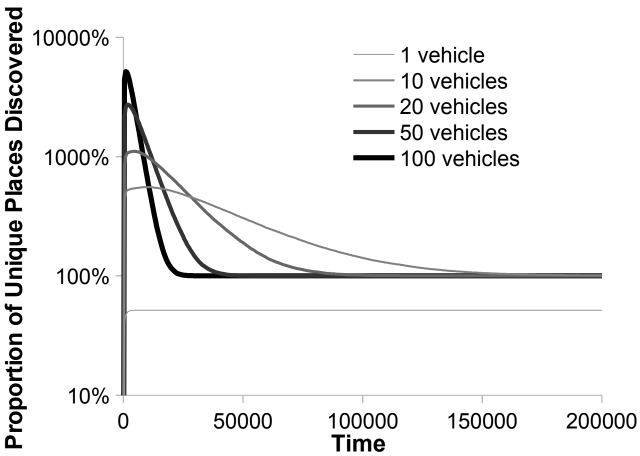


Figure 7: Shared reference frames, showing unique places discovered, averaged over 10 runs of simulations with 1, 10, 20, 50, and 100 vehicles.

shows that while the vehicles begin with no knowledge of the space (0% of place names known), a short period of simulation time is enough to lead to an explosion of known places. The total number of place names across the simulation over this period can be many times more than the actual number of locations (up to 5000%, log scale on the y axis used in Figure 7) because different vehicles may use different names to refer to the same location. However, as simulation time proceeds and vehicles share and agree on place names, the total number of place names used by all vehicles rapidly converges to one (shared) place name per location (100% in oreffig:sbv4).

The figure also shows the effect of greater numbers of vehicles, from 1 to 100 vehicles in each simulation. With 100 vehicles, the simulation shows a rapid explosion in the number of place names and a correspondingly rapid convergence on shared place names (as vehicles explore the space and agree with each other). As the number of vehicles decreases, the explosion of place names is less pronounced (since there are fewer vehicles to disagree on names), but also slower to converge (since there are also fewer vehicles to explore the space, less frequent communication opportunities). The pattern is only broken when just 1 vehicle occupies the space, in which case this lone vehicle never benefits from sharing and refining its own granular place names, yielding only around 50% knowledge of the possible places.

5. DISCUSSION

Summarizing the four SBVs in the previous section:

SBV1: Field memory. By using place recognition alone, SBV1 is able to store information about what can be sensed at different places (granular locations) it knows in space. The experiments in section 4.2 give an example of how place recognition can be used to build up a memory of the sensed spatial field over time—in short, remembering answers to questions of the form "what is the value of attribute z at place x."

SBV2: Network memory. Using a combination of place recognition and a recognition of neighborhoods between places, SBV2 is able to store information about the known network of places. Neighborhood is constructed through physical movement—if a vehicle can move directly from one place to another, it will infer that these two places are neighboring. In section 4.3 the memory of networks is demonstrated through "how can I get from place a to b?" questions that a vehicle may ask itself. Comparing the length of the shortest *known* route between two places, with the length of the shortest *possible* route between two places, provides an example of a vehicle's growing knowledge of the connections between places over time.

SBV3: Object memory. Again using a combination of place and neighborhood recognition, SBV3 is able to show how objects can be constructed from aggregates of places. In the experiments in section 4.4, knowing that places a and b are path connected inside an object provides the basis for aggregating places into objects. The experiments show how reliable memory of sensed regions (such as hot-spots) can be built up over time using this knowledge.

SBV4: Reference frames. Finally, spatially-mediated communication (communication between nearby vehicles) in combination with place/neighborhood recognition provides the basis for constructing shared frameworks for referring to space. Co-located vehicles explain to each other what each is referring to by a particular place name. The experiments in 4.5 show how shared spatial reference frames can emerge from this spatially mediated communication. Our results indicate that increases in the total number of communicating vehicles initially leads to greater "confusion," with different place names more frequently used. However, communication between this larger number of vehicles also leads more rapidly to convergence to shared and stable knowledge of place.

Mapping the core spatial concepts introduced in section 2 back the spatial constructs and behaviors of our SBVs, we can at last begin to order these by complexity. Specifically:

- Level 0: Place recognition is at the basis of all our SBVs. Place recognition maps approximately to the core concept "location," although only in the sense of qualitative location.
- Level 1: Field memory and neighborhood recognition are based on level 0 place recognition. Thus these constructs are placed at the same level of complexity, level 1.
- Level 2: Network and object memory rely on level 1 neighborhood recognition. Thus these constructs are placed together at level 2 complexity.
- Level 3: The construction of shared reference frames requires communication between nearby vehicles in addition to place and neighborhood recognition. Reference frames are also concerned with the core concept of "location," but in the more complex sense of shared or absolute systems of referring to location, such as positioning systems.

Table 2 summarizes the different SBV constructs and behaviors by level of complexity, along with the associated core

Complexity	SBV construct/behavior	Core concept
Level 0	Place	Location (qualitative)
Level 1	Neighborhood (based on place)	Neighborhood
Level 1	Field (based on place)	Field
Level 2	Network (based on place and neighborhood)	Network
Level 2	Object (based on place and neighborhood)	Object
Level 3	Reference frame (based on place/neighborhood and communication)	Location (positioning)

Table 2: Levels of SBV construct/behavior and associated core spatial concepts

concept from section 2.

Missing from the discussion above is the core concept "events." Although our simulations are dynamic in the sense that vehicles are moving and exploring the spaces around them, the environment is static. Our SBVs have not yet reached the level of complexity required to identify events occurring within a changing environment. However, it seems likely that event memory could be achieved without communication and based on an extension of our object memory SBV3 (level 2) as well as, in parallel, the field memory SBV2 (level 1).

Also missing from our discussion are the four core information concepts: granularity, accuracy, meaning, and value. Granularity is in some senses embedded in our SBVs' knowledge of the world. Place, in the sense used here, is akin to granular location descriptions. However, the SBVs so far do not explicitly ask or answer questions about the granularity of information. Our SBVs are also assumed to be entirely accurate in their knowledge of the environment (e.g., error-free sensing) and in their memory (e.g., vehicles never forget information, never misremember information, and suffer from none of the systematic distortions in spatial memory common to humans, cf. [8, 21]). Future work will explore the impact of such inaccuracies on vehicle behavior, using the same simulation-based approach as pursued in this paper. Meaning and value are also yet to be addressed by this work, going from the simple place-semantics built into SBV4 to broader notions of meaning and value of information.

6. CONCLUSIONS

This paper has extended Valentino Braitenberg's vehicles with a minimal set of spatial capabilities absent from Braitenberg's original and influential work. Specifically, three spatial constructs are proposed: recognition of place; recognition of neighborhood between places; and communication between spatiotemporally proximal vehicles. The resulting spatiotemporal Braitenberg vehicles (SBVs) exhibit a range of increasingly complex spatiotemporal behaviors. Our analysis and supporting experiments suggest an ordering in the complexity of several core spatiotemporal concepts: qualitative location (level 0); fields and neighborhoods (level 1); networks and objects (level 2); and positioning systems (level 3). Further work is required to also integrate events into this ordering, as well as the informational concepts of granularity, accuracy, meaning, and value.

A key contribution of this work is to examine in detail one route to generating complex spatiotemporal behavior from simple and mechanical rules. Through using simulations and experiments, we have attempted to make our discussions more concrete and precise than Valentino Braitenberg's pure thought experiment. However, our simulations and experiments are still illustrative, and constitute one example of a possible route from simple rules to complex behaviors. Thus, like Braitenberg's book, this paper remains at heart a thought experiment; we hope that taking this path may spark the reader's own interest and experiments.

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