Decentralized Classification in Societies of Autonomous and Heterogenous Robots

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***Abstract*— This paper addresses the classification problem for a set of autonomous robots that interact with each other. The objective is to classify agents that "behave" in "different way", due to their own physical dynamics or to the interaction protocol they are obeying to, as belonging to different "species". This paper describes a technique that allows a decentralized classification system to be built in a systematic way, once the hybrid models describing the behavior of the different species are given. This technique is based on a decentralized identification mechanism, by which every agent classifies its neighbors using only local information. By endowing every agent with such a local classifier, the overall system is enhanced with the ability to run behaviors involving individuals of the same species as well as of different ones. The mechanism can also be used to measure the level of cooperativeness of neighbors and to discover possible intruders among them. General applicability of the proposed solution is shown through examples of multi–agent systems from Biology and from Robotics.**

I. Introduction

Colonies of insects, such as ants, bees, termites, or wasps are natural distributed systems that display quite elaborate social *behaviors* at colony level. To establish complex types of interactions such as those that can be found in Nature [1], it is essential for every individual to distinguish or *classify* other individuals as belonging to the same or to other species, colonies or groups, based only on direct observations and limited information exchange. This makes every agent of a natural system capable of establishing collaborative behaviors that are strengthened by experience. For example, ants undergo cooperative colony–level behavior for prey retrieval based on nestmate identification [2]: when a prey is found by an ant, the ant itself tries to move it and, if unsuccessful for some time, recruits nestmates through direct contact (touch), chemical marking (pherormones), or visual communication (vibration) [3]–[5]. This classifying ability has also the important function of allowing each individual to detect possible predators or simply infertile relations.

Moreover, the inherent flexibility and robustness of such natural distributed systems, and indeed their ability to solve complex problems, have motivated in the last decades an abundant literature on multi–agent systems, e.g., [6]–[11]. Although in most cases, agents are modeled as identical *copies* of the same prototype, this assumption is often restrictive, as different agents may be implemented by different technologies, makers, etc. "Sociality" and heterogeneity in these artificial systems are advantageous when e.g. a problem requires interaction of agents with similar skills as well as agents with complementary capabilities. Most important, heterogeneity may be introduced to model the existence of malfunctioning agents or of *intruders* [12], [13], which are maliciously reprogrammed to implement a different behavior than the nominal one.

In this work, we address the classification problem for a set of autonomous agents, that can represent individuals of either a natural or an artificial system. The objective is to classify *heterogeneous* agents that "behave" in a different way, due to their own physical dynamics or to the rules of interaction they are obeying, as belonging to a different species. The objective is ambitious and indeed very difficult to achieve without any a priori knowledge of the rules of interaction, while a viable solution can be found if the hybrid models describing the behavior of the different species are given. Under this assumption, we provide a technique to build a decentralized *classifier* by which every agent can try to classify its neighbors using only local information. The work is based and extends previous work on intrusion detection [14] via a formalization of the hybrid observer that is built for each known species, which allows estimation of locally unavailable information. Applicability of the technique is shown by means of two examples: an automated transportation systems, with different types of drivers that represent different species, and the behavior of the polymorphic tree dwelling ant *Daceton Armigerum* during the colony foraging process.

II. Problem Formulation

Consider a "society" of n robotic agents, $\mathcal{A}_1, \dots, \mathcal{A}_n$, sharing an environment $\mathcal{Q}$, and each belonging to one species in a set $\{S^1, \cdots, S^p\}$. Each *species* is described by an interaction protocol $\mathcal{P}^r$ that specifies, for each agent $\mathcal{A}_i$, a motion model, a notion of neighborhood, a set of event–based interaction rules, and a local controller. A species is more formally described by the following components:

- A *dynamic map* $f_i : \mathcal{Q} \times \mathcal{U}_i \to T_\mathcal{Q}$, with $T_\mathcal{Q}$ the tangent space to $\mathcal{Q}$, describing how the agent's configuration $q_i \in \mathcal{Q}$ is updated:

$$\begin{cases} \dot{q}_i(t) = f_i(q_i(t), u_i(t)) \\ q_i(0) = q_i^0 \end{cases} , \; t \geq 0 \, ,$$

where q_i^0 is the initial configuration, and input $u_i \in \mathcal{U}_i$,

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with $\mathcal{U}_i$ denoting the set of admissible input values for the agent;

- A set of *topologies* $\eta_{i,1}, \cdots, \eta_{i,\kappa_i}$ on $\mathcal{Q}$, where $\eta_{i,j} : \mathcal{Q} \to 2^{\mathcal{Q}}$, defining the agent's neighborhood $N(q_i) = \cup_{j=1}^{\kappa_i} \eta_{i,j}(q_i)$, the neighbor set $M_i = \{\mathcal{A}_k \in \{\mathcal{A}_1 \cdots, \mathcal{A}_n\} \,|\, q_k \in N(q_i)\}$, the neighbor configuration set $I_i = \{q_k \in \mathcal{Q} \,|\, \mathcal{A}_k \in M_i\}$, and its *encoder map* $s_i : \mathcal{Q} \times \mathcal{Q}^{n_i} \to \mathbb{B}^{\kappa_i}$, where $n_i = \text{card}(I_i)$, and $\mathbb{B} \overset{\text{def}}{=} \{0, 1\}$, whose j–th component, $s_{i,j}$, is a logical–valued function returning true in the presence of an agent in the j–th topology $\eta_{i,j}(q_i)$, i.e.,

$$\begin{array}{rcl} s_{i,j} & : & \mathcal{Q} \times \mathcal{Q}^{n_i} \to \mathbb{B} \\ & & (q_i, I_i) \mapsto \sum_{q_k \in I_i} \mathbf{1}_{\eta_{i,j}(q_i)}(q_k) \end{array},$$

where $\sum$ represents the logical sum (*or*), and $\mathbf{1}_A(x)$ is the Indicator function of a set A;
- A finite event alphabet $E_i = \{e^{i,1}, \cdots, e^{i,\nu_i}\}$ and an event *detector map*

$$\begin{array}{rcl} e_i & : & \mathbb{B}^{\kappa_i} \to 2^{E_i} \\ & & s_i \mapsto \{e^{i,j} \in E_i \,|\, c_{i,j}(s_i) = 1\}, \end{array}$$

where each detector condition $c_{i,j}$ is a logical function

$$\begin{array}{rcl} c_{i,j} & : & \mathbb{B}^{\kappa_i} \to \mathbb{B} \\ & & s_i \mapsto \Pi_{k \in \gamma_{i,j}} s_{i,k} \, \Pi_{k \in \rho_{i,j}} \neg s_{i,k} \cdot \\ & & \cdot \Pi_{k \in \mu_{i,j}} \mathbf{1}_{\lambda_{i,k}}(q_i) \, \Pi_{k \in \nu_{i,j}} \neg \mathbf{1}_{\lambda_{i,k}}(q_i), \end{array} \tag{1}$$

with $\lambda_{i,1}, \cdots, \lambda_{i,h_i}$ constants in $2^{\mathcal{Q}}$, $\gamma_{i,j} \cup \rho_{i,j} = \{1, \cdots, \kappa_i\}$ and $\gamma_{i,j} \cap \rho_{i,j} = \emptyset$, $\mu_{i,j} \cup \nu_{i,j} = \{1, \cdots, h_i\}$ and $\mu_{i,j} \cap \nu_{i,j} = \emptyset$, and Π and $\neg$ the logical product (*and*) and negation (*not*), respectively;
- A finite set of discrete states $\Sigma_i = \{\sigma^{i,1}, \ldots, \sigma^{i,p}\}$ and a deterministic *automaton* $\delta_i : \Sigma_i \times 2^{E_i} \to \Sigma_i$, describing how the agent's discrete state σ_i is updated:

$$\left\{ \begin{array}{l} \sigma_i(t_{k+1}) = \delta_i(\sigma_i(t_k), e_i(t_{k+1})) \;\;,\;\; t_k > 0 \\ \sigma_i(0) = \sigma_i^0 \end{array} \right.,$$

where $\sigma_i^0 \in \Sigma_i$ is the initial discrete state, and t_k is the k–th instant t at which e_i detects a new event;
- A *decoder map* (or controller) $u_i : \mathcal{Q} \times \Sigma_i \to \mathcal{U}_i$ implementing a feedback–based control law of the type

$$u_i(t) = u_i(q_i(t), \sigma_i(t_k)).$$

Therefore, the state $(q_i, \sigma_i) \in \mathcal{Q} \times \Sigma_i$ of an agent $\mathcal{A}_i$, correctly following the protocol $\mathcal{P}^r$, must evolve according to the dynamics

$$\begin{array}{rcl} \dot{q}_i(t) & = & f_i(q_i(t), u_i(q_i(t), \sigma_i(t_k))) = f_i^*(q_i(t), \sigma_i(t_k)), \\ \sigma_i(t_{k+1}) & = & \delta_i(\sigma_i(t_k), e_i(s_i(q_i(t), I_i(t)))) = \\ & = & \delta_i^*(\sigma_i(t_k), q_i(t), I_i(t)), \end{array}$$

that can be written more compactly as

$$\left\{ \begin{array}{l} (\dot{q}_i(t), \sigma_i(t_{k+1})) = \mathcal{H}_i^{(r)}(q_i(t), \sigma_i(t_k), I_i(t)), \\ (q_i(0), \sigma_i(0)) = (q_i^0, \sigma_i^0), \end{array} \right. \tag{2}$$

where $\mathcal{H}_i^{(r)} : \mathcal{Q} \times \Sigma_i \times \mathcal{Q}^{n_i} \to T_{\mathcal{Q}} \times \Sigma_i$ is the agent's *hybrid dynamic map* [15].

Moreover, the agent is equipped with sensors measuring the configuration of other agents laying within a visibility region, i.e., a portion of $\mathcal{Q}$ that can be "seen" by the agent's sensors, described by a *visibility map* $\mathcal{V}_i : \mathcal{Q}^n \to 2^{\mathcal{Q}}$. We assume that local sensors are chosen so that $\mathcal{V}_i(q_1, \cdots, q_n) \supseteq N(q_i)$, which ensures that each agent has complete knowledge of its own neighborhood.

Consider e.g. a society of vehicles traveling along a highway with m lanes and following different driving rules. Standard vehicles must strictly adhere either to the European, right–hand or the left–hand traffic rules (RH and LH species), while emergency vehicles are allowed to overtake both on the left and on the right (emergency traffic rules species). The left–hand (right–hand) traffic rules species is described by the following rules: $\mathsf{rule}_1 \overset{\text{def}}{=}$ "proceed at the maximum speed along the rightmost (leftmost) free lane when possible"; $\mathsf{rule}_2 \overset{\text{def}}{=}$ "if a slower vehicle proceeds in front on the same lane, then overtake the vehicle if the next lane on the left (right) is free, or reduce the speed otherwise"; $\mathsf{rule}_3 \overset{\text{def}}{=}$ "as soon as the next lane on the right (left) becomes free, change to that lane"; $\mathsf{rule}_4 \overset{\text{def}}{=}$ "overtaking cars on the right (left) is forbidden". Rule_4 is ignored by the emergency traffic rules species, and rule_2 is modified as "if a slower vehicle proceeds in front on the same lane, then either overtake the car on the left if the next left lane is free, or overtake it on the right if the next right lane is free; otherwise reduce the speed". This basically allows an emergency vehicle to overtake everywhere it is possible. The allowed maneuvers are: FAST $\overset{\text{def}}{=}$ "accelerate up to the maximum forward speed, while aligning to the center of the current lane"; SLOW $\overset{\text{def}}{=}$ "decelerate down to null forward speed, while aligning to the center of the current lane"; LEFT $\overset{\text{def}}{=}$ "move to the next lane on the left"; RIGHT $\overset{\text{def}}{=}$ "move to the next lane on the right". This society can be formalized with the proposed protocol as described later in Section IV-B.

Based on the above proposed protocol we give the following

Definition 1: A *behavior* is the physical trajectory that an agent performs during a given period which is described by the solution, $\phi_{\mathcal{H}_i^{(r)}}(q_i^0, \sigma_i^0, \tilde{I}_i(t))$, of the system in Eq. 2, subject to the input $\tilde{I}_i(t)$ being the history of its neighbor configuration set $I_i(\tau)$, for $\tau = 0, \cdots, t$.

Definition 2: $\mathcal{A}_i$ is said to be *compatible* with the species S^r if its behavior $(\bar{q}_i(t), \bar{\sigma}_i(t_{k+1})$ is close enough to the evolution of the hybrid model $\mathcal{H}^{(r)}$, i.e.

$$\|\bar{q}_i(t) - \pi_{\mathcal{Q}}(\phi_{\mathcal{H}_i^{(r)}}(\bar{q}_i(t_k), \bar{\sigma}_i(t_k), I_i(t)))\| \le \epsilon, \quad \forall t,$$

where $\|\cdot\|$ is the Hausdorff distance, $\pi_{\mathcal{Q}}$ is the projector over the set $\mathcal{Q}$, and ϵ is an *accuracy* based on the quality of available sensors.

Definition 3: An agent is said to *belong* to the species S^r if, and only if it is compatible only with that species.

An agent $\mathcal{A}_h$ trying to learn the species another agent $\mathcal{A}_i$ belongs to needs to solve the following

Problem 1: Given the complete description of the p species, a measure of the behavior $\bar{q}_i$ and a partial measure of the agent's neighbor configuration set $I_i^{obs} = I_i \cap \mathcal{V}_h$, design a decentralized Species Classification System (SCS) of the form

$$C_i^h = \text{classifier}(\bar{q}_i, I_i^{obs})\,,$$

returning a logical vector, whose r–th component is true if, and only if $\mathcal{A}_i$'s behavior is compatible with the species S^r.

III. Proposed solution

Consider a generic agent $\mathcal{A}_h$ trying to learn which species another agent $\mathcal{A}_i$ belongs to. If a complete description of all species is available, $\mathcal{A}_h$ needs to determine to which models the observed behavior, or physical motion, of $\mathcal{A}_i$ best corresponds to. Approaches based on complete knowledge of a model's inputs (see e.g. [16]) cannot be applied as $\mathcal{A}_i$'s neighborhood N_i is generally, only partially known to $\mathcal{A}_h$. The proposed approach extends previous work on detection of "intruder" robots [17], by providing a formalization of the observer automaton to the case of many species. The proposed classifier is a two–step process: first, $\mathcal{A}_h$ computes an a–priori prediction of the set of possible behaviors that $\mathcal{A}_i$ can execute based on local information, for each species (*prediction phase*); then, the predicted behaviors are compared against the one actually executed and measured by $\mathcal{A}_h$ and those resulting close enough are selected (*classification phase*).

The prediction phase involves constructing a predictor for each species S^r, which is represented by an uncertain hybrid model $\tilde{\mathcal{H}}^{(r)}$. The model is composed of a nondeterministic automaton whose state $\tilde{\sigma}_i \in \Sigma_i$ represents the set of actions that $\mathcal{A}_i$ can perform based on local information, and whose transitions $\tilde{\delta}$ are the same as in δ. The main challenge in the construction of the automaton is the estimation of an upper approximation $\tilde{c}_i$ of each detector condition c_i, that is achieved through the following results.

Proposition 1: Given a detector condition c_i composed of a unique topology, i.e. $c_i = s_{i,1}$, a visibility-based upper approximation of it is

$$\tilde{c}_i = s_{i,1}^{(h)}\, v_{h,1} + \neg\, v_{h,1}\,,$$

where $v_{h,1}$ is the event visibility of an observer onboard agent $\mathcal{A}_h$.

Proof: Based on the observer's visibility $v_{h,1}$, the topology can be written as

$$s_{i,1} = \underbrace{\left(\sum_{q_k \in I_i^h} \mathbf{1}_{\eta_{i,1}(q_i)}(q_k)\right)}_{s_{i,1}^{(h)}} + \underbrace{\left(\sum_{q_k \in I_i \setminus I_i^h} \mathbf{1}_{\eta_{i,1}(q_i)}(q_k))\right)}_{n_{i,1}^{(h)}}\,.$$

To prove the proposition, consider factorizing the event expression as follows. If $n_{i,1}^{(h)} = 0$, the event reduces to $c_i = s_{i,1}^{(h)}$, whereas if $n_{i,1}^{(h)} = 1$, it becomes $c_i = s_{i,1}^{(h)} + 1 = 1$. Then, the event expression can be factorized as $c_i = s_{i,1}^{(h)} n_{i,1}^{(h)} + 1\, n_{i,1}^{(h)}$. Moreover, in the case of $v_{i,1} = 1$, it holds $n_{i,1}^{(h)} = 0$ (the observer has complete visibility of the topologies) that implies $c_i = s_{i,1}^{(h)}$, whereas nothing can be said on the value of $n_{i,1}^{(h)}$. Therefore, the event c_i can be factorized w.r.t. the observer's visibility as

$$c_i = s_{i,1}^{(h)}\, v_{h,1} + \left(s_{i,1}^{(h)} \neg\, n_{i,1}^{(h)} + n_{i,1}^{(h)}\right) \neg v_{h,1}$$

Hence, it holds

$$\begin{aligned} \tilde{c}_i &= \max_{n_{i,1}^{(h)} \in \mathbb{B}} c_i = \\ &= s_{i,1}^{(h)}\, v_{h,1} + \max_{n_{i,1}^{(h)} \in \mathbb{B}} \underbrace{\left(s_{i,1}^{(h)} \neg\, n_{i,1}^{(h)} + n_{i,1}^{(h)}\right)}_{A} \neg v_{h,1}\,. \end{aligned}$$

Finally, it holds $A = \max_{n_{i,1}^{(h)} \in \mathbb{B}} \left\{s_{i,1}^{(h)}, 1\right\} = 1$, which gives the thesis. ■

Proposition 2: Given a detector map c_i of the type $c_i = \neg s_{i,1}$, its visibility–based event is

$$\tilde{c}_i = s_{i,1}^{(h)}\,,$$

where $v_{h,1}$ is the event visibility of an observer onboard agent $\mathcal{A}_i$.

Proof: Based on the observer's visibility $v_{h,1}$, the topology can be written as

$$s_{i,1} = \underbrace{\left(\neg \sum_{q_k \in I_i^h} \mathbf{1}_{\eta_{i,1}(q_i)}(q_k)\right)}_{s_{i,1}^{(h)}} \underbrace{\left(\neg \sum_{q_k \in I_i \setminus I_i^h} \mathbf{1}_{\eta_{i,1}(q_i)}(q_k)\right)}_{n_{i,1}^{(h)}}\,.$$

To prove the proposition, consider factorizing the event expression as follows. If $n_{i,1}^{(h)} = 0$, the event reduces to $c_i = 0$, whereas if $n_{i,1}^{(h)} = 1$, it becomes $c_i = s_{i,1}^{(h)}$. Then, the event expression can be factorized as $c_i = 0\, n_{i,1}^{(h)} + s_{i,1}^{(h)}\, n_{i,1}^{(h)} = s_{i,1}^{(h)}\, n_{i,1}^{(h)}$. Moreover, if $v_{h,1} = 1$, it holds $n_{i,1}^{(h)} = 1$ that implies $c_i = s_{i,1}^{(h)}$, whereas nothing can be said on the value of $n_{i,1}^{(h)}$ and hence $c_i = s_{i,1}^{(h)} \neg n_{i,1}^{(h)}$. Therefore, the event c_i can be factorized w.r.t. the observer's visibility as

$$c_i = s_{i,1}^{(h)}\, v_{h,1} + s_{i,1}^{(h)}\, n_{i,1}^{(h)} \neg v_{h,1}$$

Hence, it holds

$$\begin{aligned} \tilde{c}_i &= \max_{n_{i,1}^{(h)} \in \mathbb{B}} c_i = \\ &= s_{i,1}^{(h)}\, v_{h,1} + s_{i,1}^{(h)} \underbrace{\max_{n_{i,1}^{(h)} \in \mathbb{B}} \left(s_{i,1}^{(h)}\right)}_{=1} \neg v_{h,1} = \\ &= s_{i,1}^{(h)}\, v_{h,1} + s_{i,1}^{(h)} \neg\, v_{h,1} = s_{i,1}^{(h)}\,(v_{h,1} + \neg\, v_{h,1}) = s_{i,1}^{(h)}\,, \end{aligned}$$

which gives the thesis. ■

We are ready to give the result on the general form in the following

Theorem 1: The visibility based upper estimation of a generic detector map $c_i = \Pi_k s_{i,k}\, \Pi_\rho s_{i,j}$ is

$$\tilde{c}_i = \left(\Pi_{j=1}^{\kappa} s_{i,j}^{(h)} v_{h,j} + \neg v_{h,j}\right) \left(\Pi_{j=\kappa+1}^{k} s_{i,j}^{(h)}\right) .$$

Proof: Let us proceed by induction. First assume $\rho = 0$. Prop. 1 shows that the thesis holds for $k = 1$ topologies. Supposing that the thesis holds for n topologies, i.e., given an event of the form $c_i = \Pi_{j=1}^{n} s_{i,j}$, with s_j of existence type, the visibility–based event is $\tilde{c}_i = \left(\Pi_{j=1}^{n} s_{i,j}^{(h)} v_{h,j} + \neg v_{h,j}\right)$, we need to prove it for $k+1$ topologies. First consider that

$$\begin{aligned} c_i &= \Pi_{j=1}^{k+1} s_{i,j} = \underbrace{\left(\Pi_{j=1}^{k} s_{i,j}\right)}_{z} s_{i,k+1} = \\ &= z\, s_{i,k+1} = z \left(s_{i,k+1}^{(h)} + n_{i,k+1}^{(h)}\right) . \end{aligned}$$

As above, consider factorizing the event as follows. If $n_{i,k+1}^{(h)} = 0$, the event reduces to $c_i = z\, s_{i,k+1}^{(h)}$. If $n_{i,k+1}^{(h)} = 1$, the event becomes $c_i = z$. Therefore, the event can be rewritten as

$$c_i = z \neg n_{i,k+1}^{(h)} + z\, s_{i,k+1}^{(h)} .$$

W.r.t. the observer's visibility on the last topology, $v_{h,k+1}$, the event can be factorized as follows. If $v_{h,k+1} = 1$, we have $n_{i,k+1}^{(h)} = 0$ and $c_i = z\, s_{i,k+1}^{(h)}$, whereas if $v_{h,k+1} = 0$, we have $c_i = z \neg n_{i,k+1}^{(h)} + z\, s_{i,k+1}^{(h)}$. This yields

$$c_i = z \left(s_{i,k+1}^{(h)} v_{h,k+1} + \left(s_{i,k+1}^{(h)} + \neg\, n_{i,k+1}^{(h)}\right) \neg v_{h,k+1}\right) .$$

The visibility–based event is $\tilde{c}_i = \max_{n_{i,j} \in \mathbb{B}, j=1,\cdots,k+1} c_i$, whose direct computation gives

$$\begin{gathered} \max_{n_{i,j} \in \mathbb{B}, j=1,\cdots,k} z \\ \max_{n_{i,k+1}} \left(s_{i,k+1}^{(h)} v_{h,k+1} + \left(s_{i,k+1}^{(h)} + \neg n_{i,k+1}^{(h)}\right) \neg v_{h,k+1}\right) = \\ \left(\Pi_{j=1}^{k} s_{i,j}^{(h)} v_{h,j} + \neg v_{h,j}\right) \left(s_{i,k+1}^{(h)} v_{h,k+1} + \neg v_{h,k+1}\right) , \end{gathered}$$

from which the part of the thesis relative to existence topology follows.

Consider now the case $\kappa = 0$. Prop. 2 shows that the thesis holds for one topology of such a type. The inductive step requires considering $c_i = \Pi_{j=1}^{k+1} s_{i,j} = z\, s_{i,k+1}^{(h)}\, n_{i,k+1}^{(h)}$. This event can be factorized as follows. If $n_{i,k+1}^{(h)} = 0$, the event reduces to $c_i = 0$, whereas, if $n_{i,k+1}^{(h)} = 1$, it becomes $c_i = z\, s_{i,k+1}^{(h)}$. Therefore, the event can be rewritten as

$$c_i = z\, s_{i,k+1}^{(h)}\, n_{i,k+1}^{(h)} .$$

W.r.t. the observer's visibility on the last atom, $v_{h,k+1}$, the event can be factorized as follows. If $v_{h,k+1} = 1$, we have $n_{i,k+1}^{(h)} = 1$ and $c_i = z\, s_{i,k+1}^{(h)}$, whereas if $v_{h,k+1} = 0$, we have $c_i = z\, s_{i,k+1}^{(h)}\, n_{i,k+1}^{(h)}$. This yields

$$c_i = z \left(v_{h,k+1} + n_{i,k+1}^{(h)} \neg\, v_{h,k+1}\right) s_{i,k+1}^{(h)} .$$

The visibility–based event is $\tilde{c}_i = \max_{n_{i,j} \in \mathbb{B}, j=1,\cdots,k+1} c_i$, whose direct computation gives

$$\begin{gathered} \max_{n_{i,j} \in \mathbb{B}, j=1,\cdots,k} z \\ \max_{n_{i,k+1}} \left(v_{h,k+1} + n_{i,k+1}^{(h)} \neg\, v_{h,k+1}\right) s_{i,k+1}^{(h)} = \\ = \left(\Pi_{j=1}^{k} s_{i,j}^{(h)}\right) s_{i,k+1}^{(h)} , \end{gathered}$$

from which also the second part of the thesis follows. The result straightforwardly extends to the case with $\rho, \kappa \neq 0$ (the proof is omitted for space), which concludes the thesis. ■

The predictor is initialized with the value $\tilde{\sigma}_i(0) = \Sigma_i$, which corresponds to the most conservative hypothesis on the activation of c_i. The estimated state $\tilde{\sigma}_i$ is updated according to the rule

$$\tilde{\sigma}_i^{(r)}(t_{k+1}) = \tilde{\delta}^{(r)} \left(\tilde{\sigma}_i^{(r)}(t_k), \tilde{e}_i^{(r)}(\tilde{c}_i(t_{k+1}))\right) .$$

The predictor $\tilde{\mathcal{H}}^{(r)}(\tilde{q}, \tilde{\sigma}, \tilde{I})$ of the r–th species can be constructed by using the same decoder $u^{(r)}$, encoder $s^{(r)}$, dynamics $f^{(r)}$, and the other components of the nominal model, and is valid for any visibility $\mathcal{V}_h$ of the classifying agent and any neighborhood configuration set I_i of the target agent. The set of possible behaviors $\tilde{q}_i^{(r)}$ that $\mathcal{A}_i$ can execute compatibly with the r–th species and the local knowledge of $\mathcal{A}_h$ is the solution of

$$\begin{cases} \dot{\tilde{q}}_i^{(r)}(t) = \tilde{\mathcal{H}}_i^{(r)}(\bar{q}_i(t), \bar{\sigma}_i(t_k), I_i^{obs}(t)), \quad t \in \left[t_k, t_{k+1}\right) , \\ \tilde{q}_i^{(r)}(t_k) = \bar{q}_i^{(r)}(t_k) . \end{cases} \tag{3}$$

Note that, as the cardinality of $\tilde{\sigma}_i(t_k)$ is finite and equal to $\kappa(t_k)$, then $\tilde{q}_i^{(r)} = \left\{\tilde{q}_{i,1}^{(r)}, \ldots, \tilde{q}_{i,\kappa(t_k)}^{(r)}\right\}$ can be directly computed. This is iterated for all different species for which the agent's compatibility has not been excluded yet, based on the assumption that an agent belongs always to the same species with which it is initialized.

The second step, the classification phase, starts with determining for which species there exists at least one behavior that is sufficiently close to the observed one. This can be achieved by evaluating the test

$$\|\bar{q}_i(t) - \pi_{\mathcal{Q}}(\phi_{\tilde{\mathcal{H}}^{(r)}} \bar{q}_i(t), \bar{\sigma}_i(t_k), I_i^{obs}(t))\| \leq \epsilon, \qquad \forall \quad t \in \left[t_k, t_{k+1}\right) , \tag{4}$$

that returns true if it is satisfied by at least one behavior in $\tilde{q}_i^{(r)}$. If none of the predicted behaviors satisfies the test, for a given species, then $\mathcal{A}_h$ is not compatible according to Def. 2 with that species. If, on the contrary, the test is satisfied by some behaviors — denote with $l_1, \ldots, l_m \in \mathbb{N}$ their indices — the agent is possibly compatible with the species. An estimate of agent $\mathcal{A}_i$'s current action is given by $\tilde{\sigma}_i^{(r)}(t_k) \leftarrow \left\{\tilde{\sigma}_{i,l_1}^{(r)}, \ldots, \tilde{\sigma}_{i,l_m}^{(r)}\right\}$. Finally, this allows computing a logical vector $C_i^{(h)} = \left(C_{i,1}^{(h)}, \cdots, C_{i,p}^{(h)}\right)$, where $C_{i,j}^{(h)}$ is true iff agent $\mathcal{A}_i$ is compatible with species S^r, based on local knowledge of $\mathcal{A}_h$. As soon as $C_i^{(h)}$ contains exactly one element set to true, agent $\mathcal{A}_i$ can be classified as belonging to the corresponding species, according to the assumption above. The local classifier solving Problem 1 is obtained as the series of the prediction system (Eq. 3) and the classification test (Eq. 4) described above.

IV. Applications

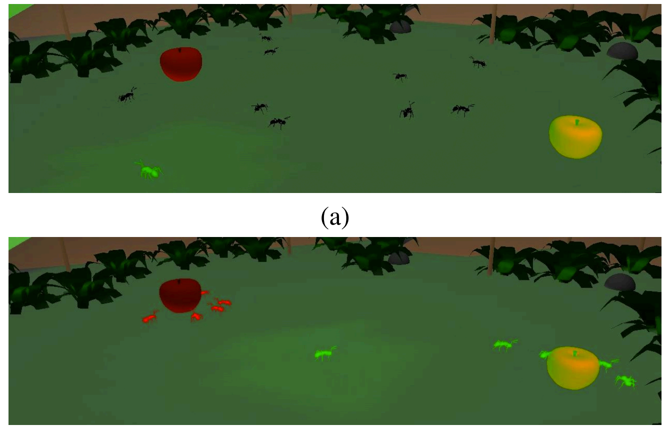
Effectiveness of the proposed distributed classifier is shown through application to a biologically–inspired system and a robotic multi agent, where the very same procedure has been applied. The video attached with the paper shows the complete simulation run.

A. Ant Classification in Biology

Ants of several species are organized in colonies, where "worker members" of a colony cooperate during the foraging process whenever a prey cannot be moved by a single ant [3], [4]. In these species, sociality should affect not only the behavior of ants, but also the brains that generate and control the behavior. In particular, the brain composition might reflect the behavioral specialization of the ant colonies. Chemical (pherormones) and mechanical communication (vibration, touch) among nestmates are hallmarks of a social lifestyle, and one might expect that sensory capabilities in ants are well developed [5], [18].

In this work we focus on the foraging behavior of the polymorphic tree dwelling ant *Daceton Armigerum*. This process involves the recruitment of nestmates of the same colony, by issuing a *distinct*, colony–dependent visual or chemical marking. Suppose that two ant colonies exist, a *Green* and a *Red* one. Green ants start moving around the prey to inform their neighbors of their impossibility to move it, whereas Red ants stop in front of it. A generic ant $\mathcal{A}_i$'s configuration is $q_i = (x_i, y_i, \theta_i, v_i)$, where (x_i, y_i) is the position of the ant's center, θ_i is its orientation w.r.t. the x–axis, and v_i is its speed of motion, and evolves following the dynamics of Eq. (5). Both species share the following set of rules: $\mathsf{rule}_1 \overset{\text{def}}{=}$ "proceed along a casual direction until a prey is found or a visual signal from a nestmate is received", $\mathsf{rule}_2 \overset{\text{def}}{=}$ "if a visual signal is received from a nestmate, go toward the nestmate and verify the actual existence of a nearby prey", $\mathsf{rule}_3 \overset{\text{def}}{=}$ "if a prey has been found, then issue a visual signal to recruite other nestmates". Their allowed maneuvers are: EXPLORATION $\overset{\text{def}}{=}$ "move straight along a casual direction", STOP $\overset{\text{def}}{=}$ "remain fixed", ALERT $\overset{\text{def}}{=}$ "go toward the nestmate", RECRUITING $\overset{\text{def}}{=}$ "issue the visual signal to recruit neighboring nestmates", RECRUITED $\overset{\text{def}}{=}$ "come closer to a nestmate and check that there is a prey". Consider, for each ant $\mathcal{A}_i$, the logical variables: $s_{i,1} \overset{\text{def}}{=}$ "there is a prey in front of $\mathcal{A}_i$", $s_{i,2} \overset{\text{def}}{=}$ "a nestmate of $\mathcal{A}_i$ has issued the recruiting signal", and $s_{i,3} \overset{\text{def}}{=}$ "$\mathcal{A}_i$ is in the recruiting point". The two species only differ from the way these logical variables, representing atoms, are combined together into events (see Table I).

Consider an example with 5 ants of the Green species and 5 of Red one. The goal of each ant is to recognize its nestmates to cooperate in the foraging process of the colony. Fig. 1-a shows the initial situation, where it is shown a classifying ant (green in figure) with insufficient information to classify its neighbors. As the simulation proceeds the ant gathers more information and is able to correctly recognize and recruit nestmates (Fig. 1-b).



(a) (b)

Fig. 1. An ant of the Green species classifying its neighbors. The simulation starts with no a priori knowledge (a) and concludes with the ant that has correctly classified all other ants (b).

B. Vehicle Classification in Highways

As described in Section II, the considered robotic society is composed of vehicles belonging to the right-hand, left-hand, or emergency traffic rule species. For space reasons only the complete specification of the right-hand species is reported below. The environment is $\mathcal{Q} = R^2$. The configuration of the generic agent $\mathcal{A}_i$ is $q_i = (x_i, y_i, v_i, \theta_i)$ and is updated according to the dynamic map

$$\begin{aligned} f_i \;\; &: \;\; \mathcal{Q} \times \mathcal{U}_i \to T_{\mathcal{Q}} \\ &\;\;\;\; q_i \mapsto (\cos(\theta_i) v_i, \sin(\theta_i) v_i, a_i, \omega_i)^T \end{aligned} \quad , \qquad (5)$$

where $\mathcal{U}_i = R^2$. We need to introduce a topology $\eta_{i,1}(q_i)$ representing a region in the immediate front of the agent, a topology $\eta_{i,2}(q_i)$ for a region on its left, a topology $\eta_{i,3}(q_i)$ for a region on its right, and a topology $\eta_{i,4}(q_i)$ for a region on its back (Fig. 2). These are formally described as

$$\begin{aligned} \eta_{i,1} \;\; &: \;\; \mathcal{Q} \to 2^{\mathcal{Q}} \\ &\;\;\;\; q_i \mapsto \{(x, y, \theta, v) \,|\, x_i \le x \le x_i + d_f, \\ &\qquad\qquad \lfloor \tfrac{y_i}{w} \rfloor w \le y \le \left(\lfloor \tfrac{y_i}{w} \rfloor + 1\right) w\} \;, \\ \eta_{i,2} \;\; &: \;\; \mathcal{Q} \to 2^{\mathcal{Q}} \\ &\;\;\;\; q_i \mapsto \{(x, y, \theta, v) \,|\, x_i - d_b \le x \le x_i + d_f, \\ &\qquad\qquad \left(\lfloor \tfrac{y_i}{w} \rfloor + 1\right) w \le y \le \left(\lfloor \tfrac{y_i}{w} \rfloor + 2\right) w\} \;, \\ \eta_{i,3} \;\; &: \;\; \mathcal{Q} \to 2^{\mathcal{Q}} \\ &\;\;\;\; q_i \mapsto \{(x, y, \theta, v) \,|\, x_i - d_b \le x \le x_i + d_f, \\ &\qquad\qquad \left(\lfloor \tfrac{y_i}{w} \rfloor - 1\right) \le y \le \lfloor \tfrac{y_i}{w} \rfloor w\} \;, \\ \eta_{i,4} \;\; &: \;\; \mathcal{Q} \to 2^{\mathcal{Q}} \\ &\;\;\;\; q_i \mapsto \{(x, y, \theta, v) \,|\, x_i - d_b \le x \le x_i, \\ &\qquad\qquad \lfloor \tfrac{y_i}{w} \rfloor w \le y \le \left(\lfloor \tfrac{y_i}{w} \rfloor + 1\right) w\} \;, \end{aligned}$$

where w is the lane width, d_f and d_b are a forward and backward safety distances, and $\lfloor \cdot \rfloor$ returns the nearest lower integer of the argument. Thus, the encoder map is $s_i : \mathcal{Q} \times \mathcal{Q}^{n_i} \to \mathbb{B}^4$, $s_i = (s_{i,1}, \cdots, s_{i,4})$, and the agent's neighborhood is $N(q_i) = \eta_{i,1}(q_i) \cup \cdots \cup \eta_{i,4}(q_i)$.

Moreover, we need to introduce two constants $\lambda_{i,1}, \lambda_{i,2}$

$\tau_i^{k,w}$	$s_{i,j}$[RED]	$s_{i,j}$[GREEN]
EXPLORATION $\longrightarrow$ EXPLORATION	$c_{i,1} = \neg s_{i,1} \neg s_{i,2}$	$c_{i,1} = \neg s_{i,1} \neg s_{i,2}$
EXPLORATION $\longrightarrow$ STOP	$c_{i,2} = s_{i,1}$	$c_{i,2} = s_{i,1}$
EXPLORATION $\longrightarrow$ ALERT	$c_{i,3} = \neg s_{i,1}\, s_{i,2} \neg s_{i,3}$	$c_{i,3} = \neg s_{i,1}\, s_{i,2} \neg s_{i,3}$
STOP $\longrightarrow$ RECRUITING	$c_{i,4} = s_{i,1}$	$c_{i,4} = s_{i,1}$
ALERT $\longrightarrow$ ALERT	$c_{i,5} = \neg s_{i,3}$	$c_{i,5} = \neg s_{i,3}$
ALERT $\longrightarrow$ RECRUITED	–	$c_{i,6} = \neg s_{i,1}\, s_{i,3}$
ALERT $\longrightarrow$ STOP	$c_{i,6} = s_{i,1}$	–
RECRUITED $\longrightarrow$ RECRUITED	–	$c_{i,7} = \neg s_{i,1}$
RECRUITED $\longrightarrow$ STOP	–	$c_{i,8} = s_{i,1}$
RECRUITING $\longrightarrow$ RECRUITING	$c_{i,7} = s_{i,1}$	$c_{i,9} = s_{i,1}$

TABLE I
TRANSITIONS OF THE AUTOMATON OF $\mathcal{A}_i$ IN THE ANT EXAMPLE.

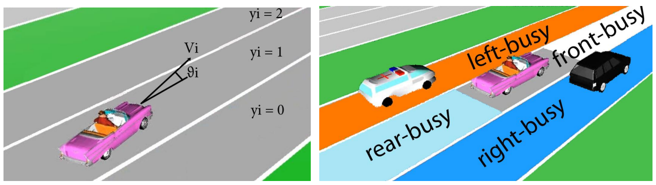


Fig. 2. Configuration and neighborhood of a generic vehicle $\mathcal{A}_i$.

representing the left–most and right–most lanes, respectively, and two constants $\lambda_{i,3}, \lambda_{i,4}$ representing the current target lane's left and right edges, respectively:

$$\begin{aligned} \lambda_{i,1} &= \{(x, y, \theta, v) \,|\, (m-1)w \le y \le m\, w\}\ , \\ \lambda_{i,2} &= \{(x, y, \theta, v) \,|\, 0 \le y \le w\}\ , \\ \lambda_{i,3} &= \left\{(x, y, \theta, v) \,|\, y = \left(\left\lfloor \tfrac{y_i(t_k)}{w} \right\rfloor + 1\right) w\right\}\ , \\ \lambda_{i,4} &= \left\{(x, y, \theta, v) \,|\, y = \left\lfloor \tfrac{y_i(t_k)}{w} \right\rfloor w\right\}\ . \end{aligned}$$

The event alphabet is $E_i = \{e^{i,1}, \cdots, e^{i,13}\}$ and the event map is

$$e_i \ : \ \mathbb{B}^{13} \to 2^{E_i}$$
$$\begin{pmatrix} 0 \\ \vdots \\ 0 \end{pmatrix} \mapsto \emptyset\,, \begin{pmatrix} 1 \\ \vdots \\ 0 \end{pmatrix} \mapsto \{e^{i,1}\}$$
$$\begin{pmatrix} 0 \\ 1 \\ \vdots \end{pmatrix} \mapsto \{e^{i,2}\}, \cdots, \begin{pmatrix} 0 \\ \vdots \\ 1 \end{pmatrix} \mapsto \{e^{i,13}\}.$$

with event conditions given by

$$\begin{gathered} c_{i,1} = \neg s_{i,1} s_{i,3}\,,\ \ c_{i,2} = \neg s_{i,1} \lambda_{i,2}\,,\ \ c_{i,3} = s_{i,1} s_{i,2}\,, \\ c_{i,4} = s_{i,1} s_{i,4}\,,\ \ c_{i,5} = s_{i,1} \lambda_{i,1}\,,\ \ c_{i,6} = s_{i,1} \neg s_{i,2} \neg s_{i,4} \neg \lambda_{i,1}\,, \\ c_{i,7} = \neg s_{i,1} \neg s_{i,3} \neg \lambda_{i,2}\,,\ \ c_{i,8} = \neg s_{i,1}\,,\ \ c_{i,9} = \lambda_{i,3}\,, \\ c_{i,10} = s_{i,1} \neg \lambda_{i,3}\,,\ \ c_{i,11} = s_{i,1}\,,\ \ c_{i,12} = \lambda_{i,4}\,, \\ c_{i,13} = \neg s_{i,1} \neg \lambda_{i,4}\,. \end{gathered}$$

The finite set of discrete states is $\Sigma_i = \{$FAST, SLOW, LEFT, RIGHT$\}$ ($p = 4$) and the automaton's dynamics is

$$\begin{aligned} \delta_i \ &: \ \Sigma_i \times 2^{E_i} \to \Sigma_i \\ &(\text{FAST}, e^{i,1}), (\text{FAST}, e^{i,2}) \ \mapsto \text{FAST}\,, \\ &(\text{FAST}, e^{i,3}), (\text{FAST}, e^{i,4}), (\text{FAST}, e^{i,5}) \ \mapsto \text{SLOW}\,, \\ &(\text{FAST}, e^{i,6}) \ \mapsto \text{LEFT}\,, \\ &(\text{FAST}, e^{i,7}) \ \mapsto \text{RIGHT}\,, \\ &(\text{SLOW}, e^{i,8}) \ \mapsto \text{FAST}\,, \\ &(\text{SLOW}, e^{i,3}), (\text{SLOW}, e^{i,4}), (\text{SLOW}, e^{i,5}) \ \mapsto \text{SLOW}\,, \\ &(\text{SLOW}, e^{i,6}) \ \mapsto \text{LEFT}\,, \\ &(\text{LEFT}, e^{i,8}), (\text{LEFT}, e^{i,9}) \ \mapsto \text{FAST}\,, \\ &(\text{LEFT}, e^{i,10}) \ \mapsto \text{LEFT}\,, \\ &(\text{RIGHT}, e^{i,11}), (\text{LEFT}, e^{i,12}) \ \mapsto \text{FAST}\,, \\ &(\text{RIGHT}, e^{i,13}) \ \mapsto \text{RIGHT}\,, \end{aligned}$$

with initial state $\sigma_i^0 =$ FAST.

The decoder map is $u_i : \ \mathcal{Q} \times \Sigma_i \to \mathcal{U}_i$, $u_i = (a_i, \omega_i)$, with

$$\begin{aligned} a_i \ &: \ \mathcal{Q} \times \Sigma_i \to \mathbb{R} \\ &\begin{matrix} (q_i, \text{FAST}), (q_i, \text{LEFT}), \\ (q_i, \text{RIGHT}) \end{matrix} \ \mapsto \begin{cases} \bar{a} & \text{if } v_i < v_{max}^i \\ 0 & \text{otherwise} \end{cases}\ , \\ &(q_i, \text{SLOW}) \ \mapsto \begin{cases} -\bar{a} & \text{if } v_i > 0 \\ 0 & \text{otherwise} \end{cases}\ , \end{aligned}$$

$$\begin{aligned} \omega_i \ &: \ \mathcal{Q} \times \Sigma_i \to \mathbb{R} \\ &\begin{matrix} (q_i, \text{FAST}), \\ (q_i, \text{SLOW}) \end{matrix} \ \mapsto \left((y^*(q_i) - y_i)\, \tfrac{\sin \theta_i}{\theta_i} - \mu\, \theta_i\right) v_i\,, \\ &(q_i, \text{LEFT}), \ \mapsto \begin{cases} \bar{\omega} & \text{if } \theta_i < \theta_{max} \\ 0 & \text{otherwise} \end{cases}\ , \\ &(q_i, \text{RIGHT}), \mapsto \begin{cases} -\bar{\omega} & \text{if } \theta_i > -\theta_{max} \\ 0 & \text{otherwise} \end{cases}\ , \end{aligned}$$

where $y^*(q_i) = \left(\left\lfloor \frac{y_i}{w} \right\rfloor + \frac{1}{2}\right) w$ is the current lane center, θ_{max} and v_{max}^i are the agent's maximum curvature angle and allowed speed, and μ, $\bar{a}$ and $\bar{\omega}$ are positive constants.The other species share the same components described above except for the event conditions and the automaton's dynamics. Some of these differences are highlighted in Table II.

Finally, the visibility map returns the set of configurations laying within a distance R_i and that are not hidden by other cars (for its computation see e.g. the known sweeping line algorithm in [19]). A formal description of the map is avoided for space reasons.

Consider 5 vehicles in a 3–lane highway (Fig. 3–a). In the simulation, an SOS vehicle (white vehicle in the figure) changes from FAST to LEFT maneuver to overtake another vehicle (purple vehicle in the figure). Moreover, there are three vehicles that are running local classifiers to classify the SOS car. Note that a FAST to LEFT transition of an agent of right-hand, or emergency traffic rules species implies that its frontal area is busy, while its left area is free (Fig. 2). In the example, the classifying vehicles, having with visibility of the influence region the emergency vehicle, are unable to classified it and remain uncertain, but still they can conclude for its compatibility with both species. On the contrary, a FAST to LEFT transition for a left–hand traffic rules vehicle implies that the frontal area is busy, while the left area is free, which is false in the example. Therefore, it is possible to exclude the left–hand species. The classification result is reported in Fig. 3–a, where $C_i^{(h)}$ is specified by a flag on the target agent. From top to down, the cells of the flag represents the classification w.r.t. the right-hand, left-hand, and emergency vehicle traffic rules species. Adopted colors are green, yellow, and red for the values compatible, uncertain, or incompatible, respectively. Dark gray and light gray regions represent $\mathcal{V}_i$ and $\bar{\mathcal{V}}_i$. Yellow regions are regions in $\bar{\mathcal{V}}_i$ that are essential to decide about the classification. For the sake of completeness, consider a successive time in the simulation, when the emergency vehicle is performing a FAST to RIGHT transition to overtake another vehicle (violet vehicle in the figure). The result of the local classification is depicted Fig. 3–b. In this case, the target agent is correctly classified as belonging to the emergency traffic rules species by two local classifiers, while a third one is unable to reach this due to its limited visibility. This shows the limit of the proposed technique and represents the motivation for future work, in which local classifiers will be allowed exchanging information and reaching a unique global decision.

V. Conclusion

This paper addressed the classification problem in multi–agents network systems. Under the hypothesis of complete knowledge of the species, a procedure to build a decentralized classifier was presented, that allows every agent to distinguish neighboring agents as belonging to one of such species, based only on local information. The described method is systematic and applies once the hybrid models describing the behavior of the different species are given. Application to a cooperative robotic system and to an example from Biology was shown. Future work will involve definition of a consensus mechanism allowing local classifiers to reach a unique global decision, which would overcome the limitations of the current solution.

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References

[1] S. Valverde, G. Theraulaz, J. Gautrais, V. Fourcassie, and R. Sole, "Self-organization patterns in wasp and open source communities," *IEEE Intelligent Systems*, vol. 21, no. 2, pp. 36–40, 2006.

[2] E. Bonabeau, G. Theraulaz, J. Deneubourg, S. Aron, and S. Camazine, "Self-organization in social insects," *Trends in Ecology & Evolution*, vol. 12, no. 5, pp. 188–193, 1997.

[3] B. Hölldobler and E. Wilson, "The multiple recruitment systems of the African weaver ant Oecophylla longinoda (Latreille)(Hymenoptera: Formicidae)," *Behavioral Ecology and Sociobiology*, vol. 3, no. 1, pp. 19–60, 1978.

[4] B. Hölldobler, R. Stanton, and H. Markl, "Recruitment and food-retrieving behavior in Novomessor (Formicidae, Hymenoptera)," *Behavioral Ecology and Sociobiology*, vol. 4, no. 2, pp. 163–181, 1978.

[5] W. Gronenberg, "Structure and function of ant (Hymenoptera: Formicidae) brains: Strength in numbers," *Myrmecological News*, vol. 11, pp. 25–36, 2008.

[6] C. Kube and E. Bonabeau, "Cooperative transport by ants and robots," *Robotics and autonomous systems*, vol. 30, no. 1-2, pp. 85–102, 2000.

[7] L. Pallottino, V. G. Scordio, A. Bicchi, and E. Frazzoli, "Decentralized cooperative policy for conflict resolution in multi-vehicle systems," *IEEE Transactions on Robotics*, 2007, sumbitted.

[8] F. Bullo, J. Cortés, and S. Martínez, "Cooperative control of robotic networks," Jul. 2007, Preprint.

[9] R. Olfati-Saber, J. Fax, and R. Murray, "Consensus and cooperation in networked multi-agent systems," *Proceedings of the IEEE*, vol. 95, no. 1, p. 215, 2007.

[10] A. Jadbabaie, J. Lin, and A. Morse, "Coordination of groups of mobile autonomous agents using nearest neighbor rules," *IEEE Transactions on Automatic Control*, vol. 48, no. 6, pp. 988–1001, 2003.

[11] J. Fax and R. Murray, "Information flow and cooperative control of vehicle formations," *IEEE Transactions on Automatic Control*, vol. 49, no. 9, pp. 1465–1476, Sept. 2004.

[12] A. Fagiolini, M. Pellinacci, G. Valenti, G. Dini, and A. Bicchi, "Consensus based Distributed Intrusion Detection for Multi Robot Systems," in *Proc. IEEE International Conf. on Robotics and Automation*, 2008, pp. 120–127.

[13] F. Pasqualetti, A. Bicchi, and F. Bullo, "Distributed intrusion detection for secure consensus computations," in *Proc. 46th IEEE Conf. on Decision and Control*, New Orleans, LA, USA, 12–14 December 2007, pp. 5594–5599.

[14] A. Fagiolini, M. Pellinacci, G. Valenti, G. Dini, and A. Bicchi, "Consensus–based distributed intrusion detection for multi–robot systems," in *IEEE International Conference on Robotics and Automation*, 2008.

[15] J. Lygeros, "Lecture notes on hybrid systems," in *Notes for an ENSIETA workshop*. Citeseer, 2004.

[16] A. Balluchi, L. Benvenuti, M. Di Benedetto, and A. Sangiovanni-Vincentelli, "Design of observers for hybrid systems," *Hybrid Systems: Computation and Control*, pp. 59–80, 2002.

[17] A. Fagiolini, G. Valenti, L. Pallottino, G. Dini, and A. Bicchi, "Decentralized intrusion detection for secure cooperative multi-agent systems," *IEEE Conf. on Decision and Control*, 2007, to appear.

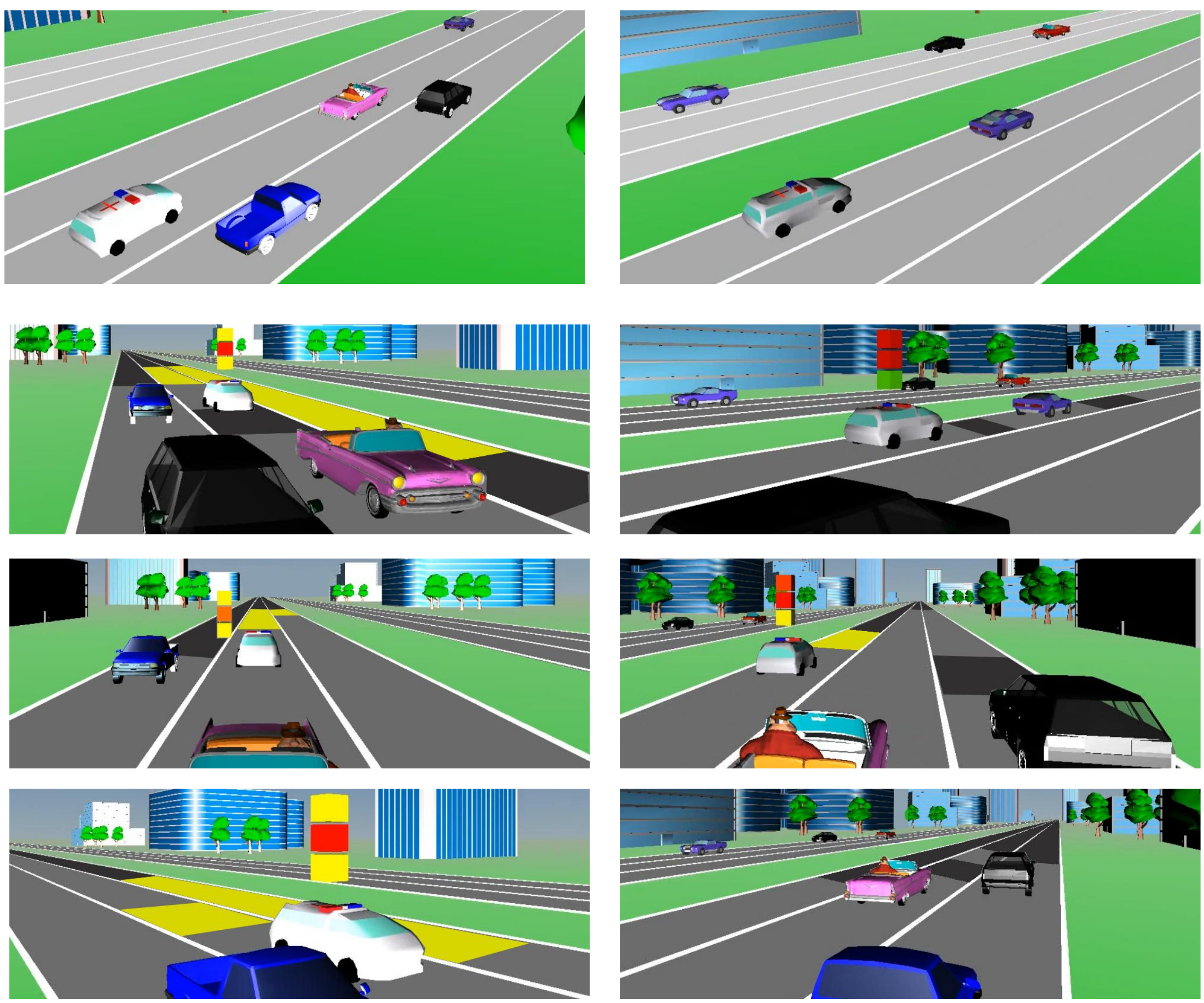
[18] Y. Madi and K. Jaffe, "On foraging behavior of the polymorphic tree dwelling ant Daceton armigerum (Hymenoptera: Formicidae)," *Entomotropica*, vol. 21, no. 2, 2006.

[19] S. Thrun, "Probabilistic robotics," *Communications of the ACM*, vol. 45, no. 3, pp. 52–57, 2002.

$\tau_i^{k,w}$	$s_{i,j}$[Right–hand]	$s_{i,j}$[Left–hand]	$s_{i,j}$[Emergency]
FAST $\longrightarrow$ FAST	$c_{i,1} = \neg s_{i,1}\, s_{i,3}$ $c_{i,2} = \neg s_{i,1} \lambda_{i,2}$	$c_{i,1} = \neg s_{i,1}\, s_{i,2}$ $c_{i,2} = \neg s_{i,1}\, s_{i,4}$	$c_{i,1} = \neg s_{i,1}$ $c_{i,2} = \neg s_{i,1}\, \lambda_{i,1}$
FAST $\longrightarrow$ SLOW	$c_{i,3} = s_{i,1}\, s_{i,2}$ $c_{i,4} = s_{i,1}\, s_{i,4}$ $c_{i,5} = s_{i,1}\, \lambda_{i,1}$ –	$c_{i,3} = s_{i,1}\, s_{i,3}$ $c_{i,4} = s_{i,1}\, \lambda_{i,2}$ $c_{i,5} = s_{i,1}\, \lambda_{i,1}$ –	$c_{i,3} = s_{i,1}\, s_{i,2}\, s_{i,3}$ $c_{i,4} = s_{i,1}\, s_{i,3}\, s_{i,4}$ $c_{i,5} = s_{i,1}\, s_{i,2}\, \lambda_{i,2}$ $c_{i,6} = s_{i,1}\, \lambda_{i,1}$
FAST $\longrightarrow$ LEFT	$c_{i,6} = s_{i,1} \neg s_{i,2} \neg s_{i,4} \neg \lambda_{i,1}$	$c_{i,6} = \neg s_{i,1} \neg s_{i,2}, \neg s_{i,4} \neg \lambda_{i,1}$	$c_{i,7} = s_{i,1} \neg s_{i,2} \neg s_{i,4} \neg \lambda_{i,1}$
FAST $\longrightarrow$ RIGHT	$c_{i,7} = \neg s_{i,1} \neg s_{i,3} \neg \lambda_{i,2}$ –	$c_{i,7} = s_{i,1} \neg s_{i,3} \neg \lambda_{i,2}$ –	$c_{i,8} = s_{i,1}\, s_{i,2} \neg s_{i,3} \neg \lambda_{i,2}$ $c_{i,9} = s_{i,1} \neg s_{i,3}\, s_{i,4} \neg \lambda_{i,1}$

TABLE II

TRANSITIONS STARTING FROM THE FAST MANEUVER OF THE AUTOMATON OF $\mathcal{A}_i$ IN THE HIGHWAY EXAMPLE.



(a) (b)

Fig. 3. Snapshots from a simulation of the highway example with vehicles belonging to the right-hand, left-hand, and emergency vehicle traffic rules species.