Multi-Agent Model for Leader Identification in Platoon System

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***Abstract*—In the past decades, the research on autonomous vehicles and transportation systems has performed a great breakthrough. Among the emergent new transportation modes, the development of platoon control solutions seems to be very promising in terms of environmental impact and traffic jam aspects. The two main approaches generally encountered in literature deal with either a global point of view or a local one. In the local approaches, the follower vehicle perceives its environment, identifies a leader and applies a function to calculate a command. This paper deals with the identification task for a local platoon control system. This identification task is made using the reactive multi-agent paradigm. In the proposed system, the identification task can be defined as a selection of one pattern from a set following several criteria. These patterns are emergent structures made of agents which aggregate on specific areas of their environment depending on their perception and their interactions. The agent environment is built using data collected by sensors. The sensors raw data are processed so as to be integrated into agent environment. The association between one physical sensor and a suitable processing algorithm is called an abstract sensor. The paper presents in detail the proposal and its applications in simulated and real environments.**

Keywords–multi-agent; platoon system; leader identification

I. Introduction

In the past decades, the research on autonomous vehicles and transportation systems has achieved a great breakthrough with a widespread use of powerful embedded systems which includes multiple sensors and top level computational resources. In parallel with the extension of the autonomous abilities of individual vehicles, new transportation systems emerged. Among them, one can cite the development of platoon control solution aimed at helping the driver in his task while bringing some interesting properties in terms of environmental impact and traffic jam aspects.

A platoon can then be defined as a set of vehicles, evolving together without material link while keeping a given geometric configuration. In literature, two families of approaches are widely developed, they are classified according to a global or local reference frame. Global approaches propose to locate vehicles in a common reference frame shared by all the vehicles of the convoy. This requires precise localisation algorithms and efficient communication exchanges between vehicles. By contrast, local approaches are more reactive and they focus on local perception abilities. In these approaches, each vehicle perceives its environment, identifies a leader and applies a function to calculate a command. Thus, the local approaches rely mainly on an identification function aimed at finding the right vehicle to follow. Several solutions can be used to perform this identification task. For instance, one can cite the use of specific visual beacons [1], the use of Fuzzy logic algorithms [2] or the use of arithmetic solutions [3]. The main drawback of these solutions is a low robustness to interference or to sensor perturbations and the lack of adaptation ability so as to make them able to face with changes in scene configuration. To overcome these limitations, we propose, in this paper, a solution based on the reactive multi-agent paradigm. This solution uses the adaptive skills and the self-organization properties of multi-agent systems so as to provide robustness and adaptability to the identification system.

In recent years, multi-agent systems have been widely used to solve dynamic problems such as dynamical obstacles avoidance [4], localization and tracking, robot coordination etc. It has been also demonstrated that reactive multi-agent system approaches are efficient for tackling complex problems such as autonomous parking control [5], cooperation of situated agents/robots [6], data fusion and problem/game-solving [7].

The goal of this paper is to present an approach for a vehicle identification problem in a platoon context. The proposed approach is based on the application of reactive multi-agent systems. The identification problem can be defined to be the activity of selecting pertinent elements from a set of data using considerations on their shape, structure, dynamic, etc. Applied to vehicle identification in local platoon context, the identification is aimed at selecting, among all the objects detected in the vehicle perception range, one vehicle that can be considered as a leader for the platoon task. Thus, the result of an identification is a set of objects containing the leader and obstacles. In our multi-agent approach, this set is defined by the observation and the study of the components and the properties of the multi-agent system. The agents we developed are immaterial and evolve in an virtual environment which is an abstraction of vehicle perception range. Agent-to-agent and agent-to-environment interactions are proposed to produce an agent dissemination into the virtual environment the spatial configuration of which is led by the data furnished by vehicle sensors. This emergent structure, which represents the global system state, is analysed by indicators which allow to differentiate a potential leader from obstacles and other vehicles.

The paper is structured as follows : Section II draws a state of the art of the platoon issue through a description of the past and current international projects on the subject. Section III describes the multi-agent model used. Section IV exposes simulations and experimentations of identification

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model associated to the platoon function and Section V draws a conclusion of this work and provides clues for future research works.

II. Background

The vehicle detection for the local platoon issue has been widely developed through a huge number of international projects. The first project (*PATH 1992-2003*) that deals with the platoon control was based on the use of radar sensors [8], which enable the detection system to measure with high accuracy the leader position. The drawback of this solution was that the following vehicle detects also obstacles and cannot separate them from the leader. Then, the *DEMO 2000* project proposes a system for the detection of obstacles in order to recognize and localize obstacles [9]. Effective on a straight road, the performance of this system is limited with curved trajectories and in an open environment. The *CHAUFFEUR* project [10] used an on-board image processing system to determine the relative position of the preceding vehicle. This system depends on the detection of the infrared light (IR) emitters attached to the back of the preceding vehicle. This solution is efficient while dealing with homogeneous platoons. In the case of trucks and regular cars being together in the same platoon, the size of IR emitters becomes a problem (some of them are too large for being attached to a small car). Moreover, the use of such artificial beacons increases the cost of the solution and the reliability of the systems depends strongly on the light conditions. As opposed to this, the *KONVOI* project [11] developed a driver assistance system (ADAS) which controls the longitudinal and lateral adjustment. This system is based on laser range finder and radar sensors. However, both devices are not usable in unstructured environments, because they are based on the retrieval of infrastructure information, such as lane markings or Geographical Information Systems as references for the longitudinal and lateral control.

III. Multi-agent model for identification

A. Global overview

As previously explained, the proposed approach is based on the application of reactive multi-agent system [12] [13]. A virtual environment is built up using processed data collected by the embedded sensors of the follower vehicle. The association of one physical sensor and of a suitable processing algorithm is named abstract sensor. Agents are then spread in this environment. Depending on their perception and their interactions, agents aggregate on specific areas of their environment. This aggregation phenomenon leads to emergent structures made of agents which are considered as patterns. The task of identification can then be defined as a selection of one pattern from a set following several criteria.

The process can then be summarized by the following main steps (Figure 1):

1) Data are collected by abstract sensors.
2) Data are projected in 2D-space which corresponds to the environment of the agents ; this space is an abstraction of the state space of the problem.
3) A population of agents interacts with the projected data in this space using a set of interaction inspired by physics. The result of these interactions are structures or patterns which emerge into the environment.
4) A static and dynamic study allows then to identify the leader vehicle and the obstacles present in the vehicle's neighbourhood.

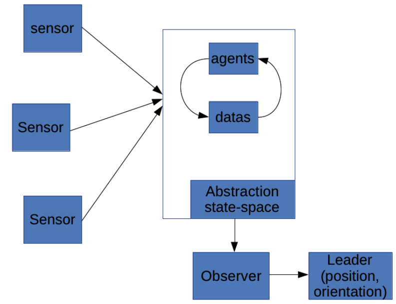

Figure 1. Global overview

B. multi-agent model

This section is aimed at giving a detailed description of the proposed Reactive Multi-Agent System (RMAS). The proposed approach puts the environment in the center of the problem-solving process. The environment corresponds to the place where the problem and its constraints are specified and presented to the perception of the agents. Then, interactions are defined in order to take into account the dynamics of the problem and its representation in the environment. These elements lead to emergent structures which are then analysed so as to extract the best solution to the problem. In the context of leader vehicle identification, the emergent structure is interpreted as a pattern with a specific geometrical shape and a particular behaviour.

1) Environment: As explained before, agents environment is the corner stone of the approach. It links vehicle's world and the identification mechanism. It is composed of entities associated to objects perceived by abstract sensors. An abstract sensor unit is composed of a sensor (software or hardware) and function of pre-processing. Objects are projected into environment as point or cloud of points.

2) Agents: The role of agents is to cover the environment, to locate and to track projected data. Two operations are considered:

- Grouping agents on the pertinent information.
- Interpreting the features of emergent structures.

In order to do this, two populations of agents are created, **label** agents and **delegate** agents.

The aim of **label** agents is to cluster, to follow and to isolate data of the virtual environment. Label agents have an internal state defined by one Label and one constraint.

- **The label**, denoted L_t^i for an agent A_i at t time, determines, for agent A_i, the membership to one group of agents according to spatial proximity. The value of the label is a natural number and is defined as follows:s

$$L_{t+1}^i(v) = \begin{cases} 0 & \text{if } \epsilon_t = \emptyset \\ \text{Rand(0,255)} & \text{if } \alpha_t = \emptyset \wedge \epsilon_t \neq \emptyset \\ min(L_t^i, L_t^j) & \text{if } \forall j \in \alpha_t \\ & (L_t^i \neq L_t^j \wedge L_t^i \neq 0) \end{cases} \quad (1)$$

where
- ϵ_t is a set of information
- α_t is a set of agents

- **The constraint** is a numerical value which represents the spatial organization of agents in the group. Considering an agent A_i, and its neighbourhood composed by the nearest two agents A_j and A_k, having the same label, the angle described by $\vec{ij}$ and $\vec{ik}$ defines the constraint. The higher the angle value is, the lower is the stress. This allows to define a pattern profile that can be used to identify the emergent structures.

The aim of **delegate** agents, is to detect and to locate groups of label agents having the same label value. Their internal state is defined by one satisfaction value and one vector named normal vector.

- The **satisfaction** is achieved when the delegate agent is near a group of label agents. The satisfaction value is progressive. Before reaching a threshold which locks its state, the delegate agent must satisfy constraints such as proximity, moving and loyalty to the group of label agents. A delegate agent who oscillates between two labels cannot be considered to be satisfied.
  The satisfaction value S^i_{t+1} increases in time, and can be calculated for an agent A_i at time t by:

$$S^i_{t+1} = \frac{1}{|\lambda|}\sum_{j\in\lambda}(1 - \frac{||\vec{r_t}\vec{j_t}||}{\pi}) + S^i_t \qquad (2)$$

where

$$\begin{aligned} \lambda &= \text{label of the group} \\ \vec{r_t} &= \text{position of the delegate agent} \\ \vec{j_t} &= \text{position of a label agent } A_j \end{aligned}$$

- The **normal vector** can be defined as a unit vector, collinear to the average motion vector of the agents pattern. It is computed when the delegate agent has reached a satisfaction threshold. The normal vector, noted $\vec{N^i}$ is defined as the mean of normal vectors of all the label agents composing the pattern using the following equation:

$$\vec{N^i} = \frac{1}{|\lambda|}\sum_{j\in\lambda}\vec{j_{dir}} \qquad (3)$$

The combination of the values of the internal states allows to cluster and to identify groups of agents.

3) Interactions: So as to reach their goals (relevant patterns of data), agents are evolving in their environment according to their perceptions and their interactions. The moves of agents are computed according to interactions inspired by classical physics. Label agents can thus be compared to particles in a force field influenced by their neighbourhood. Two types of interactions are used:

- **Agent-agent interaction** : agents are repulsing each other according to their nature (i.e. label agent repulses other label agents and delegate agent repulses other delegate agents). This ensures a homogeneous dispersion in the environment. The repulsion is computed following a classical gravitational Newton law in $1/r^2$. The force is given by :

$$\vec{Fr_{ij}} = \alpha m_i m_j \frac{\vec{A_iA_j}}{\|\vec{A_iA_j}\|^3} \qquad (4)$$

where

  - m_i is the mass of agent i.
  - A_i is the position of agent i.
  - $\alpha$is a coefficient taking into account the state of the agent (if it is locked or not for a label agent, if it is satisfied or not for a delegate agent) and the gravitational constant of the environment which is set empirically.

- **label agent-delegate agent**: an attraction force is applied between agent and environment's items. Thus, label agents are attracted by the data which corresponds to the presence of perceived objects. Moreover, delegate agents are attracted by label agents by using the same kind of force. The mathematical formulation of the attraction force is given by :

$$\vec{Fa_{ic}} = \beta_g m_i m_c \frac{\vec{A_iC}}{\|\vec{A_iC}\|^3} \qquad (5)$$

where

  - m_i is the mass of agent i.
  - A_i is the position of agent i.
  - m_c is mass of the center of attraction.
  - C is position of the center of attraction.
  - β_g is a coefficient taking into account the state of agents and environment properties.

Interactions are applied following Newton's law of motion. The system calculates at each time step, the position, the velocity and the acceleration of each agent. The acceleration is calculated as follows:

$$\begin{cases} \sum \overrightarrow{F_i} = m.\overrightarrow{\gamma_i} \\ \overrightarrow{\gamma_i} = \frac{1}{m}.\sum \overrightarrow{F_i} \\ \overrightarrow{\gamma_i} = \frac{1}{m}.(\overrightarrow{Fa} + \overrightarrow{Fr}) \end{cases} \qquad (6)$$

Forces can be generalised :$\overrightarrow{Fa}$ et $\overrightarrow{Fr}$ to all elements present in the perception field of agent A_i :

$$\begin{cases} Fr_i^X = \sum_{i\neq j}\left(m_i.m_j\frac{(x_j-x_i)}{((y_j-y_i)^2+(x_j-x_i)^2)^{\frac{3}{2}}}\right) \\ Fr_i^Y = \sum_{i\neq j}\left(m_i.m_j\frac{(y_j-y_i)}{((y_j-y_i)^2+(x_j-x_i)^2)^{\frac{3}{2}}}\right) \end{cases} \qquad (7)$$

and

$$\begin{cases} Fa_i^X = \alpha.m_i.m_c.(x_i - x_c) \\ Fa_i^Y = \alpha.m_i.m_c.(y_i - y_c) \end{cases} \qquad (8)$$

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For agent A_i :

$$\left\{ \vec{X}_i(t) = \vec{X}_i(t-1) + \left(\vec{V}_i(t-1)\delta t + \frac{(\delta t)2}{2m}\left(\overrightarrow{Fr}_i + \overrightarrow{Fa}_i\right)\right) \right. \quad (9)$$

where

- $\vec{X}_i(t)$ is the agent position.
- $\vec{V}_i(t)$ is the agent velocity

On a computer implementation point of view, the agents behaviours are ruled by a scheduler. This scheduler calls, at each time step, a function aimed at computing the forces to be applied and the future acceleration, speed and position of each agent. The result of this scheduler behaviour is a movement of all agents in the environment involving emergent structures which can then be studied by an external software module detailed in next paragraph.

C. Observation and identification

The external software module is able to retrieve, at any moment, the position and speed of the agents. The emergent structures, that appear in the environment, are patterns sharing the same label and the same delegate. To achieve the identification of objects, the constraint values of each label agent is used. These values are collected by the delegate agent of the group and form a vector which represents the profile of the detected object. This vector can be compared to a application dependant database previously defined. The database contains a set of profiles defined by an expert and takes into account the characteristics of the problem. In the context of platoon system, the useful information is classified into three types: leader, vehicle and obstacle. Among the detected vehicles, one of them must be chosen to be the leader. To do this, a multi-criteria comparison between delegate agents characteristics is performed. The criteria taken into account are: the life time of the delegate agent in the environment, the distance between the delegate agent and the follower vehicle which needs to determine its leader, the angle between the delegate and the follower vehicle, the relative speed of the delegate in the environment and the fact that the delegate already represents the current local leader.

These criteria are expressed in the form of a radar chart (Figure 2) and the selection is made by comparison of the obtained surfaces. The delegate agent who has the largest surface area is considered to be the local leader, other delegate agents are considered as obstacles.

IV. Simulations and experimentations

In this section, we present both results obtained in simulation and experimentation with real vehicles. So as to better compare both, the same protocol, scenarios, and metrics have been used.

A. Protocols

The testing protocol follows a classical workflow: data acquisition in a track involving all desired scenario, offline processing of data to produce classification, comparison between automatic classification and human classification.

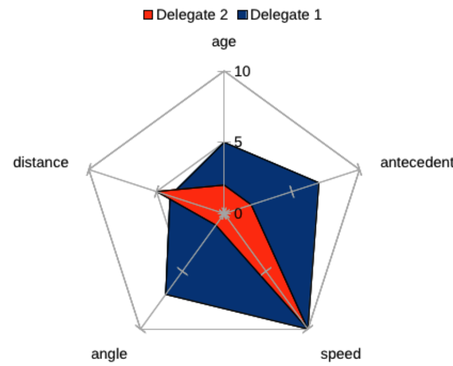

Figure 2. Delegate agents representation

1) Scenario: The scenario definition is one of the most important key points in simulations and experimentation. Tests have been made in the Technome site of Belfort. Technome site is an industrial/commercial activity area where pedestrians, parked and moving car, urban furniture can be found. Moreover, we have to the opportunity to use a 3D and geo-localised model of this area, that allows to proceed tests with the same scenario in simulation and in experimentation. The path selected for testing consists of several straight lines, a roundabout and various curves. It is surrounded by buildings and frequently crossed by pedestrians and cars. This path is repeated several times in order to obtain a sufficient amount of data.

2) Metrics: The metrics corresponds to the way the results are evaluated. Several metrics can be chosen such as the F-measure for example. In this case, we have chosen to concentrate on the application field. The metrics used are thus the classification rate between 2 or 3 classes (building, car, urban furniture, etc.), the false positive rate, the frequency and the duration of mistakes.

3) Tools:

- **VIVUS Simulator:** to assess the quality of our approach, realistic simulations have been done using VIVUS simulator [14], a vehicle simulator developed by the IRTES-SET laboratory. VIVUS is based on PhysX for real physical behaviour, and Unity3D for good 3D performance. This software can simulates the behaviours of each vehicle on several levels such as perceptions with laser range finder or cameras, physical reaction between elements (wheels, car's parts, etc.), etc. Physical reactions are computed using the same physical laws as in the real world (collision, gravity, etc.) and taking into account the properties of the environment (friction with road, materials of ground and walls, weather conditions, etc.). VIVUS has already been used to test various intelligent vehicle algorithms such as linear platoon control [13], obstacle avoidance and driving assistance [12], and intelligent crossroads simulations in [15].

- **SeT-Car platform** : the Systems and Transportation laboratory has got some electrical cars equipped for perception and autonomous navigation. The vehicle

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used for these experimentations is equipped with various sensor such as a Real Time Kinematic GPS (differential GPS), video cameras, gyroscope, laser range finder, etc. In these simulations, only the laser range finder has been used. Its characteristics are the following: 180 degrees of aperture, 80 meters of range and 1 degree of resolution.

- **Janus** is a multi-agent platform that was specifically designed to deal with the implementation and deployment of holonic and multi-agent systems. It is based on an organizational approach and its key focus is that it supports the implementation of the concepts of role and organization as first-class entities. This consideration has a significant impact on agent implementation and allows an agent to easily and dynamically change its behaviour.

B. *Simulation results*

The goal of these simulations is the validation of our system by studying the quality of the classification.

Two scenarios are simulated :

- **Trajectory in a sparse environment:** The sparse environment is composed of a small number of objects. It consists only of buildings. It highlights the system's ability to detect buildings at different speeds.
- **The trajectory in a dense environment:** The dense environment is composed of a large number of objects. It consists of buildings, different models of parked vehicles and of moving vehicles. It represents a classical dynamic urban environment. The objective of the simulation is to assess the system's ability to detect a large number of different objects, moving or not.

Simulated vehicles have laser range finder sensors and are conducted by an operator. Simulations are running out hundreds of times in order to have a significant amount of data for a reliable statistical study.

1) sparse environment results: Figure 3 shows the classification of objects in time. Two classes are represented: building and another. One can observe that the system regularly detects a large number of objects in the environment ($t = 37s$ or $t = 360s$). These detections are due to disturbances corresponding to measurement errors (soil, sidewalks, etc.).

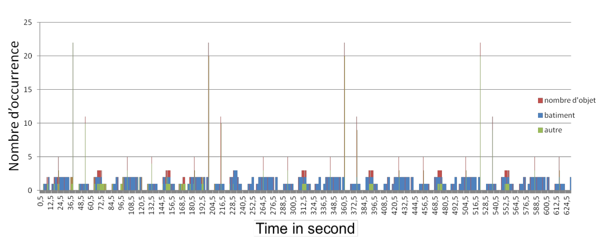

Figure 3. The evolution of the number of objects and their classification

These simulations show that in 12% of cases, a building is not detected by the system. 16% of the objects classified as buildings are false positives due to pitching of laser range finder during acceleration and braking.

2) dense environment results: Figure 4 shows the evolution of the number and type of objects detected during the simulation. We can see that increasing the number of objects does not cause a system overload. The list of identified objects is produced in less than 25 milliseconds. Note that the rate of not classified object's decreases compared to the simulation in a sparse environment. Indeed, because of the noise reduction ratio / useful information, the noise is less isolated and causes less disruption.

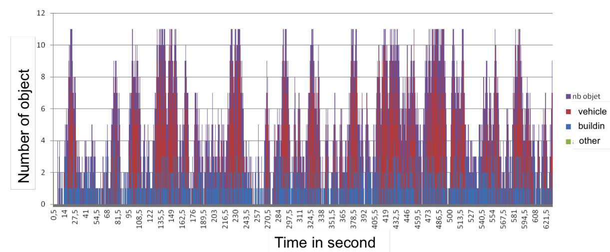

Figure 4. Distribution of classification

About misclassiffication, buildings are easier to detect than vehicles. In 82% of cases, a building is properly identified against 78% for vehicles. Similarly, the presence of the vehicle causes more false positives. This figure also shows that in these simulations, 12% of the vehicles were not detected by the system.

C. *Experimentation results*

Experimental results are based on the use of IRTES-SET vehicles. We conducted several acquisitions campaigns to obtain sufficient data to study the behaviour of our approach in real situations. For these experiments, we make an acquisition campaign in Belfort city. The vehicle is driven by an operator throughout the circulation. The environment on the trajectory is composed of parked and moving vehicles, buildings and street furniture, such as sheltered bus stops.

The results discussed in this section correspond to the study of classifications made by our approach. Two classes of interest are defined : vehicles and buildings. The other detected objects are classified as "other" category and are considered as obstacles.

Figure 5 shows the evolution of the number of detected objects and their allocation over the time. We observe that the system limit is around 15 objects. Over this number, objects become too small in relation to the sensor resolution. This limit is due to the resolution proposed by the sensor. Finer resolution would detect more objects. We can also see that the system is able to quickly adapt to its environment. The number of detected objects can vary between appraisals. The largest identified variation is +/- 9 items in 0.25 seconds.

In terms of misclassification, buildings were detected in 78% of cases and that vehicles were detected in 72% of cases. The "other" category is the biggest generator of false positives. Among the non-detected objects, buildings and vehicles are below 11%. Street furniture that is often confused with the noise is difficult to identify. 72% of the objects belonging to this class are not identified.

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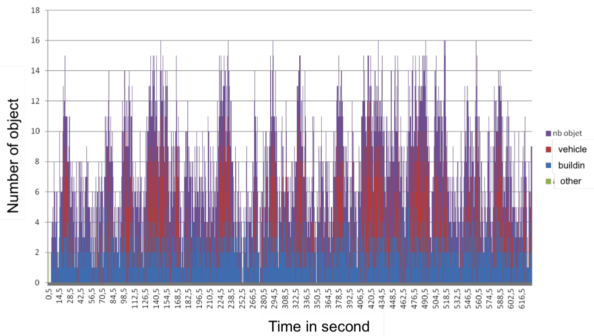

Figure 5. Classification of objects

We sought to quantify the duration of classification errors. These errors are either undetected objects, either false positives. Figure 6 shows that the error term is averaged higher for buildings than for vehicles. In almost 90% of cases, a vehicle is not detected between 0.25 and 0.5 seconds. Moreover, the distribution of misclassification of buildings is between 0.25 seconds and 1 second.

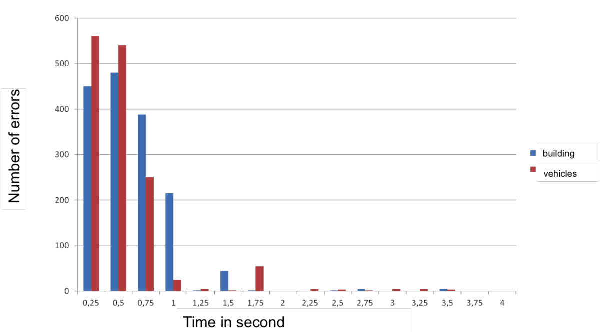

Figure 6. misclassification

We note that the real life results are worse than the simulation results, mainly due to the difference between the real and the simulated sensors. However, the simulation does not take into account the pure delays and the margins of error in the control actuators.

V. CONCLUSIONS

The paper presents a reactive agent approach for leader detection in platoon system through a generic and self-adaptive decision process. In this model, the environment is the central key element of agents system. It is the link between real world and the identification system. Agents population properties are observed to allow to choose and determine leader position in vehicle's perception and to separate it from other elements.

This solution has been successfully tested in simulation and in experimentation. The results obtained are encouraging to add and test the multi-sensor and plug and play ability of the system.

In order to continue this research, we are now working on a generic and self-adaptive approach for an agent based platoon control system.

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