Noname manuscript No.
(will be inserted by the editor)

Holonification Model for a Multilevel Agent-based System

Application to Road Traffic

Igor Haman Tchappi · Stéphane Galland · Vivient Corneille Kamla · Jean-Claude Kamgang · Cyrille Merleau Nono S. · Hui Zhao

Received: date / Accepted: date

Abstract Organizational models and holonic multi-agent systems are growing as a powerful tool for modeling and developing large-scale complex system. The main issue in deploying holonic multiagent systems is the building of the holonic model called holarchy. This paper presents a novel density approach to cluster and hierarchize population in order to build the initial holarchy. The proposal extends DBSCAN algorithm. Moreover, multilevel indicators based on standard deviation are proposed in order to evaluate the consistency of the holonification process. The proposed model is tested in a road traffic modeling in order to build the initial holarchy. The paper presents also the main research direction towards the control of internal and external stimuli of traffic over time.

Keywords DBSCAN · Holonic Multiagent System · Road Traffic · Multilevel Model · Initial Holarchy

I. Haman Tchappi
University of Ngaoundere, Faculty of sciences, Cameroon
LE2I, Univ. Bourgogne Franche-Comté, UTBM, F-90010 Belfort, France
E-mail: igortchappi@gmail.com

S. Galland
LE2I, Univ. Bourgogne Franche-Comté, UTBM, F-90010 Belfort, France

V.C. Kamla
University of Ngaoundere, ENSAI, BP:454 Ngaoundere, Cameroon

J.C. Kamgang
University of Ngaoundere, ENSAI, BP:454 Ngaoundere, Cameroon

C.M. Nono S.
Max Planck Institute for Mathematics in the Sciences, Inseistraße 22, D-04103. Leipzig, Germany

H. Zhao
LE2I, Univ. Bourgogne Franche-Comté, UTBM, F-90010 Belfort, France

1 Introduction

A complex system can be defined as a system featuring a large number of interacting components whose aggregate activity is not derivable from the summations of the activities of individual components (non-linearity) and typically exhibits hierarchical self-organization under selective constraints (Gaud et al, 2008). The organizational approach allows to model successfully complex systems, and also allows defining several abstractions levels of the system. A holon, according to Koestler (1967) is defined simultaneously as a whole and a part of the whole, thus it can be made up of other holons. Holonic modeling is used to model the intrinsic hierarchical nature of the systems. Holonic Multiagent System (HMAS) is therefore a recursive structure of holons, and well suited to model large-scale systems (Gerber et al, 1999).

In general, the life-cycle of HMAS consists of two stages: building the initial holarchy and controlling its structure against internal and external stimuli during its lifetime (Esmaeili et al, 2017). The initial holarchy represents the structure configuration of HMAS at time $t = 0$, while control structure against internal and external stimuli represents the life of HMAS at time $t > 0$. The contribution of this paper is on *building the initial holarchy of large-scale complex system at several granularity levels*. Additionally, the main research direction towards the control structure against internal and external stimuli of complex system over time is also presented. In order to build the initial holarchy, a multilevel density based holonification algorithm is proposed in order to cluster a population of interconnected agents with a bottom-up approach. Multilevel approach has proven its efficiency to model large-scale system (Gaud et al, 2008) and bottom-up design methodology is very popular for producing autonomous, scalable and adaptable systems requiring minimal or no communication (Crespi et al, 2008).

In order to build the holarchy, this paper extends the DBSCAN algorithm (Density-Based Spatial Clustering of Applications with Noise) (Ester et al, 1996). DBSCAN is very studied in literature and is awarded. It is chosen because of its capability of discovering clusters with arbitrary shape such as linear, concave, oval, etc. Moreover, in contrast with several others clustering algorithms, DBSCAN does not require the predetermination of the number of clusters a priori and has been proven its ability of processing very large databases (Birant and Kut, 2007). In DBSCAN, the density associated with a point is obtained by counting the number of points in a region of a specified radius around the point. Points with a density above a specified threshold are grouped into clusters. One of the main drawbacks of DBSCAN is its disability of supporting clusters with different sizes. Our model solves this problem from the view of holonic clustering. This paper presents a new holonic density-based algorithm, named H-DBSCAN, in order to build the holarchy of a complex system. The main difference between our approach and DBSCAN is that our approach supports clusters of different sizes, and DBSCAN groups objects (points); while our approach groups agents.

To assess our method, we have applied it on the modeling of road traffic problem. Generally, there are three main modeling and simulation road traffic approaches: microscopic, intermediate (mesoscopic and multilevel) and macroscopic approach. Microscopic models are accurate and applied generally in urban area while macroscopic models exhibit coarse behavior and generally applied in highway (Jaume, 2010). Microscopic models require a great computational cost, while macroscopic models exhibit a global behavior (Jaume, 2010). Multilevel or hybrid models integrate different levels of detail (microscopic, macroscopic, mesoscopic) within the same model and combine the advantages of microscopic, mesoscopic and macroscopic models (Tchappi et al, 2017). However, multilevel models of road traffic are difficult to realize since multilevel models require the management of the consistency of the models integrated. This paper focuses on multilevel modeling of road traffic. Most of the multilevel models from the literature, (Burghout, 2004; Mammar et al, 2006) have fixed a priori the two levels of detail (micro-meso, micro-macro, meso-macro) such that each level of detail is associated to one part of road network. Hybridization principle is therefore to manage transition between the two levels of details at the border of road network by aggregation and disaggregation of vehicles for example (Bourrel and Lesort, 2003). This multilevel approach is static and his implementation is difficult. To overcome this problem, the holonic approach of H-DBSCAN is used.

This paper is organized as follows: Section 2 presents holonic multiagent system, DBSCAN and related works. In Section 3, the explanation of the proposed holonification algorithm is given. Section 4 presents an application to road traffic, the evaluation of algorithm performance and the main research direction towards road traffic self-organization. Section 5 concludes this paper, and gives future research directions.

2 Related Works

2.1 Holonic Multiagent System

A holon, according to Koestler (1967) is defined as simultaneously a whole and a part of the whole, thus it can be made up of other holons, strictly meeting three conditions: being stable, having a capacity for autonomy and being able to cooperate. The originality of the holonic concept in relation to traditional systemic approaches is the fact that Koestler has been able to highlight a necessary condition for the viability and sustainability of social systems with his 65 rules (Adam, 2000). Holonic multiagent system is a recursive structure of holons (Gerber et al, 1999). The self-similarity of holons allows building the holarchy of the system, based on the composition of the holons. An example of holarchy is shown on Fig. 1.

Multi-agent System with the well-known Agent/Group/Role (AGR) (Ferber and Gutknecht, 1998; Ferber et al, 2004) is an appropriate tool to model complex system in order to bring out emergency. However, in the classic AGR

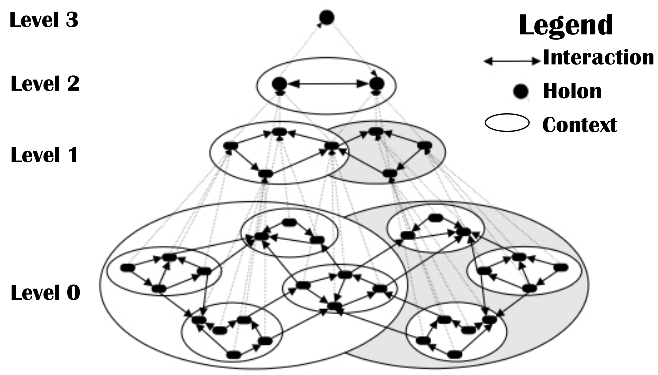

Fig. 1 A nested holarchy with four holarchical levels

methodology, abstraction levels of system are generally not hierarchic that is not well suited to deal with several recursive complex systems like human system or recursive distributed systems. In order to model these recursive complex systems, Holonic Multi-Agent System (Koestler, 1967; Gerber et al, 1999) has been proposed in literature. HMAS is more than hierarchic multilevel concept. Indeed, HMAS integrates hierarchic and whole/part observation relationship (or containing/contained observation) with the holonic view and holonic system thinking (Mella, 2009). Holonification (process of building the holarchy of system) is very critical in the design of holonic multiagent systems, and extensively affects the efficiency and complexity of the system (Esmaeili et al, 2014). The CRIO (Capacity-Role-Interaction-Organization) model (Gaud, 2007; Cossentino et al, 2010) is one of the meta-models to design holonic multiagent system. CRIO model is based on four main interrelated concepts:

- **Capacity:** A capacity is a description of a know-how/service. This description contains at least one name identifying the capacity and the set of its input and output variables which may have default values.
- **Organization:** A set of roles and their interactions pattern define an organization in a specific domain. The concept of organization combines roles and their interactions.
- **Role:** A role is the abstraction of a behavior in a certain context and confers a status within the organization. Roles may interact with other roles defined in the same organization. There are predefined roles named holonic roles in order to manage the decision process between the sub-holons within a holon. Among the holonic roles, there are `Head`, `StandAlone`, `Part` and `Multipart` roles (Rodriguez, 2005). The `Head` role is the representative (the visible face) of the super-holon outside world. The `Part` role identifies members of a single holon. `Multi-Part` role as an extension of the `Part` role emphasizes on a particular situation when a sub-holon is shared by more

than one super-holon. The `StandAlone` role is the way that an existing super-holon sees a non-member holon.

– **Interaction:** An interaction links two roles in a way that an action in the first role produces a reaction in the second.

In holonic multiagent system, there are two types of communications (Rodriguez et al, 2007):

Intra-level communication : holons communicating with holons at the same level ("horizontal communication").

Inter-level communication : when holons of two different levels communicate ("vertical communication").

The proposed holonification method uses the CRIO metamodel with intra- and inter-level communications. As stated before, the life-cycle of HMAS consists of building the initial holarchy (holonification) and controlling the system structure over the time. The initial holarchy of HMAS represents the overall composition of all holons at each abstraction level at time $t = 0$. The control structure against internal and external stimuli represents the self-organization of HMAS over time.

Several works dedicated to holonification of complex systems have already been proposed in literature. Rodriguez et al (2007) propose a framework for modeling and simulation of an important industrial plant (Peugeot car manufacturer at Sochaux, France). This work presents a model based on a multi-view analysis of a plant: Traffic Flow View (describes the structure and decomposition of the environment and the way vehicles interact with this environment) and View Family of Building (identifies the product exchange among buildings of the plant based on the available traffic information). The main drawback of this work is that it is designed for a plant, and hardly adaptable elsewhere. Another drawback is that there is no distinction between the model of system and the model of environment.

Gaud et al (2008) propose a force-based model in order to model and simulate crowds of pedestrian in 3D virtual environment. Pedestrians are grouped in a holon according to their affinity. This approach provides a scheduling model for multilevel simulations (can dynamically adapt the level of simulation). They use a set of physics-based (energy-based) indicators to evaluate the simulation accuracy. The main drawback of this method is the utilization of a forced-based model that is not suitable with other complex systems.

Esmaeili et al (2014) propose a method, inspired from social networks, to build the holonic structure of multiagent network with a bottom-up approach. The prerequisite of their method is an un-weighted undirected multiagent network model. They use urban traffic signal control to evaluate the quality of the constructed holons. The main drawback of this work is that the authors assume that the importance of an agent is based on eigenvector centrality in social networks. This assumption is restricted for a class of complex system.

This paper presents a density-based multiagent holonification to build the holarchy of complex system.

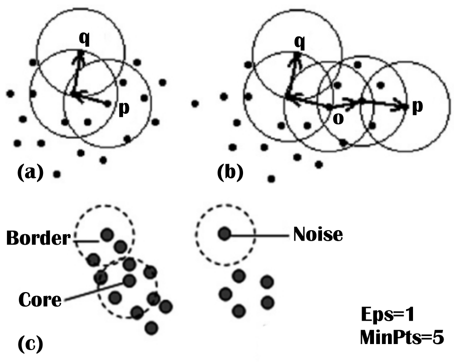

Fig. 2 Terminology of DBSCAN: (a) q density-reachable from p; (b) q and p density-connected to each other by o; (c) border, core and noise object.

2.2 Basics Concepts of DBSCAN

Ester et al (1996) propose a Density-Based Spatial Clustering of Applications with Noise (DBSCAN) for data clustering. It is a density-based clustering algorithm: given a set of points in some spaces, it groups together points that are closely packed together (points with many nearby neighbors), marking as outliers points that lie alone in low-density regions (whose nearest neighbors are too far away). DBSCAN is one of the most common clustering algorithms and also most cited[1] in scientific literature. In 2014, DBSCAN received the test of time award[2] at the leading conference on "Knowledge Discovery and Data mining" (KDD-14). The problem that DBSCAN tries to solve can be defined as follows: given a database of n data objects $D = \{o_1, o_2, ..., o_n\}$. DBSCAN partitions database D into clusters $C = \{C_1, C_2, ..., C_k\}$ based on a similarity measure. This process is called density based clustering. $C_i \subseteq D, i = \{1, .., k\}$ are called clusters. There is no nested cluster. In fact, $\forall i = \{1, .., k\}$, $\cap_{i=1}^{k} C_i = \emptyset$.

Some basics concepts and terms to explain the DBSCAN algorithm can be defined as follows (Ester et al, 1996; Birant and Kut, 2007).

Definition 1 (Neighborhood) It is determined by a distance function (e.g. Euclidean, Manhattan distance) between two points q and p, denoted $dist(q, p)$.

Definition 2 (Eps–neighborhood) The Eps-neighborhood of object q is defined by $\{p \in D : dist(q, p) \leq Eps\}$.

Definition 3 (Core object) A core object refers to such object that its neighborhood of a given radius Eps has to contain at least a minimum number $MinPts$ of other objects (Fig. 2c).

[1] More than 12,990 citations according to Google Scholar, on September 12th, 2018

[2] `http://www.kdd.org/awards/view/2014-sikdd-test-of-time-award-winners`

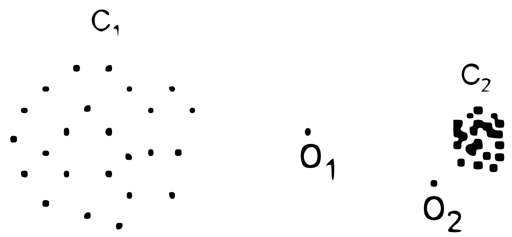

Fig. 3 DBSCAN drawback: database example which contains clusters with different densities

Definition 4 (Directly density-reachable) An object q is directly density-reachable from the object p if q is within the Eps-neighborhood of p, and p is a core object.

Definition 5 (Density-reachable) An object q is density-reachable from the object p with respect to Eps and $MinPts$ if there is a chain of objects $q_1, ..., q_n, q_1 = p$ and $q_n = p$, such that q_{i+1} is directly density-reachable from q_i with respect to Eps and $MinPts$, with $i = \{1, .., n\}, q_i \in D$ (Fig. 2a).

Definition 6 (Density-connected) An object q is density-connected to object p with respect to Eps and $MinPts$ if there is an object $o \in D$ such that both q and p are density-reachable from o with respect to Eps and $MinPts$ (Fig. 2b).

Definition 7 (Density-based cluster) A cluster C is a non-empty subset of D satisfying the "maximality" and "connectivity" requirements that is:
$\forall q, p$: if $p \in C$ and q is density-reachable from p with respect to Eps and $MinPts$ then $q \in C$
$\forall q, p \in C$: q is density-connected to p with respect to Eps and $MinPts$

Definition 8 (Border object) An object q is a border object if it is not a core object but density-reachable from another core object (Fig. 2c).

DBSCAN algorithm starts with the first point q in database D, and retrieves all neighbors of point q within Eps distance. If the total number of these neighbors is greater than $MinPts$ and q is a core point, a new cluster is created. The point q and its neighbors are assigned into this new cluster. Then, it iteratively collects the neighbors within Eps distance from the core points. The process is repeated until all of the points have been processed.

The main advantages of DBSCAN are: (i) DBSCAN does not require specifying the number of clusters in the data a priori, and (ii) DBSCAN can find arbitrary shaped clusters. However, DBSCAN doesn't support clusters with different sizes (Birant and Kut, 2007). For example, Fig. 3 presents a database with 50 objects. There are 24 objects in cluster C_1, 24 objects in cluster C_2, and two additional noise objects O_1 and O_2. C_2 is a denser cluster than C_1 (densities of clusters are different from each other). If value of Eps is

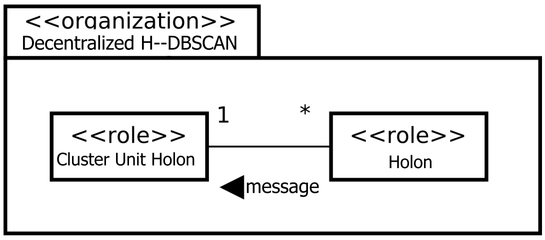

Fig. 4 Organizational model of density based decentralized model at each abstraction level according to ASPECS (Cossentino et al, 2010) methodology's formalism

less than the distance between O_2 and C_2, some objects in C_1 are considered as noise object. On the other hand, if the value of *Eps* is greater than the distance between O_2 and C_2, the object O_2 is not considered as noise object. Our model resolves this drawback with a multilevel view of system because there is no outlier agent in our model.

3 Holonic Density-Based Spatial Clustering of Applications with Noise (H-DBSCAN)

This section presents our model for building the initial holarchy. This model uses a bottom-up decentralized approach to form the holons and holarchy. Centralized method involves a single entity as a central agent, which is responsible for the whole process based on the information available from all the other agents (Sharma et al, 2016). Centralized method may ease the holonification process. Nevertheless, this method needs information about all the members at any given time, suffers from failure of the central unit, and is unable to manage large and open systems. Within a decentralized method, the agents are capable of working independently, and coordinate with each other to achieve a common goal. The decentralized systems involve no central entity that possesses the prime decision making capability for all the agents. Instead, they allow separate controllers, which make decisions for a group of agents (Sharma et al, 2016). However, decentralized architecture has its own disadvantages in terms of cost, complexity and inability to generate a global optimal solution (Sharma et al, 2016).

Goal of holonification is to cluster, and hierarchize population according to some similarity criterion like "satisfaction" (Rodriguez et al, 2007), "affinity" (Gaud et al, 2008), "centrality" (Esmaeili et al, 2014), "similarity" (Galland et al, 2014). In this paper, the grouping criterion is density. In other words, the very close agents within the environment are similar. The idea is to extend DBSCAN algorithm to cluster the similar agents. The principle of our method is to group holons in their super-holon at the immediate higher level within the holarchy, and so on. Grouping action is based on our H-DBSCAN algorithm.

The first step in the holonification process involves the modeling of system population. Then, an algorithm is needed to properly extract the overall structure of holarchy. Furthermore, multilevel indicators should be used in order to find the features, and to evaluate the quality of the super-holon behavior, which approximates the behaviors of its sub-holons.

An agent represents an individual entity within the system. All the agents represent the overall population. At the microscopic level (the more precise level), an agent is a holon. At the higher levels, a holon can be a group of agents or holons. A holon therefore can be seen either as an individual entity either as a set of sub-holons. This duality is generally called Janus[3] effect.

Our model has two types of holons:

Holons: The holons are individuals or a group of individuals of system. A holon h_i^n is the $i-th$ holon at level n.

Cluster unit holon: The cluster unit holons are a particular holons created at each abstraction level in order to simplify the holonification process. The cluster unit holons stand for a separate controllers whose goal is to perform the holonic density based clustering algorithm (H-DBSCAN) at each abstraction level, and to create suitable holons at the immediate higher abstraction level within the holarchy. A cluster unit holon $\mathcal{H}^n$ is the cluster unit holon at level n. There is always one cluster unit holon per abstraction level.

In order to represent the interaction between the holons and the cluster unit holons, Fig. 4 presents the organizational model that is applied at each level of the holarchy. As shown in this figure, at each abstraction level, the holons send messages to the cluster unit holon. This communication between holons and cluster unit holon is horizontal and the message sent represents the internal state (the features variables) of a corresponding holon. The cluster unit holon gathers the features variables of all the holons at the corresponding abstraction level and apply our holonic density based algorithm H-DBSCAN in order to build the immediate higher abstraction level. As H-DBSCAN groups "similar" holons, the result of H-DBSCAN helps the cluster unit holon to create the holons at the immediate higher abstraction level such that each group of holons found by H-DBSCAN is associated to a single holon at the immediate higher abstraction level. The cluster unit holon also creates his own super-holon (a cluster unit holon at the immediate higher level).

The building of the immediate higher abstraction level involves vertical communication between the holons as shown in Fig 5. The vertical communication is between super-holon and its sub-holons. At each level, sub-holons send a message to their super-holon. This message includes the internal state of sub-holons and standard deviation (approximation error of grouping) of sub-holons. The internal states of sub-holons help their super-holon to estimate its own internal state. The standard deviation allows ensuring the consistency of grouping sub-holons in a super-holon. Fig. 5 summarizes the model.

[3] Janus is an ancient Roman god depicted as having two faces, since he looks to the future and to the past.

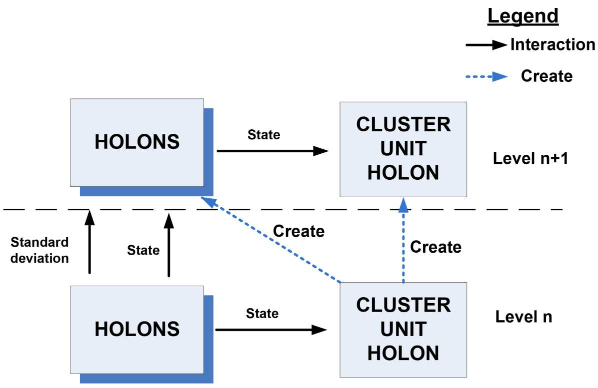

Fig. 5 Density based decentralized model

3.1 Formal definitions of the model

This paper proposes the formal definition of our holonic multiagent system. A HMAS can be defined as a triplet $\langle H, HI, VI \rangle$. H is the holarchy in term of composition. HI is the set of horizontal interaction among holons. VI is the set of vertical interaction among the different levels of the system. A holarchy H with $h \in \mathbb{N}^*$ levels is defined as in Eq. 1, where $H^n, n \in \{0, ..., h-1\}$ is the set of all holons at level n of the holarchy.

$$H = \{H^0, H^1, H^2, ..., H^{h-1}\} \tag{1}$$

Note that in definition shown by Eq 1, the holon of the $(h-1)-th$ level of the holarchy (at the macroscopic level or the top level), is a single composite holon such that:

$$|H^{h-1}| = 1 \tag{2}$$

In the same way, Eq. 3 defines the set of all holons at level n of holarchy. h_i^n is the i^{th} holon at level n. m_n is the number of holons at the n^{th} level. $\mathcal{H}^n$ is the cluster unit holon at level n. The total number of holons at level n is therefore $m_n + 1$.

$$H^n = \{h_1^n, h_2^n, ..., h_{m_n}^n, \mathcal{H}^n\} \tag{3}$$

We assume that holons can't be nested (disjoints holons) that is:

$$\forall n \in \{1, ..., h-2\}; i, j \in \{1, ..., m_n\}; i \neq j \Rightarrow h_i^n \cap h_j^n = \emptyset \tag{4}$$

In addition to the holon set, there are interactions sets. HI is the horizontal interaction set among holons and be define by Eq. 5

$$HI = \{HI^0, HI^1, ..., HI^{h-1}\} \tag{5}$$

Because the holons cannot overlap with each other, they play the `Part` role, never `MultiPart`. Nevertheless, the cluster unit holon plays `Multipart` role.

The cluster unit holon at a given level interacts directly with all the holons at the same level. Eq. 6 defines the horizontal interaction at each abstraction level.

$$HI^n = \{(h_i^n, \mathcal{H}^n),\ h_i^n \in H^n,\ i = \{1, .., m_n\}\} \tag{6}$$

$(h_i^n, \mathcal{H}^n)$ means: the holon h_i^n interacts with the cluster unit holon $\mathcal{H}^n$. This interaction can be made through messages.

In addition to the horizontal interactions, there are vertical interactions. Vertical interaction is made by holons in two adjacent levels within the holarchy. VI is the set of interactions among levels, and is defined by Eq. 7

$$VI = \{VI^{(0,1)}, VI^{(1,2)}, ..., VI^{(h-2,h-1)}\} \tag{7}$$

Inter-level communication is between sub-holons and their super-holon. In fact, since a super-holon is a parent of their sub-holons, sub-holons communicate with their super-holon.

$$\begin{gathered} VI^{(n,n+1)} = \{(h_i^n, h_k^{n+1}) : h_i^n \in h_k^{n+1}, \\ i = \{1, ..., m_n\},\ k = \{1, ..., m_{n+1}\},\ h_i^n \in H^n,\ h_k^{n+1} \in H^{n+1}\} \end{gathered} \tag{8}$$

$h_i^n \in h_k^{n+1}$ means that holon h_i^n is a sub-holon of holon h_k^{n+1}. m_n, m_{n+1} are the respective numbers of holon at level n and level $n+1$.

3.2 Model parameters

DBSCAN algorithm needs two parameters and a database of objects as input. These parameters are the distance *Eps* and the minimum number of objects $MinPts$. The parameter $MinPts$ is a discrete variable and can be decided easily (Ester et al, 1996). The selection of the value of the parameter *Eps* is the main issue in DBSCAN (Neha and Amit, 2016). There are several works dedicated to the automatic determination of *Eps* and $MinPts$ in DBSCAN (Ester et al, 1996; Neha and Amit, 2016).

As DBSCAN, our H-DBSCAN algorithm needs two parameters: $MinHol$ and *Eps*. $MinHol$ is the minimum number of sub-holons that is required to form and create a super-holon, and *Eps* is the distance metric. At each level of holarchy, the model could use the most widely used approach for *Eps* calculation proposed in Ester et al (1996).

DBSCAN is not satisfactory when clusters of different densities exist; and only one distance parameter *Eps* is used to measure the similarity of spatial data with one dimension (Birant and Kut, 2007). In order to overtake this drawback, Birant and Kut (2007) have proposed two distances metrics Eps_1 and Eps_2, and the similarity among the objects is defined by a conjunction of two densities tests, such that Eps_1 is used for spatial values to measure the closeness of two points geographically, and Eps_2 is used to measure the similarity of non-spatial values. We argue that this approach of defining several distances metrics is suitable for building the initial holarchy. In fact, since our model has h holarchical level, $h-1$ distance[4] metrics: $Eps^{(0)}, Eps^{(1)}, ..., Eps^{(h-2)}$ are defined. The macroscopic level (level $h-1$) doesn't need a distance metric, because there is only one holon. The parameters values of $Eps^{(0)}, Eps^{(1)}, ..., Eps^{(h-2)}$ could be automatically determined. $Eps^{(n)}$ is the distance metric value at level n. Table 1 provides the inputs and outputs of our multilevel model.

Given:

- A set $A = H^0$ of all agents. Each agent has its own internal state described by a set of features variables.
- A minimum number of sub-holons required to form a super-holon noted $MinHol$

Outputs:

- The overall holarchy with h levels.
- The standard deviation of each holon that measures the clustering error.

Table 1 Inputs/outputs of our multilevel model.

3.3 Multilevel Indicators

Multilevel indicators help to ensure the consistency of the grouping process. In other words, multilevel indicators constitute a tool for validating that an aggregated behavior of a given super-holon is an acceptable approximation of all the behaviors of its sub-holons. In order to ensure the consistency of this approximation, standard deviation is used. Standard deviation is a statistical concept used to measure the dispersion of a dataset. Lower is the standard deviation value; higher is the quality of the data grouping: the data are sensibly homogeneous within each group. This statistical concept is used for verifying the homogeneity of the sub-holons within a super-holon. Standard deviation is applied on the variables of a holon. Each super-holon h_i^n at level n receives the standard deviation from all its sub-holons at level $n-1$.

Let h_i^n a super-holon at level n such that $h_i^n = \{h_1^{n-1}, h_2^{n-1}, ..., h_p^{n-1}\}$, that means, $h_j^{n-1},\ j \in \{1,..,p\}$ are sub-holons of super-holon h_i^n. Let $\sigma(h_1^{n-1}), \sigma(h_2^{n-1}), ..., \sigma(h_p^{n-1})$ the respective standard deviations of these sub-holons.

Let $\sigma_{state}(h_i^n)$ the standard deviation obtained by the super-holon h_i^n when computing its own internal state.

The overall standard deviation $\sigma(h_i^n)$ of the holon h_i^n is given by Eq. 9.

$$\sigma(h_i^n) = max\{\sigma_{state}(h_i^n), \sigma(h_1^{n-1}), \sigma(h_2^{n-1}), ..., \sigma(h_p^{n-1})\} \tag{9}$$

[4] Index of Epsilon is in exponent for a conform notation with holons. We add the parentheses to signify that it is not Eps exponent n

In order to apply H-DBSCAN, a distance measure is needed between holons at the same level, $dist(h_i^n, h_j^n)$. It tells how far holon h_i^n and h_j^n are. There are several distance measures in literature (Manhattan distance, Euclidean distance, Minkowski distance, etc.). In order to have a generic model, no specific distance in the model is formally chosen. Consequently, $dist(h_i^n, h_j^n)$ is the distance between the two holons h_i^n and h_j^n at the same level n. Euclidean distance, which is well established within Euclidean geometry is used in our traffic application.

The paper applies the mean of the feature variables within the sub-holons' group in order to retrieve the features variables of their super-holon.

3.4 Algorithms

Our holonification method follows a density-based bottom-up approach for holarchy construction. As stated before, a super-holon estimates its own internal state from the values of the internal states of its sub-holons. It sends its state to cluster unit holon and to its super-holon. Each super-holons computes also its own standard deviation from the standard deviations of its sub-holons. It sends this deviation to its super-holon. Algorithm 1 presents the pseudo code of a holon.

Algorithm 1 Holon at abstraction level $0 < n \leq h - 1$

```
procedure HOLON(n)
    Receive internal states from all its sub-holons at level n − 1
    Receive standard deviation from all its sub-holons at level n − 1
    Compute its own internal state at level n
    Compute its own standard deviation at level n
    Send its internal state to cluster unit holon at level n
    Send its internal state to super-holon (if super-holon exist) at level n + 1
    Send its standard deviation to super-holon (if super-holon exist) at level n + 1
end procedure
```

The behavior of an agent is similar to a holon. The difference is that the term "agent" is used for the holons at the level $n = 0$ (Gaud et al, 2008). Standard deviation of an agent is $\sigma = 0$. Algorithm 2 presents the pseudo code of an agent (holon at level 0).

Algorithm 2 Agent at abstraction level $n = 0$

```
procedure AGENT
    Compute its internal state according to perception
    Standard deviation = 0
    Send its internal state to cluster unit holon at level n
    Send its internal state to super-holon at level n + 1
    Send its standard deviation to super-holon at level n + 1
end procedure
```

The cluster unit holon is the aggregator at each level. It receives the internal states of all the holons, applies H-DBSCAN and creates the corresponding required holons at the immediate upper level. Algorithm 3 presents the pseudo code of cluster unit holon at level n.

Algorithm 3 Cluster Unit Holon at abstraction level $0 \leq n \leq h-1$

```
procedure CUH(n, Eps^(n), MinHol)
    if n < h − 1 then
        Receive internal state from all holons at level n
        SuperHolons ← HDBSCAN(H^n, Eps^(n), MinHol)
        Create |SuperHolons| holons at level n + 1
        Create cluster unit holon at level n + 1
    else
        Create HolonPopulation                    ▷ The holon at the macroscopic level
        HolonPopulation ← All the sub-holons at level n-1
    end if
end procedure
```

Algorithm 4 Holonic DBSCAN: H-DBSCAN

```
function HDBSCAN(H, Eps, MinHol)
    SupHol ← 0;
    AllCompositeHol ← ∅
    for each not visited holon h ∈ H do
        Mark h as visited
        Neighbours = RANGEQUERY(H, h, Eps)
        if |Neighbours| < MinHol then
            Mark h as single
        else
            SupHol ← new super-holon                ▷ A composite super-holon
            EXTENDCLUSTER(H, h, Neighbours, SupHol, Eps, MinHol)
            AllCompositeHol ← AllCompositeHol ∪ SupHol
        end if
    end for
    for each holon h ∈ H \ AllcompositeHol do
        SupHol ← new super-holon                    ▷ A single super-holon
        Add holon h to super-holon SupHol
    end for
    return SupHol
end function
```

H-DBSCAN clusters the holons according to their internal states. Algorithm 4 presents this clustering algorithm. Like DBSCAN, H-DBSCAN algorithm has several advantages:

- H-DBSCAN does not require specifying the number of clusters (super-holons) a priori. We can therefore have a variable number of holons at each level within the holarchy.
- H-DBSCAN has the ability of discovering clusters with various arbitrary shapes. In fact, in some case, when applying H-DBSCAN algorithm, the

Algorithm 5 Build the holon (a composite holon)

```
procedure ExtendCluster(H, h, Neighbours, SupHol, Eps, MinHol)
    Add holon h to super-holon SupHol
    for each holon h′ ∈ Neighbours do
        if h′ has not been visited then
            Mark h′ as visited
            Neighbours′ ← RangeQuery(H, h′, Eps)
            if |Neighbours′| ≥ MinHol then
                Neighbours′ ← Neighbours ∪ Neighbours′
            end if
        end if
        if h′ do not belong to any super-holon then
            Add holon h′ to super-holon SupHol
        end if
    end for
end procedure
```

Algorithm 6 Build the Neighbourd of holon h

```
function RangeQuery(H, h, Eps)
    N ← ∅
    for each holon q ∈ H do
        if dist(q, h) ≤ Eps then
            N ← N ∪ {q}
        end if
    end for
    return N
end function
```

formed cluster has a regular or geometric shape. The obtained shape is application-dependent.

In opposite to DBSCAN, Algorithm 4 doesn't have the outliers. All the outliers are assigned (lines 16 and 17) to a single super-holon (not composite holon). The formed cluster is assigned to a composite super-holon (lines 10 and 11). Algorithm 4 needs two additional algorithms: Algorithms 5 and 6. These algorithms are sensibly the same with the original DBSCAN.

4 Application to Road Traffic

Road transport is a development tool because it allows the mobility of goods, persons and contributes to the improvement of growth. Moreover, mobility is a human necessity. Road transport is the most widespread transport system worldwide. However, although useful, road traffic poses several problems related to security, environmental, health, economic, energy, etc. An efficient road transport system is therefore necessary for the prosperity of a modern society. In order to better manage, improve and optimize the traffic flow, traffic simulation studies are regularly carried out. The modeling and simulation of road traffic contribute to bringing answers to the problems of improving the circulation conditions of goods and peoples, in terms of regulation and infrastructure. Several approaches are presented to model traffic in literature (Jaume, 2010): microscopic, intermediate (mesoscopic and hybrid or multilevel) and macroscopic approaches. Macroscopic approach is unable to manage destination of vehicles and generally is applied on highway with an acceptable computational cost while microscopic approach requires a high computational cost and generally is applied on small urban area scale with a high degree of accuracy. Multilevel models were developed in order to study the situations in which macroscopic and microscopic models are not well adapted like modeling and simulation of large scale traffic (Mammar et al, 2006). Multilevel models combine the advantages of macro and micro models but it's difficult to realize. Holonic modeling is a suitable approach to deal with multilevel modeling and simulation (Gerber et al, 1999). Holonic models have been widely used for multilevel modeling and simulation of traffic and transportation. The reader is referred to Tchappi et al (2018) for a brief review of holonic models in traffic and transportation field.

In our application model, each couple driver-vehicle is an autonomous agent with his own behavior. Vèque et al (2013) assert that *"the geographical position of vehicles is one of the most important criteria in clustering."* In the same paper, they assert *"since vehicles move in a space constrained by routes, others criteria are also significant such as speed and direction."* According to these assertions, the variables which describe the internal state of any agent vehicle are position x, speed y, and lane l.

The paper builds the holonic structure of road traffic through holonic methodology. The purpose of holonification is to cluster, and hierarchize population according to some similarity criterion like "satisfaction" (Rodriguez et al, 2007), "affinity" (Gaud et al, 2008), "centrality" (Esmaeili et al, 2014), "similarity" (Galland et al, 2014). In this application, similarity is based on the vehicle density or closeness.

Road traffic is a dynamic phenomenon characterized by selfish behavior of drivers and change lane which leads to a highly fluctuating states of traffic (overall layout or overall configuration of traffic on the road). However, traffic congestion, generated by several causes like peak hours, leads to a reduction of the overall fluctuation states of traffic. Congestion is a recurring phenomenon in road traffic. Indeed, TomTom[5] in his report of 2013 states that in cities like Moscow, Rio de Janeiro, Mexico City, Istanbul and Beijing, people on average spend $> 75\%$ extra time traveling due to traffic. Moreover, Texas Transportation Institute[6] which conducts a survey of traffic congestion in United States urban areas each year states in his 2009 report, that in 2007 congestion caused an estimated 4.2 billion hours of travel delay. Congestion brings out the group of vehicles particularly on peak hours. In fact, on both highways and urban areas, vehicles follow one another on a line and tend to regroup in convoys (Vèque et al, 2013). The convoys' phenomenon or more

[5] TomTom is a leading company that produces traffic navigation and mapping products. `https://corporate.tomtom.com/`

[6] The Texas A&M Transportation Institute is the largest transportation research agency in the United States. `https://tti.tamu.edu/`

generally vehicle platooning has been widely studied in traffic modeling and simulation (Kavathekar and Chen, 2011; Jean-Michel et al, 2007; Wang and Han, 1998; Vèque et al, 2013). Kavathekar and Chen (2011) assert in 2011 that a search using the keyword “platoon string stability” have given a result composed by 130 publications. Stability in leader-follower platoons or stability in convoys has been a topic of great concern (Kavathekar and Chen, 2011). The vehicles in convoy with quasi-identical speed constitute a relatively stable structure (Vèque et al, 2013; Jean-Michel et al, 2007). The stability of convoys leads the paper to seek to deal with multilevel models of road traffic by the using of clusters of vehicles in order to link several abstraction levels to better understand congestion and to allow large scale multilevel modeling of traffic. Fig. 6 depicts a real picture of convoy more or less which keep the overall layout of traffic for a longer or shorter period.

As stated before, modeling and simulation of large scale complex system need compromise. Indeed, at the microscopic level, simulation is more accurate and therefore close to the real behavior of entities but need a high computational cost. In contrary at the macroscopic level, the computational cost is acceptable but simulation is less accurate. Holarchy seeks to provide a solution to manage the compromise between simulation accuracy and available computational resources (Gaud et al, 2008). In fact while going up in holarchy, we observe a reduction of the number of entities involved, which leads to a saving of computational resources, but also to a loss of accuracy. In the proposal standard deviation helps to manage this compromise.

DBSCAN classifies a data-set into two categories of elements: the clusters and the outliers. H-DBSCAN classifies the vehicles at each level in two categories: the clusters (group of vehicles) and free (`StandAlone`: single vehicle). Among vehicles in cluster, there is one vehicle which particularly affects all the cluster: the head of cluster. The vehicle head of cluster imposes its speed to all the cluster, particularly if change lane is not possible. In our model, the vehicle head of cluster plays the `Head` role. The other vehicles within the cluster play the `Follower` role. A holon vehicle which does not belong to any cluster plays the `Free` role. All the vehicles holons play the `Part` holonic role. Among the clusters are convoys. In general the stable convoys appears at level 1 of the holarchy. Convoy is an emergent structure due to the interaction between the vehicles which manifest itself by a closeness of vehicle. We define therefore convoy by Definition 9. A picture of convoy is shown by Fig. 6 which presents a road with 4 lanes, and in each lane there is one convoy composed by several vehicles. If we plot graphic of vehicles which are in-convoy, position on x-axis and speed on y-axis, we may observe a right line with a slope which tends to zero.

Definition 9 (Convoy: inspired by (Vèque et al, 2013)) A group of vehicles is within a convoy if:

(i) they have approximately the same speed
(ii) they move on the same lane
(iii) the gap between them is approximately equal

Fig. 6 Traffic congestion on four lanes – Each lane is composed by one convoy. Several vehicles belong to each convoy

A holon vehicle is either an agent vehicle either a group of agents vehicles. To apply the holonic density-based approach a distance function between two holons vehicles is needed. The distance function between two holons h_q^n, h_p^n at level n is based on the value of their respective features variables. It is a Euclidean distance and defined by Eq. 10. If the vehicles are not on the same lane, the distance tends towards infinity.

$$dist(h_q^n, h_p^n) = \begin{cases} \sqrt{(x(h_q^n) - x(h_p^n))^2 + (y(h_q^n) - y(h_p^n))^2}, \\ \qquad\qquad\qquad \text{if} \quad l(h_q^n) = l(h_p^n)) \\ \infty, \quad \text{else} \end{cases} \tag{10}$$

4.1 Contextualized Definition

Inspired by the definition given by Ester et al (1996) in Section 2.2, the corresponding definitions for traffic simulation are the followings.

Definition 10 (holon neighborhood) It is determined by a distance function (Euclidean, Manhattan etc.) between two holons h_q^n and h_p^n, denoted $dist(h_q^n, h_p^n)$ as in Eq. 10.

Definition 11 (Eps-neighborhood) The Eps-neighborhood of a holon h_q^n is defined by holons $\{h_i^n \in H^n \setminus \mathcal{H}^n : dist(h_q^n, h_p^n) \leq Eps\}$.

Definition 12 (core holon) A core holon refers to such holon that its neighborhood of a given radius Eps has to contain at least a minimum number $MinHol$ of other holons.

Definition 13 (directly density-reachable) A holon h_q^n is directly density-reachable from the holon h_p^n if holon h_q^n is within the Eps-neighborhood of holon h_p^n, and h_p^n is a core holon.

Definition 14 (density-reachable) A holon h_q^n is density-reachable from the holon h_p^n with respect to Eps and $MinHol$ if there is a chain of holon $g_1, ..., g_n, g_1 = h_p^n$ and $g_n = h_p^n$ such that g_{i+1} is directly density-reachable from g_i with respect to Eps and $MinHol$, with $i = \{1, .., n\}$, $g_i \in H^n \setminus \mathcal{H}$

Definition 15 (density-connected) A holon h_q^n is density-connected to holon h_p^n with respect to Eps and $MinHol$ if there is a holon $g \in H^n \setminus \mathcal{H}$ such that both h_q^n and h_p^n are density-reachable from g with respect to Eps and $MinHol$

Definition 16 (cluster) A cluster C is a non-empty subset of $H^n \setminus \mathcal{H}$ satisfying the "maximality" and "connectivity" requirements:
(1) $\forall h_q^n, h_p^n : if\ h_p^n \in C$ and h_q^n is density-reachable from h_p^n with respect to Eps and $MinHol$ then $h_q^n \in C$
(2) $\forall h_q^n, h_p^n \in C$: h_q^n is density-connected to h_p^n with respect to Eps and $MinHol$

Definition 17 (convoy) A convoy c is a cluster C such that the value of standard deviation of the elements of convoy tends to zero.
Note that Definition 9 are equivalent to Definition 17.

Definition 18 (head holon) A holon h_q^n playing the `Head` role, named h_q^n, is a border holon (it is not a core holon but density-reachable from another core holon) with the maximum value of position.

Definition 19 (free holon) A holon playing the `Free` role is a holon, which belongs to any cluster.

4.2 Find the Characteristics of a Super-Holon

Since we consider different abstraction levels within the same model, the transition issue between these levels becomes crucial. Microscopic is the most accurate level. When considering higher levels of abstraction than the microscopic level, the accuracy of the modeling and simulation decreases. The mesoscopic or macroscopic levels are only an approximation of the system behavior from a certain point of view.

In traffic application, different abstraction levels are considered for the `Vehicle` role. The most precise level corresponds to the microscopic level: a vehicle is associated with a holon. At the upper levels, mesoscopic or macroscopic, each super-holon approximates the behavior of a group of vehicles. The group is considered as a full vehicle. The `Vehicle` role played by the super-holon remains the same as at the lower level with his own features variables computed from his sub-holons.

Let $h_i^n = \{h_1^{n-1}, h_2^{n-1}, ..., h_p^{n-1}\}$ the i^{th} holon at abstraction level n such that $(x_1, y_1, l_1), (x_2, y_2, l_2), ..., (x_p, y_p, l_p)$ are respective features of its sub-holons $h_1^{n-1}, h_2^{n-1}, ..., h_p^{n-1}$.

The feature variables of holons h_i^n are given as follow:

– Speed. Speed of a given super-holon is a mean of speed of his sub-holons as in Eq. (11).

$$y(h_i^n) = \frac{1}{p} \sum_{k=1}^{p} y_k \tag{11}$$

– Lane. Lane of a given super-holon is the same lane of its sub-holons as in Eq. (12).

$$l(h_i^n) = l_k, k = 1, ..., p \tag{12}$$

– Position. Among the sub-holons of the super-holon h_i^n, there is one holon, which has a great influence on the group: the head holon. A head vehicle plays the `Head` role as defined in Definition 18. Position of a given super-holon is given by Eq. (13).

$$x(h_i^n) = x_k, \ k = 1, ..., p \quad \text{such that} \ \ x_k \text{ plays } \texttt{Head} \text{ role} \tag{13}$$

– Representation of super holon in simulated universe. The representation of a super holon in a simulated universe is the aggregate body of all his sub-holons.
– Standard deviation. In order to compute standard deviation, the model uses Least Squares method such that x is an exogenous variable and y is an endogenous variable. Least Squares method finds the best straight line, which minimizes the sum of the squared residuals. Overall standard deviation of holon h_i^n is given by Eq. 9. The deviation of the process of finding the internal state of super-holon has a deviation that is given by Eq. 14.

$$\sigma_{state}(h_i^n) = \sqrt{\frac{1}{p}\sum_{k=1}^{p}(y_k - \hat{y}_k)^2} \qquad \text{such that:} \tag{14}$$

$$\begin{aligned} &\hat{y} = ax + b \\ &a = \frac{\sum_{k=1}^{p}(x_k - \overline{x})(y_k - \overline{y})}{\sum_{k=1}^{p}(x_k - \overline{x})^2}, \\ &\text{with} \quad \overline{x} = \tfrac{1}{p}\textstyle\sum_{k=1}^{p} x_k, \quad \text{and} \quad \overline{y} = \tfrac{1}{p}\textstyle\sum_{k=1}^{p} y_k \\ &b = \overline{y} - a\overline{x} \end{aligned} \tag{15}$$

4.3 Case study

Microscopic models don't scale. Fig 7 presents the computational cost of a traffic case with Intelligent Driver Model (Treiber et al, 2000). As shown on Fig. 7, the computational cost growth rapidly up with the number of entities involved. One interest of the holarchy is the reduction of entities involved when going up to the top of the holarchy which leads to a reduction of computational cost. Moreover, the computational cost of holonification is generally low for several HMAS (Gaud et al, 2008). Likewise, the computational cost of H-DBSCAN holonification is acceptable according to Fig. 13.

Generally, in road traffic modeling and simulation, vehicles are generated and distributed on a road network throw an Origin/Destination matrix. Let

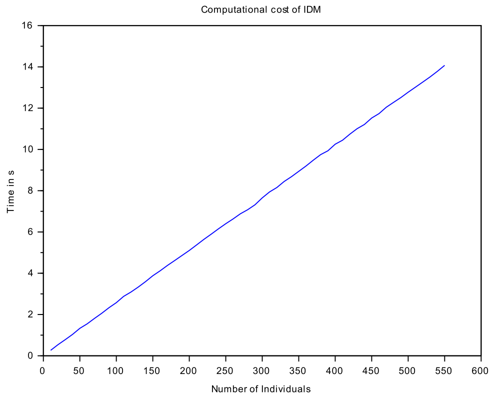

Fig. 7 Computational cost execution of IDM

Fig. 8 represents vehicles on three lanes at time $t = 0$. The initial characteristics of the vehicles are recorded in Table 2.

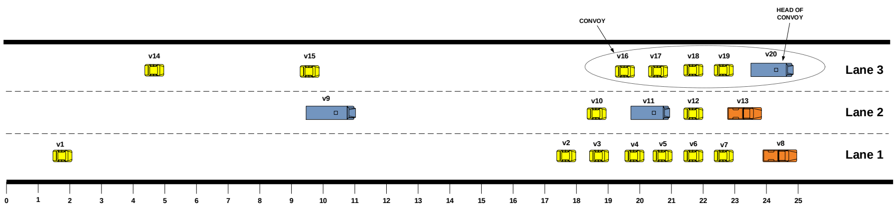

Fig. 8 Traffic short case

	v_1	v_2	v_3	v_4	v_5	v_6	v_7	v_8	v_9	v_{10}
x	2	18	19	20	21	22	23	25	11	19
y	45	25	25.1	25	24.9	25	25.1	24.9	32	25
l	1	1	1	1	1	1	1	1	2	2

	v_{11}	v_{12}	v_{13}	v_{14}	v_{15}	v_{16}	v_{17}	v_{18}	v_{19}	v_{20}
x	21	22	24	5	10	20	21	22	23	25
y	25	25.1	25	30	31	24.9	25	24.8	25	25.1
l	2	2	2	3	3	3	3	3	3	3

Table 2 Triplet (position, speed, lane) of each agent vehicle in Fig. 8

Application of our model gives the holarchy shown on Fig. 9 ranging from microscopic level to macroscopic level and holons composition at each abstrac-

Level	Parameters	Holons	Features variables	Standard deviation
0		$h(0,1)=\{v_1\}$; $h(0,2)=\{v_2\}$; $h(0,3)=\{v_3\}$; $h(0,4)=\{v_4\}$; $h(0,5)=\{v_5\}$; $h(0,6)=\{v_6\}$; $h(0,7)=\{v_7\}$; $h(0,8)=\{v_8\}$; $h(0,9)=\{v_9\}$; $h(0,10)=\{v_{10}\}$; $h(0,11)=\{v_{11}\}$; $h(0,12)=\{v_{12}\}$; $h(0,13)=\{v_{13}\}$; $h(0,14)=\{v_{14}\}$; $h(0,15)=\{v_{15}\}$; $h(0,16)=\{v_{16}\}$; $h(0,17)=\{v_{17}\}$; $h(0,18)=\{v_{18}\}$; $h(0,19)=\{v_{19}\}$; $h(0,20)=\{v_{20}\}$		
1	$MinHol=2$; $Eps=2.1$	$h(1,1)=\{h(0,1)\}$; $h(1,2)=\{h(0,2),h(0,3),h(0,4),h(0,5),h(0,6),h(0,7),h(0,8)\}$; $h(1,3)=\{h(0,9)\}$; $h(1,4)=\{h(0,10),h(0,11),h(0,12),h(0,13)\}$; $h(1,5)=\{h(0,14)\}$; $h(1,6)=\{h(0,15)\}$; $h(1,7)=\{h(0,16),h(0,17),h(0,18),h(0,19),h(0,20)\}$;	$x_{h(1,2)}=25$ $y_{h(1,2)}=25$ $x_{h(1,4)}=24$ $y_{h(1,4)}=25.025$ $x_{h(1,7)}=25$ $y_{h(1,7)}=24.96$	$\sigma_{h(1,2)}=0.0711$ $\sigma_{h(1,4)}=0.0427$ $\sigma_{h(1,7)}=0.0803$
2	$MinHol=2$; $Eps=6$	$h(2,1)=\{h(1,1)\}$; $h(2,2)=\{h(1,2)\}$; $h(2,3)=\{h(1,3)\}$; $h(2,4)=\{h(1,4)\}$; $h(2,5)=\{h(1,5),h(1,6)\}$; $h(2,6)=\{h(1,7)\}$;	$x_{h(2,5)}=10$ $y_{h(2,5)}=30.5$	$\sigma_{h(2,5)}=2.5$
3	$MinHol=2$; $Eps=16$	$h(3,1)=\{h(2,1)\}$; $h(3,2)=\{h(2,2)\}$; $h(3,3)=\{h(2,3),h(2,4)\}$; $h(3,4)=\{h(2,5),h(2,6)\}$;	$x_{h(3,3)}=24$ $y_{h(3,3)}=28.51$ $x_{h(3,4)}=25$ $y_{h(3,4)}=27.73$	$\sigma_{h(3,3)}=6.5$ $\sigma_{h(3,4)}=7.5$
4	$MinHol=2$; $Eps=31$	$h(4,1)=\{h(3,1),h(3,2)\}$; $h(4,2)=\{h(3,3)\}$; $h(4,3)=\{h(3,4)\}$	$x_{h(4,1)}=25$ $y_{h(4,1)}=35$	$\sigma_{h(4,1)}=11.5$
5		$h(5,1)=\{h(4,1),h(4,2),h(4,3)\}$;	$x_{h(5,1)}=25$ $y_{h(5,1)}=30.414$	$\sigma_{h(5,1)}=11.5$

Table 3 Holons composition in holarchy presented in Fig 9

tion level are given by Table 3. As the standard deviation of a group consisting of a single member is zero, there were no trivial values inserted, so the Table 3 will not be saturated.

4.4 Discussion

The interest of the paper is discussed in this section:

(a) Although it is widely recognized that the presence of groups influences microscopic and aggregated pedestrian or vehicles dynamics, a precise characterization of the phenomenon still calls for evidences and insights (Crociani et al, 2017). Several works analyzed the influence of group behavior on the individual. However, there is still need for additional insights, for instance on the spatial patterns assumed by groups in their movement and in general on the interaction among different factors influencing overall vehicles dynamics (Crociani et al, 2017). One of the main issues in road traffic is how to understand congestion? Another issue is how congestion influences the behavior of a driver? The paper takes a step toward the understanding the relationship between the different levels ranging from the microscopic level to the macroscopic level as shown in Fig. 9. In fact, the paper presents

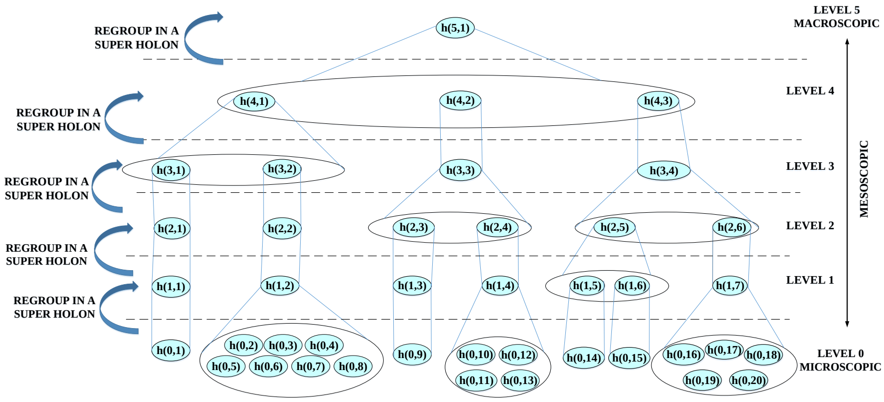

Fig. 9 Initial holarchy of vehicles built with our method based on H-DBSCAN for the case study.

a holarchy that bring out the containing/contained of holarchical levels and the relationship between these holarchical levels. In the holarchy, the behavior of a holon is more and more reactive towards the bottom of the holarchy (towards the microscope level). On the other hand the behavior of a holon is more and more cognitive towards the top of the holarchy (towards the macroscopic level).

(b) In general, multilevel modeling and simulation of traffic combines simultaneously different traffic models in one model (Mammar et al, 2006; Poschinger et al, 2002). These hybrid or multilevel models mainly differentiate by the choice of the models to be interfaced. Each model is associated to a part of road network. Since the models do not have the same features, the goal of hybridization is to ensure the compatibility of the models integrated. In other words, hybridization principle manages the transition of the models at the border. Most of the multilevel models focus only on two abstraction levels (micro and macro, macro and meso, meso and micro). This limitation is unable to bring out a right emergency behavior. To this end, we argue that a combination of three main abstraction levels is needed (micro, meso and macro) in the same model. One of the important characteristics of HMAS is that, HMAS deals with micro, meso and macro levels. In fact, in Fig. 9 for example, level 0 corresponds to microscopic level, level 1 to level 4 corresponds to mesoscopic level and level 5 corresponds to macroscopic level.

(c) As stated before, the hybridization of multilevel model manages the transition at the border of models selected. Consequently, most of the existing hybrid models of traffic flow are static and define a priori the different abstraction levels (Tchappi et al, 2017). However, to be able to observe congestion formation or to find the exact location of a jam in a macro section, a dynamic hybrid modeling approach is needed (Bouha et al, 2015).

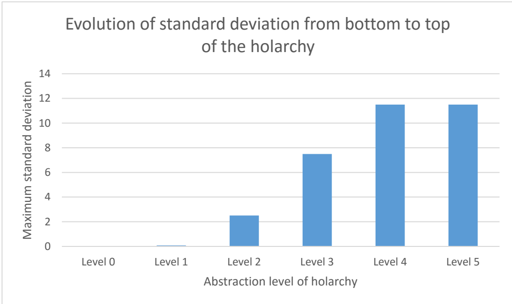

Fig. 10 Evolution of values of standard deviation at each level of holarchy for the case study presented in Fig. 8

There are a very few works dedicated to the dynamic multilevel modeling and simulation of road traffic flow (Bouha et al, 2015). Tchappi et al (2017) identify two works, which propose to switch dynamically and automatically into the system representation: the works of the team of G. Morvan (Abouassa et al, 2014; Bouha et al, 2015) and the work of Sewall et al (2011). Although there is a lot of works on the different models of traffic, there is a few works dedicated to the dynamic multilevel model of traffic. HMAS allows to model and simulate dynamic multilevel traffic (Gaud et al, 2008).

In fact, in our road traffic application, several abstraction levels are considered for the vehicles. The more precise level corresponds to the microscopic level (level 0 in the case study): a vehicle is associated with a holon. At the upper level called macroscopic (level 5 of case study), the behavior of the super-holon approximates a group of vehicles. The interest of this work (the holarchy) is to switch between abstraction levels according to the simulation's objectives (visualization, etc.) or available computational resources. For example, without constraints, system can be modeled and simulated at the most precise level (microscopic). Nevertheless, with constraints like simulation's objectives or computational resources, system can be modeled and simulated at the higher abstraction levels. The main research question is therefore to ensure the consistency of the upper levels modeling and simulation. Standard deviation helps us to ensure this consistency. For example in our example, at level 3, the value of standard deviation of holon $h(3,3)$ is 6.5 which is a high value for standard deviation. Consequently, the features variables of the sub-holons of holon $h(3,3)$ are very dispersed. In this case, we conclude that holon $h(3,3)$ for example seems not to be a good approximation of its sub-holons $h(2,3), h(2,4)$. Nevertheless, at level 1 of the holarchy in Fig. 9, the values of the standard deviation of all the holons

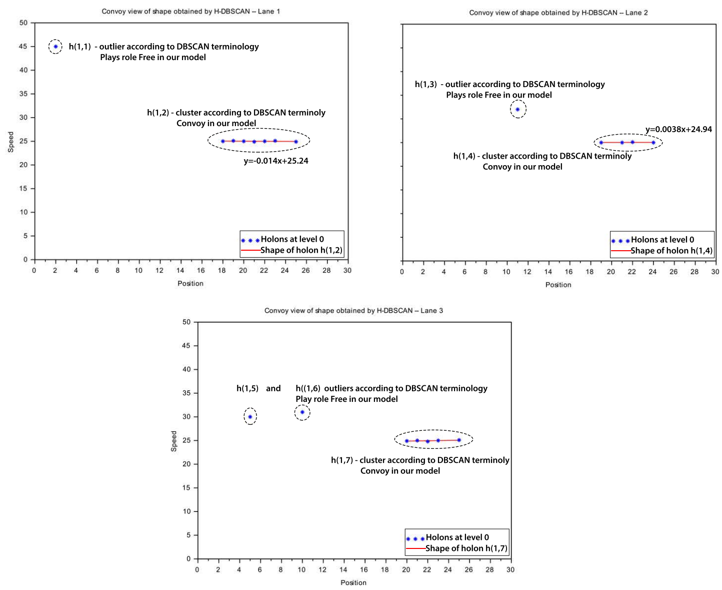

Fig. 11 Shape of convoys obtained at level 1 for the case study in Fig. 8

tend to zero that means in each cluster, vehicles have sensibly the same speed, and the gap between them is approximately equal. These clusters of vehicles are called convoys. Fig. 11 depicts the shape of convoy at level 1 of holarchy for the case study presented in Fig. 8. As shown on Fig. 11, the shape of convoy is a right line with a slope which tends to zero (the right line tends to be horizontal). We argue therefore that, if computational resources are insufficient, holon $h(1,2)$ for example can be an acceptable approximation of his sub-holons $h(0,2), h(0,3), h(0,4), h(0,5), h(0,6), h(0,7), h(0,8)$. Likewise, holons $h(1,4)$ and holons $h(1,7)$ are acceptable approximation of their sub-holons and therefore, the system can be represented with an acceptable approximation at level 1. Fig. 10 shows the evolution of standard deviation values when growing up to the top of the holarchy for the case study presented in Fig. 8. Indeed, when growing up to the holarchy, the values of standard deviation increase that means the loss of precision increases. Moreover, the shape of the clusters of vehicles lose more and more their horizontality (slope moves away positively or negatively from zero) as shown on Fig 12 that means stability of clusters of vehicles decreases when going up in holarchy. Standard deviation helps to deal with compromise between simulation accuracy and available computational resources by choosing to represent the system at an appropriate level witch fit with the lowest value of standard deviation and the computational resources available.

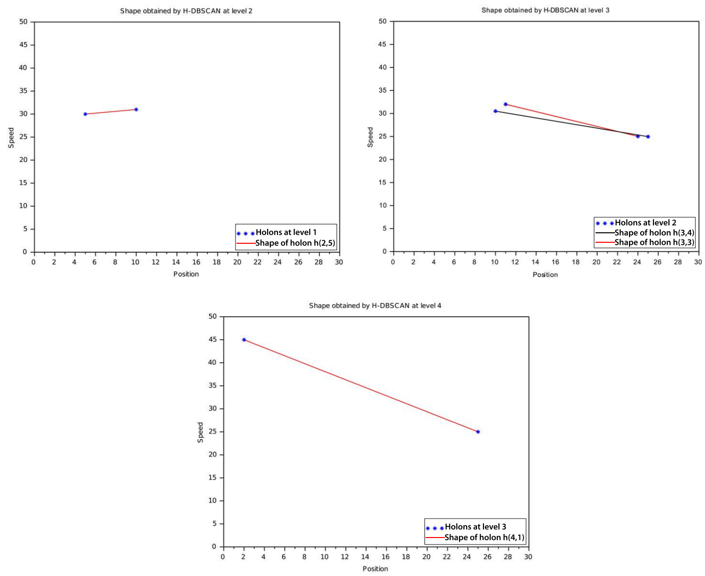

Fig. 12 Shape of clusters obtained at levels 2, 3, 4 for the case study in Fig. 8

4.5 Experimental Results

In this paper, a density-based holonification process is presented. The cluster unit holon perform H-DBSCAN algorithm. We have used the SARL agent-programming language (Rodriguez et al, 2014) and the Janus framework (Galland et al, 2017, 2010) for implementing and running our model. SARL is a general-purpose agent-oriented programming language, which focus on holonic modeling and simulation.

Fig. 13 presents the performance of the H-DBSCAN execution with three traffic conditions, ranging from the best case to the worst case. According to Fig. 13, the execution time seems to be linear. The corresponding linear regression line, which approximate the worst case distribution has the following equation: $y = 0.0346x - 0.798$. We assert that H-DBSCAN has a good performance, because the slope of the linear regression of the worst case tends to zero.

Convoy approximates the behavior of a group of vehicles at level 1 of the holarchy. Approximation error is based on standard deviation. Fig. 14 presents the values of standard deviation of several super-holons at level 1 (convoy view). All these values of standard deviation tend to zero that means the super-holons at level 1 tends to be an acceptable approximation of their sub-holons (the real vehicles). These lows values of standard deviation at level 1 contributes to understand the stability of convoy. In fact, vehicles in convoy with quasi-identical speed constitute a relatively stable structure (Vèque et al, 2013). Approximation of road traffic in general at level 1 of holarchy is

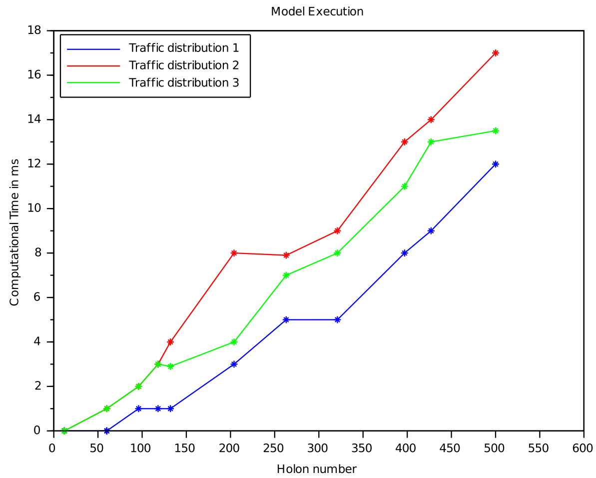

Fig. 13 H-DBSCAN performances

therefore acceptable if computational resources is insufficient. For the upper levels, furthers works is requiring for the validation. It should be noted that the internal states of the agents are generated for running the model. They should be replaced by internal states issued from field interviews.

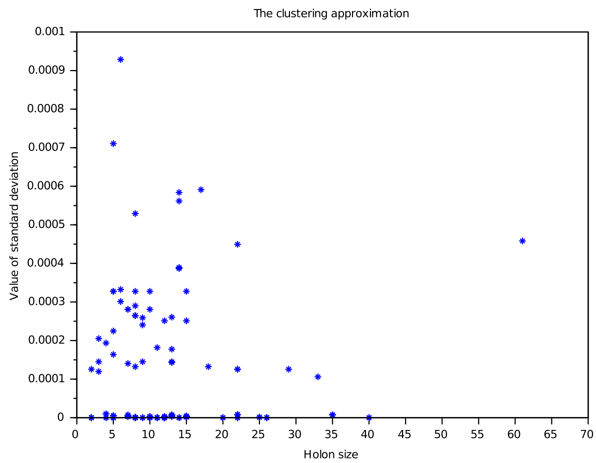

Fig. 14 The clustering approximation at level 1

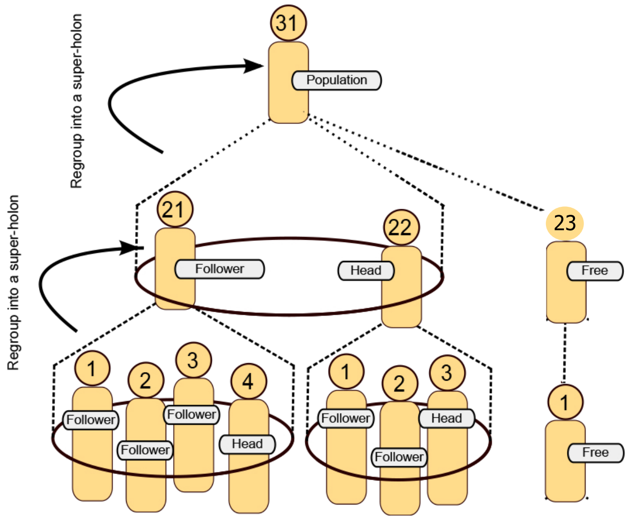

Fig. 15 Example of a traffic holarchy after the building of initial holarchy

4.6 Towards the self-organization of road traffic system

HMAS allows understanding the relation between micro, meso and macro levels. Simulation of HMAS enables to switch between different levels of detail according to computational resources (Gaud et al, 2008). If the simulation of HMAS has all the computing resources needed, the simulation will be performed at the most accurate level, otherwise the simulation is performed at a higher abstraction level.

Holonification process builds the initial holarchy. The lowest holarchy level corresponds to the microscopic level where each vehicle is associated with a holon. Vehicles are then grouped, and each group is associated with a super-holon whose members are individual vehicles. This process of composition continues based on our density based approach until a complete holarchy is achieved with a single super-holon at the top. The latter represents the vehicle population as a whole as shown in the example presented by Fig 15.

After building the initial holarchy of HMAS, the next stage is the control system against internal and external stimuli over time. This second stage builds the next holarchies and brings out the dynamic of system. Dynamic in a multi-level model refers both to temporal dynamic, and spatial dynamic. The dynamic of system therefore exhibits the self-organization of hierarchical open structures over time. To ensure this self-organization, coordination models that define the holons interactions in terms of interaction protocols and interaction rules are needed (Di Marzo Serugendo et al, 2004). The coordination model defines how holons interact, and the composition of holons over time. This includes : (i) dynamic creation and destruction of holons, (ii) join and quit a holon, (iii) control of exchanging horizontal message between holons over time, (iv) control of exchanging vertical message between holons over time.

Traffic is an open system that means, vehicles can enter to system and vehicles can get out of the system any time. The action space for a holon, is defined as follows:

- Action 1: Nothing if the system configuration has not evolved;
- Action 2: Join a holon if these holons are similar;
- Action 3: Leave a holon if the aggregated behavior associated with the super-holon is no longer an acceptable approximation of this member's behavior.

To manage the coordination model, it's important to answer the following research questions: what is the states' space of the holons? How are the transitions between the states managed through holons actions? What is the optimal implementation approach for holonic traffic self-organization? These research questions will lead us to the future proposition of a self-organized road traffic system.

5 Conclusion and future works

Holonic multiagent system is an effective tool to model large-scale multilevel complex system. One of the main issues concerning holonic systems is the way how the holarchy is structured. The contributions of this paper are a formal definition of the holonic structure, and a density-based method, in order to build the holonic structure with a bottom-up approach. The famous DBSCAN algorithm is extended for obtaining H-DBSCAN. Several multilevel indicators are also proposed, based on standard deviation, in order to evaluate the consistency of the created holons. As stated before, future works include dynamic self-organization of the holons in order to simulate traffic by switching into levels according to computational resources.

References

Abouassa H, Kubera Y, Morvan G (2014) Dynamic hybrid traffic flow modeling DOI arXiv:1401.6773v1

Adam E (2000) Modèle d'organisation multi-agent pour l'aide au travail coopératif dans les processus d'entreprise : application aux systèmes administratifs complexes. PhD thesis, Université de Valenciennes et du Hainaut-Cambresis, in French

Birant D, Kut A (2007) St-dbscan: An algorithm for clustering spatial-temporal data. Data & Knowledge Engineering pp 208–221

Bouha N, Morvan G, Hassane A, Kubera Y (2015) A first step towards dynamic hybrid traffic modelling. In: Proc. of 29th European Conf. on modelling and simulation (ECMS), pp 64–70

Bourrel E, Lesort J (2003) Mixing micro and macro representations of traffic flow: a hybrid model based on the lwr theory. In: 82th Annual Meeting of the Transportation Research Board

Burghout W (2004) Hybrid microscopic-mesoscopic traffic simulation. PhD thesis, Royal Institute of Technology

Cossentino M, Gaud N, Hilaire V, Galland S, Koukam A (2010) Aspecs: an agent-oriented software process for engineering complex systems. Autonomous Agents and Multi-Agent Systems 20(2):260–304, DOI 10.1007/s10458-009-9099-4, URL https://doi.org/10.1007/s10458-009-9099-4

Crespi V, Galstyan A, Lerman K (2008) Top-down vs bottom-up methodologies in multi-agent system design. Autonomous Robots 24(3):303–313, DOI 10.1007/s10514-007-9080-5, URL https://doi.org/10.1007/s10514-007-9080-5

Crociani L, Gorrini A, Feliciani C, Vizzari G, Nishinari K, Bandini S (2017) Micro and macro pedestrian dynamics in counterflow: the impact of social groups. CoRR abs/1711.08225, URL http://arxiv.org/abs/1711.08225, 1711.08225

Di Marzo Serugendo G, Foukia N, Hassas S, Karageorgos A, Mostéfaoui SK, Rana OF, Ulieru M, Valckenaers P, Van Aart C (2004) Self-organisation: Paradigms and applications. In: Di Marzo Serugendo G, Karageorgos A, Rana OF, Zambonelli F (eds) Engineering Self-Organising Systems, Springer Berlin Heidelberg, Berlin, Heidelberg, pp 1–19

Esmaeili A, Mozayani N, Motlagh MRJ (2014) Multi-level holonification of multi-agent networks. In: 2014 Iranian Conference on Intelligent Systems (ICIS), pp 1–5, DOI 10.1109/IranianCIS.2014.6802553

Esmaeili A, Mozayani N, Motlagh M, Matson E (2017) A socially-based distributed self-organizing algorithm for holonic multi-agent systems: Case study in a task environment. Cognitive Systems Research pp 21–44

Ester M, Kriegel HP, Sander J, Xu X (1996) A density-based algorithm for discovering clusters in large spatial databases with noise. In: 2nd International Conference on Knowledge Discovery and Data mining, pp 226–231

Ferber J, Gutknecht O (1998) A meta-model for the analysis and design of organizations in multi-agent systems. In: Proceedings International Conference on Multi Agent Systems (Cat. No.98EX160), pp 128–135

Ferber J, Gutknecht O, Michel F (2004) From agents to organizations: An organizational view of multi-agent systems. In: Giorgini P, Müller JP, Odell J (eds) Agent-Oriented Software Engineering IV, Springer Berlin Heidelberg, pp 214–230

Galland S, Gaud N, Rodriguez S, Hilaire V (2010) Janus: Another yet general-purpose multiagent platform. In: the 7th Agent- Oriented Software Engineering Technical Forum (TFGAOSE-10), IEEE Computer Society Press, Paris, France

Galland S, Knapen L, Yasar Auh, Gaud N, Janssens D, Lamotte O, Koukam A, Wets G (2014) Multi-agent simulation of individual mobility behavior in carpooling. International Journal on Transport Research Part C 45:83–98, DOI 10.1016/j.trc.2013.12.012, URL http://www.sciencedirect.com/

science/article/pii/S0968090X14000035

Galland S, Rodriguez S, Gaud N (2017) Run-time environment for the sarl agent-programming language: the example of the janus platform pp –, DOI https://doi.org/10.1016/j.future.2017.10.020

Gaud N (2007) Holonic multi-agent systems: From the analysis to the implementation. metamodel, methodology and multilevel simulation. PhD thesis, Université de Technologie de Belfort-Montbéliard, Belfort, France, in French

Gaud N, Galland S, Gechter F, Hilaire V, Koukam A (2008) Holonic multilevel simulation of complex systems: Application to real-time pedestrians simulation in virtual urban environment. Simulation Modelling Practice and Theory, Elsevier pp 1659–1676

Gerber C, Siekmann J, Vierke G (1999) Holonic multi-agent systems. Research Center for Artificial Intelligence (DFKI) Tech Rep 681, German

Jaume B (2010) Fundamentals of Traffic Simulation. Springer

Jean-Michel C, Franck G, Pablo G, Abder K (2007) Physics inspired multiagent system for vehicle platooning. In: Proceedings of the 6th International Joint Conference on Autonomous Agents and Multiagent Systems, ACM, New York, NY, USA, AAMAS '07, pp 184:1–184:3, DOI 10.1145/1329125.1329348, URL http://doi.acm.org/10.1145/1329125.1329348

Kavathekar P, Chen Y (2011) Vehicle platooning: A brief survey and categorization. In: Proceedings of the ASME Design Engineering Technical Conference, vol 3, pp 829–845, URL http://www.scopus.com/inward/record.url?eid=2-s2.0-84863562922&partnerID=40&md5=0b40fc176f5c0bb4700e1b3e2afd1e33

Koestler A (1967) The Ghost in The Machine. Hutchinson

Mammar S, Mammar S, Lebacque J (2006) Highway traffic hybrid macro-micro simulation model. In: 11th IFAC Symposium on Control in Transportation System

Mella P (2009) Piero mella the holonic revolution holons, holarchies and holonic networks the ghost in the production machine piero mella t he holonic re volution pp –, DOI 10.13140/2.1.1954.5922

Neha S, Amit G (2016) Aged (automatic generation of eps for dbscan). International Journal of Computer Science and Information Security (IJCSIS)

Poschinger A, Kates R, Keller H (2002) Coupling of concurrent macroscopic and microscopic traffic flow models using hybrid stochastic and deterministic disaggregation. Transportation and Traffic Theory for the 21st century

Rodriguez S (2005) From analysis to design of holonic multi-agent systems: A framework, methodological guidelines and applications. PhD thesis, Université de Technologie de Belfort-Montbéliard

Rodriguez S, Hilaire V, Koukam A (2007) Towards a holonic multiple aspect analysis and modeling approach for complex systems: Application to the simulation of industrial plants. Simulation Modelling Practice and Theory, Elsevier pp 521–543

Rodriguez S, Gaud N, Galland S (2014) SARL: a general-purpose agent-oriented programming language. In: the 2014 IEEE/WIC/ACM International Conference on Intelligent Agent Technology, IEEE Computer Society

Press, Warsaw, Poland

Sewall J, Wilkie D, Lin MC (2011) Interactive hybrid simulation of large-scale traffic. ACM Trans Graph 30(6):135:1–135:12, DOI 10.1145/2070781.2024169, URL http://doi.acm.org/10.1145/2070781.2024169

Sharma A, Srinivasan D, Kumar DS (2016) A comparative analysis of centralized and decentralized multi-agent architecture for service restoration. In: 2016 IEEE Congress on Evolutionary Computation (CEC), pp 311–318, DOI 10.1109/CEC.2016.7743810

Tchappi I, Kamla V, Galland S, Kamgang J (2017) Towards an multilevel agent-based model for traffic simulation. pp 887–892

Tchappi IH, Galland S, Kamla VC, Kamgang JC (2018) A brief review of holonic multi-agent models for traffic and transportation systems. Procedia Computer Science 134:137 – 144, DOI https://doi.org/10.1016/j.procs.2018.07.154, URL http://www.sciencedirect.com/science/article/pii/S1877050918311177, the 15th International Conference on Mobile Systems and Pervasive Computing (MobiSPC 2018) / The 13th International Conference on Future Networks and Communications (FNC-2018) / Affiliated Workshops

Treiber M, Hennecke A, Helbing D (2000) Congested traffic states in empirical observations and microscopic simulations. Physical Review E 62

Vèque V, Kaisser F, Johnen C, A B (2013) Convoy: a new cluster-based routing protocol for vehicular networks. In: Vehicular Networks: Models and Algorithms, ISTE Publishing Knowledge /John Wiley and Sons Inc

Wang Y, Han Z (1998) Stability of an automated vehicle platoon. In: Proceedings of the 1998 American Control Conference. ACC (IEEE Cat. No.98CH36207), vol 2, pp 950–954 vol.2, DOI 10.1109/ACC.1998.703548