First Studies to Apply the Theory of Mind to Green and Smart Mobility by Using Gaussian Area Clustering

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Abstract

This paper investigates emerging pattern in users green and smart mobility. Our focus is finding an optimal clusterization of vehicles based on user demand in the metropolitan city of Barcelona and analyze the users' behavior with a theory of mind framework. The notions of clusters, algorithms definitions and optimization procedure are introduced in this study. The following assumption will be considered: the task is a dynamic multi-agent problem settled in a city on a group of scooters. Given the conditions and the data set, the algorithm consists of two phases. First we estimate the vehicles density during the day, hour and location, and we analyze the users' behavior and draw conclusion on their habits. Then we propose a unsupervised clustering technique based on Gaussian area, that takes into consideration point of interests and dis-interest, shaping the area accordingly. Our focus is on simplicity and reproducibility, for this reason our formulation and solution can be considered a general approach that can be adapted based on specific needs.

Keywords

Resource Allocation, Smart mobility,

1. Introduction

Private Transport Systems, or more commonly private cars, are among the major contributors (about 18%) to local air pollution, traffic danger, congestion and poor physical health due to lack of exercise[1]. If the final goal of a green sustainable development is to sustain or improve the quality of life for all, now and into the long-term future, the current growth in private car use is clearly unsustainable. Understanding why most people prefer using a car over other modes of transport for their daily travel, and how they can be persuaded to use less their cars less or even abandon them altogether, is therefore an important goal, expecially after the pandemics of COVID-19 and the physical and mental limitations introduced by it [2, 3, 4] . However in order to get such knowledge we must tackle with the complex system of personal and behaviour factors that are typically studied by neuropsychology. Organizing the way we travel in a more sustainable way will be the key challenge in green transport systems for the near future. At the moment there is a trend in transport from the design of transport means towards the provision of access to activities and destinations. This perspective changes the definition of transportation problems, the influencing factors as well as the types of solutions that are considered. However, it requires a sound understanding of people's travel behaviour. In order to to study the potential for modal shift by passenger cars towards integrated smart transport systems and targets in particular the working class and middle-aged adults, it should be necessary to design and implement support systems based on user behavioral analysis in order to improve current knowledge-based techniques for smart applications mobility, with particular interest in the optimal planning of individual routes and shared transport systems for the minimization of the ecological footprint and the reduction of greenhouse gas emissions. Such studies should take into account the theory of mind when trying to model the user's behaviour. In fact there is a range of reasons that, despite their personal attitudes, could trigger people to act in a pro-environmental fashion. This process of behaviour change can be only triggered by means of precise factors that are mainly related to non-conscious behavioural attitudes which implicitly and unwillingly reflects on conscious actions. Sometime this implicit cause-effect relationship is strong enough to cause an effective cognitive dissonance, also on those people that may express a positive attitude towards a greener transportation system. Moreover, attitudinal research on sustainable transport often only measures perceptions of the instrumental costs and benefits of driving, in terms of time, money and effort, completely ignoring the inner reasoning that trigger human decisions on the matter, as well as other affective

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and symbolic aspects are particularly relevant for private car use.

A common problem with smart mobility is vehicles allocation. With hundreds of vehicles scattered across a city, it is important to have strategies that allow to redistribute the resources taking into account the users and company needs. The focus of this work is to develop a practical resource allocation algorithm suitable for this kind of problem, taking into consideration users' behavior and belief states.

Our aim is to divide the operating area, in this case the metropolitan city of Barcelona, into sectors of quite regular shape with some known characteristics that can be used to drive the resource allocation. For example knowing that in a certain area there is an high probability of having discharged vehicles at a specific time of the day is for sure a valuable aspect to be considered when doing resource allocation.

The proposed solution uses a dataset containing the vehicles position and state during a certain period of time. This information allow us to extract a probability distribution representing the typical vehicles state. Then, given the learned distribution and eventually some relevant points in the map, the operating area is divided in section based on the value of a potential function expressing the aspects we are interested in.

Our focus is on simplicity and ease of use. For this reason our method can be considered a generic approach that can be modified and adapted based on specific needs.

2. Related work

In recent years task allocation and routing problem was studied deeply with many solutions and algorithms proposed for different scenarios and multi agent environments. A whole variety of researchers has given their opinion and approaches for task allocation within agents [5], also taking into account the users' behaviors. Such approaches span between different filed, the main ones being:

- Game theory
- Theory of Mind
- Gaussian Clustering

2.1. Game theory

As part of the game theory approach, each agent participates in negotiations with other agents about the tasks to be completed. Players are considered agents, and allocating the task is a strategy that results in the best payoff [5]. Players converge on the Nash equilibrium, a stable solution, which is that once the strategies are established, agents cannot deviate from their chosen course as they cannot do better. Based on [6, 7] the problem of task allocation has been formulated as a Markov game. In the first step, a utility function must be defined, but due to difficulties in deriving the agents utility function, a series of static potential games was approximated [5]. The utility function of each agent tends to be maximized. However, any changes in strategy will result in a change in global utility. The goal is for each agent to achieve their own best interests, while keeping the global good in mind. Using game theory to analyze the overall behavior is the next step. At the end of each cycle, the agents utility function, state, and location converge to a Nash equilibrium. Various simulators have applied this approach, resulting in highly efficient relocation. Additionally, this approach has some disadvantages such as its sensitivity to environment changes and the need for constant negotiation between agents. The authors of this paper [8] demonstrated that this approach is highly successful for disaster rescue scenarios. As the conditions in this study are different, this approach will not be used since our agents will not need to negotiate since the paper focuses on assigning the closest scooters.

2.2. Theory of Mind

As humans, we tend to build a belief model of how other humans may react to certain stimuli and update it with each new observation [9, 10, 11]. This behavior was first theorized in [11] and named Theory of Mind [ToM], after the humans' ability to represent the mental states of others. More recently, [12] applied ToM to let artificial agent build a model of other agents' observation and behavior alone.

The ToM can also be applied to infer human intention from artificial settings , such as vehicles location during the day. Indeed [13] advocates how theory of mind should focus on practical application rather than being studied only as a theoretical framework. Indeed, in [14], the authors propose a computational model based on ToM that is able to infer emotions based on indirect cues. Moreover they lay out a road-map for future work in which they stress the importance of prioritizing modeling affective cognition on naturalistic data.

2.3. Gaussian Clustering

Maximum likelihood clustering [MLC] approaches [15, 16] encompass many clustering algorithm which can be considered sufficiently general for non task specific purposes. Many variations of MLC have been implemented considering model based approaches [17, 18, 19, 20, 21], mixture models [22, 23, 24] and fuzzy logic [25, 26, 27, 28].

In their work, [20] present a detailed review on the literature of Gaussian modeling, where they follow the evolution of model based clustering. A notable example is [17], where the authors deploy a MLC algorithm where they rely on the common structure of MRI in order to reparametrize the clusters' coveriance matrices. They show how some parameters are similar between clusters and how the main features can be considered in a more efficient way. The [18] algorithms by comparison demonstrate how to exploit the structure of a Gaussian model in order to generate efficient algorithms for agglomerative hierarchical clustering.

Moreover, [23] define a generalized version of [29], where the role of each variable is specified without any previous assumptions about the link between the selected and discarded variables. They show how their algorithm is more versatile than the original one and can be deployed for high dimensional dataset.

Finally, [27] propose an unsupervised model based Gaussian clustering based on fuzzy logic. Their approach is built on top of [17] and extends it solving both the initialization problem as well as automatically obtain an optimal number of clusters.

3. Methodology

A potential function express the interest regarding different areas of the city. It can be computed taking into account different elements, one of which is the vehicles' position distribution. Once such function is computed, the sectors borders are defined by the equipotential curves. For simplicity, the potential computation considers only the multivariate 2D Gaussian describing the vehicles distribution and some additional relevant positions. Possible extension of the method will be mentioned in the conclusion.

Gaussian estimation The first step is to compute the Gaussian parameters based on the available data. Since a Gaussian distribution is completely described by its mean vector μ and covariance matrix Σ, our goal is to estimate these quantities. In this implementation the focus is on vehicles distribution at the end of a day, so we extract the position of each vehicle at the end of a day i and compute μ_i, Σ_i. This procedure is repeated for n days and the Gaussian parameters are obtained by averaging the results. In this way, the resulting distribution will represent the probability of having a vehicle in a certain position with a reasonable certainty.

Area division Our next objective is to divide the area in sectors. To do so, we start by computing a potential function $U(x)$. A very simple choice is to set

$$U(x) = f(x), \tag{1}$$

where f is the probability density function of the estimated distribution. Moreover, we consider some point

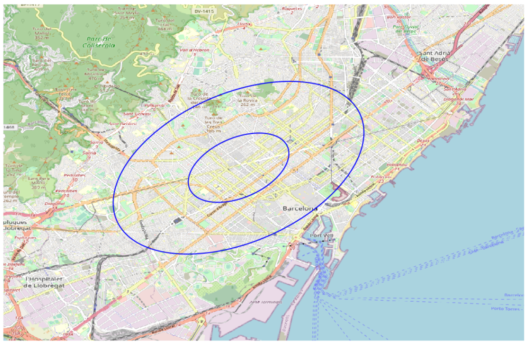

Figure 1: Potential representation using method (1).

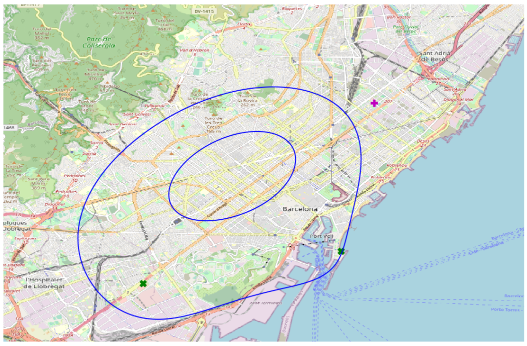

Figure 2: Potential representation using method (2).

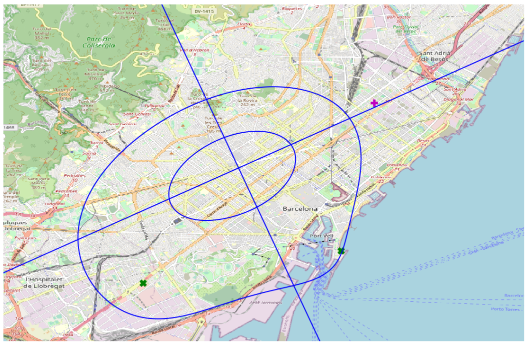

Figure 3: Map subdivision with additional lines using method (2).

of interest and some point of disinterest. Each point of interest $p_{a,i}$ generates a potential $U_{p_{a,i}}(x)$, where $U_{p_{a,i}}$ is a probability density function of a 2D multivariate Gaussian centered in $p_{a,i}$ with a fixed covariance matrix. The same is done by each point of disinterest $p_{b,i}$, but with opposite sign. In this way the final potential can be computed as

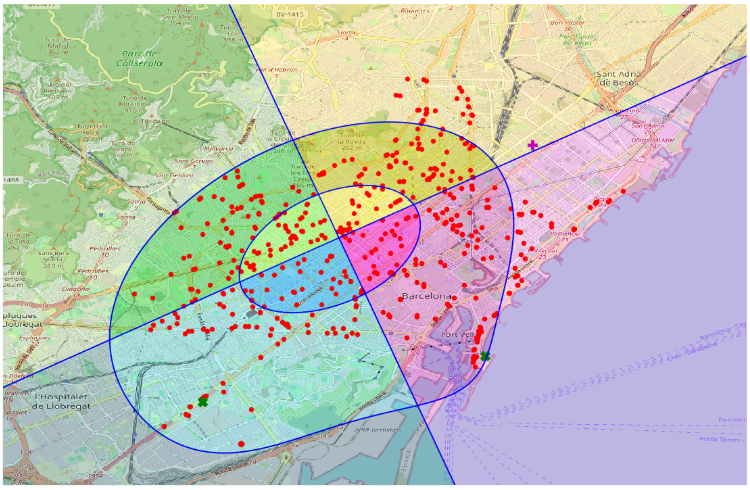

Figure 4: Final map subdivision together with vehicles position at a given time-stamp.

$$U(x) = k_1 f(x) + k_2 \sum_i U_{p_{a,i}}(x) - k_3 \sum_i U_{p_{b,i}}(x) \tag{2}$$

where $k_1, k_2, k_3 > 0$ are adjustable parameters.

With the latter equation, we can split the operating area by using equipotential curves and additional segments. This phase is highly dependant on the operating area and on the resource allocation requirements. In the next chapter some solutions will be presented and compared.

4. Experiments and Results

The evaluation of the proposed method takes to account the city of Barcelona, used as the operating area. The given dataset contains 813197 records, each having a position detection event with information about the vehicle id, the site id, latitude, longitude, altitude, battery percentage, date of the last fix, status (e.g. free, running) and the time-stamp of the detection.

The records have been collected between *20/08/2020* and *19/09/2020* in the same site id (Barcelona) for around 500 different vehicles. For simplicity, we only considered the vehicle id, latitude, longitude and the time-stamp.

We first apply a position filtering where any vehicles outside of the operating area [1] are excluded. This reduces the number of records by 43%.

As already mentioned the choice of the potential function has many options. The easiest solution computes the potential as (1). The normalized values are reported in Figure 1, where the equipotential curves are $0.25, 0.8$.

Additionally, we present results (2) when additional point of dis/interests are present in the requirements. In the Figure 2 the potential computed with parameters $k_1 = 1, k_2 = 0.5, k_3 = 0.3$ is presented. Two points of interest are reported with green "$\times$", while the point of disinterest with a purple "$+$". Also in this case the values are normalized and the equipotential curves refers to the values $0.25, 0.8$.

As can be seen from these figures, in many cases the equipotential curves are not enough to define sectors with simple shapes, for this reason some additional division lines should be extracted from the data. A trivial solution is to consider the line passing through the eigenvectors of the covariance matrix of the estimated distribution, i.e. the axes of the equipotential ellipses of the Gaussian. The resulting subdivision for the latter method is shown in Figure 3.

This result allows for an additional subdivision that is suitable for resource allocation tasks. the reader should note how these results are highly dependant on the points of interest/disinterest, so manual tuning is required for optimal sector splits.

Finally, we report 4 a map subdivision with sectors coloring where vehicles' positions are also shown.

As the reader can see, the 12 identified sectors are descriptive of the vehicles distribution in the different zones of the city.

For completeness, in Figure 5 we show the potentials obtained by considering the vehicles distribution at different time of the day. It can be noticed that the vehicles distribution doesn't change significantly during the day, but nonetheless this analysis is necessary.

[1]Latitude $= (41.3419, 41.4465)$
Longitude $= (2.0878, 2.2454)$

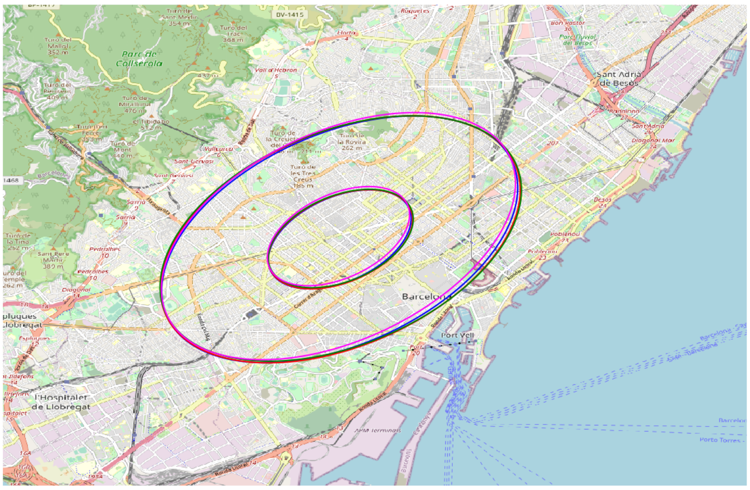

Figure 5: Potentials comparison when learning the distributions at 10:00 (blue), 14:00 (red), 18:00 (green) and 24:00 (purple) of each day.

From the above mentioned analysis, we can infer the general behavior of the users based on vehicles location through the week. This is a preliminary study which can aid future research in the direction of a ToM approach to model users' mental state.

5. Conclusions

In conclusion the method proposed is a generic approach to smart vehicle resource allocation and, specifically, to split a metropolitan city into sectors. The power of this method relies in in its simplicity and ability to suit a variety of different context. The main disadvantage is that the sectors subdivision requires some tuning and a human supervision.

Further extensions can be considered, specially regarding the potential function definition. Multiple Guassian distributions representing different vehicles conditions (e.g. time of the day, holidays and working hours) can be weighted differently in the potential computation, so to take into account particular needs. Also the potentials generated by the point of interest or disinterested can be modified with ad hoc functions based on the specific of each point. Overall, our method is valuable and can be used as a starting point to model human belief states with a Theory of Mind framework. For future improvement it should be taken into account the automation in the sectors recognition phase, so to obtain a stand alone process.

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