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Let My Car Alone: Parking Strategies with Social-Distance Preservation in the Age of COVID-19

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Abstract

Searching for an available parking space is a time-consuming and frustrating task for drivers, which also leads to huge amounts of fuel waste. Far from being solved, as the COVID-19 crisis slowly resolves, we can expect an increase in the use of private cars in comparison with public transportation, which will further aggravate the problem.

Therefore, the use of smart parking solutions that help drivers to find an available parking space will become key to alleviate this problem. Moreover, existing solutions should be extended and adapted to incorporate the concept of social distancing, which is the only prevention measure (along with proper hygiene) which has been able to stop the virus so far. In this paper, we present an approach for the recommendation of parking spaces that considers social distance metrics to decide which parking spaces should be suggested to each driver. As far was we know, this problem has not been considered before in the literature. We illustrate the proposal with a use case scenario of a parking lot. Our experimental evaluation shows its feasibility and benefits.

Keywords: Data management; COVID-19; social distancing; mobile computing; smart parking

1. Introduction

With the advent of COVID-19, almost all countries in the world are facing an unprecedented pandemic in modern history. Even though the progress of research is impressive since the beginning of this crisis, many questions remain unanswered. In particular, the propagation modes of the virus are yet not completely known. Subsequently, different recommendations have been published to avoid the virus transmission, such as washing hands regularly, wearing a mask outside (and indoors with other people), and preserving social distance with other people. Thus, keeping at least a one-meter distance (and, usually, 1.5-2 meters) between people is now strongly recommended in many countries.

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To try to limit the spread of the coronavirus and avoid the saturation of emergency departments in hospitals, confinement strategies have also been adopted by many countries. By limiting the traffic of vehicles, these confinements have temporarily alleviated the huge difficulties usually encountered by drivers for finding an available parking space in city centers. For instance, Figure 1 shows the average evolution of available parking spaces in April 2019 (in a normal situation) and in April 2020 (during the global confinement in France), by hour and day of the week, for one parking lot in Lille (France) called *Parking Euralille*, located near a huge commercial center[1]. Unsurprisingly, this clearly shows a very significant reduction of the number of parking spaces occupied in April 2020 in peak hours compared with the usual trend. Moreover, we can observe that during off-peak periods the number of occupied slot was also reduced in April 2020 compared with April 2019. This is probably due to the fact that some people left the city during the confinement period and others went to the commercial center much less frequently.

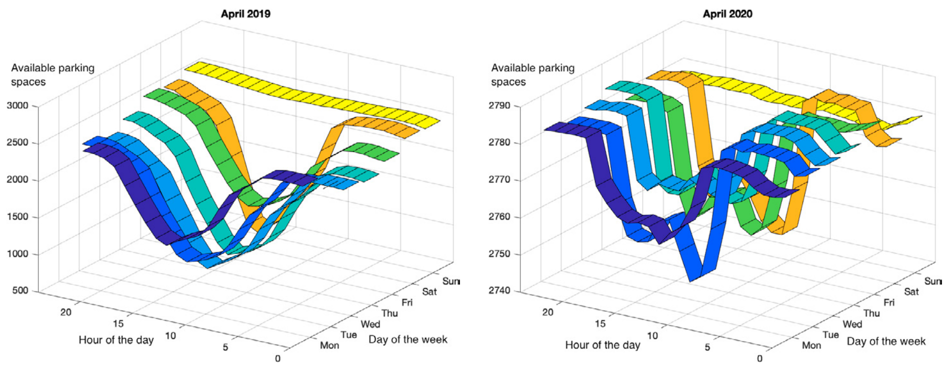

Fig. 1. Available parking spaces by hour and day of the week in April 2019 (left) and April 2020 (right) in Parking Euralille (Lille, France).

Obviously, the situation has quickly changed as the post-lockdown progressed and people are now finding the usual difficulties to find a free parking space. Moreover, the problems to find a parking space could increase significantly, as people will be more afraid to take public transportation options and prefer to move in private cars whenever possible, in order to avoid the possibility of contacts with potentially-infected people or surfaces that may be more likely infected (touched by many people) in the public transport (buses, trams, subways, etc.). Finally, a number of studies have found a correlation between the spread of respiratory infections like the COVID-19 and air pollution (e.g., see [3, 7, 23]) and the emissions of vehicles of parking searching is a well-known source of air pollution (e.g., see [14, 18, 19, 22]); therefore, in case this correlation actually entails some causality, improving parking search could lead to reduce pollution and a potential decrease in the spread of respiratory infections.

The situation caused by COVID-19 has definitely changed the social rules. Although the current status could be alleviated as the health crisis resolves, future outbreaks of this or similar epidemics are possible, which would require again strict measures of social distancing [16]. Motivated by this, we strongly believe that new constraints should now be integrated in Smart Parking Management Systems [13]. Such systems use various technologies, such as Vehicular Ad Hoc Networks (VANETs) [8] and the Internet of Things (IoT) [12], to help drivers find an available parking space according to criteria such as the driving time to reach the parking area, the walking distance to reach the target destination, the parking price, or the probability to still find the space available when reaching its location [4]. In the context of the global crisis we are experiencing, with proper extensions and adaptations, these systems can indeed play a key role in the preservation of social distance between people. Indeed, for many people, parking represents the initial stage from which it is necessary to preserve social distancing. Therefore, when allocating or announcing a parking space to a driver, a smart parking system should facilitate the social distancing by making sure that nobody will be too close to the driver when s/he leaves her/his car.

To illustrate our purpose, let us consider parents who are driving their young children to school. These parents need to find a parking space where the social distance will be easily preserved while they take the stroller and the

[1] These figures were generated using data provided by the open data platform of the European metropolis of Lille; see `https://opendata.lillemetropole.fr/explore/dataset/disponibilite-parkings/information/` for more information.

children out of the car. In case there are other children close to the vehicles, they could easily touch each other while their parents are caring their younger sisters/brothers. The same need arises when people fill the trunk of their car with the goods purchased in the supermarket, just before leaving the supermarket. Even if the parking space next to that vehicle is free, it should not be occupied by another driver until those customers get inside their vehicle and leave.

In the following, we analyze how smart parking systems can help to decrease the risk of virus dissemination by advertising the right parking space at the right moment. The structure of the rest of the paper is as follows. First, in Section 2, we present some background relative to existing smart parking management solutions and the main criteria used to decide which parking spaces are relevant to be allocated or communicated to specific drivers. In Section 3, we propose our novel parking recommendation strategy that considers the need to preserve the social distance. In Section 4, we present an experimental evaluation that illustrates the feasibility and performance of our proposal. Finally, in Section 5, we present our conclusions and some prospective lines for future work.

2. Related Work

The implementation of smart parking solutions highly depends on the target environment. Indeed, the technical solutions that can be used to provide drivers with real-time information on parking opportunities may differ significantly from one scenario to another. For instance, the guidance of drivers towards a parking space allocated or communicated to them can rely on the GPS system when considering outdoor parking, whereas display panels should be used in an indoor context. Another example to illustrate the huge heterogeneity of solutions concerns the detection of available parking spaces, for which various solutions have been proposed in the literature. Some of them have considered the use of smartphones [24], parking meters [25] or video cameras [1]. Moreover, several working systems exploit sensors that allow checking online the availability of parking spaces. Among these existing systems, one of the popular examples generally cited is SFPark [21], in San Francisco; the information is obtained thanks to wireless parking sensors equipped with magnetometers embedded in the pavement, that monitor the occupancy status of the different slots. Other solutions even rely on the use of vehicles equipped with GPS receivers and ultrasonic sensors to determine parking spot occupancy [15].

As an example of a representative approach, ParkAssistant [17] is an algorithm that facilitates the search of a parking space while minimizing the price and time to reach the destination. ParkAssistant also integrates drivers' preferences such as the intended parking duration, time flexibility, price elasticity, and willingness to walk. These parking preferences are then converted into an appropriate utility function used by ParkAssistant to recommend a parking route. As another example, in [9], the authors focus on guiding drivers inside parking lots and propose a parking space recommendation model that takes into consideration different parameters such as the walking distance to the exit, the total driving distance in the parking lot, the type of parking space, the status of adjacent ones that may ease the maneuvers needed to park, and finally the traffic conditions on the parking lanes. The interested reader is referred to [8] for an analysis of different types of solutions for the recommendation of parking spaces.

The important observation to note is that existing works focus on the parking space searching problem from a classical perspective, without considering social distancing. As far as we know, this is the first work that introduces the use of social distancing for parking space assignment and advertising.

3. Social-Distance Aware Approach for Smart Parking

In this section, we focus on the problem of how to ensure social-distance preservation in smart parking solutions. We argue that, in addition to the different preferences provided by each driver (e.g., price to pay, walking distance, driving distance, etc.), the allocation process of an available parking space should help preserve the social distance when a driver parks her/his vehicle. To illustrate this, let us consider the scenario depicted in Figure 2. In this example, Olivia arrives in her yellow car close to her destination (the white house) and starts looking for an available parking space. Three parking spaces (*a*, *b* and *c*) are available in the neighboring parking lot. Whereas parking spaces *b* and *c* minimize both the driving time to the destination and the walking distance, parking space *a* could be recommended at that moment by a parking management system preserving the social distance. Parking space *a* is indeed the parking space with the lowest number of pedestrians nearby. If parking space *b* or *c* is chosen instead, then there is a high risk that she will not be able to keep the social distance with other pedestrians.

In the following, in Section 3.1, we first describe the method proposed to obtain candidate parking spaces based on the detection of risky areas, which is the basis of our proposal. Then, in Section 3.2, we explain the cost function that can be used to rank the candidate parking spaces that can be finally recommended to the driver.

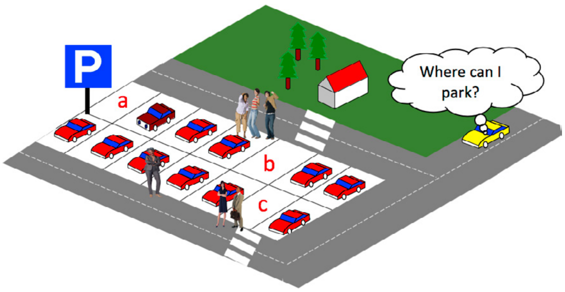

Fig. 2. Social-distance aware parking scenario.

3.1. Retrieval of Candidate Parking Spaces

In this section, we describe our proposal to detect risky areas, which is based on the application of clustering algorithms on the locations of people. So, the first task is to identify clusters of pedestrians. As a clustering algorithm, we apply DBSCAN [5, 10, 20], which is a density-based clustering algorithm. It has two input parameters: the value *Eps*, that determines the size of the *neighborhood* considered by the algorithm, and the minimum number of points per cluster *MinPts*. In order to build a cluster, DBSCAN requires that for each point in the cluster there is a point in the cluster such that the first point is within the *Eps-neighborhood* of the second point (i.e., it is at a distance no greater than *Eps*) and that the neighborhood contains at least *MinPts* points. In our case, each pedestrian is a point and we aim at detecting clusters of pedestrians to be aware of. For us, even a single pedestrian may represent a danger, as we must keep the safety distance regarding that pedestrian, and therefore we set *MinPts* to 1. On the other hand, we set *Eps* to the value of the required safety distance that must be maintained, which is usually 1.5 meters (recommended safety distance in many countries at the time of writing). With this strategy, we identify groups of people that are not respecting the safety distance among themselves (these people may be unconscious people that do not respect the rules of social distancing or individuals that are already living together) as well as individuals not forming any group; for an example, see the left part of Figure 3, where the different clusters are represented by using different colors for their members (i.e., pedestrians within each cluster).

It should be noted that, as the computation of the risky areas relies on the detection of clusters of pedestrians, we assume that the locations of the members of a cluster are captured by their GPS receivers on their devices and communicated to our system. We believe that this is a reasonable assumption, given that many users are willing to share their location information for a variety of mobile apps they use daily. Besides, the popularity of *Mobile Contact Tracing Apps (MCTA)* [2, 6, 26] is also going in this direction. If we want to consider non-collaborative pedestrians or pedestrians not using our application, then we would need additional methods for the detection of pedestrians (e.g., using surveillance images and/or information provided by other collaborative users), not relying on the location information provided directly by them. In extreme scenarios where pedestrians are completely undetectable, at least it can be assumed that it is very likely that there are pedestrians near vehicles that have been parked very recently. Our approach works independently of the specific method used to detect or infer the presence of pedestrians.

After detecting the clusters, we consider two different alternative methods to detect risky areas, which are evaluated experimentally in Section 4. One method relies on the computation of the euclidean distance between the centroid of the clusters and the parking space (*centroid-based method*); with this method, we add a penalty value to the parking space if the distance between the center of the parking space and the centroid of the cluster is smaller than the required safety distance (the completely risk-free parking spaces are those with no penalty). The second method determines the portion of each parking space intersected by a risky area around a cluster and also considers the density of the cluster to compute a specific safety distance for that cluster (*intersection and density-based method*). In the following, we explain this second method in more detail.

In the intersection and density-based method, we first identify the minimum 2D boundary (polygon) containing all the points in each cluster (see the right part of Figure 3); in case all the points in the cluster lie in a straight line, a small jittering is first applied to the points in order to move slightly their position from the straight line and thus be able to determine a minimum 2D boundary containing the points using standard approaches.

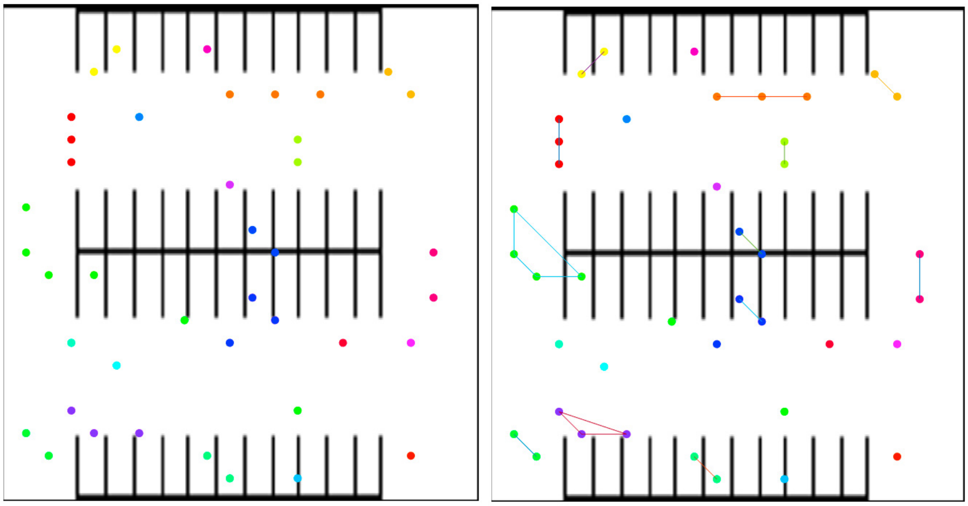

Fig. 3. Clusters identified in a simple example scenario of a parking lot (left) and the boundaries of the clusters (right).

Then, we apply a *buffering* operation [11] on the identified boundaries, by extending those boundaries in each direction by a *cluster-specific safety distance*. In case the cluster is composed by a single point, then rather than computing its boundary and applying the buffering operation, we simply consider a circle centered on that single point and radius the corresponding *cluster-specific safety distance*. These final spatial areas are called *risky areas*, as they should be avoided in order to try to preserve social distancing in the best possible way.

The *cluster-specific safety distance* for a cluster i ($safety\_distance_i$) will be the usual *required safety distance* (determined by the social distancing rules) for many clusters, but for some clusters we add an additional *extra safety margin* depending on the risk score of the cluster (see Equation 1). More specifically, if the density of the cluster (number of pedestrians per square meter) is above the expected medium density in the area (that we call the *density threshold*), an additional extra distance is considered to compute the cluster-specific safety distance. In other words, we penalize clusters that are very compact, as their presence represents additional difficulties to keep the social distance. In Equation 1, ω_i represents an application-dependent formula whose value increases with the density of pedestrians in the cluster (e.g., we can set $\omega_i = density(i)$); it depends on how much we would like to penalize a cluster depending on its density. The MAX (maximum) operator ensures that at least the required safety distance will always be respected.

$$\begin{aligned}
&safety_distance_i = MAX(required_safety_distance, op(required_safety_distance, risk_factor_i))\\
&\text{where } op \text{ is a function of the required safety distance and the risk factor, such as } op(x, y) = y\\
&\qquad risk_factor_i = \begin{cases} \omega_i & \text{if it is a risky cluster, with } \omega_i \geq 1 \\ 1 & \text{otherwise} \end{cases}\\
&\text{where cluster } i \text{ is considered to be a risky cluster if } density(i) > density_threshold
\end{aligned} \tag{1}$$

Once the risky areas are computed, we obtain the list of parking spaces that are not intersected by such areas, considering these parking spaces as a list of potential candidate parking spaces that can be recommended to the driver.

3.2. Ranking of Parking Spaces Using a Cost Function

We now briefly explain how the final allocation of an available parking space to a vehicle can be made, based on the list of candidate parking spaces obtained in the previous step where the risky areas were identified. In order to rank the candidate parking spaces, a global cost function can be considered, which includes several costs associated with the available parking spaces; we consider the driving time to the parking space and the walking time from the parking space to the destination to reach by walking (e.g., the closest exit of the parking lot), as shown in Equation 2.

$$\sum_{i=1}^{n} \alpha \cdot C_{driving_i} + \beta \cdot C_{walking_i} \tag{2}$$

where $C_{driving_i}$ is the driving time to reach parking space i, $C_{walking_i}$ is the walking time from parking space i to the point to be reached by walking, and α and β are coefficients to balance the relative importance of these costs.

4. Experimental Evaluation

In this section, we present an experimental evaluation that shows the feasibility and the interest of our approach, considering a parking lot as a use case scenario. Our goal is to show that our solution is able to provide a suitable available parking space to a vehicle arriving at the parking lot. We have tested different configuration scenarios, varying the density of pedestrians and considering different (limited) numbers of available parking spaces. We have considered a configuration where groups of pedestrians not respecting social-distancing systematically appear on the parking lot (configuration with groups of pedestrians) and another configuration where all the individual pedestrians are randomly distributed over the whole parking lot (configuration with random distribution of the pedestrians). Moreover, the safety distance has been computed using the two different approaches described in Section 3.1: the *centroid-based method (A)* and the *intersection and density-based method (B)*. In the experiments shown in this section, the required safety distance is 1.5 meters, the density threshold is 2 pedestrians per square meter, we have set the value of ω_i equal to the density of pedestrians in the cluster ($density_i$) and $op(required\_safety\_distance, risk\_factor_i) = risk\_factor_i$, while considering a maximum safe distance of 7 meters.

In Figure 4, we show an example of the risky areas detected with the intersection and density-based method considering the parking lot used in the experiments along with a specific configuration of pedestrians (represented as points) and a given number of available parking paces (rectangles in the figure); the total size of the parking lot is 45 by 67.5 meters and the size of each parking space is 5 by 2.5 meters. Besides, in the figure we also show in green the parking spaces that are considered risk-free with the centroid-based method, in orange those considered as of little risk by that method, and in red those considered as not-valid parking spaces according to that method; the occupied (not available) parking spaces are shown in black.

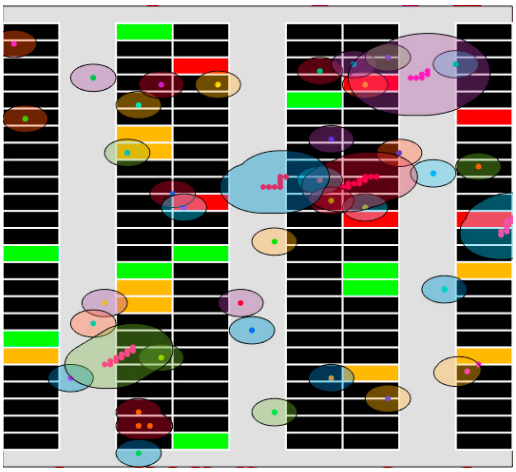

Fig. 4. Risky areas identified by the intersection and density-based method, and results of the centroid-based method, in one configuration example.

For each configuration evaluated, we measured the number of eligible (risk-free) parking spaces detected as available for parking by the solutions A and B. Table 1 shows the results obtained when the pedestrians are randomly distributed, as well as the results when groups of pedestrians not respecting the social distance systematically appear in the scenario. In the tables, the "clusters identified" column corresponds to the number of clusters identified by the DBSCAN clustering in each case, the "risk-free" columns contain the number of parking spaces that have no risk according to the corresponding method (A or B), and the "min-risk" columns provide additional parking spaces that (even though they are not completely risk-free) have a low risk (small intersection with risky areas). We logically observe that the number of risk-free parking spaces decreases as the number of pedestrians on the parking lot increases. Nevertheless, for all realistic scenarios (with a number of pedestrians not greater than the total number of parking spaces in the parking lot, as we only expect pedestrians in the parking lot mostly when leaving the car or coming back for the car to leave) our solution provides at least one risk-free parking space even in the worst case.

Table 1. Risk-free parking spaces with pedestrians randomly distributed and with groups of pedestrians not respecting the social distance.

Parking settings			**Risk estimation**				
Total spaces	Total free spaces	Number of pedestrians	Clusters identified	Risk-free A	Risk-free B	Min-risk A	Min-risk B.
With pedestrians randomly distributed							
150	21,6	75	63,5	7,2	8,1	6,5	6
150	20,9	151	107,5	2,8	5,4	2,3	4,3
150	21,7	226	133,4	1	4,1	0,5	2,7
150	22,1	302	144,8	0,7	3,6	0,2	1,6
With the generation of groups of pedestrians not respecting the social distance							
150	21,9	79,5	39,8	9	5,8	8,4	5
150	22,4	153,4	69,7	4,2	5,1	3,5	4,5
150	21,5	229,5	91,9	1,9	4	1,4	3,3
150	21,6	305,2	108,1	1,7	2,8	1,1	2,3

The results show that our approach (with both methods) is usually able to find a suitable parking space to allocate to a vehicle, that is expected to be risk-free regarding the preservation of social distancing. So, we achieve the goal of identifying the best places to park with the lowest risk. Moreover, in high-density scenarios where satisfying this desirable risk-free condition might not be possible, it is possible to warn the driver and recommend a space with an existing but low risk. The results presented in the tables of this section are calculated as an average of 50 executions; we also computed confidence intervals and did not notice significant differences between the results of different runs. We have performed more experiments but, due to space constraints, we show the results only for some representative configurations and omit the information about the confidence intervals.

5. Conclusions and Future Work

In this paper, we have studied the problem of managing parking spaces taking into account the need to preserve the social distance between people, as required in the current COVID-19 age to help prevent the spread of the virus. More specifically, we have presented an approach for the recommendation of parking spaces that considers social distance metrics to decide which parking spaces should be communicated to a driver. Up to the author's knowledge, this relevant problem has not been considered before in the literature. An experimental evaluation with parking lots shows the feasibility of the proposal and its ability to provide suitable suggestions about available parking spaces while maximizing the safety of the passengers of the vehicle and the people present in the parking lot.

We are currently improving our proposal in several directions, extending our experimental evaluation by considering other configurations and evaluating alternative approaches to compute risky areas. Besides, we plan to consider other use cases. In particular, we would like to analyze the impact of the proposed strategies for city-scale on-street parking and how the combination of several technologies (such as peer-to-peer interactions in vehicular and mobile networks, wide-area information services, and/or cloud services) could help. We could also analyze issues that may affect the preservation of the social distance once the driver leaves her/his car and walks towards her/his final destination.

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