*Road transport,
observation points,
optimal positioning*

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ASSESSMENT OF OBSERVER POSITIONS FOR GIVEN BEHAVIOR OF DRIVERS

In a series of recent papers [1, 2, 3] the concept of tracing stolen cars was introduced and developed. Generally, the aim is to intercept wanted cars, hence course prediction is a crucial issue. Unlike e.g. ballistic missiles, the route of a road vehicle is controlled continuously by decisions of its driver. In this paper, we develop several models of drivers' behavior and analyze their impact on the predictability of future positions. Next, two sets of observation points are compared with respect to their hit rate on a sample of vehicle paths generated according to a given type of behavior.

OCENA POZYCJI PUNKTÓW OBSERWACYJNYCH DLA ZADANEGO TYPU KIEROWCY

W serii artykułów [1, 2, 3] wprowadzono i rozwinięto koncepcję systemu służącego do lokalizacji określonych samochodów. Celem ogólnym jest przechwycenie poszukiwanych pojazdów, w tym względzie istotnym punktem jest trafna prognoza ich dalszych tras. W odróżnieniu od innych aplikacji – jak np. przy badaniu pocisków balystycznych – kurs pojazdu drogowego podlega nieustannym interwencjom jego kierowcy. W niniejszym artykule rozwija się kilka modeli zachowania kierowców. Badany jest ich wpływ na trafność prognoz przyszłych pozycji. Ponadto porównuje się dwa sposoby rozmieszczenia punktów obserwacyjnych pod względem liczby widzianych pojazdów z próbki losowanej zgodnie z zadanym typem kierowcy.

1. INTRODUCTION

A major task in telematics is to obtain and process information about remote objects. In application to road transport, this is typically the acquisition of data about cars, in particular their position. Generally, data may be collected by stationary devices, mounted on constructions like bridges or posts close to a road or crossing, or by mobile sensors installed in a vehicle, in particular, but not necessarily, in the car which is monitored. Stationary sensors serve often to obtain numbers of cars on a given length of road or numbers of cars passing a certain point in a certain interval of time. Mobile equipment may inform about such data as for instance position coordinates and information about speed, temperature, state of the engine. In any case, the transmission of data from sensor to the site, where the

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actual analysis is performed, is a crucial task. In this paper, following [1, 2, 3], we concentrate on monitoring the positions of specific cars. While usually it can be assumed that the vehicles under consideration support the effort actively by sending information from some sort of on-board unit, this is not assured e.g. when tracing stolen cars. Analogous situations may occur in the case of locating pedestrians or bicyclists. Consequently, we focus on information obtained from optical observation by means of traffic or street cams. As opposed to usual observation of traffic, we need to identify the objects seen by the cam, compare with a watch list and transfer information about *sightings*.

Further, from collected information about a sequence of sightings, a course prediction may be carried out and lead to a successful interception by the authorities, [2]. To this end, a continuous exchange of data between the proposed system and the police is necessary, cf. [1, 3]. In one direction, number plate information of wanted cars has to be transferred and updated. The observation net sends back current data about registered positions and forecasts the further course of a car, whenever sufficient information has been collected. Usually, a series of several sightings is required to perform a sensitive prediction, cf. [2].

The concept of a network of intelligent observers has been outlined in [1, 3]. The idea of the prediction method has been presented in [2]. It was noticed that results strongly depend on the assumed behavior of drivers and on the positions of the traffic cams. These factors will be investigated in more detail in this paper. In the next section, three types of drivers will be introduced and analyzed, while in the following section statistical experiments with two sets of observation points will be performed.

2. TYPES OF DRIVERS

Car thefts happen every day many times, and there are very different types of people committing those criminal acts. There are kids merely borrowing a vehicle for joyriding, and there is organized crime aiming at profit from re-sale of the stolen cars as a whole or as spare parts. Accordingly, decisions about where to turn at intersections may be taken either totally at random or with the purpose to reach a certain destination. Nonetheless, also the course of a vehicle aiming towards given coordinates is subject to a certain randomness, which has to be taken into account when simulating the action of a tracing network. In the next three subsections we focus on three chosen types of drivers, without claiming to be exhaustive.

Fig.1. Street maze

In reality, motion of vehicles is usually restricted to a network of streets or roads, e.g. Fig. 1 captured from [6] shows the street net of Manhattan in two different scales. For the purpose of this study, however, it is more convenient to assume a simpler structure, namely a cartesian grid of streets and avenues. Fig. 2 shows an abstract street net together with some chosen positions of street cams and the path of some vehicle. On the left, none of the cams sees the vehicle, while on the right the car passes two times underneath a camera. In the next section, we are going to simulate the motion of a large number of vehicles and study their visibility on given sets of observation points. A common feature of all studied models in this paper is that the current position of a vehicle has always integer values in both coordinates (x_k, y_k). The index k counts the number of *blocks* traveled so far and plays the role of time in this simplified approach.

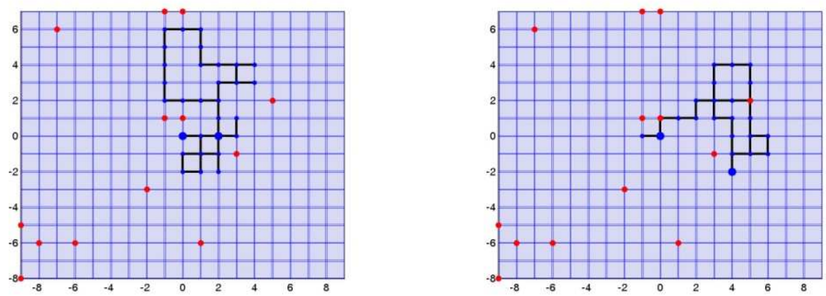

Fig.2. Grid of the City of Cratopolis

The length unit will be called a *block*. The transition to the next position $(\Delta x, \Delta y)$ has the properties:

$$\{\Delta x, \Delta y\} \subset \{-1, 0, 1\} \tag{1}$$

$$|\Delta x| + |\Delta y| = 1 \tag{2}$$

The current position is hence given by:

$$x_k = \sum_{l=0}^{k-1} \Delta x_l \tag{3}$$

$$y_k = \sum_{l=0}^{k-1} \Delta y_l \tag{4}$$

This way we have $x_0 = y_0 = 0$, $x_1 = \Delta x_0$, $y_1 = \Delta y_0$, i.e. all trajectories start from the origin of the co-ordinate system. The discrete probability distribution of the vectors $(\Delta x, \Delta y)$ will determine the specific type of driver. We start from the uniform case.

2.1 Random Cruising

Assume the type of a driver who simply likes a ride in an expensive car. He has no specific destination, and is going straight, turning left or right or taking U-turns just at random – for the fun of it. Notice that this sort of behavior was already studied in [4, 5].

Fig. 2 shows the general idea of motion on a rectangular grid with random behavior at each crossing. For an overview on the topic of random walks and their applications compare. For the simulation of this type of behavior, a random sample from a discrete uniform distribution on a four element space has to be drawn.

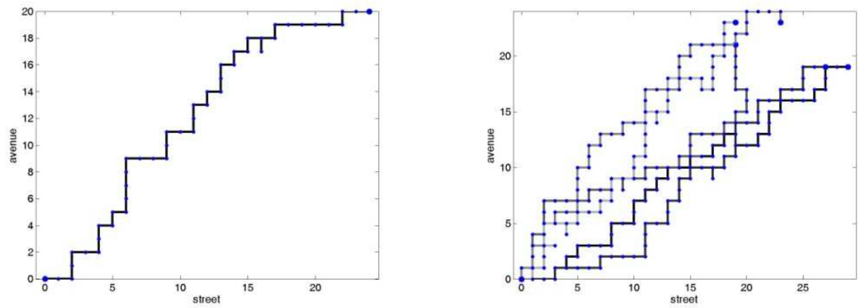

Fig.3. Directed walk

Let us denote the probability of a move in direction *(1, 0)* by P_E, likewise P_N, P_W and P_S are named as in East, North, West and South, e.g.

$$P(\{\Delta x = 0, \Delta y = 1\}) = P_N = 0.25 \tag{5}$$

It is worthwhile to notice that for that type the whole sequence can be sampled at once and in any order, because the direction taken in a later step does not depend on the previous moves. Further, let us mention that this basic type may be easily modified for instance by assuming different probabilities for the possible directions. A more serious modification would consist in assigning different probabilities to straight travel and right, left and U-turns. Anyway, it is obvious that this type of driver is too random for a successful prediction. All that can be said is that the position of the car is spread around the position where it was last seen, see Fig. 5, and the deviation grows with the square root of the elapsed time, cf. [5].

2.2 Travel in a General Direction

Now we propose a second type of behavior. A car is stolen with the purpose to go for a trip in some general direction, e.g. to the seaside or into the mountains. Still, there is no specific final destination, just a general vector of motion. Fig. 3 shows a typical randomized straight walk in the plane. Changes of direction deviate around some chosen direction. On the left, a single representation of this type is presented. On the right, we see the deviation in a group of several drivers fitting to the same general type. The motivation of this type of driver may be, obviously, the wish to go to the mountainside or to the coast. However, this sort of behavior may also be observed if the real destination is far behind the range covered by the network under consideration. Imagine vehicles being driven to Minsk but observed only on polish territory. Then their routes seem to diverge – all that can be deduced is a general common vector of their motion.

Technically, in order to achieve such a mean direction (d_x,d_y) of random courses, we draw the sample in such a way that

$$(P_N - P_S)d_x = (P_E - P_W)d_y \tag{6}$$

Of course, all four elementary probabilities have to sum up to one,

$$P_E + P_N + P_W + P_S = 1 \tag{7}$$

While for the mean direction only the proportion of the effective probabilities is of importance, the distribution between P_N and P_S, likewise between P_E and P_W, controls the deviation from a straight course. Again, this type of driver can be simulated all at once – there is no history dependence of the driver's decisions. A drift of his course to either side is not compensated by a higher probability of moves in the opposite direction. In the next subsection, eventually, this sort of compensating motion will be considered.

2.3 Travel to a Destination

Finally, a driver may be bound to a specific location. In that case, one may assume that the random choice taken at each crossing is dependent on his relative position to the destination. A step is taken with a higher probability if it decreases the remaining distance, it becomes more and more unlikely the smaller the reduction of the distance to the end point. Nonetheless, even temporary increases of the distance may occur, however, they are less likely than steps directed towards the designated end point. Notice that the best possible reduction is by one grid size, or block, which we assumed as length measure for this paper. The worst case is an increase by one block – both extreme cases may only happen if present and final position lay on a common street or avenue. Hence, we define a discrete probability distribution with a sample space containing four elements, as before. However, the atomic probabilities are now defined in a monotonous way on the interval *[−1, 1]*, and they depend on the history of previous moves. Technically, we introduce the distances to the destination

$$\rho^2 = (x - x_f)^2 + (y - y_f)^2 \tag{8}$$

$$\rho_E^{\ 2} = (x + 1 - x_f)^2 + (y - y_f)^2 \qquad \rho_N^{\ 2} = (x - x_f)^2 + (y + 1 - y_f)^2$$

$$\rho_W{}^2 = (x-1-x_f)^2 + (y-y_f)^2 \qquad\qquad \rho_S{}^2 = (x-x_f)^2 + (y-1-y_f)^2$$

The change of distance gained by move is $\delta_L=\rho_L-\rho$, $L\in\{E, N, W, S\}$. Now, the probabilities P_L are calculated to be proportional to:

$$\alpha + (1-\delta_L)^\beta \tag{9}$$

and of course to sum up to one. In the next section, for simulations, behavioristic parameters α and β were chosen to be $\alpha = 0.05$, $\beta = 2$.

3. SIMULATIONS

Just as a proof of concept, we test the three types of driver models on an artificial topography. For simplicity, we assumed a rectangular grid of roads with regular distances between crossings, but the procedure can be easily generalized to any road net. We will send a large number of drivers of type one from the origin on random cruises and study the distribution of their positions after some given interval of time. Analogously, a large number of drivers is sent from the origin in a certain general direction, allowing for random variations of the direct path as assumed for the second model of drivers.

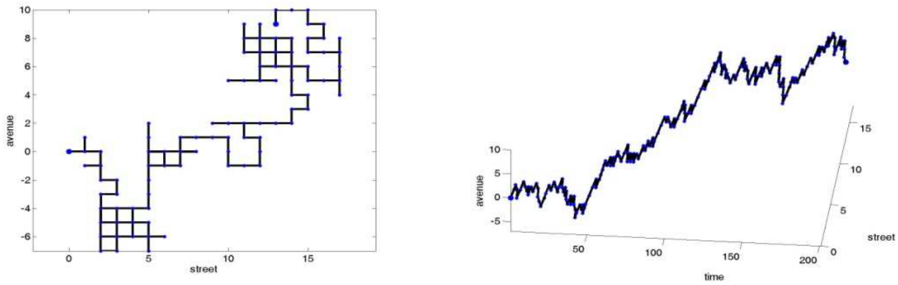

Fig.4. Random walk

Fig. 4 shows a typical random walk on a rectangular grid. Notice that the temporal sequence of steps is not clear from the plain view on the left. For that reason, on the right we present the trajectory as function of time.

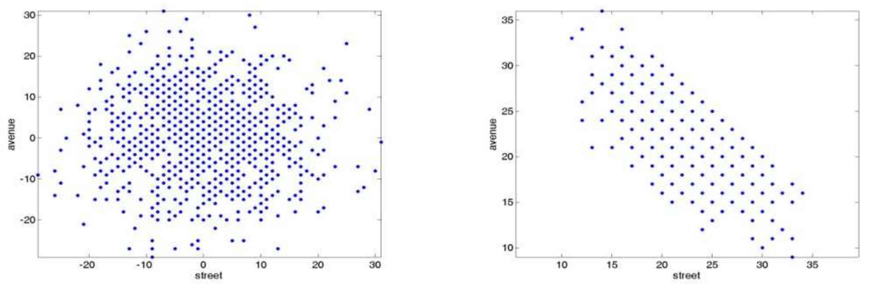

Fig.5. End points

Fig. 5 shows the destinations reached by the chosen models after $k = 200$ steps. In the random case, ie. the type described in Sec. 2.1, no bong distance is reached. It is likely to find a car quite close to the place, where it was stolen. In the case of a more directed path, as discussed in Sec. 2.2., the final position is distributed around the endpoint of the prescribed vector. Obviously, for the third type of driver the position reached is, for a sufficiently large number of steps, equal to the destination, so there is no figure of this case.

4. ASSESSMENT OF OBSERVATION POINTS

In the previous section we studied different types of driver behavior by simulating trajectories according to the chosen characteristic. Obviously, the resulting trajectories – and the way they are distributed in the integer plane – also depend on the parameters describing the drivers in detail. Along the calculated (randomly!) trajectories, we counted the number of incidences with camera positions. The latter where previously chosen, randomly as well. As a next step towards the aim formulated in [3], it is required to assess configurations of observation points, e.g. on the basis of the numbers of observations they produce. Short: A chosen set of observation points is better than another, if more of the set of wanted cars is sighted and sightings occur more often. Finally, it is desirable to find optimal configurations by applying nonlinear programming techniques.

Obviously, the terms of comparing sets of observation points need a more precise formulation. Since we count sightings of vehicles during random walks, the results will be random as well. Hence, what we really compare will be expected values, i.e. the average number of sightings over a large sample of trajectories. Further, the sets we compare should be of the same size, and the observation periods identical. We clarify these ideas on the following example. We assume a type of driver with a specified destination, starting from the origin to a point with coordinates $(x_f, y_f) = (15, 12)$. Our goal is to place a chosen number $O = 10$ of observers at crossings to maximize the (empirical) expectance of sightings. As a first step towards this endeavor, we picked two configurations, each counting *10* points, see Fig. 6, basing on common sense.

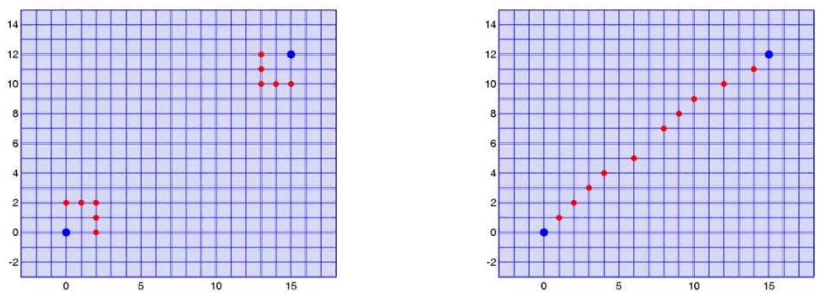

Fig.6. Camera positions

On the left of Fig. 6, the observers are arranged to screen off destination and origin from each other. It is to be expected that reasonable paths cross each of the screens at least once. On the right, however, observers are lined up along a likely path of a vehicle. Chances are that some random courses may meet observer positions several times, the risk is that some may avoid all of the chosen positions. Which one will be preferable has to be assessed by computer simulation – which obviously depends on the assumed driver model. To this end we simulated the courses of $S = 1000$ vehicles on the trip from $(0, 0)$ to (x_f, y_f), counting the number of hits for both sets. At the same time, we also counted the traffic at all crossroads.

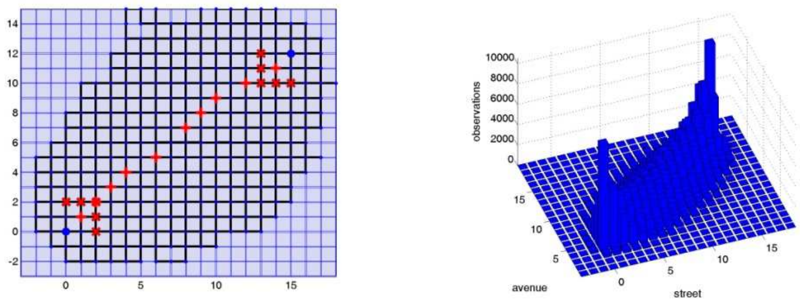

Fig.7. Traffic count

Fig. 7 presents the subset of vertices reached by cars on a directed course from the chosen origin to the chosen destination. The numbers of vehicles crossing – in any direction – the vertices of the abstract road net are depicted on the right part of that figure. Theoretically, the shape of this distribution of traffic density may be imagined as a saddle, see Fig. 8.

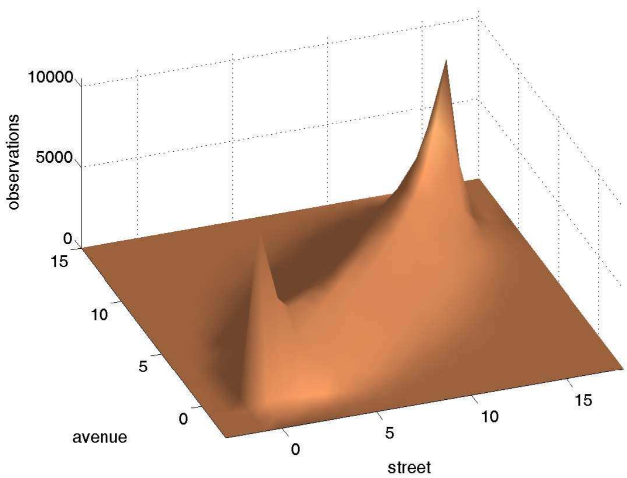

Fig.8. Saddle

The highest values occur near origin and destination, reasonably high values – but lower than around origin and destination, are taken in the region in between. To the left and to the right of the direct linear connection between the end points, the traffic density decays rapidly. Of course, for the purpose of evaluating a set of observation points, the total number of seen vehicles is an important factor. However, as shown in [2], for the successful interception of a stolen vehicle, several sightings are required to enable the prediction of the path and to bring a police car in place. For that reason, we also count how many vehicles are how often spotted on their path by the two given nets of cameras. Fig. 9 shows the counts for both sets. The heights of bars correspond to the cases, where zero, one, two etc. observations of a vehicle where made. We consider it preferable to have a higher number of long series of observations, if compared to an even higher number of total observations, but not in sequence.

For the given choice of driver behavior and parameters, the second set of observation points is superior – it results in a higher chance of seeing a stolen vehicle on one of the observation sites. Actually, it scored in a simulation of *10000* cruises *39741* sightings, as opposed to *36361* in the case of the alternative positions. The mean value is hence significantly higher. Moreover, while the first set of camera positions gives very high frequencies in the low range up to 4 sightings, the second one gives also a good share of *5* to *10* sightings per cruise, see Fig. 9.

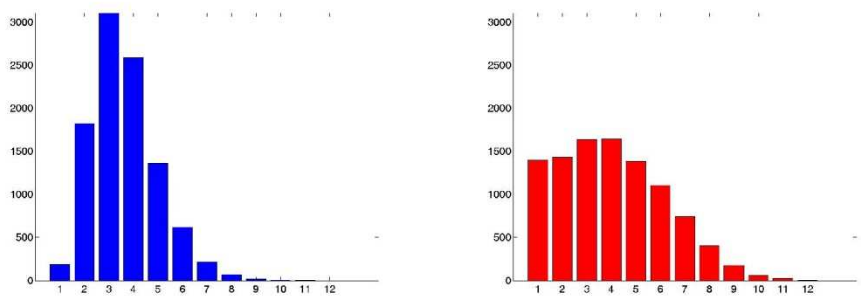

Fig.9. Comparison of hit rates

With respect to the chance of a successful prediction and possible interception, this is the most important fraction of the whole sample. In practice, one has to take into account that escape routes start from different points and lead to different destinations.

Further, several types of drivers are present at the same time. In more realistic simulations, some a priori statistical information about the distribution of car thefts has to be taken into account. Finally, the real road net has to be implemented into the simulation. It is to be expected that optimal positions will be sensitive to this sort of input data, which means that optimization has to be done individually for each concrete social and geographical situation.

5. CONCLUSIONS

The more randomness or spontaneity there in the decisions of a driver, the smaller are the chances to predict correctly future positions of his vehicle. However, a certain percentage of stolen cars follow a direct course to some given destination, which may be inferred from observations. A system by which stolen cars are to be traced should be prepared for a whole palette of driver types. Optimization should take into account probabilities of random motions as well as extrapolations of directed courses. The present study concerning the assessment of observer positions was performed on a regular rectangular grid for given starting position and destination of drivers. For real world application, non-regular grids with weighted edges need to be introduced, and end points of paths have to be randomized basing on a priori distributions of car thefts and trade with stolen vehicles.

Finally, the network of observers is to be optimized. Given the simplest possible structure of an objective – which is a sum of contributions from each of the observers – positions may be evaluated by their hit rates. In the case of this criterion, it is relatively easy to obtain optimal positions of observers. It suffices to pick positions with the highest count, cf. Fig. 7. To avoid clustering, optimization may be performed under the constraint of a prescribed minimal distance between observers.

Further, the efficiency of the system depends on the performance of data transfer and processing. Consequently, also the specification of the telecommunication infrastructure may be subjected to optimization, in particular, antenna positions are prospective decision variables in that context, see [3].

6. REFERENCES

[1] Górska M.: *Tracing multiple mobile objects by a network of intelligent detectors*, Logistyka 3/2011

[2] Górska M.: *Course Prediction for Mobile Object Tracing Network*, in: Proceedings of the 4th International Interdisciplinary Technical Conference of Young Scientists, TU Poznań, 18-20.05.2011

[3] Górska M., Jackowski S.: *Optymalizacja sieci inteligentnych obserwatorów*, XV International Conference TransComp, Zakopane, 05-08.12.2011

[4] Pearson K.: *The problem of the Random Walk*, Nature, 72, 1905

[5] Pólya G.: *Über eine Aufgabe der Wahrscheinlichkeitsrechnung betreffend die Irrfahrt im Strassennetz*, Mathematische Annalen, 84 (1-2), pp 149–160, 1921

[6] Internet: http://maps.google.pl, retrieved 15.09.2011, 09:15