

RemoteHorizon.KOM: Dynamic Cloud-based eHorizon

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Kurzfassung

Assistenzsysteme in Fahrzeugen greifen in der Regel auf Umfeld-Informationen zu, welche durch lokale Sensorik erfasst werden. Seit einiger Zeit werden auch digitale Straßenkarten als ein zusätzlicher vorausschauender Sensor eingesetzt. In neusten Entwicklungen wird dieser s.g. elektronische Horizont (eHorizont) mit Daten aus der Cloud ergänzt, oder sogar vollständig aus der Cloud als Service bereit gestellt. Die vernetzten Fahrzeuge dienen hierbei als Informationsquellen über deren Umfeld und ermöglichen ein ständiges aktualisieren der cloudbasierten Kartendaten. Auch Fahrzeuge ohne aufwändige Sensorik können trotzdem mit einem eHorizont versorgt werden. Allerdings erfordert die Anbindung über Mobilfunknetze das Umgehen mit Bandbreitenschwankungen, Verbindungsverlusten, wechselnden Paketfehler-raten, veränderlicher Latenz und möglichen Einbrüchen in der Kanalkapazität. Wir schlagen eine Lösung vor, welche versucht die Unvorhersagbarkeit der verfügbaren Konnektivität zu überwinden. Ziel ist die effiziente Nutzung verfügbarer Bandbreite und Sicherstellung einer Mindestqualität an Informationen im Fahrzeug. Basis ist eine standortbezogene Vorhersagbarkeit der Konnektivität. Der elektronische Fahrzeughorizont wird serverseitig als Dienst bereitgestellt. Die Übertragung der einzelnen Informationssegmente erfolgt angepasst an kollektiv erfasste Konnektivitäts-Parameter. Ziel ist die Kommunikation für den eHorizont als Hintergrunddienst mit möglichst niedriger Bandbreite zu betreiben. Die verfügbare Bandbreite für andere Applikationen und Dienste soll nicht merkbar beeinflusst werden. Gleichzeitig muss aber auch sichergestellt werden, dass vor Streckenabschnitten mit unzureichender Konnektivität, die Kommunikation entsprechend adaptiert wird und mehr Daten vorgeladen werden. Die vorgestellte Lösung beschreibt einen serverbasierten eHorizont als Dienst mit adaptiver Übertragung der Horizontinformationen.

Abstract

Vehicular driver assistance systems are commonly based on local sensor information about the vehicle surroundings. For some time past, also digital map data is used as additional predictive sensor. Current development tries to extend this so called electronic horizon (eHorizon) by the use of cloud data or even to completely provide the eHorizon as cloud service. In such a system, connected vehicles serve as information sources about their surroundings and enable continuously updates of the cloud based map data. Furthermore, it is possible to provide such an eHorizon also to vehicles without complex surroundings sensors. However, the vehicle connectivity over mobile networks requires to deal with bandwidth variations, connectivity interruptions and losses, changing packet error rates, variable latency and possible declines in the channel capacity. We propose a solution that tries to overcome the unpredictability of available connectivity. The goal is the efficient use of the available bandwidth and guarantee a minimum information quality within the vehicle. Basis is the location-based predictability of connectivity. The eHorizon is provided as a service on the server side. Transmission of the individual information segments is adapted to collaborative gathered connectivity parameters. Objective is the transmission of an eHorizon as background service with the lowest possible bandwidth consumption. The available bandwidth for other applications and services should preferably not be noticeable affected. At the same time it must be ensured to adapt the transmission accordingly and to preload more data before a vehicle enters road sections with insufficient connectivity. Within this paper we present a server-based eHorizon with adaptive transmission of the eHorizon information.

1 Introduction

Collaborative data collection is emerging in Advanced Driver Assistance Systems (ADAS) to increase driving comfort and safety. Systems make use of sensors to gather information of the vehicle surroundings. The connected vehicles in this scenario serve as information sources and enable continuous updates of cloud based map data. One challenge of such a system is sending the relevant data back to the vehicles. The objective of the server based electronic

horizon (eHorizon) is to reduce the transmitted data to the relevant road segments on the vehicle's path. The application uses digital maps enriched with additional sensor values as a predictive sensor. If the route is unknown, basic systems use vehicle speed, heading and the actual vehicle position to determine the path, the vehicle is most probably continuing to travel. In literature available eHorizon applications mainly differ in the methods used to define the most probable path (MPP). Most solutions are based on probabilistic methods. Such systems are presented by

Gee-Lake and Stählin [1] as well as Ibrahim [2]. Other systems make use of historical information to improve the MPP performance. Examples are provided by Ress et al. [3], Engel et al. [4], and Karimi et al. [5]. The aim of this work was to combine existing solutions for locally generated eHorizon applications and to adapt them to a remote solution. An illustration is depicted in Figure 1. Our system is maintained remotely and cannot directly make use of dynamic sensor values such as gear grading, turn signals or acceleration. Another challenge is the high latency of wireless networks. Therefore, we developed a new MPP algorithm based on probabilistic approaches, since they represent a promising approach in handling uncertainties associated to trajectory prediction. Although, the objective of this work is providing a remote eHorizon, a remaining challenge is the unpredictability and high costs of mobile networks. Network bandwidth suffers under fluctuation, which influence the performance of the developed application [6]. Therefore, we propose a bandwidth predictive solution that overcomes problems caused by temporary connection loss, high packet error rate or insufficient channel capacity. Another aim was to provide the remote eHorizon as a background service to reduce. Therefore, we propose a solution where the server selects which and how much data to send to the vehicle, based on historical bandwidth values. The system is inspired by adaptive streaming systems like Dynamic Adaptive Systems (DASH).

In the following section we give an overview about related work, followed by a description of our static eHorizon approach. In Section 4 we introduce the predictive remote eHorizon and in Section 5 we present our results and give a comparison of both approaches. We summarize our work and provide an outlook on future work in Section 6.

2 Related Work & Background

Digital maps can be used as predictive sensor for systems that increase the driver safety, comfort and driving economy. Several methods are proposed in literature to generate an eHorizon. Most of them are based on vehicle speed, position and digital data to determine the likelihood for each path on a junction to be the road in which the vehicle will continue the trip [5, 7]. The determination of the eHorizon and its performance highly depends on the prediction of the path that the vehicle will travel. Further challenges depend on the horizon size. In the following we summarize related work in the field of eHorizon and bandwidth prediction.

eHorizon & Most Probable Path

State of the art in generating the eHorizon is to predict the road geometry, including related attributes, located ahead of the vehicle out of the vehicle position and velocity, gyroscope information and the use of digital maps [1, 2, 4, 8, 7]. Several related work considers alternative methods for generating and improving the eHorizon. Gee-Lake et al. have developed a method, which can generate the eHorizon with a sufficient accuracy, even when the computing power of the eHorizon provider is relatively low [1]. The authors propose a planning table, which contains according to the



Figure 1 System overview.

available computing power not only the MPP and the respective attributes, but also additional side paths. Furthermore, they propose providing multiple planning tables stored in different memories. This method is suitable for devices with a limited memory or computing power, like mobile phones or head units. In our scenario, the aim is to generate a remote eHorizon as a backend service with potentially high memory and computing power. As main challenge the system has to deal with network unpredictability. This work provides good advices on handling various environment conditions. The planning table is used in our scenario to adapt the MPP to the network conditions. A good overview and method in determining the MPP is presented by Ibrahim [2]. He provides a method of selecting the most likely path from a list of candidate paths. The MPP is defined based on cost functions, based on the environment type. Each parameter has a different precedence level, depending on the effect that the parameter would have towards predicting the vehicle MPP. Used parameters are vehicle lateral velocity, lateral position, turn signal, boundary type, position of the acceleration pedal and the deceleration of the vehicle. Each of these parameters is assigned a precedence level, beginning with 1 for the signal with the lowest priority. This algorithm is implemented in the vehicle to realize short reaction times. A remote eHorizon cannot use dynamic vehicle information because of network unpredictability and potentially high network latencies. However, the work provides good advices on how to handle multiple parameters by assigning a precedence level and it also confirms probabilistic methods as promising approach in MPP estimation.

Some other methods for location prediction are developed within the aim of Location Based Services (LBS). Karimi and Liu propose the Predictive Location Model (PLM) [5]. The aim is to make application related optimisations based on the geographic location of mobile users and upcoming road segments. They build a temporary probability matrix for each intersection to overcome uncertainties at intersections. They populate the matrix based on historical information of taking a certain road after the intersection. But this method has a good performance only on previously driven road segments. Using historical data in determining the MPP is a well-known approach and used in multiple works [4, 5, 7, 9].

Latest developments in ADAS tend to use sensor fusion, i.e., the use of multiple combined sensor values. Moreover, map data should be up-to-date in order to increase

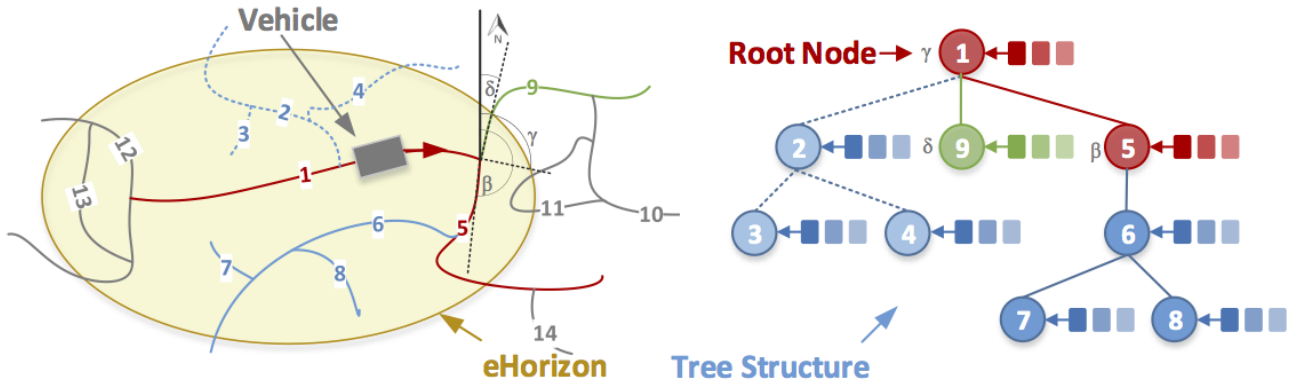


Figure 2 eHorizon and Most Probable Path Algorithm.

accuracy. Therefore, there is an increased interest in providing the eHorizon as a backend service from the Cloud. First ideas about this solution were proposed by Engel et al. and Manoliu et al. [4, 7]. Continental AG presented in January 2015 at the CES in Las Vegas the dynamic electronic horizon [10]. The project is a collaboration with IBM and the location cloud company HERE. Information is gathered under crowdsourcing principle from multiple vehicles. Continental uses the remote eHorizon at applications like sealing, coasting or energy regeneration. Latest developments and interest in industry shows the high potential of the eHorizon. However, to the best of our knowledge none of the existing solutions publishes evaluation results.

Bandwidth Prediction

A remaining challenge in the remote eHorizon application is the network unpredictability. Network bandwidth suffers under fluctuations that influence the performance of the developed applications [6]. This section analyses existing works in bit-rate adaptation systems, which try to overcome problems caused by temporary connection loss, high packet error rate or insufficient channel capacity. Most systems propose bandwidth prediction based on time and location based bandwidth measurements. Many are streaming systems, since they are at most delay sensitive and adaptive systems should increase the Quality of Experience (QoE). Important in our context is adaptive bit-rate streaming, which adapts the streaming quality to the current available bandwidth. Adaptive video formats like DASH offer techniques to change the video quality, depending on currently available bandwidth. Lacking knowledge about future connectivity for a moving mobile client may cause buffer underruns or even interruptions. In our scenario the equivalent would be missing information about road segments and respective annotated information. The aim of this work is to use an algorithm to adapt the size of the eHorizon and the amount of attributes according to the available network bandwidth. Different studies have confirmed a strong correlation between the geographic location and the wireless network bandwidth [11, 12, 13]. Inspired by these results Yao et al. have exploited bandwidth predictability [12]. They have conducted multiple measurements on a repeated trip and have observed a high correlation between loca-

tion and bandwidth. The same authors have developed a system completely based on past bandwidth observations [13]. Their measurements were used in simulations and showed a reduction of packet loss of up to 70%. A system based on the same principle is proposed by Riiser et al. [14]. It relies on monitoring the receivers download rate, which is periodically reported to a database and mapped with the respective GNSS Position. The system is evaluated using real world traces where the server knows the whole route information in advance. Curcio et al. propose a similar system for geo-predictive media delivery in mobile devices [15]. They measure the bit-rate at regular time intervals and focus on predicting networks outages and adjusting buffering parameters. Hao et al. has developed a geo-predictive streaming system named GTube [16]. It enables mobile clients to use intelligently the location-specific bandwidth information to adapt the bit-rate.

3 Static Remote eHorizon

This section introduces the functional architecture and algorithms of the developed system. The static remote eHorizon is based on selecting the road segments and additional attributes located ahead of the actual vehicle position. This application uses map data and additional attributes gathered collaboratively and located in a remote database. The system consists of two main components. The eHorizon Provider on the server side constructs the eHorizon and generates messages to be transmitted. On the vehicle side the eHorizon reconstructor is responsible to rebuild the eHorizon out of the transmitted messages. We use the publish subscribe pattern for communication between the vehicles and the server side to realize asynchronous and scalable communication. In particular we use the lightweight MQTT protocol. In our prototype we have used the Mosquitto¹ message broker. For message serialization we make use of Google Protocol Buffers that is very efficient, language neutral and in particular extensible. Figure 2 depicts a vehicle on a section of a map. The eHorizon is generated as tree structure as depicted on the right side of Figure 2. Each node corresponds to a road segment. Each road segment has additional annotated information,

¹<http://mosquitto.org>

e.g. about static or even dynamic objects. Attached information is described by offsets to the segment starting point. All road segments in driving direction within a certain radius, depicted by the yellow area, are considered for the eHorizon generation. The nodes are connected by edges that represent the stubs, i.e., intersections and forks. The respective node of the road segment the vehicle is currently driving on is always selected as root node. This leads to an automatic discarding of segments the vehicle has passed. Tree-leaves are the outgoing sub-paths. The tree-structure is updated each time the vehicle changes the actual path. This working principle is based on the ADASIS protocol. For each vehicle the eHorizon is maintained at the server side. Each time a new request comes from the vehicle, the tree-structure is updated. The vehicle sends a new request as soon the remaining eHorizon size falls below a threshold. Only the new paths, missing at the vehicle side, are sent to the vehicle to save bandwidth.

The size of the eHorizon is not determined by a radius distance from the corresponding vehicle. A size calculator component decides about the length of the eHorizon and which sub-paths are going to be included in the tree-structure. In city environments, with relatively low speed and frequent turns, the considered eHorizon area is small. This compensates that the MPP is difficult to predict in city environments and reduces the transmission of information about unimportant road segments. On motorways the considered area is increased, since the vehicle speed is much higher and the determination of the MPP performs much better. The component responsible to generate the MPP in our eHorizon provider is the Look Ahead Module. The prediction is based on the GNSS position of the vehicle, velocity and heading of the vehicle, as well as classifiers representing the different road types and the angles between connected road segments of different types. Road type classifiers were used according to the road classes used within OpenStreetMap². Out of the candidate paths within the generated eHorizon an algorithm selects the most probable one, i.e., the MPP. It is based on a probabilistic approach. A higher road class type gets a higher priority. A lower angle between road segments at intersections and forks, compared to the approaching road segment, gets also a higher priority. Due to a minimization of communication we have to deal with a lack of dynamic information like gear grading, turn signals or acceleration. This leads to a lower dynamic in MPP and eHorizon adaption. Therefore, the transmission includes not only the MPP but additional side paths based on their weights.

For our probabilistic approach we determine two weights, a weight for the road class Θ_{RC_i} and a weight for relative angle of the road segment Θ_{α_i} . The weight of the road class Θ_{RC_i} of a branching road segment Seg_i at an intersection is the fraction of the respective road class RC_i and the sum of the road class of all N branching road segments, according to equation 1. We subtract this value from 1 to get a higher value for a higher street type (e.g. a motorway),

since it has a lower class type number (as e.g. a road).

$$\Theta_{RC_i} = 1 - \frac{RC_i}{\sum_{n=1}^N RC_n} \quad (1)$$

Equation 2 gives the weight Θ_{α_i} of the angle α_i of a branching road segment Seg_i at an intersection as fraction of the angle α_i to the sum of the angles of all N branching road segments.

$$\Theta_{\alpha_i} = 1 - \frac{\alpha_i}{\sum_{n=1}^N \alpha_n} \quad (2)$$

Figure 2 illustrates this scenario at the intersection between the road segments 1, 5 and 9. All angles are considered relative to the approaching road segment Seg_i , even if all angles are internally managed relatively to geographic north. For weighting calculation we use the magnitude of the difference of the angle of the approaching road segment α_a and the angle of the road segment under consideration α_{Seg_i} , $|\alpha_i = \alpha_a - \alpha_{Seg_i}|$. Due to the zero crossing, one has to subtract 360° in case $|\alpha_i|$ is larger 180° . In case of the example in Figure 2, $\alpha_9 = |\gamma - \delta|$. Both weights, Θ_{RC_i} and Θ_{α_i} are handled not equally within the total weight calculation that is the basis for probability estimation. We multiply Θ_{RC_i} with a factor β that we set to five, since it is much more likely to stay on the same road type, even if the angle at an intersection is larger. To get the a probability of the respective road segment, we normalize the calculated value according to equation 3.

$$p_{Seg_i} = \frac{\beta \cdot \Theta_{RC_i} + \Theta_{\alpha_i}}{\beta + 1} \quad (3)$$

4 Adaptive Remote eHorizon

As an extension we can operate the eHorizon adaptive to the available bandwidth. First of all, all data of the eHorizon is packed into single messages and reordered according to a pre-calculated priority. Each tree node represents a road segment and forms message. All attached information, e.g., traffic signs, form separate messages. The priority class of each information type is different, e.g., a traffic sign has a higher priority as a PoI. At each branch within the tree, i.e., intersection or fork, the priorities of the respective messages are multiplied with the according probability of the path. In a next step all these messages are reordered according to this calculated priority. These messages are then put into an output buffer and sent as background service with a transmission rate of max. $5kBps$. At the end of each tree node, i.e., intersection or fork, the vehicle sends a short message with a position update back to the server side. On the vehicle side a map matching is performed on the already known eHorizon information. If this matching is successful, the position is just coded as ID of the newly entered road segment and an offset, else the GNSS position is used. The position information is used to update the eHorizon and the output buffer at the server side. All information in the output buffer according to already passed road segments is deleted. This reduces the amount of transmitted data since information that is not of interest anymore will not be send. To ensure a sufficient amount of

²<https://www.openstreetmap.org>

Table 1 Performance comparison of the static and adaptive eHorizon.

	Total Amount of Data (KBit)	Number of Requests	Average eHorizon Length (Km)	Average Sending Interval (s)	Request quality
Remote eHorizon	18454.7	81	1.3	-	75%
Adaptive eHorizon	3101.5	20	1.7	2.6	95%

information at the vehicle side, the transmission rate is increased before the vehicle reaches road segments with low bandwidth coverage, e.g., caused by tunnels. The bandwidth prediction is based on a bandwidth information that we have annotated to the single road segments. In a test drive we have sampled the available bandwidth as average values per 100 meters and attached according information as average value per road segment to our map database. However, details of creating bandwidth maps is out of the scope of this paper.

5 Results and Comparisons

In the following we compare both implementations, the remote and the adaptive eHorizon. The aim is to find a trade off between application performance and bandwidth consumption. We used a real world test and gathered vehicle and connectivity data on a trip about 30km between two cities in Hesse, Germany. The eHorizon was enriched with several additional information data. In this scenario we had an average eHorizon size of about 451 kB. In case of the adaptive eHorizon, the total data transmission would need about 85s. With an average speed of 100 km/h the vehicle would move about 2.4 km within this time. In case of smaller road segments this will cause the adaptive application to discard already passed side paths before transmission. Both applications were compared in a simulation based on the collected data, i.e, the test drive was replayed and the collected bandwidth values were used to control the connectivity. Considered parameters have been the total amount of transmitted Data, number of requests, average eHorizon length, average sending interval and request quality. We defined request quality as the ability of the system to provide enough data to the vehicle and not let it “blind” on a road segment. Since in this implementation an update is always requested closed to the end of the known eHorizon of the vehicle. This corresponds to the ability to directly deliver an eHorizon update to a request from the vehicle. The network load and bandwidth consumption of both eHorizon applications are given in Table 1. The adaptive eHorizon is preselecting the data based on their probability which leads to a better performance for a larger amount of data. The static remote horizon is a rudimentary implementation that is updated when vehicle comes to end of eHorizon. If then the connectivity is bad the client sends requests until an answer is received from the server. This can lead to a period of missing eHorizon information at the vehicle side. In comparison the adaptive eHorizon has a longer average eHorizon with less side paths. This leads to reduction of data transmission of about 83% and the accuracy is also much higher. This is caused by adapting the

horizon size to the bandwidth values. When the path on the MPP has a bandwidth lower than 5k Bps , the length of the MPP is increased by 0.3 km. This is done until the last path of the eHorizon has a stable bandwidth or the predefined maximum size of 10km is exceeded. The difference in the response size is due to the different working principle. The static remote eHorizon is sent as single message. In case of the adaptive eHorizon, each path and attached information is sent as separate messages. Therefore the packet sizes in the adaptive eHorizon are much smaller. The adaptive eHorizon introduces some additional overhead of about 45%, caused by position update messages. However, the saved bandwidth by sending less data is much bigger. In 25% of the cases the client did not get a direct response to a request. Even if the adaptive application performs better than the remote application, there are still some drawbacks to be overwhelmed. This is noticeable especially on motorways. Due to the higher road class of the motorway, the transmission of side paths, e.g. the exits, are sometimes not sent before the vehicle overpasses.

6 Conclusion and Future Work

The usage of digital maps and location based data is increasing beyond navigation purposes. Map data enriched with additional sensor values can be used as predictive sensor, the so called eHorizon. Available systems commonly rely on map data and sensor values available within the vehicle. Within this work we propose a remote eHorizon. The eHorizon generation is based on algorithms developed for on-board systems. Due to the lack of dynamic vehicle information on the server side, the solution had to be adapted to determine path probabilities. A challenge of the remote eHorizon is the network unpredictability. Network bandwidth suffers under fluctuations. The proposed adaptive eHorizon is adapting the horizon size to the bandwidth availability. This is done by the use of historically gathered bandwidth values. The eHorizon size is increased until the last path of the eHorizon has a stable bandwidth. Vehicles send position update messages each time it crosses an intersection or fork. Paths and additional information lying behind this position that are not yet sent to the vehicle, are discarded. The aim is to find a trade-off between application performance and the bandwidth consumption. The adaptive eHorizon has shown a better performance. However, our prototype implementation is still in an early stage with many options for improvement. The performance of the determination of the MPP can be improved by the use of historical data. Additionally the MPP could be determined within the vehicle. This MPP can be efficiently send back to the server side just as list of road segment IDs with

according probabilities. Until now the usage of bandwidth information is very simple. An improvement would be to consider time dependent bandwidth values and connected vehicles should be used to continuously update bandwidth information. Furthermore some promising approaches exist in the area of network prediction that rely on multiple parameters. Another improvement would be data transmission adapted to the vehicle speed and the position update points could be optimized. Together with position updates from the vehicle some additional information, like the current vehicle speed, could be send to improve the server accuracy. Another important aspect would be the consideration of latency effects in a field test.

Main advantages of the proposed server based eHorizon, or eHorizon as a Service, are the ability to provide thin clients with eHorizon based applications and to use always latest up to date map data from a dynamically updated server. Furthermore, the up to date eHorizon from the server can be treated as map update at the vehicle side.

References

- [1] R. Gee-Lake and U. Stählin, “Predictive ehorizon,” Patent US 20 130 006 531 A1, Jan. 3 13, 2013.
 - [2] F. A.-K. Ibrahim, “System to Determine the Path of a Vehicle,” Patent US 7 474 961 B2, 01 6, 2009.
 - [3] C. Ress, A. Etemad, D. Kuck, and M. Boerger, “Electronic Horizon-Supporting ADAS applications with predictive map data,” in *Proceedings of the 13th ITS World Congress, London, 8-12 October 2006*, 2006.
 - [4] P. Engel, W. Balkema, and A. Varchmin, “Verfahren und Anordnung zum Bestimmen eines am ehesten wahrscheinlichen Fahrpfads eines Fahrzeugs,” Patent DE 102 011 078 946 A1, 01 17, 2013.
 - [5] H. A. Karimi and X. Liu, “A predictive location model for location-based services,” in *Proceedings of the 11th ACM international symposium on Advances in geographic information systems*. ACM, 2003, pp. 126–133.
 - [6] K. Jang, M. Han, S. Cho, H.-K. Ryu, J. Lee, Y. Lee, and S. B. Moon, “3G and 3.5G wireless network performance measured from moving cars and high-speed trains,” in *Proceedings of the 1st ACM workshop on Mobile internet through cellular networks*. ACM, 2009, pp. 19–24.
 - [7] A.-V. Manoliu, A. Serbanescu, Y. S. Trofimov, A. Ruginsky, S. Zheltov, L. Koponen, and J. Schaminee, “Methods and systems for generating a horizon for use in an advanced driver assistance system (ADAS),” Patent WO2 014 068 094 A1, 05 08, 2014.
 - [8] G. Ghisio, “System and method for estimating the most probable path of a vehicle travelling on a road,” Patent EP 2 610 838 A1, 07 03, 2013.
 - [9] H. Jeung, M. L. Yiu, X. Zhou, and C. S. Jensen, “Path prediction and predictive range querying in road network databases,” *The VLDB Journal*, vol. 19, no. 4, pp. 585–602, 2010.
 - [10] “Der Dynamische eHorizon - Ein Cloud-basierter Sensor.” [Online]. Available: http://www.continental-corporation.com/www/presseportal_com_de/themen/pressemitteilungen/3_automotive_group/automotive/press-releases/pr_2015_01_06_ces_2015_de.html
 - [11] J. Ormont, J. Walker, S. Banerjee, A. Sridharan, M. Seshadri, and S. Machiraju, “A city-wide vehicular infrastructure for wide-area wireless experimentation,” in *Proceedings of the third ACM international workshop on Wireless network testbeds, experimental evaluation and characterization*. ACM, 2008, pp. 3–10.
 - [12] J. Yao, S. S. Kanhere, and M. Hassan, “An empirical study of bandwidth predictability in mobile computing,” in *Proceedings of the third ACM international workshop on Wireless network testbeds, experimental evaluation and characterization*. ACM, 2008, pp. 11–18.
 - [13] —, “Improving QoS in high-speed mobility using bandwidth maps,” *Mobile Computing, IEEE Transactions on*, vol. 11, no. 4, pp. 603–617, 2012.
 - [14] H. Riiser, T. Endestad, P. Vigmstad, C. Griwodz, and P. Halvorsen, “Video streaming using a location-based bandwidth-lookup service for bitrate planning,” *ACM Transactions on Multimedia Computing, Communications, and Applications (TOMM)*, vol. 8, no. 3, p. 24, 2012.
 - [15] I. D. Curcio, V. K. M. Vadakital, and M. M. Hanuksela, “Geo-predictive real-time media delivery in mobile environment,” in *Proceedings of the 3rd workshop on Mobile video delivery*. ACM, 2010, pp. 3–8.
 - [16] J. Hao, R. Zimmermann, and H. Ma, “Gtube: Geo-predictive video streaming over http in mobile environments,” in *Proceedings of the 5th ACM Multimedia Systems Conference*. ACM, 2014, pp. 259–270.
- All online references in this paper were last accessed and validated in January 2016.