GPS BASED VEHICLE TRAJECTORY PREDICTION AND ERROR ANALYSIS

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Abstract

One of the most effective ways to make traffic safer is to improve the efficiency of driver assistant systems. Positioning systems, as an important part of driver assistance systems, can be used to predict the future trajectory of a vehicle. Applications, such as collision prevention, are possible using vehicle-to-vehicle (V2V) communication systems, where the predicted trajectories of the vehicles are sent to nearby cars. The present paper investigates the error of GPS based linear and nonlinear trajectory prediction methods. The analysis shows how the prediction error depends on the shape of trajectory, prediction distance and the number of past samples used for estimation. The measurements were established using an embedded vehicle control system "smarty" developed by our research team. As a result a GPS based positioning and vehicle trajectory prediction module has been developed as a part of an intelligent driver assistant system.

Keywords:

Trajectory prediction, global positioning system (GPS), driver assistance systems, intelligent transportation systems

1. Introduction

Communication opens up new ways towards the development of cooperative services in the field of driver assistant systems [1], [2]. One potential application can be the forecasting of risky situations based on GPS coordinates and motion of nearby vehicles. The driving assistant can send alert signals to own and nearby drivers obtaining predicted trajectories of adjacent vehicles using V2V communication. In the literature [6-11] one can find a lot of candidate approaches for trajectory prediction such as

GPS coordinate positions,

Motion model of the vehicle: e.g. Constant Yaw Rate* and Acceleration model,

Maneuver recognition systems (knowledge database containing learned trajectories of typical maneuvers),

GIS - Geographical Information System: maps, including streets maps, roads, obstacles,

Turn indicator, driver's eye movements (it can predict intention of turn or lane change);

Desired route fed into a GPS navigator (the direction of pass on can be estimated with high probability in a crossing)

or any mixture of these methods (*yaw-rate is the vehicle's angular velocity around its vertical axis).

This paper concerns with GPS-based trajectory prediction, because of our embedded control system has the ability to obtain 5 Hz GPS position data. Barrios et al. [3] and Han-Shue Tan et al [4] investigate the option of using global positioning system (GPS). The results show that the main bottlenecks of GPS based trajectory prediction are accuracy, latency, and reliability. Although the details of the requirements also depend on the specific configurations and implementations of other modules in a system, the following requirements must be considered:

1) Accuracy: The positioning system should at least be able to distinguish between lanes. Since most lane widths are within 3–4 m, the vehicle position should be measured with an error of within 1 m.

2) Latency and bandwidth: The timing and update rate of sensors and signal processing should be fast enough compared to vehicle dynamics (typically below 2–3 Hz). Trajectory estimation can be based on the average human reaction time of 1.5 s to stop a vehicle. The reaction time and the time needed to stop the vehicle inevitably depends on the speed and the type of the vehicle, road and weather conditions.

3) Reliability and availability: The positioning system should be able to provide accurate positioning information under all normal operational conditions and locations. As a minimum a clear indication has to be given in the case of GPS outages.

This paper addresses these questions considering a conventional GPS receiver and a real time embedded vehicle controller equipped by collision alert software. The analysis has been shown that GPS position data can satisfy the accuracy requirement in special case. As a result, in order to establish a robust driver assistant application sophisticated signal processing and sensor fusion techniques has to be added such as

Kalman-Filter

motion model
map-matching techniques
Differential Global Positioning System (DGPS).

2. Trajectory prediction model

However it is known that GPS data may suffer from errors [5] coming from different sources such as the inaccuracy of satellite positions, orbital fluctuation, multipath, relativistic and atmospheric effects, clock and rounding inaccuracies, our purpose is to analyze the performance of pure GPS based trajectory prediction. As a prediction tool we applied polynomial fitting on past known samples. The prediction was carried out for latitudinal and longitudinal coordinates separately (while the elevation data was omitted for the sake of simplicity). First and second order polynomial fitting (i.e. linear and quadratic least squares fitting) was compared on a basis of the number of past samples used for prediction (see Figure 1.). Let *N* be the number of past samples used to fit and *M* be the number of predicted points. The prediction functions for every $t = N+1, N+2, \dots, N+M$ are:

$$y_{predicted\ linear}(t) = c_0 + c_1 t$$

$$y_{predicted\ quadratic}(t) = c_0 + c_1 t + c_2 t^2$$

The goal is to minimize the square error (ε) between the measured and predicted points:

$$\varepsilon = \sum_{i=1}^{N} (y(i) - y_{predicted}(i))^2$$

$$Linear: \min_{c_0, c_1} \varepsilon \quad Quadratic: \min_{c_0, c_1, c_2} \varepsilon$$

In this case the formulae to find the coefficients $c_{j,opt}$ (linear: j = {0,1}; quadratic: j = {0,1,2}) are:

$$\sum_{i=0}^{1} c_i \sum_{k=1}^{N} t_k^{i+j} = \sum_{k=1}^{N} y_k t_k^j$$

$$\sum_{i=0}^{2} c_i \sum_{k=1}^{N} t_k^{i+j} = \sum_{k=1}^{N} y_k t_k^j$$

where c_0, c_1, c_2 are the coefficients of the systems of linear equations, and past sample coordinates are measured in time instants $t_1, t_2, \dots, t_N$ with $y_1, y_2, \dots, y_N$ values.

3. "Smarty" embedded system utilizing trajectory prediction

The embedded module "smarty" (Figure 2.) was designed by our research group to be used in a vehicle to serve as a driver assistance system. It was programmed in ANSI-C under ChibiOS/RT Real Time Operating System. The hardware is built around the STM3F407 32 bit MCU which has an FPU unit and runs DSP commands as well. Functional blocks are: GPS data receiver, wireless communication module (WLAN), Real Time Clock, analogue 3-axis accelerometer and yaw-rate sensors, Temperature and humidity sensor.

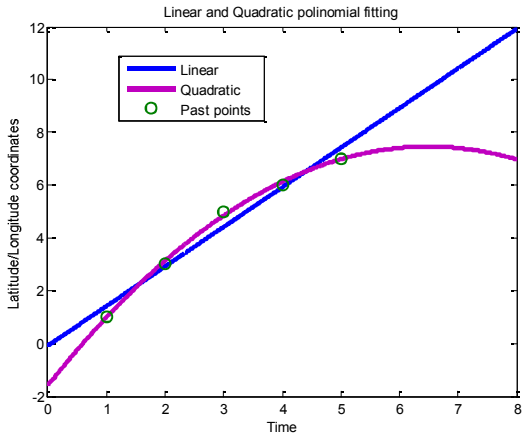

Figure 1. Linear and quadratic polynomial fitting

The software of the smarty is built on a tasks system (implemented as static threads in ChibiOS) with functionally separated state machines.

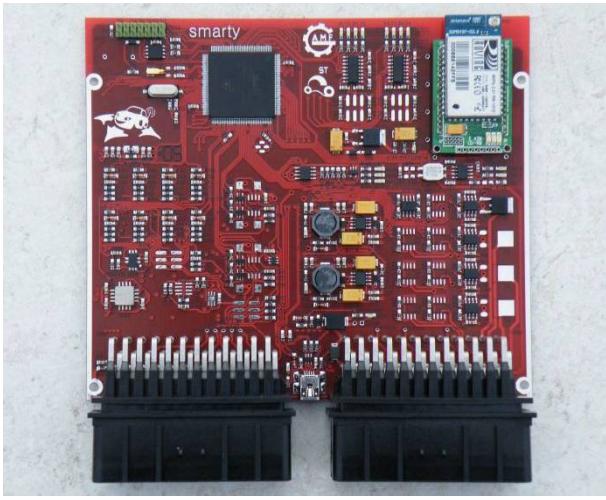

Figure 2. "Smarty" embedded system

A separated visualization and diagnostic tool has been developed in .NET for PC, which can acquire the packages shared by the Smartys, and were used in this paper to evaluate and analyze the result of predictions in real routes (Figure 3).

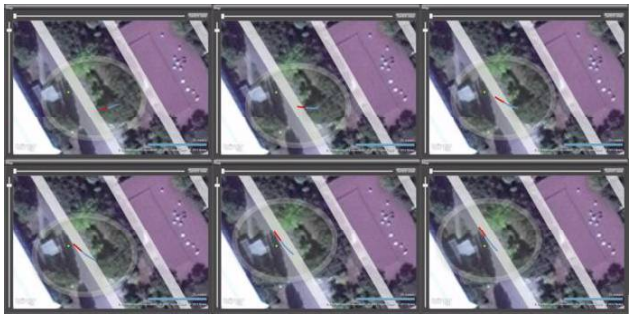

Figure 3. Result of predictions in real routes

4. Error analysis

This paper aims to detect the dependency of the prediction error – in the case of prediction model (1) and (2) – from the shape of real trajectory and number of past samples used for prediction. In order to obtain these results two trajectories were used during the measurements: a near straight and a circular one for testing near constant flex. As a result the following scenarios were analyzed:

Straight path, linear fitting,
Straight path, quadratic fitting,
Circular path, linear fitting,
Circular path, quadratic fitting,

Measurements were conducted in a car equipped with a "smarty" embedded controller and a Garmin GPS18x 5Hz receiver. Straight path was driven via an East-West direction (Figure 4) and circular path on a closed road segment (see Figure 5).

The prediction error highly depends on the prediction distance (i.e. the time distance between the current timeslot and the timeslot of the target of prediction); hence, prediction distance is also an important issue in our analysis.

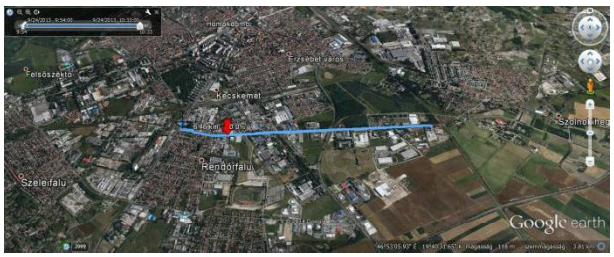

Figure 4. Straight path

Figure 5. Circular path

4.1. Straight path, linear fitting

As a reference we have investigated the simplest case: straight path, linear fitting. The results on absolute mean and maximum error for latitude coordinates are depicted on Figure 6. by solid and dashed lines, respectively. One can deduce from the curves that the mean error only slightly depends on both the number of past samples and prediction distance. The mean error is between 3-4 meters in the case of 3 seconds of prediction distance (which is twice the human reaction time). The value of the maximum error is very high (12-17m). The origin of these large values is the turn backs at the end of the session.

On Figure 7. the longitude prediction error can be seen. Here the best is to use 7 past points for the linear fitting which gives 1.16 meters error in average and 13.22 meters maximum error for 3 seconds of prediction distance. The average error is much smaller in the longitude (east-west) direction, since the road is also east-west, hence in the north-south (latitude) direction there is only measurement noise to which fitting is not effective.

Figure 8 depicts the mean Euclidean distance error as a function of the number of past samples and prediction distance in the case of straight trajectory and linear prediction. As a result for 3 seconds of prediction distance using 3 past samples (optimal number of past samples) one can obtain an average of 3.69 meters of Euclidean distance error. This value is higher than the desire of 1 m, so cannot be used for lane detection, however it can be useful for perpendicular collision alert applications.

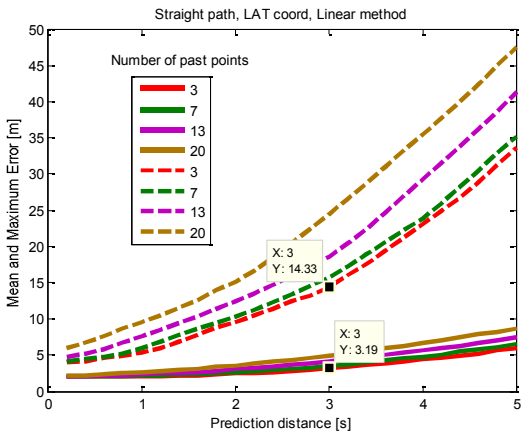

Figure 6. Straight path, Latitude coordinate, linear fitting (solid lines: mean error, dashed lines: maximum error)

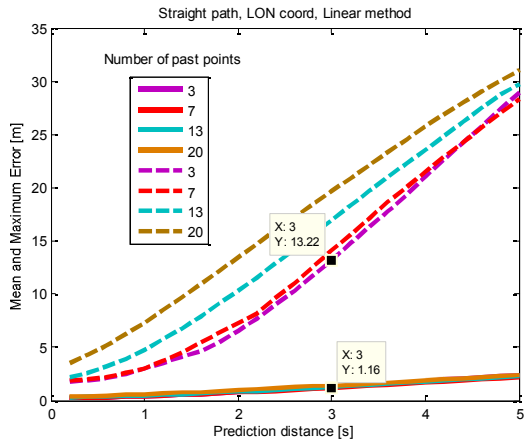

Figure 7. Straight path, Longitude coordinate, linear fitting

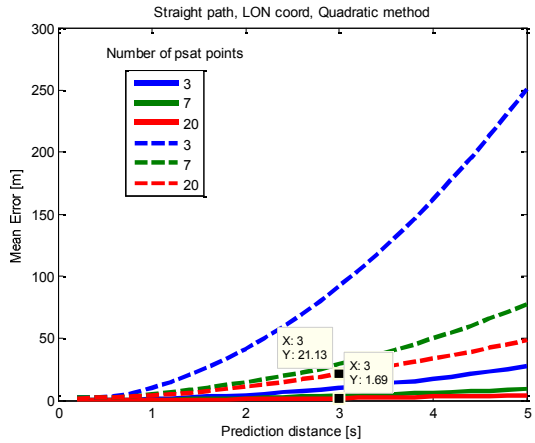

Figure 10. Straight path, Lon. c., Quadratic fitting

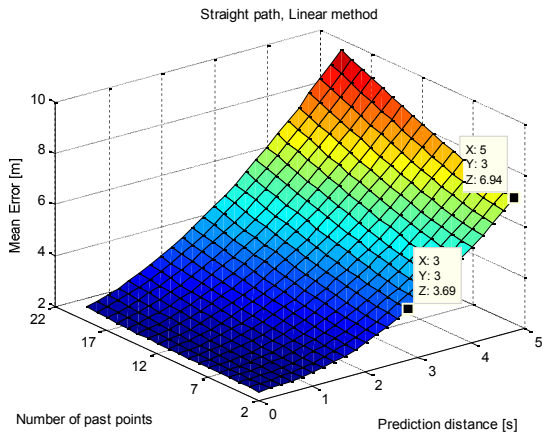

Figure 8. Mean error of Euclidean distance on straight path with linear fitting

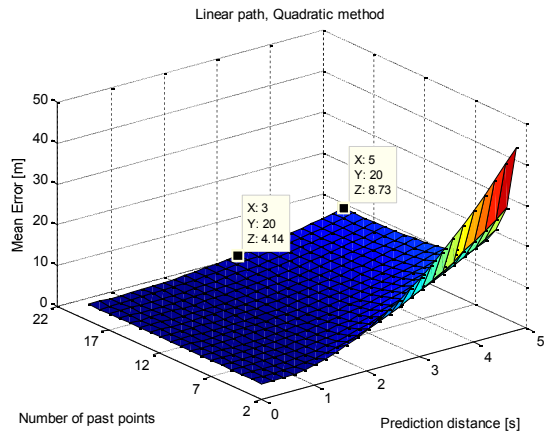

Figure 11. Mean error of Euclidean distance on straight path with quadratic fitting

4.2. Straight path, quadratic fit

Our preliminary hypothesis was that on straight path the quadratic fitting gives higher mean errors that the linear method. The results support our hypothesis as it depicted in Figure 9, 10 and 11, even in the case of small number of used past samples for fitting.

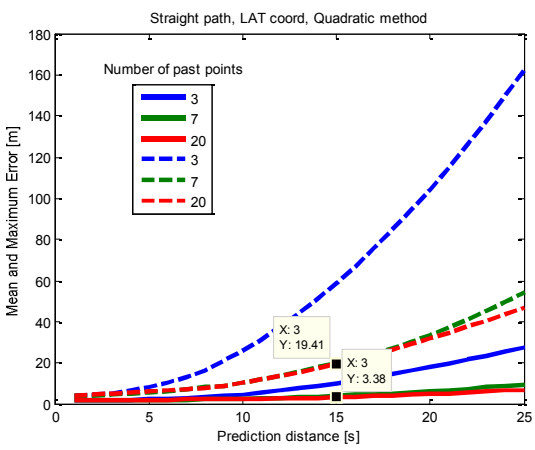

Figure 9. Straight path, Lat. c., Quadratic fitting

Using 20 past samples one can obtain only a slight performance degradation (3.38 meter error in latitude coordinates, 1.69 meters in longitude coordinates and 4.14 in Euclidean distance) related to the linear fitting (3 past points one can obtain an average of 3.69 meters of Euclidean distance error)

As a result, in the case of straight path linear fitting based on a few (3-5) past samples has been proven to be the most effective solution.

4.3. Circular path, linear and quadratic fit

In the case of circular path, nonlinear fitting comes to the fore. These subsection deals with the investigation of the difference between linear and quadratic polynomial fitting. In Figure 12, 13 and 14 one can see the absolute mean and maximum error of linear fitting method for latitude coordinates. Comparing to the results of quadratic polynomial fitting depicted on Figure 15, 16 and 17 one can highlight the fact that for shorter prediction distance (ca. 3 seconds) the quadratic method gives smaller error in average but it is worse in maximum error.

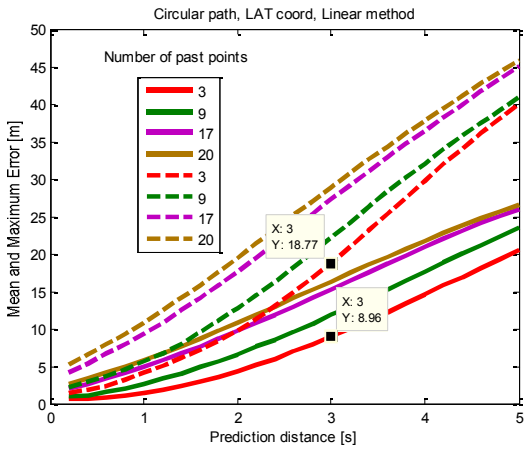

Figure 12. Circular path, Lat. c., Linear fitting

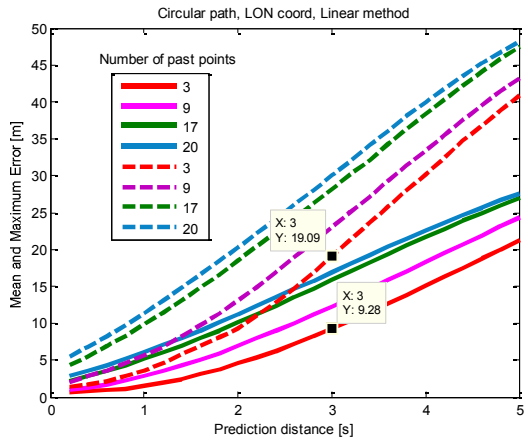

Figure 13. Circular path, Lon. c., Linear fitting

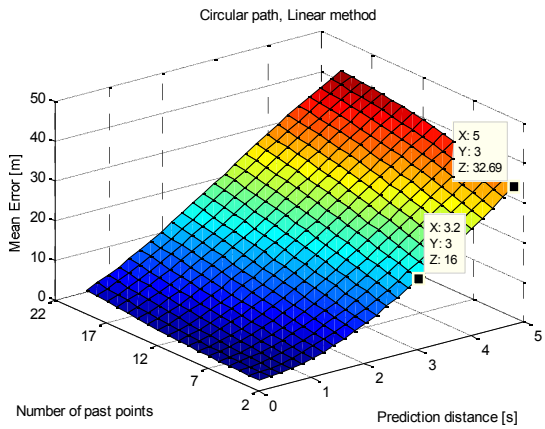

Figure 14. Mean error of Euclidean distance on circular path with linear fitting

For longer prediction distance (ca. 5 seconds) linear fitting gives better results than the quadratic one. The reason of this phenomenon is explained by Figure 18 (where the yellow line shows the past path while the predicted curves are drawn with white (20 past samples) and red colors (3 past samples)), where one can see that quadratic fitting for longer distances can be quite misleading, when one branch of the parabola is fit to a quasi linear session.

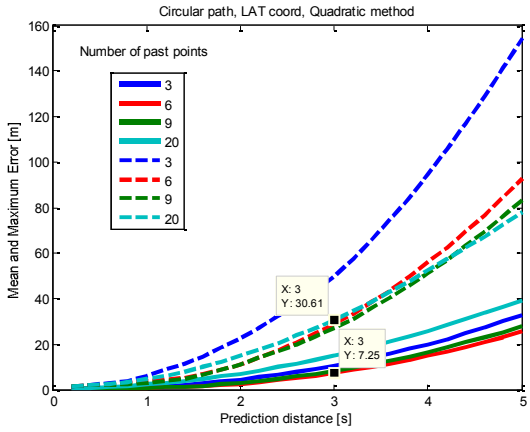

Figure 15. Circular path, Lat. c., Quadratic fitting

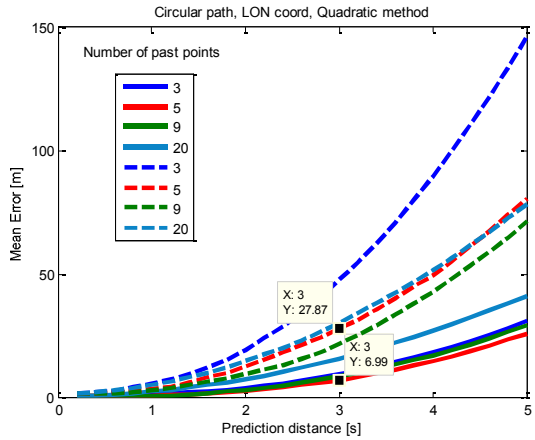

Figure 16. Circular path, Lon. c., Quadratic fitting

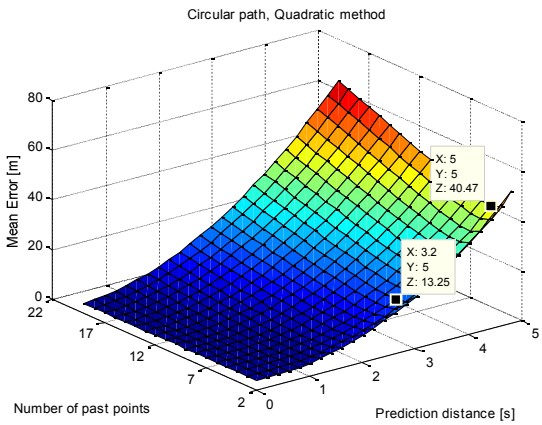

Figure 17. Mean error of Euclidean distance on circular path with quadratic fitting

5. Conclusion

In this paper the measurement-based performance analysis of GPS-based trajectory prediction error has been investigated. Both linear and quadratic polynomial fitting to past samples of a 5 Hz GPS receiver were analyzed as a function of the shape of the trajectory. The results demonstrate that

optimal number of past samples using to fit is very low (3 samples) in the case of linear fitting, and is about 5 samples for quadratic fitting
the average error increases near linearly with increasing prediction distance regardless the trajectory shape and method;
linear fitting leads to smaller average error when only a few (3-5) past samples are using for prediction.
quadratic fitting leads to smaller average error in the case of circular path in the case of 5-7 past samples;
the average absolute error in the case of 3 seconds prediction distance (about twice the reaction time of a driver) can be kept under 5 m using the methods described in this paper.

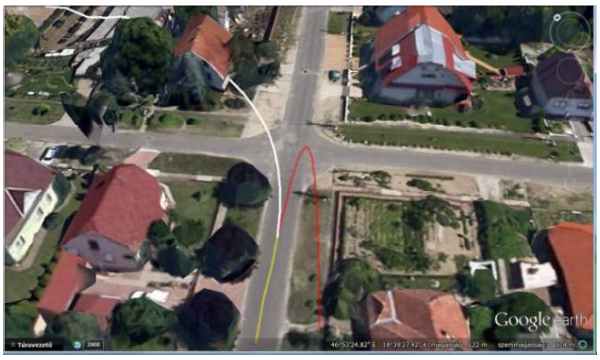

Figure 18. Error in prediction with quadratic polynomial fitting ahead a crossing

However the measured average absolute error is higher than required (1m), it can be enough for perpendicular collision alert applications.

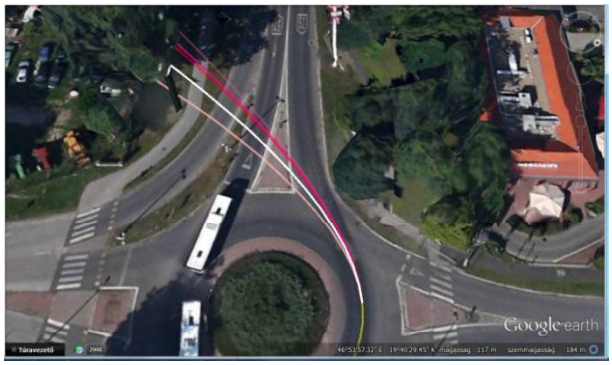

Figure 19. Prediction with quadratic polynomial fitting using different number of past points in a roundabout

The high value of maximum error can lead to too frequent false alarm. As a result, in order to establish a robust and enhanced quality of service solution to collision alert application additional sensor information (yaw-rate, acceleration, compass) should be incorporated, which is the target of future work.

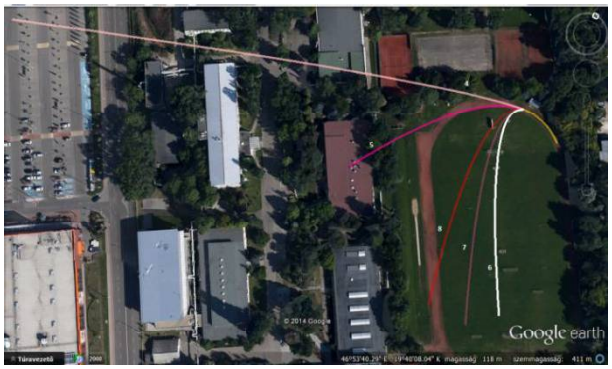

Figure 20. Prediction with quadratic polynomial fitting using different number of past points on a curved path

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