Location Prediction Mechanisms for Tracking Lost Unmanned Vehicles

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Summary

The growth of technologies has made it possible for the introducti on and use of autonomous vehicles that can be operated in any ha zardous environment. Unmanned Ground Vehicles, a kind of auto nomous vehicles are widely seen in military/defense departments and mining areas. Unmanned Ground vehicle (UGV) is intended t o move on a land or any surface. The significance of such vehicle s is that they can be extensively used for longer duration and circu mstances which are harmful to people. Tracking the mobility of s uch vehicle is an essential component to ensure the success of the operation. Vehicles may be lost due to any natural or manmade ca lamities, in which case, tracking becomes a critical issue. Someti mes, the position of UGV cannot be located by the controller (at r emote) due to communication link failures. To locate the lost vehi cle and also to define safety of the vehicle, location prediction me chanisms become an essential solution. In this paper, we have foc used on a frame work to track the location of the lost UGVs, using various prediction methodologies.

Keywords:

Unmanned Vehicle, Mobile Data, Location Prediction, GPS

1. Introduction

With the recent advances in wireless communications and positioning technologies, location prediction methodologies are providing important services to almost all kinds of applications. Delivering location dependent information to users is one such service that has significance in varieties of domains. Location based techniques are mostly useful for predicting the next possible locations of any moving entity such as unmanned vehicle, robot or any mobile user.

In this direction, location prediction mechanisms of UGV have got high research potential. UGVs are useful in applications such as military department, mining department and civil applications. UGVs moving in any predefined boundary may be tracked using positioning technologies. In unknown circumstances, UGVs may be lost thereby posing difficulties for the controllers to trace the current location of such vehicle.

In such case, the need for tracking their locations become mandatory. This paper focuses on using location prediction methodologies to locate the possible future locations of UGV.

1.1 Unmanned Ground Vehicles (UGV)

Unmanned ground vehicles are normally seen in both civilian and military applications. They are intended to perform dull and dangerous activities. There exists two broad categories of unmanned ground vehicles:

(i) Teleoperated
(ii) Autonomous

A teleoperated UGV is controlled at remote by any human operator using wired or wireless connection. These vehicles replace humans in harmful or unsafe environment. Examples are explosives and bomb disabling vehicles.

An autonomous UGV is kind of robot which is operated on the ground surface. An autonomous UGV can be used to collect the information about the environment, and to perform work continuously without human assistance and to avoid some critical situations that are unsafe to people or property. UGVs can be equipped with two major components sensors and/or GPS devices to define communication between the controllers and the vehicles.

Problem Formulation

UGVs are designated to do some assigned task to travel from one point to other. Tracking UGVs during mobility is an essential activity to ensure the traveling. Sensors and related processing devices will be highly useful to track the traveling path of UGV (Figure 1). Also, safety of UGV is an important issue to be considered for the successful completion of assigned task. Safety issues are related to (i) support and functioning of sensors (ii) use of continuous monitoring systems (iii) road and weather conditions and (iv) the natural or manmade calamities.

Details pertaining to status and mobility of UGVs are obtained through sensors, but the controller may face difficulties to access the status/condition of UGVs, if sensors noises arise or sensors failures happen. Keeping alternate sensors (multiple) may be a possible solution to inform the status to the controller, even if any sensor fails. But the design complexity may be increased.

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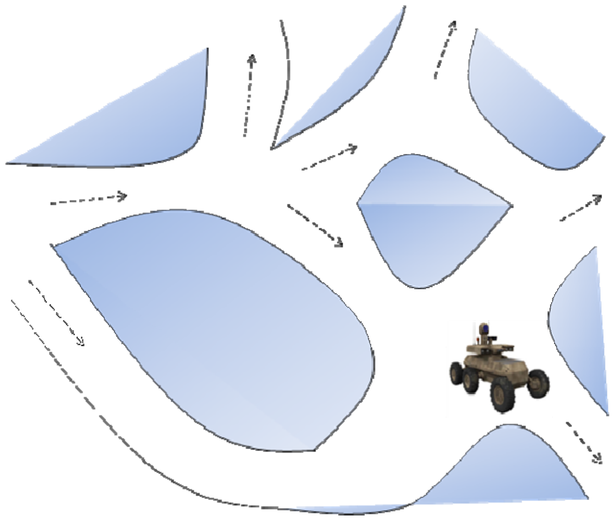

Fig. 1 Unmanned Vehicle

Similarly, GPS technologies embedded in UGVs may act as good communication device but even if the GPS services delinked, the controller will find it difficult to track the vehicle location.
In this context, we propose location prediction mechanisms to find the position of vehicles based on the travel history (mobile data).

2. Related Works

Much research is seen related to the vehicle motion, communication between vehicles and tracking vehicles. Shahram Rezaei et.al have proposed CASS (Cooperative Active Safety System)that uses information communicated from neighboring vehicles via wireless network in order to actively evaluate driving situations and provide warnings or other forms of assistance to drivers [1].
YongsoonYoon et.al have studied an active steering problem of a UGV (Unmanned Ground Vehicle) with obstacle avoidance in complex environments, using a model- predictive method. Also they considered the online obstacle avoidance as well as navigation towards the destination using a model-predictive approach [2]. Shi Shen et.al have presented a radar-based vehicle tracking algorithm that uses the road geometric structure as a constraint to target kinematics with accurate state estimates [3].
Kok-Meng Lee et.al have focused on real-time, robust, cost effective vision sensor development and its applications in autonomous vehicle control [4]. Uwe Kiencke et.al have reviewed current key problems and general trends and accomplishments shared by all transportation applications as well as those which were specific to selected certain fields. Such fields were included automotive systems, marine systems, intelligent autonomous vehicles etc.[5],
Amal Elnahas and Noha Adly have classified the various approaches used for location management of mobile users. Basically, they classified them into two main categories: strategies that focused on reducing the update cost versus strategies that focused on reducing the lookup cost, as explained with system model [6]. Thi Hong et.al have proposed a new movement Rule-based Location Prediction method (RLP) for finding the future locations of mobile users with the past movements which was enhancing the reliability, automation, and performance of LBSs system [7].
The approach proposed by A. Arora et al. deals with fine-grained detection and tracking within an area but along any arbitrary 2-dimensional path. In this model, intrusion data were processed locally at each node, shared with neighboring nodes if an anomaly is detected, and communicated to an exfiltration gateway with wide area networking capability. They were suggesting a distributed approach that allows individual sensor nodes, or clusters of nodes, to perform localized processing, filtering, and triggering functions [8].

3. Mobile Data Management

Technological growth has made it possible to access any information from any place at anytime. Internet, wireless communication and handheld devices have created an ubiquitous medium of information transformation. Especially the emergence of mobile computing paradigm has revolutionized the information access and management in a highly sophisticated way.
Recently, mobile database systems are becoming popular dealing with information available in the mobile computing environment. The GPS enabled mobile devices can store a part of database on its storage space and utilize the data in mobility. Whenever the devices need an additional data apart from its local data, the devices can use the wireless medium and establish the connection to the mobile server through the nearest mobile support station. This area of data management called mobile data management is finding its importance in almost all applications such as Military services, Insurance companies, Traffic control, Taxi dispatch, E-commerce, emergency services etc. The major goal of mobile data management is to ensure the availability of data anywhere and anytime on both mobile and fixed hosts in seamless way.

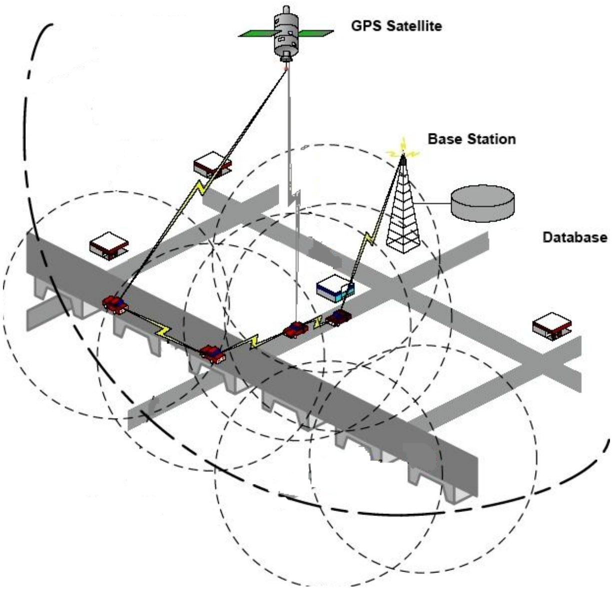

Fig. 2 Mobile Data Management

A Mobile Database System (MDS) consists of structural and functional properties such as distributed system with mobile connectivity, full database system capability, complete spatial mobility, wireless and wired communication capabilities (Figure 2).

The new technological revolutions created by mobile media extend the features of traditional computing and allow users to have anytime, anywhere access to information and applications [9]. One such kind of features is involved in location based services.

Location based information is vital for applications, such as navigation system, ubiquitous location services and communication establishment.

4. Location Prediction

Location prediction is one of the major activities in mobile applications that in turn helps to efficiently manage mobile data. It is used to locate mobile users/devices worldwide, within a metropolitan area, within a campus, in a particular building, or within a single room. Quality of service can be improved through location predictions in applications involving location management, handoff management and resource reservation.

Prominent areas such as transportation, air traffic control, weather forecasting, emergency response and mobile workforce etc are enjoying the benefits of location prediction mechanisms.

4.1 Location Prediction Methods

Let us assume that the unmanned vehicle is attached with a GPS receiver and returns a (longitude, latitude) pair, which may be used to find the locations of the vehicle during mobility. A server is used to store the past history of vehicle locations along with speed and direction parameters in the database as shown in Figure 3.

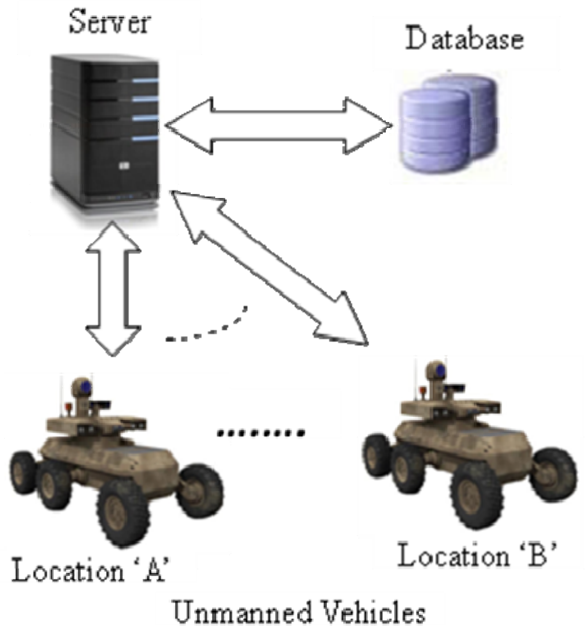

Fig. 3 UMV Controller Architecture

In this paper, we have discussed the following Location Prediction methods for finding the unmanned vehicles during the failures of communication links.

(i) Unmanned vehicle with same speed and direction
(ii) Unmanned vehicle with same speed and different direction
(iii) Unmanned vehicle with different speed and different direction

Location Prediction with Same Speed and Direction (SSSD)

When an unmanned vehicle moves on a land, it can go from one point to designated place via the assigned route. This is intended to move in same direction with a constant speed. During the journey of a vehicle, the communication link may be blocked or damaged due to manmade accidents or any other natural calamities.

To do the location prediction in this situation, the current direction, the past traversed locations and the speed are utilized.

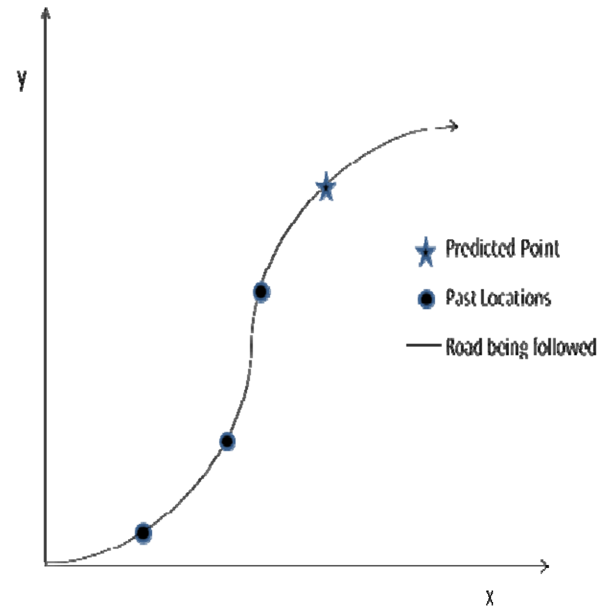

Fig. 4 Location Prediction with same speed and direction

A traveling path of a moving unmanned vehicle can be represented in three-dimensional space (two-dimensional geography, time), with sequence of points (x_1, y_1, t_1),(x_2, y_2, t_2), ..., (x_n, y_n, t_n), where $\{t_1 < t_2 < ... < t_n\}$.

The route of a path is projected on the X-Y plane [10]. Let us assume that vehicle locations during mobility are (x_i, y_i), (x_{i+1}, y_{i+1}), (x_{i+2}, y_{i+2}) etc. During the travel, the vehicle may encounter some communication failure.

The last reported location of a vehicle (before the occurrence of failure) can be considered as the current location (x_n,y_n), which is used to predict the future possible location (x_{n+1},y_{n+1}) of the vehicle (Figure 4).

The future position of the vehicle is calculated as follows :

$$|d| = \sqrt{(x_n + x_{n-1})^2 + (y_n + y_{n-1})^2}$$

$$\text{Therefore } x_{n+1} = x_n + d,$$

$$\text{and} \quad y_{n+1} = y_n + d$$

Location Prediction with Same Speed and Different Direction (SSDD)

The second method is used to find the unmanned vehicle under the constraints of same speed and different direction.

Figure 5 represents all the variables used in the below prediction calculation.

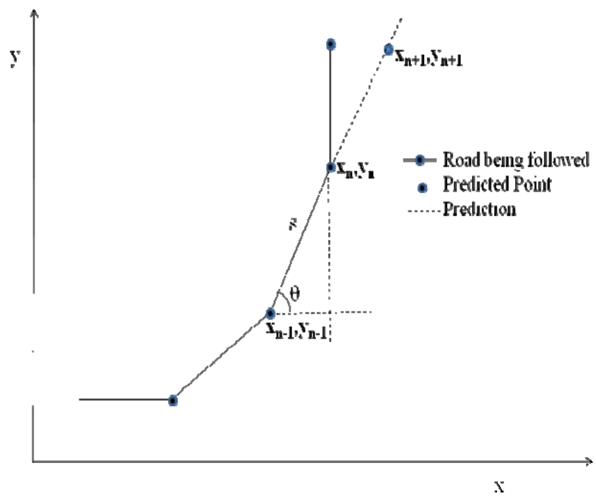

Fig. 5 Location Prediction With Same Speed and Different Direction

Assuming (x_n, y_n) and (x_{n-1},y_{n-1}) as the current and the past locations, the future position (x_{n+1}, y_{n+1}) of a vehicle can be predicted using the equations (1),(2),(3) and (4).

$$x_{n+1} = x_n + s * \cos(\theta) . \qquad (1)$$

$$y_{n+1} = y_n + s * \sin(\theta) . \qquad (2)$$

$$\text{Where} \quad \theta = \arctan \left[\frac{y_n - y_{n-1}}{x_n - x_{n-1}} \right] \qquad (3)$$

$$\text{and } s = \sqrt{(x_n + x_{n-1})^2 + (y_n + y_{n-1})^2} \qquad (4)$$

Location Prediction with Different Speed and Different Direction (DSDD)

This method is used to find the location of a lost unmanned vehicle traveling in different direction with variable speed (Figure 6).

The past traveling history of the unmanned vehicle locations are taken in t_1,t_2,t_3 and t_4 time intervals and the future location of a lost vehicle at time t_5,t_6,… can be calculated by the following model.

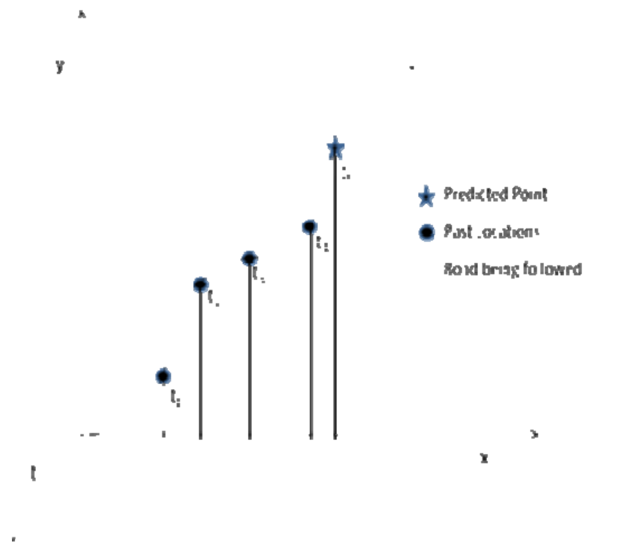

Fig. 6 Location Prediction With Different Speed and Same Direction

Here, we have proposed the Markov-model based prediction scheme that provides the future locations of any lost UGV.

The Markov Chain Model

Let us consider a system which can be expressed at any time as being in one of set of 'n' distinct states. X is a set of stochastic variables and a discrete time stochastic process $\{ X_n : n = 0,1,2\ldots\}$ with discrete space $s_n = (0,1,2,3\ldots.n)$ is a Markov Chain if,

$$P(X_n = s_n \mid X_0 = s_0, X_1 = s_1,\ldots\ldots X_{n-1} = s_{n-1})$$

$$\Rightarrow \quad P\,(X_n = s_n \mid X_{n-1} = s_{n-1})$$

A stochastic process which fulfils the above Markov property [11] is called a first order Markov chain. For the first-order Markov Chain model [12], the next state depends only on the current state.

The system undergoes a change of state (possibly back to the same state) according to set of probabilities associated with the state.

If a_{ij} is the transition probability from state i at time k to state j at time k+1, then the transition probability matrix P of the Markov chain can be represented as shown by the following equation:

$$P \begin{pmatrix} a_{00} & a_{01} \ldots. a_{0n} \\ a_{10} & a_{11}\ldots\ldots a_{1n} \\ . & . \ldots\ldots . \\ a_{n0} & a_{n1}\ldots\ldots.. a_{nn} \end{pmatrix}$$

The conditional probability of transitions to an n^{th} state given that k = n-1 previous states have occurred, gives the k^{th} order Markov Chain and is computed as follows :

$$P(X_n \mid X_{n-1},\ldots X_{n-k}) = p\,(X_n = s_n \mid X_{n-1},\ldots X_{n-k})$$

In this process the probability of getting into the next state depends upon the 'n' previous states.

For a sequence S of length L, the probability of the observed sequence for the first-order Markov chain is computed as follows :

$$P(S) = p(s_L \mid s_{L-1},\ldots s_1)\, p(s_{L-1} \mid s_{L-2},\ldots. s_1)\ldots p(s_1)$$

$$= p(s_L \mid s_{L-1})\, p(s_{L-1} \mid s_{L-2})\ldots p(s_1)$$

$$= p(s_1) \prod_{i=2}^{L} p\,(s_i \mid s_{i-1})$$

Transitions, i.e. probabilities of transitions between states are calculated from previous data. In order to convert GPS data into sequences of road segments (states of Markov model) for exploiting predictions about vehicle's future path, elevation and turns [13].

The result of the computation can be used to identify the location of lost UGVs during the dynamic environment and the rescue operation will be performed quickly with the help of this prediction scheme.

5. Location Identification Frame Work

Let us assume that the UMV is traversing in a known geographical area specified by G. Let T be the path traversed by the UMV. Let L be the last reported location of vehicle (Figure 7).

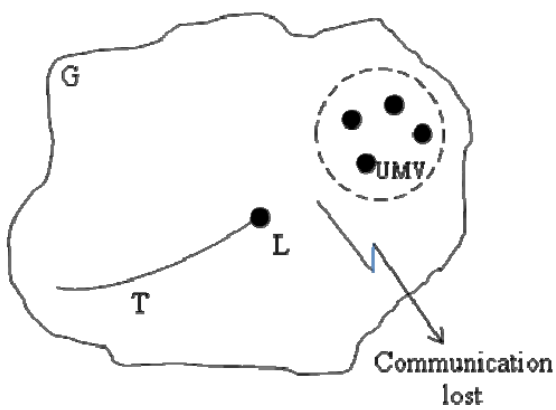

Fig. 7 UMV and its Context

Table 1 represents the details of G (latitude,longitude and location name).

Table 1: Region Database

Location Name	***Location Details***	
	Latitude – 'x' Value	***Longitude – 'y' Value***
L1	**8.17805**	**77.43430**
L2	**8.72453**	**77.68454**
L3	**9.58361**	**77.95834**
..		
..		
Ln	**11.69052**	**79.28739**

The location prediction of lost UMV deals with the following major modules to be performed.

1. Acquire Location Movement Details (acquireLocMovement)
   This involves gathering vital data related to past locations traversed, the speed and direction of mobility. These data are collected at regular intervals.
2. Decide Speed and Direction Attributes (findSpeedDirStatus)
   This module is used to decide upon the modality (SAME or DIFFERENT) of speed and direction parameters of the UMV. To ascertain the modality status as SAME or DIFFERENT, the past historical data are used. Once it is observed that, the vehicle is lost, i.e. once the communication is delinked from the vehicle, it is necessary to locate the possible future position of the vehicle.
3. Predicting the future location (predictNextLocation)
   Based on the last reported location, the future position of the vehicle is calculated. The methodology to locate the future position may be any one of SSSD, SSDD or DSDD.
4. Extracting locations from the Region Database (extractLocations)
   Once the future position (fp) is found, the possible nearer locations are suggested by locating fp in the Region Database.

The framework for performing the above tasks is illustrated in Figure 8.

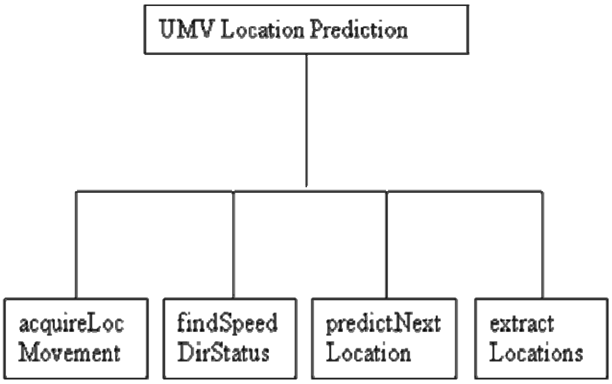

Fig. 8 Location Prediction

6. Conclusion

Mostly, unmanned vehicles are designated to perform difficult tasks in complex environment. There may be possibilities for the vehicles to lose their track of travel or they may be lost due to calamities. As the safety of the vehicles is a primary issue, it becomes necessary to track the traveling status of the vehicles. This paper discusses some methodologies useful for locating the lost unmanned vehicles and enables the decision makers to take appropriate actions.

References

[1] Shahram Rezaei, Raja Sengupta, Hariharan Krishnan, Xu Guan and Raman Bhatia, "Tracking the position of neighboring vehicles using wireless communications", *Transportation Research Part C,* Elsevier Publications,2009.

[2] YongsoonYoon, JonghoShin, H.JinKim, Yongwoon Park and ShankarSastry, "Model-predictive active steering and obstacle avoidance for autonomous ground vehicles", *Control Engineering Practice (17)*, Elsevier Publications, 2009, pp741–750.

[3] Shi Shen, Lang Hong, Shan Cong, "Reliable road vehicle collision prediction with constrained filtering", *Signal Processing (86)*, Elsevier Publications, 2006, pp 3339–3356.

[4] Kok-Meng Lee, Zhi Zhou, Robert Blenis and Erik Blasch, "Real-Time Vision Based Tracking Control of an Unmanned Vehicle", *Mechatronics Vol 5, No.8*, Elsevier Sciences Ltd ,1995,pp 973-991.

[5] Uwe Kiencke, Lars Nielsen, Robert Sutton, Klaus Schilling, Markos Papageorgiou and Hajime Asama, "The impact of automatic control on recent developments in transportation and vehicle systems", *Annual Reviews in Control(30)* , Elsevier Publications ,2006, pp81–89.

[6] Amal Elnahas and Noha Adly, "Location management techniques for mobile systems", *Information Sciences(130)*, Elsevier Publications, 2000,pp1-22.
[7] Thi Hong Nhan Vu , Keun Ho Ryu and Namkyu Park, "A method for predicting future location of mobile user for location-based services system", *Computers & Industrial Engineering (57)*, Elsevier Publications, 2009, pp91–105.
[8] A. Arora, P. Dutta, S. Bapat, V. Kulathumani, H. Zhang, V. Naik, V. Mittal, H. Cao, M. Demirbas, M. Gouda, Y. Choi, T. Herman, S. Kulkarni, U. Arumugam, M.Nesterenko, A. Vora and M. Miyashita, "A line in the sand: a wireless sensor network for target detection, classification, and tracking", Computer Networks (46), Elsevier Publications,2004,pp605–634.
[9] Vijay Kumar, Mobile Database Systems, John Wiley & Sons, Inc. Publication,2006.
[10] Ouri Wolfson and Huabei Yin, "Accuracy and Resource Consumption in Tracking and Location Prediction", Research supported by NSF Grants,2003.
[11] C. Kohlschein, "An introduction to Hidden Markov Models. Probability and Randomization in Computer Science", Seminar in Winter semester 2006/2007at Aachen University.
[12] Beata J. Wysocki and Arek Dadej, "Advanced wired and wireless networks", *Multimedia systems and applications series, Vol 26*, Springer Publications,2005.
[13] J. Krumm. "A Markov Model for Driver Turn Prediction". SAE World Congress, 2008.

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