Proceedings of the 11th International Conference "Reliability and Statistics in Transportation and Communication" (RelStat'11), 19–22 October 2011, Riga, Latvia, p. 284-292. ISBN 978-9984-818-46-7
Transport and Telecommunication Institute, Lomonosova 1, LV-1019, Riga, Latvia

VEHICLE DYNAMIC LOCALIZATION IN INTELLIGENT TRANSPORTATION SYSTEMS BASED ON SENSOR NETWORKS

***Victor Krebss*[1], *Boris Tsilker*[2]**

[1]*CPS Ltd, Skanstes 13, Riga, LV 1013, Latvia*
Ph: +371 29243923, e-mai: victor@cps.lvl

[2]*Transport and Telecommunication Institute*
Lomonosova str.1, Riga, LV 1019, Latvia
Ph: +371 67100604, fax: +371 67100560, e-mail: tsilker@tsi.lv

Localization is a fundamental service required by many modern in-vehicle navigation and safety applications. Vehicle self-localization, the ability of a vehicle to determine its own location, is vital for many aspects of the Intelligent Transportation Systems (ITS) and telematics. The fundamentals of locating and tracking RF emitting devices differ greatly from those of data communications. Localization might be realized in two ways, geometric methods (Trilateration, triangulation, hyperbolic methods) and fingerprinting methods (Signal mapping). The first major challenge in localization is the fact that the accuracy of distance measurements may be degraded by noise. The impact of the ranging error usually depends on the estimation algorithm, the bandwidth of pulses, application scenarios, etc. Second, the position information provided by some anchor nodes may be inaccurate. It is clear that a single localization technique is not enough to meet the requirements of critical applications at the same time, such as being available anywhere and anytime, with highly accurate and reliable position computations. As a result, Data-fusion techniques to combine different localization methods and protocols in a single localization system are required, such as moving average, least squares, Kalman, particle filters Bayesian inference and Dempster-Shafer methods. In order to improve the localization precision several statistical based approaches have been proposed in [1, 2]. However, the statistical methods may not be able to provide enough accuracy if the data quantity is not sufficient. There is also the probabilistic approach considered in order to improve the localization precision. The inaccuracies are characterized by modeling the range measurements as a set of probability density functions. These functions can be used to compute the probabilistic constraints that reduce the uncertainties of the nodes positions. This approach can lead to significant enhancements in the localization accuracy compared to the least squares estimate.

Keywords: Intelligent Transportation System, sensor network, localization, cooperative positioning, data fusion

Introduction

Among the wide range of transportation problems, more or less successfully solvable by means of the intellectual transportation systems (ITS), the road safety problem undoubtedly is the most significant. Such kind ITS, due to the real time processing of information, incoming both from onboard and road infrastructure sensors, give a chance to ensure the on-time response on the vehicle movement within the traffic stream.

One of the most promising vehicular safety applications is the development of an advanced cooperative collision warning system [1]. It is envisioned that the system will use vehicle-to-vehicle radio communications to create a cooperative collision warning system, where vehicles cooperatively share information (i.e. location, speed, heading, acceleration, etc.) for collision anticipation.

In most of today vehicular safety applications location there is the most essential context. Location knowledge of nodes in a network is essential for many tasks such as routing, cooperative sensing, or service delivery in ad hoc, mobile, or sensor networks.

Almost all existing localization approaches basically consist of two stages: 1 measuring geographic information from the ground truth of network deployment and 2 computing node locations according to the measured data.

Perhaps the simplest method of providing localization is to equip every sensor node with a GPS receiver. However, a GPS receiver is expensive in terms of money, size and energy. Moreover, their accurate measure is not always available because of GPS signal losses or multipath. Important problem with the GPS is that it cannot receive signals inside buildings, underground or in tunnels. Also, vehicles are not necessarily equipped with GPS and even they cannot obtain availability of line of sight access to the satellites, particularly when they enter tunnels.

The most common alternative for localizing the nodes involves using a limited number of nodes (perhaps the base stations) equipped with GPS receivers (called beacon or anchor nodes) to localize all of the other nodes (commonly called unknown nodes).

Wireless sensor network localization techniques are used to estimate the locations of the sensors with unknown positions in a network using the a priori available knowledge of positions of, typically, a few specific sensors in the network and inter-sensor measurements such as distance, time difference of arrival, angle of arrival and connectivity. Sensor network localization techniques involve further challenges in several aspects: (1) a variety of measurements may be used in sensor network localization; (2) the environments in which sensor networks are deployed are often complicated, involving urban environments, indoor environments and non-line-of-sight conditions; (3) wireless sensors are often small and low-cost sensors with limited computational capabilities; (4) sensor network localization techniques are often required to be implemented using the available measurements and with minimal hardware investment; (5) sensor network localization techniques are often required to be suitable for deployment in the large scale multi-hop networks; and (6) the choice of sensor network localization techniques to be used often involves consideration of the trade-off among cost, size and localization accuracy to suit the requirements of a variety of applications [2].

This paper investigates the different aspects of the error induced by measurement error component in multi-hop localization setups. In particular, we will discuss the techniques for estimating the range between wireless sensor nodes using radio frequency (RF) measurements and ranging accuracy is limited by noise, multipath channel effects, clock synchronization, clock frequency accuracy, and sampling artifacts. Then we characterize and discuss the error components typical to the localization algorithms.

1. Problem Formulation

At localization of vehicle with unknown coordinates when GPS or other device assisted the location technology is not available we must have at least 3 anchor nodes or nodes with a prior knowledge of their location (vehicles equipped with GPS or infrastructure nodes). The vehicle localize itself by means of trilateration based on the measured range of measurements with respect to these anchor nodes and their known location. Later vehicles being localized become the new anchors for other vehicles.

Three or more independent range measurements with respect to anchor nodes can then be used to solve a 2D trilateration problem.

In general, the trilateration problem can be formulated as follows: given set of references X_i, Y_i, and a set of range measurements R_i, a system of linear equations needs to be solved for unknown U_i.

$$\begin{bmatrix} (X_1-U_x)^2+(Y_1-U_y)^2 \\ (X_2-U_x)^2+(Y_2-U_y)^2 \\ . \\ . \\ . \\ (X_n-U_x)^2+(Y_n-U_y)^2 \end{bmatrix} = \begin{bmatrix} R_1^2 \\ R_2^2 \\ . \\ . \\ . \\ R_n^2 \end{bmatrix}.$$

The accuracy derived through trilateration depends heavily on great number of different factors, such as the geometry of the position references, accuracy of anchor coordinates the accuracy of the range measurements, and so on.

Taking into account only accuracy of the anchor position and the measurement accuracy, we can transform the previous expression by introducing corresponding errors

$$\begin{bmatrix} (X_1+e_{X_1}^v-U_x)^2+(Y_1+e_{Y_1}^v-U_y)^2 \\ (X_2+e_{X_2}^v-U_x)^2+(Y_2+e_{Y_2}^v-U_y)^2 \\ . \\ . \\ . \\ (X_n+e_{X_n}^v-U_x)^2+(Y_n+e_{Y_n}^v-U_y)^2 \end{bmatrix} = \begin{bmatrix} (R_1+e_1^e)^2 \\ (R_2+e_2^e)^2 \\ . \\ . \\ . \\ (R_n+e_n^e)^2 \end{bmatrix},$$

where $e^v_{X_i}, e^v_{Y_i}$ are vertex error (explained later) components for anchor node *i*, e^e_i - edge (distance measurement) error for i anchor node and examined vehicle.

The focus of this work is in evaluating of measurement and vertex errors from the viewpoint of their influence on the accuracy of vehicle localizations. No other factors will be examined. It will be the subject of next investigations.

2. Classification of Error Components

The localization error comes from two sources:

- Vertex errors $\{e^v\}$ (for all node $\in N$): this is the error in neighboring nodes, since their location information may contain error, especially for non-anchor neighbors. For anchor nodes, the vertex error is simply zero.
- Edge error $\{e^e\}$ (for all edges between *t* and node $\in N$): this is the error in distance measurements. For regular distances, a Gaussian white noise is assumed.
- The error $\hat{e}_t$ in the location estimate is a function of both vertex and edge errors:

$$\hat{e}_t = g\left(\left\{e^v_i\right\} i \in N, \left\{e^e_i\right\} i \in N\right).$$

This allows not only compute a location estimate $\hat{x}_t$, but also document the “quality" of the estimate using $\hat{e}_t$.

3. Measurement Error Characterization

The most of sensor measurements, both with respect to localization and relative distances, but also with respect to a general sensor observation, need to be associated with a common time reference in order to be properly fused together. If the time synchronization in the wireless sensor network is acceptable, then node-pairs can exchange information and measurements and readily use the information for localization. Network time synchronization protocols used over the fixed network are not applicable, due to the volatile and possibly time varying connectivity and the clock drift of the low complexity sensor devices.

Node *i* can have known or unknown position p^i_t at each time instant. Depending on measurement type and whether one, two or more nodes have to collaborate to form an observation, the following notation can be used:

$$x^i_t = h_{type}\left(p^i_t\right) + e^i_t,$$

$$x^{ij}_t = h_{type}\left(p^i_t, p^j_t\right) + e^{ij}_t,$$

$$x^{ijk}_t = h_{type}\left(p^i_t, p^j_t\, p^k_t\right) + e^{ijk}_t,$$

where x^i_t is location estimate, e^i_t corresponding estimation error and h_{type} stands for localization type mentioned further in the article.

In all specific measurement models, the measurement noise is additive. The first and convenient approximation is that the measurement is unbiased and the noise is white and Gaussian with a standard deviation σ_e. Appropriate accuracy levels depend on both the type of measurement and the network architecture. The generally applicable assumption is that the measurement error is Gaussian with a probability density function

$$p_E\left(e_t\right) = N\left(0, \sigma\right).$$

Depending on sensor capabilities and the nodes synchronization and communication capabilities, three different types of observations can be distinguished:

- *Waveform observations.* A highly capable sensor node is able to operate on the signal waveform and this observation can be shared with other nodes if bandwidth allows. Sensors which are very close to each other (in the order of half a wavelength) can form a sensor array and correlate the phase of the emitted signal to get a direction of arrival estimates. For sensors being further separated, there will be an integer problem in the ambiguity of the number of periods that may be resolved by merging other information.
- *Timing observations.* If a known or easily distinguished signature is embedded in the signal, the sensor can correlate the signal with the signature to accurately estimate time of arrival. The timing estimation accuracy depends on the signature as well as the sensor capability.
- *Power observations.* Another possibility is that the sensor estimates the received signal power (received signal strength – RSS). In essence, this means integrating the received signal power within a certain frequency band during an integration interval to estimate the received signal energy during the time interval. If the emitted power is known, RSS provides a coarse range information.

Table 1 summarizes the discussed sensor observations.

Table 1 Mathematical notation of available sensor observations in the wireless sensor networks

Measurement Type	**Nonlinear Measurements**	**Accuracy**
Direction of arrival	$h_{DOA} = angle\left(p_t^i - p_t^j\right)$	5º - 10º
Time of arrival	$h_{TOA} = \left\|p_t^i - p_t^j\right\|$	5 – 100 m
Time difference of arrival	$h_{TDOA} = \left\|p_t^i - p_t^j\right\| - \left\|p_t^i - p_t^k\right\|$	10 – 60 m
Interferometrics	$h_{TDOA} = \left\|p_t^A - p_t^D\right\| - \left\|p_t^B - p_t^D\right\| + \left\|p_t^B - p_t^C\right\| - \left\|p_t^A - p_t^C\right\|$	0.1 – 1 m
Received signal strength	$h_{RSS,\log} = P_0^i - n_{i,j}\left(\left\|p_t^i - p_t^j\right\|\right)$ $h_{RSS,lin} = \overline{P}_0^i \left\|p_t^i - p_t^j\right\|^{-n_{i,j}}$	4 – 12 dB
Digital map information	$h_{MAP}^j\left(p_t^i, p_t^j\right)$	(RSS MAP 3dB)
Position estimates Inertial sensors	$h_{POS} = p_t^i$ $h_{INS}\left(p_t^i, p_t^j\right)$	5 – 20 m (GPS)

4. Accuracy Limits

The achievable accuracy of ranging systems is limited by four primary factors which are noise, time synchronization, sampling artifacts, and multipath channel effects. These factors introduce random, time and spatially varying errors into the estimate resulting in reduced accuracy. Frequency accuracy between the devices involved in the measurement can also impact ranging system accuracy significantly. Each effect can dominate the error under the different circumstances, and a system must be designed so that the combination of these effects does not degrade accuracy beyond useful limits. Because the introduced errors are stochastic, the errors can never be eliminated, but it is possible that measurement techniques can be used to mitigate these effects.

4.1. Noise

Noise and interference introduce unknown errors into measurements. The effect of white noise processes such as thermal and electronic noise is well understood and can be quantified. A range measurement degraded only by noise is limited in accuracy by the signal energy to noise ratio at the receiver and the occupied bandwidth.

A ranging system suffers in low signal to noise ratio (SNR) environments because the exact time of an event cannot be resolved precisely. In a simple example "edge detection" ranging system, the ranging signal is a step function sent by the transmitter at t = 0 and the receiver measures the time of the rising edge it observes. When this signal is received, the edge time may be detected slightly early or slightly late due to the noise added to the signal.

The mathematical expression that links SNR and bandwidth together to give a bound on ranging performance can be derived from the Cramér-Rao lower bound (CRB). The CRB can be calculated for any unbiased estimate of an unknown parameter. The CRB can be used to calculate a lower bound for the variance of the estimate for the range, $\hat{r}$, as

$$\sigma_{\hat{r}}^2 \geq \frac{c^2}{(2\pi B)^2 \frac{E_s}{N_0}} \left(1 + \frac{1}{\frac{E_s}{N_0}} \right) m ,$$

where $\sigma_{\hat{r}}^2$ ^r is the variance of the range estimate, *c* is the speed of light, *B* is the occupied signal and width in Hertz, and E_s / N_0 is the signal energy to noise density ratio. The SNR is related to E_s / N_0 that

$$SNR = \frac{P_s}{P_n} = \frac{E_s}{N_0 t_s B} ,$$

where P_s is the signal power, P_n is the noise power, t_s is the signal duration during which the bandwidth *B*, is occupied. In many common signals, the bandwidth and duration are tied together such that $t_s B \approx 1$. Therefore, the E_s / N_0 ratio is approximately equal to the SNR. By exchanging the locations of the factors

$$\frac{E_s}{N_0} = t_s B \cdot SNR$$

For a fixed signal energy and noise density, increasing the bandwidth provides significant improvements in noise performance. This fact is one argument for increasing the bandwidth of RF based ranging systems

4.2. Time Synchronization

RF time of flight measurement systems must be able to estimate the time of transmission and arrival using a common time base for the accurate measurements. When two wireless devices, *A* and *B* perform the range estimation, the most straightforward method is for *A* to send a signal at *t = 0* and for *B* to start a timer at *t = 0* and stop it when it receives the signal sent by *A*. The value of the timer at *B* is equal to the time of flight (TOF). If the clocks are not perfectly time synchronized, however, and *B* notion of *t = 0* is offset in time from *A*, then this offset, Δt, directly adds a bias to the measurement. Time synchronized wireless networks are typically synchronized to on the order of 1 μs resulting in errors of up to 300 m, but high power and expensive systems can achieve the time synchronization of better than 10 ns or 3 m.

If *A* and *B* have full duplex radios, that is, they can transmit and receive at the same time, then a two way or a round trip measurement can be made. *A* sends a signal to *B* at a carrier frequency f_{c1} and *B* translates this signal to a different carrier frequency f_{c2} and retransmits that signal in real time. The signal is received back at *A* at f_{c2} such that *A* can compare the signal it is receiving from *B* to the signal it is sending to *B*. By measuring the delay between these two signals, the round trip TOF, $\hat{\tau}_{RT}$, is estimated, and the range estimate is $c \cdot \frac{\hat{\tau}_{RT}}{2}$.

4.3. Sampling Artifacts

Ranging systems estimate the time of arrival of a signal and compare that time with the time the signal was transmitted to calculate the time of flight and thus the range. It is commonly assumed that the ranging accuracy is limited to c / f_s^2 where f_s is the receiver sampling rate. This limit is known as a range binning, and it can impact the resolution if steps are not taken to mitigate its impact. A common implementation is to estimate the time of arrival using a matched filter that is sampled at the signal bandwidth resulting in time resolution of *1/B*. This sampling adds error to the estimate because the estimate space is divided up into range bins that are *c/B* wide. The error associated with this process is

uniformly distributed inside the range bin. By using the variance of the uniform distribution, the impact of sampling can be found

$$\sigma_{sample}^2 = \frac{1}{12 \cdot f_s^2}.$$

4.4. Multipath Channel Effects

When a ranging system has been well designed, it often still fails to achieve the expected performance because the measurement is not taken in free space. In real environments the RF signals bounce off objects in the environment causing the signal to arrive at the receiving antenna through the multiple paths as shown in Figure 1. In this figure, the direct path is obstructed by walls, but the other paths are not.

This is common indoors, and it is likely that the non-direct paths have the higher power than the direct path. The communication environment is called the channel, and multipath channels.

They not only vary by the type of environment (office building, residential or outdoors) but also they are specific to the geometry of the transmitter and receiver in that environment. The channel is often time varying resulting in a multipath environment that changes from one time to another.

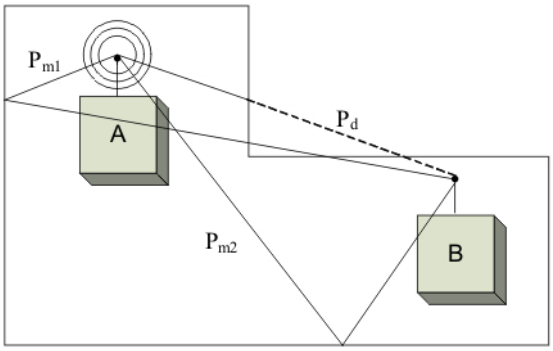

Figure 1. A multipath environment

The bandwidth required to achieve a very fine resolution in a Gaussian white noise environment is far smaller than that required to achieve the equivalent resolution in a typical indoor multipath environment, and the techniques to improve the multipath performance are far more computationally intensive than those to combat noise. Many measurements in indoor environments will not have a resolvable direct path using any method or bandwidth, and the resulting range estimate will be highly inaccurate.

5. Vertex Error Characterization

Different sources of errors in multi-hop localization systems can be categorized in three broad classes [3] setup error, channel error and algorithmic error. Setup error is induced by intrinsic measurement error and it is reflected in the network configuration parameters such as network density, concentration of beacons (or other landmarks), network size and measurement error characteristics known prior to deployment and certainty of beacon locations.

Channel error is a result of the extrinsic measurement error and represents the physical channel effects on sensor measurements. Multipath and shadowing, multiple access interference, the presence of obstructions that results in unpredictable non-line of sight components, and fluctuations in the signal propagation speeds are just a few of these effects that can introduce error into the computation of locations. The magnitude of these effects on the distance measurement process is typically specific to the particular measurement technology and the environment in which they operate; hence, different considerations should be applied for each technology.

Finally, the multi-hop nature of the problem and the different operational requirements introduce another level of complexity and subsequently more errors. The results of a multi-hop localization process are based on a series of single hop multilaterations in an iterative manner. At each step localized vehicle becomes the anchor, which can be used at next steps. In such a process, errors, coming from each step of multilateration, propagate and accumulate.

To control the error propagation, [4] proposes a mechanism to keep the track of estimation error and determines which neighbors have the reliable location information and which don't.

This mechanism filters out outliers (“the bad seeds"), preventing them from propagating further. To keep the track of estimation error, first is considered the simplified problem of localizing a node *t* given *N*, the set of neighbors in distance constraint graph (DCG) with known locations. For the shortest path approximation, *N* includes those 3~5 closest anchors to the node.

Taking trilateration as a representative of multilateration, [5] focuses on the accuracy issue of localization under noisy ranging measurement. In order to address the above challenges, as a “quality" measure concept of Quality of Trilateration (QoT) is considered, which is inspired by the key observation that different geometric forms of trilaterations providing different levels of localization accuracy.

The metric QoT quantitatively describes such differences and, more importantly, helps to compare and make choices of trilaterations. This mechanism enables the ability of distinguishing and avoiding poor trilaterations with much uncertainty or potential flip ambiguity.

The based fact that the geometric relation of reference nodes affects the localization effect significantly, a fine grained method is necessary. QoT is beyond a binary output function, providing a quantitative evaluation of different forms of trilaterations. Indeed, QoT can be extended to multilateration straightforwardly.

Let $t = Tri\left(s, \{i = 1,2,3\}\right)$ denote a trilateration for *s* based on three reference nodes s_i. Let *p(s)* be the real location of sensor node *s* and let *pt(s)* be the estimated location of *s* by trilateration *t*. Let $d(s_i, s_j)$ denote the real distance between two neighbor nodes s_i and s_j. We assume it possesses some probability distribution denoted by $f_{s_i,s_j}(x)$, where $x \in [0,+\infty)$ denotes the distance value. Any point *p* in a 2D plane, the probability density of *p* is given by

$$f_t(p) = \prod_{i=1}^{3} f_{s_i,s_j}\left(d\left(p, p(s_i)\right)\right)$$

Then, *Disk(p, R)* is defined as a disk area centered at *p* with radius *R*. The parameter *R* is an application specified for the different requirements of localization accuracy. The quality of trilateration t is defined as:

$$Q(t) = \int_p f_t(p)dp, p \in Disk\left(p(s), R\right)$$

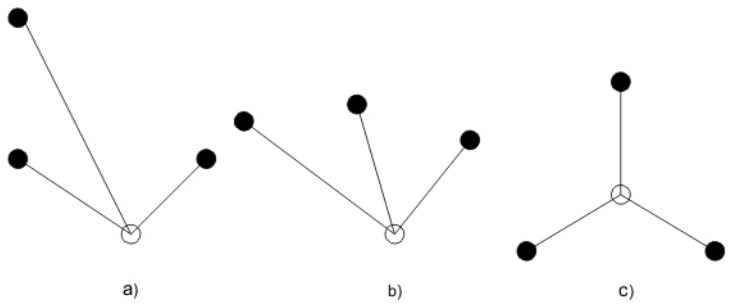

Figure 2. Three cases of trilaterations

Figure 2(a), (b), and (c) shows three cases of trilaterations. Assuming normal noises in ranging measurement in the first case, Figure 2(a) displays the probability distribution of a general case. In the second case, Figure 2(b) indicates a high probability of the flip ambiguity as three reference nodes almost lie in a line. In the third case, Figure 2(c) plots a concentrated probability distribution which is accord with the fact that three references are well separated around the node to be localized.

Some other researchers [6] have considered error distribution based probabilistic approach to further improve localization accuracy for the wireless sensor networks.

Scenario is depicted in Fig. 3(a), where four anchor nodes have known or pre-deployed positions. We use these four anchors to locate any event occurred in the region, which is represented by point *B* in the figure. The anchors are initially assumed to be on the unit grid. Assume the actual distance and the measurement error between anchors A_i and *B* are d_i and λ_i, respectively, where $\lambda_i << d_i$ and $i \in [1,2,3,4]$, the measured distance is then given by $d_i + \lambda_i$. For the following analytical modeling, error in measured

distance, λ_i, is proportional to the distance. The uncertainty ratio ρ is assumed to be uniformly distributed and is within the range $[-\delta,\delta]$. Thus, $m_i = d_i + \lambda = d_i(1+\rho)$ where $\rho \in [-\delta,\delta]$

With the measured distances, any two anchors may produce a position estimate using methods such as a circle-based method [7] or a hyperbola-based method [8]. For example, using anchors A_1 and A_2, the resulting estimation is B_1, shown in Fig. 3(b) (with the other estimate dropped out).

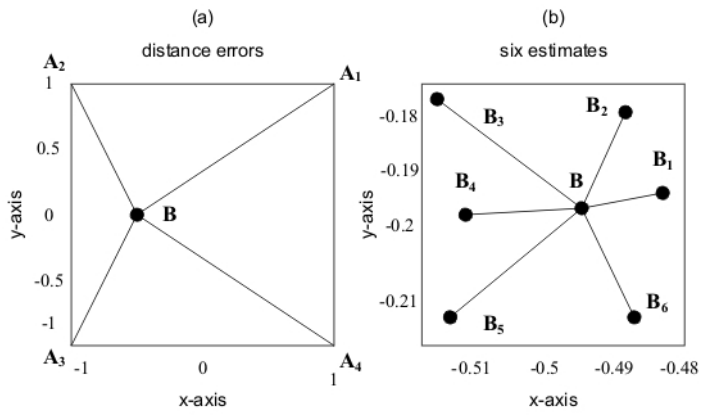

Figure 3. Localization with measurement errors

Four anchors will yield a total of six estimates, as shown in Fig. 3(b). If the measurements contain no errors, then all the position estimates will coincide to the exact event location. However, in practice, these estimates will be distributed in a region due to the measurement noise; the size of the region depends on the intensity of the noise. This method identifies the final location using the error probability distribution.

Probabilistic based localization method, first, utilizes two anchors to obtain the position of an event. Then probability density distribution of the estimate is developed basing on the measurement error distribution. Then with four anchor nodes, the combination of any two anchors will give a probability density distribution. By combining these distributions, a probability density function for final location estimation can be obtained. The location with the highest probability density will be chosen as a final result. Each pair of anchors is used instead of three or more anchors to obtain the initial locations because the methods using three or more anchors normally base localization process on the least squares, whereas the least squares add in errors to localization.

6. Conclusion

Two main types of errors influencing the common accuracy of the vehicle localization were examined. The results of evaluation may be useful at selection of the most effective method of trilateration, giving the highest precision of the vehicle position estimation. It is clear that these two factors are sufficient, but not sole in ensuring the precise vehicle localization. The other factors and their effect as well as the selection of the most appropriate method of lateration will be the subject of further investigations.

References

1. Parker R., Valaee S. Vehicle Localization in Vehicular Networks, *Vehicular Technology Conference*, 2006. VTC-2006 fall. IEEE 64th, pp. 1–5.
2. Mao G., Fidan B. *Localization Algorithms and Strategies for Wireless Sensor Networks.* Porttland: Book News Inc, 2009. 510 p.
3. Savides A., Garber W., Adlakha S., Moses R., Srivastava B. On the Error Characteristics of Multihop Node Localization in Ad-Hoc Sensor Networks. In: *IPSN'03 Proceedings of the 2nd international conference on Information processing in sensor networks*. Springer, 2003, pp. 317-332.
4. Juan Liu, Ying Zhang, and Feng Zhao. Robust distributed node localization with error management. In: *MobiHoc '06: Proceedings of the seventh ACM international symposium on Mobile ad hoc networking and computing*, ,New York, ACM Press, 2006, pp. 250–261.

5. Zheng Yang; Liu, Y. Quality of Trilateration: Confidence based Iterative Localization. In: *IEEE Transactions on Parallel and Distributed Systems,* Vol. 21, No 5, May 2010, pp. 631-640.
6. Bian, T. Venkatesan, R. Li, C. An improved localization method using error probability distribution for underwater sensors. In: *Communications (ICC), 2010 IEEE International Conference,* 23-27 May 2010, pp. 1-6.
7. S. Dong, P. Agrawal, and K. Sivalingam, Localization error evaluation in heterogeneous sensor networks. In *Proc. of the 2008 IEEE Global Telecommunications Conference (GLOBECOM'08)*, New Orleans, USA, November 2008. pp. 1-5.
8. R. Fan, H. Jiang, S. Wu, and N. Zhang, Ranging error-tolerable localization in wireless sensor networks with inaccurately positioned anchor nodes, *Wireless Communications and Mobile Computing*, Vol. 9, No. 5, May 2009, pp. 705-717.