An application of the Kalman filter in automated guided vehicles

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Abstract. The article presents an example of using the Kalman filter in the navigation process of an automated guided vehicles (AGV). Odometry – computational navigation is the basis for determining the location of automated guided vehicles. Many errors affect this method of determining the vehicle's position. In order to eliminate these errors in modern vehicles, additional systems are used to increase the accuracy of determining the position of the vehicle. In the latest navigation systems, probabilistic methods are applied to adjust the route and the position. The Kalman filters are most commonly used.

1. Introduction

Automated guided vehicles are increasingly used in many areas of human activity. At present, the vast majority of these vehicles are used for transport work inside factories, warehouses, office buildings and in closed areas. One of the basic requirements that must be met when constructing a vehicle as well as its exploitation is to equip the vehicle with an appropriate guidance system enabling a movement from the starting point to the end point along a predetermined or dynamically generated trajectory. Various navigation techniques are used to drive a vehicle. The most popular at the moment is odometry, which is the technique of counting navigation. It consists in determining the current position of the vehicle based on the distance travelled by the characteristic point of the vehicle. Odometry, due to imperfections of the real object (manufacturing errors) and the working conditions of the vehicle (wheel slip, surface irregularities), is burdened with numerous errors, which in extreme cases become aggregated – increase in the position determination [1, 2]. An increasing number of measuring methods are used to correct errors. The increase in the number of these methods results from the continuous development of measurement techniques. In the broadly understood robotics, laser measurements [3–5] are very often used. Measurements can be made at a fixed frequency (GPS, laser, gyroscope) or after approaching a specific point, line, reference surface (magnetic, video, laser, ultrasonic) [6]. After the measurement, the vehicle's course is corrected.

In more complicated systems, probabilistic methods are used in which, based on the estimation of errors in subsequent items, the computer program implemented makes corrections in the computational algorithm [7, 8]. The simplest solution of this type based only on odometry is described in [9, 10]. Based on the measurement of the end position error in two runs of opposite directions, the implemented program determines and introduces corrections to the computational algorithm. Another simple example of using the probabilistic method is described in [11]. For the intended route of the
vehicle, the areas of error are determined. On the parts of the route where there is a high probability of collision, measurements are made on the basis of which the route correction is made.

In the case of using additional measurement systems (laser, ultrasonic, vision) and probabilistic methods, the state vector is determined. The components of this vector are the position and orientation of the vehicle. Most of these methods use a variety of filters. In works [12, 13], for the construction of a closed working space map where the vehicle moves, filters based on the Bayes theorem were used.

Many works use the Kalman filter and its modifications. An example of the Kalman filter application are works [14, 15]. The work [14] presents the vehicle intended for agricultural work. During the movement, the vehicle uses odometry and additional measurement systems such as gyroscopic, laser, vision and measurement of torques applied to the drive wheels. The Kalman filtration algorithm described in the paper is based on the previously mentioned measurement systems and detects a wheel slip. As a result, the vehicle can adapt to the changing properties of the ground.

The second example of an application of a probabilistic method using the Kalman filter is work [15]. In the presented work, the vehicle uses odometry and an additional ultrasonic system. Odometry errors are compensated by comparing the positions determined from the odometry and the environment map. The environment map is created on the basis of readings from the ultrasonic sensor. In paper [16], the authors proposed the use of the extended Kalman filter in an algorithm for a simultaneous map creation and the vehicle location. It was shown that the linearization of the generated nonlinearities both in vehicle motion and in the sensor model allowed obtaining good results in the algorithm applied. In the case of Chung's and co-authors work [17], they proposed a method where the gyroscopes were calibrated and the Kalman filter was used to estimate the position of the vehicle.

The paper [18] describes the use of the Kalman filter for analyzing data from laser rangefinders. The data filtered made it possible to determine precisely the position of the vehicle relative to the reference line and to calibrate the navigation system.

In the case of a vehicle equipped with two independently driven wheels with incorrectly estimated values of rolling radiuses, the actual movement of the vehicle does not take place along a straight line but on a curvature with a constant radius. In the work [19] an assessment was made of the effectiveness of various types of filters when determining the reference line being a part of the arch.

In many practical applications, the position update using additional measuring techniques cannot be carried out continuously. In these cases, it is preferable to determine the selected base surfaces. Such solutions are used in work areas where the environmental conditions are definitely changing, for example, the travel from the building to the building, where the distance of the possible reference surface exceeds the measuring range of the sensors installed.

The purpose of this article was to present an example of using the Kalman filter in the process of driving an automated guided vehicle on the selected sections of the route. Within these sections, the current position of the vehicle is corrected and corrections to the targeting algorithm are made. The use of such a procedure allows extending the sections travelled by the vehicle without correction of the position. These solutions simplify and reduce the costs of the navigation system.

2. Movement description

Odometry is the basic method of calculating the position of automated guided vehicles [1, 18, 19]. This method consists in determining the current position of the vehicle, based on the distance travelled by the characteristic point of the K vehicle. In practical solutions, three types of odometry of land vehicles apply. These methods differ from each other in the way of measuring and determining the angle of direction. The research presented in the article uses a vehicle moving by means of odometry, which applies the difference in velocity of the driving wheels $v_L$ and $v_P$ to determine the directional angle $\theta$. The essence of this solution is presented in figure 1.
The method used is based on continuous counting of the distance travelled by left (K_L) and right (K_R) wheels and on determining in each iteration the change of the directional angle of vehicle movement \( \theta \) [18, 19]. It is used in vehicles where independently driven two drive wheels are used for steering. The appropriate variation of the rotational speed of these wheels forces the vehicle to rotate around a vertical axis of rotation passing through the point O and change the directional angle \( \theta \).

If the position of the selected vehicle point O driven by two independently driven wheels K_L and K_R in the base reference system X_0\(O_0Y_0\) (figure 1) in the iteration \( k \) is determined by the state vector \((x(k), y(k), \theta(k))\), the position of the vehicle in iteration \( k + 1 \) is expressed by:

\[
\begin{bmatrix}
x(k + 1) \\
y(k + 1) \\
\theta(k + 1)
\end{bmatrix} =
\begin{bmatrix}
x(k) \\
y(k) \\
\theta(k)
\end{bmatrix} +
\begin{bmatrix}
\Delta t \cdot v_O(k + 1) \cdot \cos(\theta(k) + \Delta t \cdot \omega(k + 1)) \\
\Delta t \cdot v_O(k + 1) \cdot \sin(\theta(k) + \Delta t \cdot \omega(k + 1)) \\
\Delta t \cdot \omega(k + 1)
\end{bmatrix}
\] (1)

Speeds \( v_O(k + 1) \) and \( \omega(k + 1) \) can be determined from dependencies (2), (3):

\[
v_O(k + 1) = \frac{(v_R(k + 1) + v_L(k + 1))}{2}
\] (2)

\[
\omega(k + 1) = \frac{(v_R(k + 1) - v_L(k + 1))}{b}
\] (3)

where: \( v_R(k + 1) \) – speed of the right wheel K_R, \( v_L(k + 1) \) – speed of the left wheel K_L, \( b \) – wheelbase of the driven wheels.

Speeds \( v_R(k + 1) \) and \( v_L(k + 1) \) are expressed in the following dependencies:

\[
v_R(k + 1) = \omega_R(k + 1) \cdot r
\] (4)

\[
v_L(k + 1) = \omega_L(k + 1) \cdot r
\] (5)

After taking into account the dependences (4), (5), the angular speed \( \omega(k + 1) \) (6) and speed \( v_O(k + 1) \) (7) are obtained in a function determined directly from the angular velocity measurements of the drive wheels \( \omega_R(k + 1) \) and \( \omega_L(k + 1) \):

\[
\omega(k + 1) = \frac{(\omega_R(k + 1) - \omega_L(k + 1)) \cdot r}{b}
\] (6)

\[
v_O(k + 1) = \frac{(\omega_R(k + 1) + \omega_L(k + 1)) \cdot r}{2}
\] (7)

where: \( \omega_R(k + 1) \) – angular speed of the right wheel, \( \omega_L(k + 1) \) – angular speed of the left wheel, \( r \) – the radius of the drive wheels is the same for the left and right wheels.

In the above considerations, it was assumed that the wheels are rigid and roll without a slip, the contact of the wheel with the ground is punctual and the radiiuses \( r \) of the drive wheels are equal.
3. Fundamentals of Kalman filtering

The Kalman filters find an application in many fields of science. They are most often used in engineering, mainly in sensory systems of robots, automated guided vehicles, planes and space ferries. This method is readily used in AGV navigation where the systems of perception of the environment play a very important role.

The location of an automated guided vehicle using probabilistic methods consists in estimating the vector of the dynamic state of the environment based on sensory measurements. With regard to automated guided vehicles, the state vectors are, for example, the Cartesian coordinates of the centre of the vehicle, and its orientation. Measurements are made by odometry techniques and additionally by sensors such as laser rangefinders, sonars or cameras. The key idea of probabilistic methods is recursive, in time \( k \), estimating the probability density in the entire state space, provided the data obtained until time \( k \). One of the probabilistic techniques of locating a mobile robot is the use of the Kalman filter [18, 20].

Mathematical models are used to describe the process as well as the measurement system. The linear system:

\[
x(k+1) = F(k)x(k) + G(k)u(k) + v(k) \\
z(k) = H(k)x(k) + w(k)
\]

The first equation is a process model that is partly deterministic and partly random. It is the connection of the previous state with the current one by the matrix \( F \), \( v \) is the process noise (random part). The second equation is the measurement model, where \( H \) is the matrix that connects the measurement with the state, \( w \) is distortion.

The Kalman filter is a two-phase recursive algorithm. The first phase of the algorithm is called the prediction. Equations performed during this phase are called a time update. The second phase is called correction, and its equation is a measuring update (figure 2).

![Figure 2. The scheme of calculations of the Kalman filter algorithm [18]](image)

During the prediction, based on the state from the previous step, the estimated value of state \( \hat{x} \) and its covariance are determined and these are a priori values. The measurement in the second phase is a form of feedback. On its basis, a posteriori value is determined for the state and its covariance.

The Kalman filter algorithm can be used to identify dynamically the parameters of a linear system and to "untangle" signals, i.e. to estimate one of the interleaved signals based on the knowledge of the second signal and the result of the convolution.

The prediction:

\[
\hat{x}(k+1|k) = F(k)\hat{x}(k|k) + G(k)u(k) \\
P(k+1|k) = F(k)P(k|k)F^T(k) + Q(k)
\]
The update:

\[
\tilde{x}(k+1|k+1) = \tilde{x}(k+1|k) + W(k+1)v(k+1)
\]

\[
P(k+1|k+1) = P(k+1|k) - W(k+1)S\nu\nu(k+1|k)W^T(k+1)
\]

where:

\[
v(k+1) = z(k+1) - H(k+1)\tilde{x}(k+1|k)
\]

\[
S\nu\nu(k+1|k) = H(k+1)P(k+1|k)H^T(k+1) + R(k+1)
\]

\[
W(k+1) = P(k+1|k)H^T(k+1)S^{-1}\nu\nu(k+1|k)
\]

During the Kalman filter operation, all available information about the controlled system is processed to determine the variables of interest. Information such as the dynamics of the system and measuring devices, a statistical description of disturbances in the system, a description of measurement errors and information on the initial values of the variables determined are taken into account. Its operation is based on the prediction of, for example, the current location of the vehicle based on past displacements and current observation of the environment in such a way that the error is statistically minimized. The Kalman filter is used to track vehicle position and orientation changes in relation to the known location of the vehicle at the initial moment. To make it possible to use, the control system must have a model that can be written in a linear form, and the disturbances in the system must be of the Gaussian [18, 20, 21].

4. Measurement scheme and test object

The object of the study was an automated guided vehicle intended for transporting loads (figure 3). The vehicle was set in motion and driven by two independently driven wheels. The object studied was equipped with an on-board computer, a set of data acquisition cards and appropriate control and measurement equipment. Due to the lack of flexible suspension, the vehicle was designed to move on smooth surfaces. The vehicle was built based on a three-wheel structure with two drive wheels and one independent rotary drive. Such a solution, with great structural simplicity, ensures good maneuverability of the vehicle.

Basic technical parameters of the vehicle:

- the mass of the vehicle ready to work together with the batteries is 200 kg,
- maximum working speed of 1 m s\(^{-1}\),
- two DC motors were used to drive the road wheels,
- the vehicle is capable of carrying loads of up to 100 kg.

The vehicle has a steel frame made of ready-made profiles to which all components are attached.
Drive wheels made of metal on the circumference have a vulcanised rubber rim. The wheel is attached to the hub located on the reducer axis. The drive from the motors to the reducer is transmitted by a belt and gear transmission. The self-aligning wheel has the ability to rotate about an axis perpendicular to the vehicle base.

The on-board steering system controls the movement of the vehicle along the set trajectory. This system includes: a PC on board computer, National Instruments NI PCI-6221 and NI PCI-6601 data acquisition cards, sensors and a computer program with implemented control algorithm written in C++.

The vehicle used sensors to measure distance, angular position and deviation from the direction set. The basic source of information used to determine the position and the direction of vehicle movement were the data read from the encoder – optoelectronic rotary-pulse converters from the MHK40 series from Autonics. Laser LT3 sensors from Banner were used as additional sensors.

5. Research and an analysis of results
As part of experimental tests, the vehicle performed a predetermined rectilinear trajectory along the corridor. Two types of navigation were used during the movement. As part of the first section of the route, the vehicle was run along the base reference area. During this stage, the exact position and orientation of the vehicle relative to the environment took place.

In some cases, before starting the vehicle's movement, its wheels as in figure 3b) were not set straight ahead. In this case, the task of this stage was also to set properly the wheels of the vehicle. The basic role in this stage while driving was measured data from laser rangefinders. After passing a specific distance or characteristic signs on the base surfaces, only odometry was used to further determine the position.

The accuracy of determining the position and orientation in the first stage had a significant impact on the entire route covered. In connection with the above, the article focuses only on the presentation and an analysis of the results from this first part of the research.

In the tests carried out, the vehicle moved at a speed $v$ along the corridor. During the movement, it was guided at a given distance $x_s$ from the base surface as shown in figure 4a. The corridor wall or the metal strip was assumed as the base surface. On the metal strip there were markers with adjustable spacing defining the beginning and the end of the section of the route where the vehicle was led along the wall using measurements from the laser rangefinder. Odometry was used to navigate after completing the route along the base surface. An example of the course from registered tests is shown in figure 4b. Further movement of the vehicle depends on the accuracy of determining the position of the vehicle in the final part of the first stage. Figure 4b shows that after passing the final marker, the actual trajectory does not coincide with the assumed one. This deviation is not large and is acceptable for the conditions of our research.

![Figure 4](image-url). Diagram of the measurement method: $l_z$ – length of the reference surface, $x_s$ – measured by the laser rangefinder distance from the reference surface a), an example of the course from the registered tests b).
The laser rangefinders used are characterized by high accuracy in stationary conditions. In the case of measurements made from a moving vehicle, a significant increase in the dispersion of the obtained measurement results was observed. Dispersion of results is caused by vehicle vibrations and inequality of measured reference surfaces (internal walls of the building). In order to eliminate these inconveniences, it was necessary to apply an appropriate filtration method aimed at smoothing the results. Most common at the moment is a probabilistic method based on recursive Kalman filter.

Figure 5a shows the course of the measured distance of the vehicle from the wall obtained from the laser rangefinder during the movement of the vehicle, while figure 5b shows the same course subjected to Kalman filtration.

![Figure 5](image1.png)

**Figure 5.** The route of the vehicle designated on the basis of laser rangefinder data: a) before filtration, b) after filtration.

The main problem in the measurements is the base surface – the corridor wall. This wall was never flat. During movement, these deviations introduced disturbances into the control system. This effect is visible in figure 5, where the distance from the base surface shown is the sum of vehicle motion oscillation and wall unevenness. Since the unevenness of the wall resulted in the dispersion of the obtained results in the second stage of experimental tests in order to eliminate the unevenness of the wall during the tests, the vehicle followed a special reference surface made of an aluminum slat. In two places on the strip at a given distance from each other are placed special markers with a width of 0.03 m (figure 6), which is a source of information for the measuring system at the beginning and end of the measuring section.

![Figure 6](image2.png)

**Figure 6.** Distance measurements from a special reference surface in rectilinear motion: a) unfiltered course, b) filtered course.

Figure 6 shows the course of measurements using distance markers. For a better illustration of the applied measurement method in figures 6a and 6b, on the left side a reference line is drawn where the
markers are visible. The course obtained after the application of filtration was smoothed out. However, the tags themselves were distorted. The course obtained after the application of filtration was smoothed out. However, the tags themselves were distorted. This distortion does not have the major impact on the vehicle control process.

6. Conclusion
Automated guided vehicles used in various economic processes are required to maintain adequately high accuracy in the implementation of the set route and acceptable costs of the measurement and navigational systems used. In connection with the above, there are various solutions sought to reconcile these two opposing requirements. The article presented shows a method to ensure adequate accuracy for specific working conditions. The experimental tests conducted showed the correctness of using such a navigation system assuming the use of base reference areas. The use of Kalman filtration in turn allowed limiting measurement errors, and thus more precise operation of the vehicle traffic control system along the reference base surface.

7. References
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