Low-cost positioning system for agricultural vehicles

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***Abstract* - Accurate positioning is needed for agricultural vehicles now and in the future. Position is currently needed for mapping, precision farming, auto-steering vehicles and light-bar navigation and in the future for agrorobotic solutions. Although the accuracy of GPS based positioning can be improved using differential or RTK-solutions, such application may be too highly-priced. In this paper tractor positioning with a cheap GPS-receiver is improved by using inertial navigation and odometry. Kalman filtering is used for sensor fusion. In compensation of the bias type slow error in GPS measurements the low cost additional measurements are not sufficient. However, positioning in blind areas of GPS can be done with them.**

***Index Terms* - Navigation, positioning, GPS, inertial navigation, sensor fusion, crop farming.**

I. INTRODUCTION

Accurate positioning is needed for agricultural vehicles now and in the future. Traditionally in family-size farms farmers have known their fields well due to limited area of fields and years of experience. When farmed field area increases, the farmers cannot any more manage details of soil variations. Position specific information management and automatic control support the farmer to cope with more complicated situations, this is called as precision farming or precision agriculture.

The driver of a modern agricultural vehicle has to control many simultaneous operations and subsystems, not only the driving wheel and the hitch control as previously. The driver should have enough time to monitor the system and make decisions. The demand of easy driving exists. There are some commercially available auto-steering products, where steering of the vehicle is automated in straight driving lines, known also as parallel swathing. Auto-steering improves the quality of farming, because the parallel driving lines can be driven seamlessly. This requires very accurate positioning and most manufacturers rely on RTK-GPS (Real-Time-Kinematic) or Differential GPS. For agricultural applications the disadvantage of RTK-GPS is the price, initial cost of over ten thousand euros plus operating cost when using GSM as data link.

The accuracy of a cheap GPS-receiver can be improved using supplementary measurements like odometry and attitude. Rate measurements can be integrated to position and orientation, but errors accumulate during operation. Cheap GPS position measurement is good during long periods but individual measurements are noisy. In principle it is possible to combine the good properties of both using sensor fusion, for example Kalman filtering.

In this paper a cheap GPS-receiver is used together with an inertial measurement unit and an odometer in a tractor. Sensor information is fused with Kalman filter.

This research is part of the project Agrix. In the project Agrix the main research topic is the automation system of agricultural machines. Positioning and navigation is used for precision farming and field mapping. [1]

Good results of merging inertial measurements to GPS in agricultural solutions are reported e.g. in [2],[3],[4]. In [2] a cheap DGPS-receiver is used together with low cost inertial measurement unit (IMU), and an extended Kalman filter. The resulting accuracy of position is between 0.1m and 0.5m.

II. HARDWARE

A. Tractor and implements

In the project Agrix, a commercial tractor is used. The tractor is four-wheeled, the front wheels are steerable. Th tractor is ISO 11783 (ISOBUS) -compatible, so wheel-based and ground-based velocities are available on the bus. ISO 11783 is a new standard for data communication in agricultural vehicles and used mainly for integrating the tractor and implements. [1]

The steering angle of the front wheels is measured with potentiometer integrated into the front-axle. Wheel-based velocity comes from the transmission and ground-based velocity is measured with radar installed by the manufacturer. The radar signal is used in the tractor system to control slip. It was found out that the radar-based velocity estimate has good dynamic response, but the signal contains outlier type noise.

Two different towed implements (drills) are used with the Agrix-system. The position of the functional part of the implement is interesting, not only the position of the tractor. An angle sensor was developed and installed between tractor drawhook and tow-bar.

B. GPS-receiver

The aim was to use a cheap GPS-receiver. The receiver was selected on the basis of price and EGNOS/WAAS supported Haicom HI-204E was chosen.

The accuracy of the receiver was first tested in open area and the variation of position measurement was studied when the receiver was immobile. The chosen receiver and also other one, Trimble Nav-Guide+ (used without differential correction signal) were tested. The reference position was obtained from Trimble 7400MSi RTK-GPS. The test period was 16 hours long. RTK-GPS position is supposed to be correct, and the standard deviation of RTK-position was found to be less than one centimeter. The other measurements are compared to the long time RTK-position average.

In Fig 1, the histograms of errors of both simple GPS receivers are presented for the whole period. It can be seen that the mean value of position measurement is not zero. Because of this it is not possible to remove the noise even if ultimately accurate inertial sensors are used. The common measure for the accuracy of GPS receiver is the radius of the circle which covers in 95% of measurement errors.

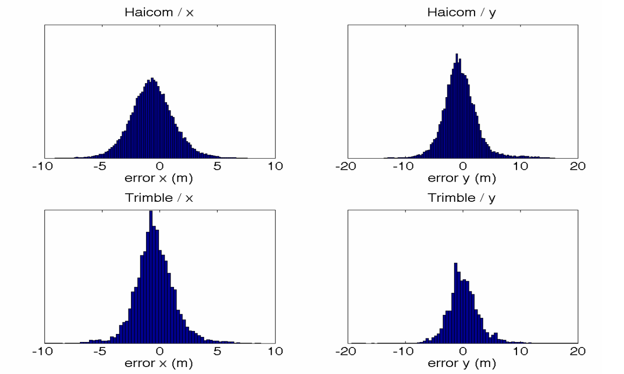

Fig. 1 Horizontal position variation of GPS-receivers

For Haicom receiver the radius was found to be 6.7 meters and for Trimble it was 6.3 meters. For RTK-GPS it was 2 centimeters.

On the basis of time-series analysis it was found that the errors of the measurements have different dynamical properties. A stationary GPS receiver was considered as a stochastic process and state space model was identified using subspace identification [5]. Third order dynamics were selected. Impulse responses of identified error dynamics for each channel are presented in Fig 2. It can be seen that Haicom receiver contains more short-time error than Trimble receiver but Trimble has bigger long-period crawling. It can be said that Haicom receiver is better for this research purpose due to the latter property. Numerical values and equations for Haicom's x-component are presented in (1)-(2), δ_x is the state vector of the noise model, w is white noise with variance 1 and Δp_x is the error in the position measurement. Error dynamics are characteristic for each receiver type, a general noise model does not exist.

$$\dot{\delta}_x(t) = \begin{bmatrix} -5.97\cdot10^{-4} & -9.35\cdot10^{-2} & 1.78\cdot10^{-2} \\ 7.89\cdot10^{-2} & -8.21\cdot10^{-2} & 2.79\cdot10^{-1} \\ 1.73\cdot10^{-3} & -8.24\cdot10^{-2} & -4.54\cdot10^{-2} \end{bmatrix} \delta_x(t) + \begin{bmatrix} 1.81\cdot10^{-3} \\ -1.74\cdot10^{-2} \\ -4.82\cdot10^{-3} \end{bmatrix} w(t) \qquad (1)$$

$$\Delta p_x(k) = \begin{bmatrix} 486 & -20 & -3.80 \end{bmatrix} \delta_x(k) \qquad (2)$$

It was found also that the cross-correlation between position measurement errors of the two receivers was insignificant.

C. *Inertial Measurement Unit (IMU)*

The aim was to use a cheap commercial IMU-sensor system. The sensor system was selected on the basis of price and Xsens Technologies MT9-B was chosen. [6]

The MT9 is a miniature inertial measurement unit providing serial digital output of 3D acceleration, 3D rate of turn (gyroscope) and 3D earth-magnetic field data (magnetometer). The IMU is attached to the ceiling of tractor.

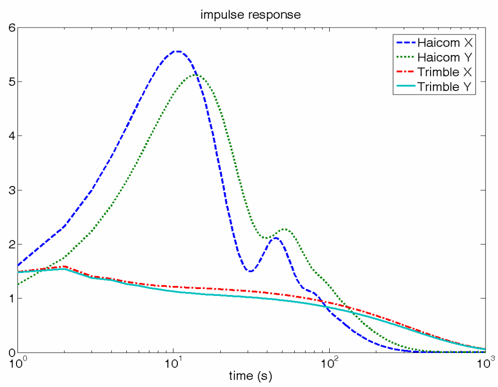

Fig. 2 Impulse responses of error noise models

IMU has an internal filter which produces orientation information and can express it in different coordinate systems. Here Euler angles are used. Orientation is calculated by integrating the signals from the gyroscopes. The accelerometers and the magnetometers provide an absolute orientation reference and are used to eliminate the drift from the integration of gyroscope data. The IMU calculates roll ϕ^i_{raw}, pitch θ^i_{raw} and yaw ψ^i_{raw} angles between IMU and global coordinate system. [6]

It was found out that all the measurements from MT9 were biased, especially the gyroscope. Also the heading angle was unusable due to local disturbances in the earth magnetic field in the tractor. Prefiltering of IMU measurements is needed.

III. CALIBRATION

A. *Magnetometers*

The earth magnetic field sensors are subject to other magnetic fields (tractor, large-capacity electric lines, etc.). As mentioned earlier, the course given by a cheap GPS-receiver is delayed, but if the receiver is moving rectilinearly, the absolute value of the course is quite good even if delayed.

In the developed calibration procedure the driver has to drive an arbitrary path with the tractor, with enough variation in the course. Thus the constant error in the magnetic field caused by the tractor may be eliminated by minimizing the error square sum (LS-method) of magnetometer based heading ω_i and GPS course data.

Calibration results of the magnetometer heading are presented in Fig 3. A two second delay in GPS course data is compensated.

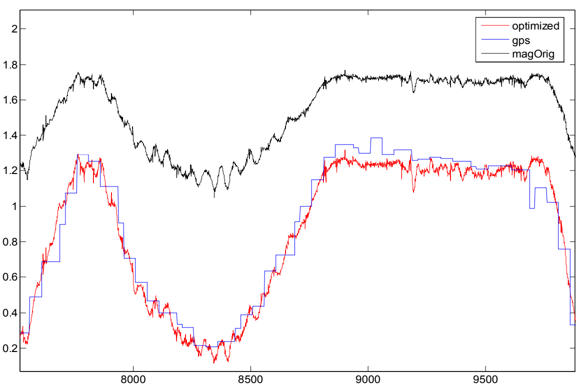

Fig. 3 Magnetometer heading calibration results

B. Orientation

It is difficult to install the IMU into cabin so that IMU coordinate system would be parallel to the tractor's coordinate system. The installation error in rotation may be compensated with a calibration procedure. Yaw-angle of IMU orientation is not used in system, so only roll- and pitch-angles are calibrated.

Two alternative calibration procedures are presented. Both of them are based on the principle that roll- and pitch-angles should be opposite valued if the tractor's course (rotation around z-axis) is changed by 180 degrees. The first procedure is that the tractor is let to be stationary for a while, roll and pitch average values are gathered and in the second phase the tractor is turned in opposite direction and a new set of measurements is collected. The second procedure relies on driving on a known structural path in opposite directions and matching pairs (same place, opposite direction) are gathered using pure GPS-data. The first procedure is less sensitive for noise but more sensitive to the displacement of the tractor and in the second those properties are opposite.

IV. Coordinate Systems

GPS receivers give the position in WGS84 system, as longitude and latitude. In navigation systems the model dynamics are more easily represented in cartesian coordinates. Here the Finnish Coordinate System YKJ projection is used. [7]

Four coordinate systems in navigation system are considered: global coordinate system, tractor coordinate system, IMU coordinate system and GPS-receiver coordinate system, as superscripts or subscripts *YKJ*, *t*, *i* and *GPS*.

Tractor coordinate system origin is located at the ground level of the tractor, under the center point of the tractor's rear axle. x-axis points to the head of the tractor, z-axis up and y-direction is determined using the right-hand-rule. IMU coordinate system origin is at the IMU, translation and rotation between tractor and IMU coordinate system depends on installation of IMU in the tractor. Coordinate system locations are presented in figure 4.

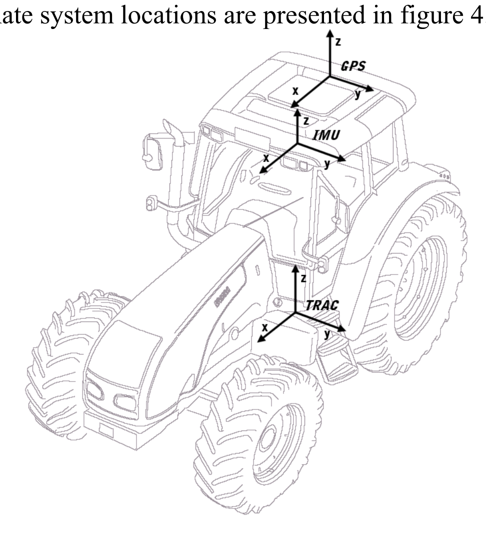

Fig. 4 Coordinate systems

Coordinate transformations are needed. Tractor position is estimated in global coordinate system so IMU and GPS measurements need to be mapped to tractor coordinate system. To move GPS-measurements from GPS coordinate system to tractor coordinate system is quite simple, since no rotation is needed and the position of GPS receiver in tractor coordinate system is known. Rotation of the IMU in tractor coordinate system is determined during the calibration phase presented in chapter III.

V. Model and Filter

A. Extended Kalman filter

A commonly used sensor fusion method is Kalman filtering. In a Kalman filter a state space model of the system is used to describe the dynamics. In one cycle an a priori estimate is predicted with the dynamic model and the measurement information is taken into account in updating the a priori estimate in to an a posteriori estimate.

Kalman filter applies only for linear models. If the dynamical model is nonlinear, the Extended Kalman filter (EKF) can be used. In EKF the model nonlinearities are simply linearized and Kalman filter applied. In this paper the first-order Extended Kalman filter is used, the symbols are equal to equations in [9]. The continuous state model is used together with discrete measurements. The continuous model is discretized using first order integration method. [7]

B. Measurement preprocessing

Measured positions and velocities are divided to its components in global coordinates. Also measured headings are rotated to global coordinates.

The radar based velocity obtained from the bus of tractor has no direction information. Radar velocity is considered to be an absolute value of velocity and the sign is assigned from wheel-based velocity measurement.

Tractor position in global coordinates is

$$\mathbf{p}_t^{YKJ} = \begin{bmatrix} p_{t_E}^{YKJ} \\ p_{t_N}^{YKJ} \\ p_{t_U}^{YKJ} \end{bmatrix} = \begin{bmatrix} p_{GPS_E}^{YKJ} \\ p_{GPS_N}^{YKJ} \\ p_{GPS_U}^{YKJ} \end{bmatrix} - {}^{YKJ}_{t}\mathbf{R}\,\mathbf{r}^{GPS}, \tag{3}$$

where $p_{GPS_{E,N,U}}^{YKJ}$ are the measured positions from GPS-receiver in cartesian coordinates.

The 2D velocity measured by the GPS is divided to its components using the following equations.

$$v_{GPS_x}^{YKJ} = \cos\psi^{YKJ}\ v_{GPS} \tag{4}$$

$$v_{GPS_y}^{YKJ} = \sin\psi^{YKJ}\ v_{GPS}, \tag{5}$$

where v_{GPS} is the measured velocity from the GPS-receiver.

Tractor radar and wheel based velocities are divided in components using (6) and (7).

$$v_{tgs}^{YKJ} = \begin{bmatrix} v_{tgs_x}^{YKJ} \\ v_{tgs_y}^{YKJ} \\ v_{tgs_z}^{YKJ} \end{bmatrix} = {}^{YKJ}_{t}R \begin{bmatrix} v_{gs}^{t} \\ 0 \\ 0 \end{bmatrix}, \tag{6}$$

where v_{tgs}^{YKJ} and v_{gs}^{t} are the tractor radar based velocity in global coordinates and the measured tractor radar based velocity.

$$v_{tws}^{YKJ} = \begin{bmatrix} v_{tws_x}^{YKJ} \\ v_{tws_y}^{YKJ} \\ v_{tws_z}^{YKJ} \end{bmatrix} = {}_{t}^{YKJ}R \cdot \begin{bmatrix} v_{ws}^{t} \\ 0 \\ 0 \end{bmatrix}, \tag{7}$$

where v_{tws}^{YKJ} and v_{ws}^{t} are the tractor wheel based velocity in global coordinates and the measured tractor wheel based velocity.

C. Input preprocessing

The angular velocities given by gyroscopes are converted from IMU coordinate system to tractor coordinate system with (8), where ${}_{i}^{YKJ}E$ is Euler angle differential equation matrix (9). [8]

$$\omega^{YKJ} = \begin{bmatrix} \omega_x^{YKJ} \\ \omega_y^{YKJ} \\ \omega_z^{YKJ} \end{bmatrix} = {}_{i}^{YKJ}E \cdot \omega_{filt}^{i}, \tag{8}$$

$${}_{i}^{YKJ}E = \begin{bmatrix} 1 & \sin\phi_{raw}^{i}\tan\theta_{raw}^{i} & \cos\phi_{raw}^{i}\tan\theta_{raw}^{i} \\ 0 & \cos\phi_{raw}^{i} & -\sin\phi_{raw}^{i} \\ 0 & \sin\phi_{raw}^{i}/\cos\theta_{raw}^{i} & \cos\phi_{raw}^{i}/\cos\theta_{raw}^{i} \end{bmatrix} \tag{9}$$

Acceleration measurement in IMU coordinate system contains also accelerations of rotational movement, tangential and normal acceleration as well as gravity. Transformation from IMU to global coordinate system is presented in (10),

$$a^{YKJ} = \begin{bmatrix} a_x^{YKJ} \\ a_y^{YKJ} \\ a_z^{YKJ} \end{bmatrix} = {}_{i}^{YKJ}R \cdot \left(a_{raw}^{i} - \dot{\Omega}_{YKJi}^{i} r^{i} - \Omega_{YKJi}^{i}\Omega_{YKJi}^{i} r^{i}\right) - \Delta a^{YKJ} \tag{10}$$

where ${}_{i}^{YKJ}R$ is standard rotation matrix, $\dot{\Omega}_{YKJi}^{i}$ is angular acceleration and Ω_{YKJi}^{i} is angular rate both in matrix form of cross product. $\dot{\Omega}_{YKJi}^{i} r^{i}$ is angular acceleration, $\Omega_{YKJi}^{i}\Omega_{YKJi}^{i} r^{i}$ is centrifugal acceleration. The angular accelerations are numerically differentiated from gyroscope measurements. [9], [10]

D. GPS-position measurement colored noise estimation

Dynamics of GPS-receiver position error were identified in chapter II, which describes colored noise. Kalman filter requires error noise to be white. The identified model can be used in filter to whiten position error. Separate models for x- and y-components are used. Noise covariance matrix is acquired from subspace identification, these are put to Q-matrix.

E. The model

The dynamic model for the tractor is presented in eq. (11)-(15). The dynamic function is continuous and it is discretized using Euler integration method (16).

$$\boldsymbol{x} = \begin{bmatrix} p_x^{YKJ} & p_y^{YKJ} & p_z^{YKJ} & v_x^{YKJ} & v_y^{YKJ} & v_z^{YKJ} & \psi^{YKJ} & \delta_x & \delta_y \end{bmatrix}^T \tag{11}$$

$$\boldsymbol{u} = \begin{bmatrix} a_x^{YKJ} & a_y^{YKJ} & a_z^{YKJ} & \omega_z^{YKJ} \end{bmatrix}^T \tag{12}$$

$$\boldsymbol{z} = \begin{bmatrix} p_{t_E}^{YKJ} & p_{t_N}^{YKJ} & p_{t_U}^{YKJ} & v_{GPS_x}^{YKJ} & v_{GPS_y}^{YKJ} \\ v_{tgs_x}^{YKJ} & v_{tgs_y}^{YKJ} & v_{tgs_z}^{YKJ} & v_{tws_x}^{YKJ} & v_{tws_y}^{YKJ} & v_{tws_z}^{YKJ} \\ \psi_{GPS}^{YKJ} & \psi_{mag}^{YKJ} & \psi_{GPS}^{YKJ} & \psi_{mag}^{YKJ} \end{bmatrix}^T \tag{13}$$

$$\dot{\boldsymbol{x}} = f(\boldsymbol{x}, \boldsymbol{u}) = \begin{bmatrix} x_4 & x_5 & x_6 & u_1 & u_2 & u_3 & u_4 & \dot{\delta}_x & \dot{\delta}_y \end{bmatrix}^T \tag{14}$$

$$\begin{aligned} \hat{z}(k+1|k) &= h\left[k+1, \hat{\boldsymbol{x}}(k+1|k)\right]... \\ &= \begin{bmatrix} \hat{x}_1 + \Delta p_x & \hat{x}_2 + \Delta p_y & \hat{x}_3 & \hat{x}_4 & \hat{x}_5 ... \\ \hat{x}_4 & \hat{x}_5 & \hat{x}_6 & \hat{x}_4 & \hat{x}_5 ... \\ \hat{x}_6 & \hat{x}_7 & \hat{x}_7 & \arctan(\frac{\hat{x}_5}{\hat{x}_4}) & \arctan(\frac{\hat{x}_5}{\hat{x}_4}) \end{bmatrix}^T \end{aligned} \tag{15}$$

$$\hat{\boldsymbol{x}}(k+1|k) = \hat{\boldsymbol{x}}(k|k) + \Delta t * f(\boldsymbol{x}(k), \boldsymbol{u}(k)) \tag{16}$$

In the measurement vector (13) the subscript refers to real measurement used to calculate the residual.

The state noise covariance matrix (Q) and measurement noise covariance matrix (R) are both diagonal. The element values in matrix R are determined from measurements and Q is tuned by hand. In matrix R, the covariance of GPS-based measurements is increased when the measurement is not fresh. The values used in tests are presented in tables I and II.

VI. Test Results

In field tests the RTK-GPS was used as reference. The radius of circle which covers in 95% of measurement errors was used to measure the precision. Because of the fact that GPS has always non-zero bias in position, the filter system (below called EKF) position error is also compared to the relative path. The relative path is generated by smoothing the error between RTK-GPS and Haicom GPS with gaussian filter and the smoothed error is added to the RTK-GPS path. To measure how much better the filter system positioning accuracy is, the 95% circle areas are compared.

TABLE I
Q, DIAGONAL STATE NOISE COVARIANCE MATRIX, ELEMENTS

Element	Symbol	Value
$q_{1,1}$	$(\sigma p_x^{YKJ})^2$	$(0.3m)^2$
$q_{2,2}$	$(\sigma p_y^{YKJ})^2$	$(0.3m)^2$
$q_{3,3}$	$(\sigma p_z^{YKJ})^2$	$(0.05m)^2$
$q_{4,4}$	$(\sigma v_x^{YKJ})^2$	$(0.03 m/s)^2$
$q_{5,5}$	$(\sigma v_y^{YKJ})^2$	$(0.03 m/s)^2$
$q_{6,6}$	$(\sigma v_z^{YKJ})^2$	$(0.01 m/s)^2$
$q_{7,7}$	$(\sigma \psi^{YKJ})^2$	$(0.017 rad)^2$

TABLE II
R, DIAGONAL MEASUREMENT NOISE COVARIANCE MATRIX, ELEMENTS

Element	Symbol	Value
$r_{1,1}$	$\left(\sigma p_{t_E}^{YKJ}\right)^2$	$\left(HDOP*1m\right)^2$
$r_{2,2}$	$\left(\sigma p_{t_N}^{YKJ}\right)^2$	$\left(HDOP*1m\right)^2$
$r_{3,3}$	$\left(\sigma p_{t_U}^{YKJ}\right)^2$	$\left(VDOP*15m\right)^2$
$r_{4,4}$	$\left(\sigma v_{GPS_x}^{YKJ}\right)^2$	$\left(1\, {}^{m}\!/_{s}\right)^2$
$r_{5,5}$	$\left(\sigma v_{GPS_y}^{YKJ}\right)^2$	$\left(1\, {}^{m}\!/_{s}\right)^2$
$r_{6,6}$	$\left(\sigma v_{tgs_x}^{YKJ}\right)^2$	$\left(0.5\, {}^{m}\!/_{s}\right)^2$
$r_{7,7}$	$\left(\sigma v_{tgs_y}^{YKJ}\right)^2$	$\left(0.5\, {}^{m}\!/_{s}\right)^2$
$r_{8,8}$	$\left(\sigma v_{tgs_z}^{YKJ}\right)^2$	$\left(0.5\, {}^{m}\!/_{s}\right)^2$
$r_{9,9}$	$\left(\sigma v_{tws_x}^{YKJ}\right)^2$	$\left(0.25\, {}^{m}\!/_{s}\right)^2$
$r_{10,10}$	$\left(\sigma v_{tws_y}^{YKJ}\right)^2$	$\left(0.25\, {}^{m}\!/_{s}\right)^2$
$r_{11,11}$	$\left(\sigma v_{tws_z}^{YKJ}\right)^2$	$\left(0.25\, {}^{m}\!/_{s}\right)^2$
$r_{12,12}$	$\left(\sigma \psi_{GPS}^{YKJ}\right)^2$	$\left(2\deg\right)^2$
$r_{13,13}$	$\left(\sigma \psi_{mag}^{YKJ}\right)^2$	$\left(7\deg\right)^2$
$r_{14,14}$	$\left(\sigma \psi_{GPS}^{YKJ}\right)^2$	$\left(2\deg\right)^2$
$r_{15,15}$	$\left(\sigma \psi_{mag}^{YKJ}\right)^2$	$\left(7\deg\right)^2$

Different type driving situations were made, two parallel drive types, one field around drive, one random drive and one road drive. The improvement of positioning precision in different situations are presented in table III.

TABLE III
PRECISION IMPROVEMENT IN PERCENTS

Test type	Absolute (%)	Relative (%)
Parallel I	-0.3	50.7
Parallel II	63.6	53.5
Around field	51.7	73.7
Random	66.2	75.7
Road test	15.8	47.4

One of test drive situations is presented in Fig 6. It can be seen that Haicom GPS receiver position is far from the real position, so is position of EKF. But it can be seen that the shape of EKF position is similar than RTK-GPS, only the position is different. Thus relative accuracy is good, but absolute bad. EKF position is much better for parallel-swathing applications than pure GPS.

In Fig 7 and 8 the estimates of velocity and heading estimation are presented. Both estimates are good, mainly due to multiple measurements. This applies to all tests, good velocity and heading estimates are required in order to estimate position during GPS in shadow.

As well known, the altitude measurement of a cheap GPS receiver is far from real, both the variation and the average value are bad. However EKF can improve the relative accuracy of altitude as seen in Fig 9. The shape is similar to RTK-GPS after convergence of filter estimates. Estimation of altitude is not studied as much as horizontal position because it is not so important in agricultural applications. Good altitude estimation would need also an error model. The deviances of error distances are presented in figure 10, error deviation is decreased considerably, this characterizes the accuracy similarly as the values in table III.

One of the main benefits of sensor fusion with GPS is the ability of the filter to estimate the position even if GPS receiver signal is lost due to temporary shadow region. The loss of GPS was simulated with the filter. An example of such situation is presented in Fig 11. In this example all GPS signals were lost for 60 seconds. The filter can keep the position in track.

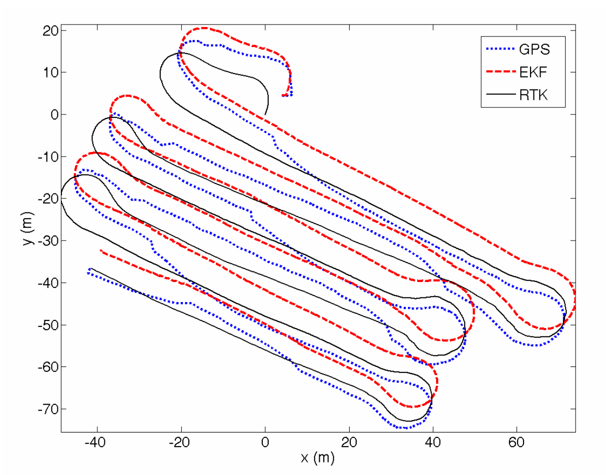

Fig. 6 The drive path in Parallel II

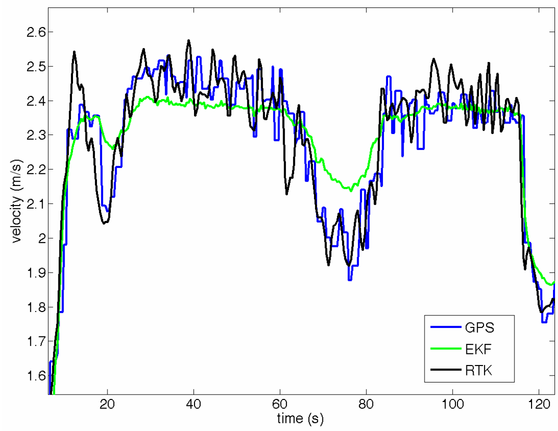

Fig. 7 Example of velocity estimation in Parallel II

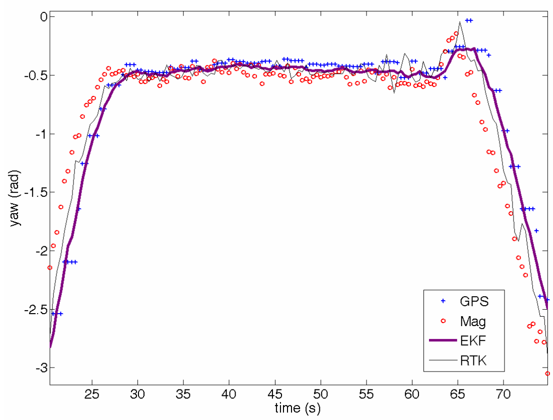

Fig. 8 Example of test drive heading

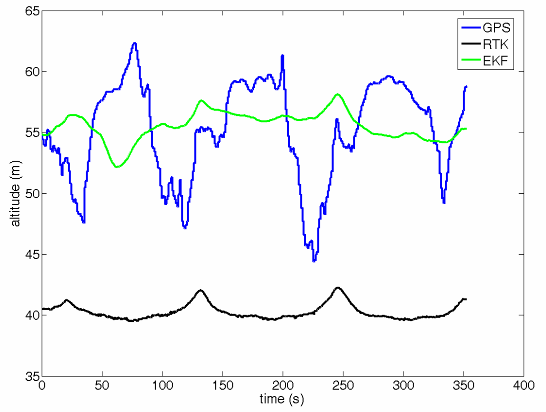

Fig. 9 Example of test drive altitude

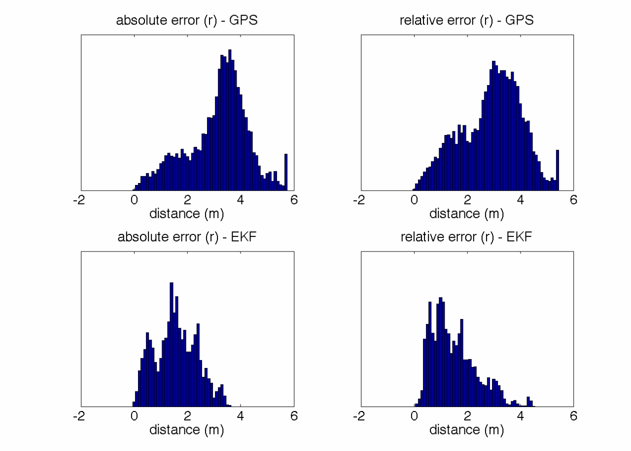

Fig. 10 Deviance of position errors

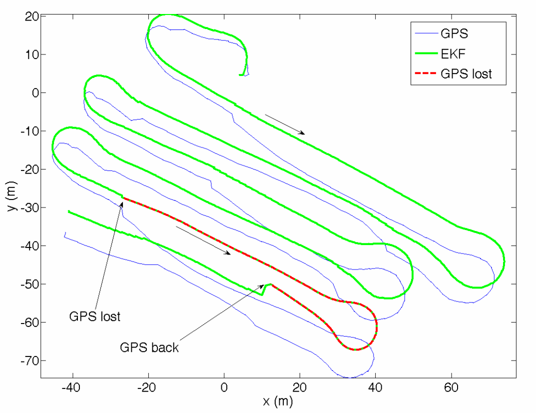

Fig. 11 Simulation of GPS signal lost for one minute

VII. CONCLUSION

It was found out that the position measurements of simple GPS receivers are biased, i.e. the long time average of the error is nonzero. It is not possible to improve absolute position accuracy much even if local, relative measurements were precise, since the only absolute position measurement is GPS. It was found out that the crosscorrelation of measurement error of two different GPS-receivers is insignificant. If the measurement errors do not correlate the position estimate could be improved using multiple GPS-receivers.

Combining inertial measurements to GPS position was tried. A first order extended Kalman filter was used in sensor fusion. The current model does not use odometry, it will be combined in the future.

It was found out that it was possible to eliminate short time noise type error in position, but long time bias type error is impossible to eliminate.

It was possible to improve the relative position accuracy considerably, but improving absolute position accuracy depends on the situation. Relative accuracy is enough for auto-steering and parallel swathing purposes, constant bias in horizontal position does not matter. Relative altitude measurement of GPS was improved considerably, absolute altitude measurement is difficult to improve due to constant error in simple GPS receiver measurement.

With the system developed it was possible to keep the position estimate quite good even if GPS position signal was lost for short time.

GPS position error model was used to whiten the noise. This improved estimation considerably compared to non-whitened estimation. Estimation of position and its error was found to be difficult because only one absolute position measurement was used. Therefore another cheap GPS-receiver will be added to system in the future. Also measurement bias estimation will be added in the future.

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