GPS NAVIGATION FOR PRECISION FARMING

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ABSTRACT:

Precision farming, sometimes called site-specific agriculture, is a strategic task for agriculture: indeed it has the potential to reduce costs through more efficient and effective applications of crop inputs; it can also reduce environmental impacts by allowing farmers to apply inputs only where they are needed at the appropriate rate. Precision farming requires the use of new technologies, such as GPS, environmental sensors, satellites or aerial images and GIS to asses and understand variations.
The present research deals with potentialities and limits of GPS for navigation in agricultural applications. GPS needs for farming applications are:

- low cost in order to allow farmers to buy GPS technologies;
- high precision in order to reduce the use of pesticides and fertilizers by means of an exact track.

At first, static and kinematic tests have been performed, simulating the typical behaviour of an agricultural vehicle and using different kinds of GPS receivers and navigation softwares; the experimental results are presented: particularly, advantages and disadvantages of the popular Kalman filtering on trajectories are discussed. Starting from the analyses of the previous results, and taking into account the typical user requirements, a preliminary design for a new prototype has been done; particularly, both needed instrumentations and their costs and a proposal of a new navigation algorithm will be presented.

1. INTRODUCTION

Precision farming is a method of crop management by which areas of land within a field may be managed with different levels of input depending upon the yield potential of the crop in that particular area of land. The benefits of so doing are two fold:

- the cost of producing the crop in that area can be reduced;
- the risk of environmental pollution from agrochemicals applied at levels greater than those required by the crop can be reduced.

Precision farming is an integrated agricultural management system incorporating several technologies. The technological tools often include the global positioning system GPS, geographical information system GIS, remote sensing, yield monitor and variable rate technology.
The paper talks about the use of GPS to support agricultural vehicle guidance. Equipment for this purpose consists on a yield monitor installed: the system supports human guide by means of a display mapping with a GIS the exact direction produced by GPS receiver put on vehicle top: the driver follows it to cover in an optimal path the full field.
GPS receivers for this applications require, not only an high accuracy to ensure the reduction of input products, but even an easy and immediate way of use for farmers; without forgetting low costs.
Obviously the technology to achieve high precision still exists but it is too expensive and difficult to use for not skilled people. Survey modality usually adopted in agricultural applications is real time kinematic positioning, DGPS RTK, which enable to have a good accuracy by means of corrections received. In this experimentation the aim is to obtain a sub-metric accuracy using low cost receivers, which can provide only point positioning. These receivers have been developed for maritime navigation purposes; our aim is their optimization in order to apply them for land navigation in particular for farming activities. Some tests using these receivers were carried out, but results were not satisfying and probably the reason has to be assigned to the implementation of a Kalman filtering inside the receiver software. This is the starting point for a new project, at the moment still in progress, which aim to develop a new algorithm based on Kalman filter. Its purpose is to improve low cost receiver outputs in order to optimize trajectories and to reach needed accuracy in vehicle positioning during agricultural activities.

2. TRIAL AND ERROR

2.1 Instruments and tests

Experimentation has been carried out using Leica Geosystems instruments; in particular the low cost receiver discussed in the paper is the TruRover Leica. Its mainly features are: it is an antenna-receiver integrated instrument, it has a 5 Hz tracking time, the report is in the NMEA string format, it cannot neither store positions nor show them in real time, it requires a computer to view NMEA data stream. TruRover performances were compared with geodetic receiver one, which are considerably better, so they are the perfect comparison condition to estimate Trurover positioning quality.
Geodetic receiver used is the GX1230 Leica, able to receive double frequency (both code and phase).

Both static and kinematic tests were performed, simulating the typical behaviour of an agricultural vehicle (straight and parallel trajectories with reduced velocity, such as 20÷40 km/h) and using, at the same time, the two different kinds of GPS receivers described above. At the top of the vehicle, both TruRover and geodetic antenna, connected to the receiver, were placed at a distance of 50 cm. Three static stops with 20 minutes time length were performed, spaced with two steps in motion. Geodetic receiver were set with a 1 second tracking time and a cut off angle of 10 degree. Tests length were about two hours.
Another geodetic receiver were placed for a single point positioning and used as the Master station for the following data processing.

2.2 Data processing

Master station coordinates were determined by means of a static processing in relation to two different GPS permanent station in order to check result: one placed in Modena, where tests have been carried out, led by INGV and the other located near Bologna, led by ASI Telespazio.
TruRover NMEA data already contain coordinates and Visual GPS software has been utilized to show and store them. These positions have been compared to data stored by double frequency receiver during kinematic tests. These data were utilized to estimate the exact trajectory, which was estimated by the postprocessing in kinematic differential modality. Software for data processing was Leica Geo Office. To be honest this trajectory is not exact because even kinematic postprocessing data have some errors; however this modality has a centimetric accuracy, better than the required from agricultural applications one so it is not a mistake to consider this track as an exact one.
TruRover track and the exact one are not yet comparable because 50 cm shift still exists: a kind of overlap has been done by means of setting vehicle motion direction thanks to postprocessed trajectory.

2.3 Results analysis

The results of the comparison between TruRover track and double frequency receiver one are not satisfying; indeed receivers utilized in experiments show some problems in curves, where the estimated track is larger than the exact one. This bad performance may be due to the presence of a Kalman filter inside the system, that is not optimized for the specific application. Probably at each epoch this filter uses previous estimated positions in order to anticipate the future one on a constant velocity, linear trajectory assumption. In that way when vehicle curves the filter understand it as a mistake and modify the position; this behaviour causes a delay in curving and consequently a shift in positioning. Figure 1 shows this orderly problem on curve.
Higher precision for agricultural applications is not required in curves but in straight directions, where farmers make their main activities on yield. However curves have a great importance mainly at their end because there it is necessary for the vehicle trajectory to be parallel to the previous one. The main reason for that is to economize input products spread about field. Kinematic trajectory is considered the exact one, the reference for a comparison between pseudo-range and kinematic tracks. The results show distances greater than 1 meter (the target aimed) but always inside the method precision (10 meters). Statistical parameters, as means and standard deviations, confirm the same things. Table 2 and 3 relate these statistical valuers. At the beginning the idea was that Kalman filter needs a period of assessment time to work better; on the contrary, with the elapsed time the differences increase with a worrying time drift.

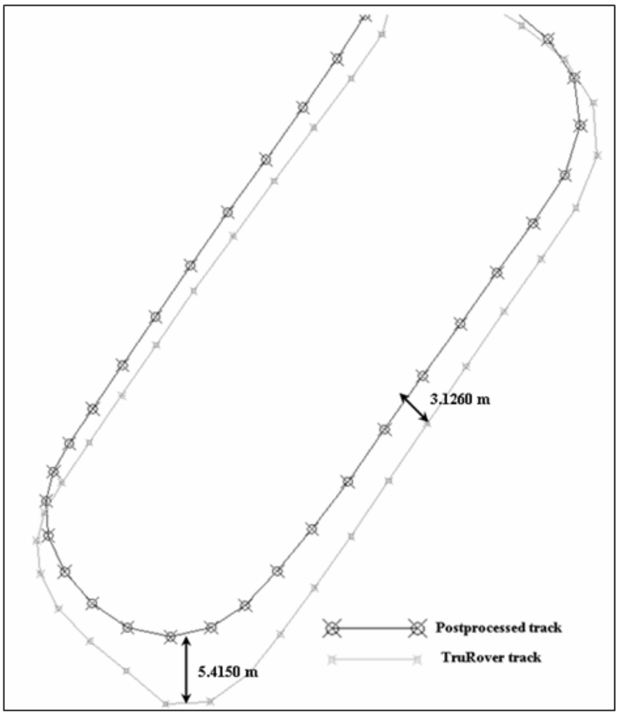

Figure 1. Shift between postprocessed track and TruRover track.

Statistical parameters	First track	Second track
	[m]	[m]
$\sigma_{\Delta E}$	0.7816	0.7555
$\sigma_{\Delta N}$	1.1183	1.2799
Mean ΔE	0.169	-0.175
Mean ΔN	1.948	1.573
Max distance	5.733	7.742
Min distance	0.091	0.080

Table 2. Statistical parameters, means and standard deviations, in kinematic paths..

Statistical parameters	First stop	Second stop	Third stop
	[m]	[m]	[m]
$\sigma_{\Delta E}$	0.4743	0.3018	0.3163
$\sigma_{\Delta N}$	0.7210	0.5001	0.3907
Mean ΔE	0.221	-0.725	-0.848
Mean ΔN	0.534	2.081	1.086
Max distance	2.022	3.184	2.138
Min distance	0.007	1.262	0.476

Table 3. Statistical parameters, means and standard deviations, in static stops.

3. DEVELOPMENT OF A NEW ALGORITHM BASED ON KALMAN FILTERING

The reason for problems in curve is probably the presence of a Kalman filtering inside TruRover, not especially studied for farming applications. Thereof the need of trying a kind of

TruRover performances improvement pursued by means of the development and the implementation of a new algorithm based on Kalman filtering and, at the same time, optimized for agricultural requirements.
The first problem was the choice of the process modelling to put in Kalman equations. In particular two trials have been done and described in the following: the constant velocity model and the constant acceleration model. Before the models description, it will be shortly illustrated Kalman filter principles.

3.1 Kalman filter algorithm

The Kalman prediction, provided by the following algebraic computations, is a statistically optimal predictor of the process ξ. This specific filter consists of two sets of equations:

- the prediction, sometimes called equations of time update

$$\begin{aligned} \hat{x}_{k+1} &= \Phi x_k \\ C_{\hat{x}_{k+1}} &= \Phi C_{x_k} \Phi^T + C_{ww} \end{aligned} \quad (1)$$

- the filtering, sometimes called equations of measurement update

$$\begin{aligned} G_{k+1} &= C_{\hat{x}_{k+1}} A^T (A C_{\hat{x}_{k+1}} A^T + C_{nn}) \\ x_{k+1} &= \hat{x}_{k+1} + G(z_{k+1} - A\hat{x}_{k+1}) \\ C_{x_{k+1}} &= (I - GA) C_{\hat{x}_{k+1}} \end{aligned} \quad (2)$$

Each set of equations is defined in terms of the state vector x, its covariance matrix C_{xx}, transition matrix Φ, covariance matrix of the system noise C_{ww}, covariance matrix of the observations noise C_{nn} and G represents the Kalman gain.

3.2 The constant velocity model

Let $\varphi(t)$, $\lambda(t)$, $h(t)$ be the vehicle position vector and $v_\varphi(t)$, $v_\lambda(t)$, $v_h(t)$ its velocity vector at the same epoch in the north, east and up direction. Data are provided from GPS receiver so we consider a constant tracking Δt, but what we will describe can be generalized using variable time lengths.
The following time propagation law (constant velocity model) is assumed:

$$\begin{bmatrix} \varphi_{k+1} \\ \lambda_{k+1} \\ h_{k+1} \\ v_{\varphi_{k+1}} \\ v_{\lambda_{k+1}} \\ v_{h_{k+1}} \end{bmatrix} = \begin{bmatrix} 1 & 0 & 0 & \Delta t & 0 & 0 \\ 0 & 1 & 0 & 0 & \Delta t & 0 \\ 0 & 0 & 1 & 0 & 0 & \Delta t \\ 0 & 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} \varphi_k \\ \lambda_k \\ h_k \\ v_{\varphi_k} \\ v_{\lambda_k} \\ v_{h_k} \end{bmatrix} + \begin{bmatrix} w_\varphi \\ w_\lambda \\ w_h \\ w_{v_\varphi} \\ w_{v_\lambda} \\ w_{v_h} \end{bmatrix} \quad (3)$$

With a compact notation the time propagation law can be written as:

$$\xi_{k+1=} \begin{bmatrix} x_{k+1} \\ v_{k+1} \end{bmatrix} = \begin{bmatrix} I & \Delta T \\ 0 & I \end{bmatrix} \begin{bmatrix} x_k \\ v_k \end{bmatrix} = \Phi_{k+1,k} \xi_k + w_{k+1.k} \quad (4)$$

Single epoch observation equation:

$$\begin{bmatrix} \varphi_{k+1} \\ \lambda_{k+1} \\ h_{k+1} \end{bmatrix}_{OBS} = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 & 0 \end{bmatrix} \begin{bmatrix} \varphi_{k+1} \\ \lambda_{k+1} \\ h_{k+1} \\ v_{\varphi_{k+1}} \\ v_{\lambda_{k+1}} \\ v_{h_{k+1}} \end{bmatrix} + \begin{bmatrix} n_\varphi \\ n_\lambda \\ n_h \end{bmatrix} \quad (5)$$

In a compact notation:

$$x_{O,k+1} = \begin{bmatrix} I & 0 \end{bmatrix} \begin{bmatrix} x_{k+1} \\ v_{k+1} \end{bmatrix} = A\xi_{k+1} + n_{k+1} \quad (6)$$

Where n_{k+1} is the observation error, for which the classical zero mean and normal distribution hypotheses ($\mathbf{n}_{k+1} \approx \mathcal{N}[0, \mathbf{C}_{\mathbf{nn},k+1}]$) hold. As described before, observation vectors are only defined by the three position coordinates, no velocity measurements are provided.
The starting epoch ($t=0$) is considered the last one before vehicle moving. Initialization at that time is provided as follows:

$$\xi_0 = \begin{bmatrix} x_0 \\ 0 \end{bmatrix}, x_0 = \frac{1}{N} \sum_{i=-N,-1} x_{O,i} \quad (7)$$

To be more precise, the position at the beginning of the movement is calculated as a mean of coordinates tracked during the single point positioning, supposed previous to motion. Starting epoch covariance matrix is:

$$C_{\xi\xi,0} = \begin{bmatrix} C_{nn,0} & 0 \\ 0 & 0 \end{bmatrix} \quad (8)$$

$$C_{nn,0} = \frac{1}{N^2} \sum_{i=-N,-1} C_{nn,i} \quad (9)$$

where measurement noise at a single tracking epoch is so adopted:

$$C_{nn,i} = \sigma_0^2 \begin{bmatrix} HDOP_i & 0 & 0 \\ 0 & HDOP_i & 0 \\ 0 & 0 & c^2 VDOP_i \end{bmatrix} \qquad (10)$$

C_{nn} is the measurement covariance matrix and it is related to satellite constellation, for this reason main diagonal is defined using DOPs parameters. They are variable in each epochs, despite that first algorithm tests have been made using constant values for HDOP and VDOP. VDOP is amplified with a constant c taking into account that vertical measurements are worse than planimetric one. The assumption on constant parameters are: $c=2$ and $\sigma_0=1m^2$.

Covariance matrix of the system noise C_{ww} represents the error we commit considering a particular model rather than another one. In this case, the error considering the constant velocity model results from the propagation of the state vector covariance using transformation matrix. The final C_{ww} form is:

$$C_{ww_{k+1,k}} = \sigma_v^2 \begin{bmatrix} \Delta T^2 & \Delta T \\ \Delta T & 0 \end{bmatrix} \qquad (11)$$

where $\sigma_v^2 = 0.5\ m/s$.

3.3 The constant acceleration model

The constant acceleration case can be modelled by including accelerations in north, east and up direction in the state vector, $a_\varphi(t)$, $a_\lambda(t)$, $a_h(t)$. The other components are the same: $\varphi(t)$, $\lambda(t)$, $h(t)$ represents the vehicle position vector and $v_\varphi(t)$, $v_\lambda(t)$, $v_h(t)$ its velocity vector at the same epoch. The following time propagation law (constant acceleration model) is assumed:

$$\begin{bmatrix} \varphi_{k+1} \\ \lambda_{k+1} \\ h_{k+1} \\ v_{\varphi_{k+1}} \\ v_{\lambda_{k+1}} \\ v_{h_{k+1}} \\ a_{\varphi_{k+1}} \\ a_{\lambda_{k+1}} \\ a_{h_{k+1}} \end{bmatrix} = \begin{bmatrix} 1 & 0 & 0 & \Delta t & 0 & 0 & \Delta t^2/2 & 0 & 0 \\ 0 & 1 & 0 & 0 & \Delta t & 0 & 0 & \Delta t^2/2 & 0 \\ 0 & 0 & 1 & 0 & 0 & \Delta t & 0 & 0 & \Delta t^2/2 \\ 0 & 0 & 0 & 1 & 0 & 0 & \Delta t & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 & 0 & 0 & \Delta t & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & \Delta t \\ 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} \varphi_k \\ \lambda_k \\ h_k \\ v_{\varphi_k} \\ v_{\lambda_k} \\ v_{h_k} \\ a_{\varphi_k} \\ a_{\lambda_k} \\ a_{h_k} \end{bmatrix} + \begin{bmatrix} w_\varphi \\ w_\lambda \\ w_h \\ w_{v_\varphi} \\ w_{v_\lambda} \\ w_{v_h} \\ w_{a_\varphi} \\ w_{a_\lambda} \\ w_{a_h} \end{bmatrix} \qquad (12)$$

With a compact notation the time propagation law can be written as:

$$\xi_{k+1} = \begin{bmatrix} x_{k+1} \\ v_{k+1} \\ a_{k+1} \end{bmatrix} = \begin{bmatrix} I & \Delta T & \Delta T^2/2 \\ 0 & I & \Delta T \\ 0 & 0 & I \end{bmatrix} \begin{bmatrix} x_k \\ v_k \\ a_k \end{bmatrix} = \Phi_{k+1,k}\xi_k + w_{k+1,k} \qquad (13)$$

Single epoch observation equation is the same showed for constant velocity model with the acceleration terms in addition to the state vector; the compact notation is the following:

$$x_{O,k+1} = \begin{bmatrix} I & 0 & 0 \end{bmatrix} \begin{bmatrix} x_{k+1} \\ v_{k+1} \\ a_{k+1} \end{bmatrix} = A\,\xi_{k+1} + n_{k+1} \qquad (14)$$

What have been said about measurement noise and initialization at the previous section (3.2) is still right.

Covariance matrix related to the process C_{ww} is a little bit different but it is always obtained thanks to the state propagation. The results is as follows:

$$C_{ww_{k+1,k}} = \sigma_a^2 \begin{bmatrix} \Delta T^4/4 & \Delta T^3/2 & \Delta T^2/2 \\ \Delta T^3/2 & \Delta T^2 & \Delta T \\ \Delta T^2/2 & \Delta T & I \end{bmatrix} \qquad (15)$$

where $\sigma_a^2 = 0.5\ m/s$.

4. CONCLUSIONS

The above described problems are a great problem for precision farming because bad tracks in the field cause wastes of material, without considering economical and environmental impacts. So that, starting from the analyses of the previous results and taking into account the typical user requirements, a preliminary design for the new algorithm based on Kalman filtering has been done. The idea underlying the new navigation system is to implement a simplified version of the so called adaptive Kalman filtering; the filter takes into account both the typical behaviour of an agricultural vehicle and the a priori knowledge of the planned track and works continuously testing alternate hypotheses in predicting the track. The new Kalman algorithm should both eliminate drifts in curves and occasional spikes in satellite configuration changes. This research project is still in progress; at the moment we have implemented the new algorithm which consists on a double filtering using the constant velocity model in straight trajectories and the constant acceleration model for curve tracks. First results are presented in appendix. Problems during algorithm testing were mainly the lack of raw data, in fact TruRover NMEA reports are still filtered and there is not the possibility to remove the previous filter implemented inside the receiver and it is not mathematically correct utilizing them for another filtering. For this reason data inputs for new algorithm have been provided from double frequency receiver without post-processing (raw data really as they have been stored). Results confirm the importance to adopt a model based on acceleration in curve, but at the same time it is necessary looking at these results in a critical way because they are outputs originated from inputs better than Trurover data. In the tests the attention will be mainly focused on variables which have a great importance in the model and parameters choice, such as process covariance and measurement noise. Next steps will be two-fold:

- trying to vary covariance weighs both in system noise matrix and in measurement noise matrix;
- test double filtering with raw data not yet filtered and tracked by a low cost and single frequency receiver, showing located spikes.

The purpose to improve TruRover performances and to optimize them for precision farming is challenging, especially having at our disposal only raw data. Other possible solutions are:

- connecting an odometer and a steering wheel to the system, integrated with the GPS receiver, which supports human vehicle guide. It could be the input to choose, at the right time, the best process model to adopt inside Kalman filter (constant velocity or constant acceleration model).
- utilizing differential positioning, DGPS, improving coordinates thanks to corrections received from a Master station close to the field.

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7. APPENDIX

In this section first results of the new algorithm implementation are presented. As explained before, it is a double filtering, based on Kalman prediction, which utilizes both constant velocity model and constant acceleration model. The acceleration addition term is very important in curves (just the most problematic areas); to confirm that, we show the different comparison between input data and outputs obtained with constant velocity model in one case and constant acceleration model in the other.

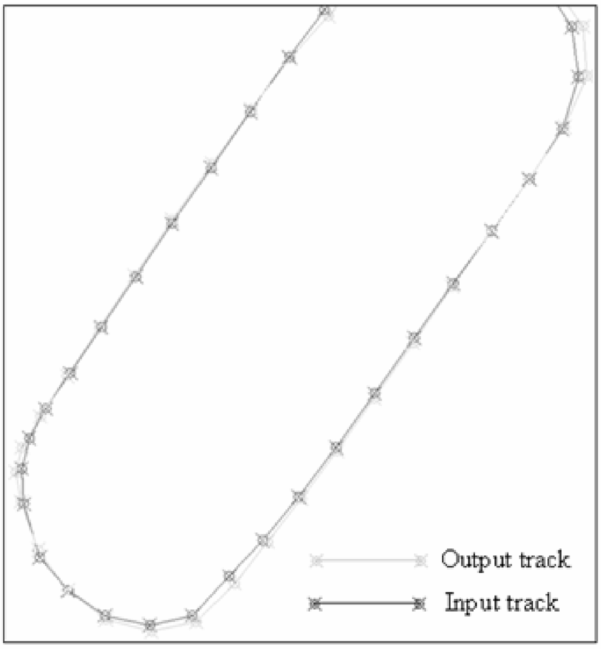

Figure 4. New algorithm implemented: input data compared with constant acceleration model output.

It is clear how the two trajectories, input and output, are quite overlapped adopting a constant acceleration model in curves.
Figure 5 shows how a certain shift persists adopting a constant velocity model even in curves where there are the great problems of distance between tracks. So the choice to implement a differentiate filtering seems to provide good results.

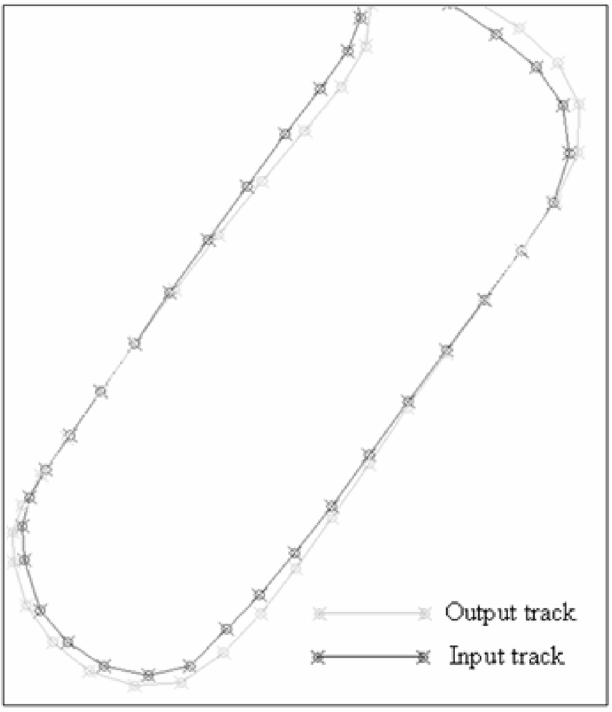

Figure 5. New algorithm implemented: input data compared with constant velocity model output.