Extended Information Filtering and nonlinear control for cooperating robot harvesters

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***Abstract*—A method for autonomous navigation of agricultural robots under a master-slave scheme is developed. The method uses: (i) a nonlinear controller that makes the robots track with precision the desirable trajectories, (ii) a distributed filtering scheme (Extended Information Filter) for estimating the motion characteristics of the vehicles through the fusion of measurements coming from on-board sensors, as well as measurements about the vehicles' coordinates coming from multiple position sensors (e.g. multiple GPS devices). The autonomous navigation of the cooperating agricultural robots is finally implemented through state estimation-based control. The nonlinear controller uses the estimated state vector of the robots, as provided by an Extended Information Filter. In this manner, the control signal that defines the robots speed and heading angle is generated.**

I. Introduction

There are many types of field operations that are performed by cooperating tractors. The need for collaborating farming robots that will be able to carry out complicated tasks under synchronization and within desirable precision levels is anticipated to grow in the following years [1]. In several applications a master-slave scheme is required for the robots coordination, which means that a master tractor generates a reference path and the motion characteristics (velocity, acceleration, orientation) that the slave tractor has to follow. When harvesting hay on grassland, it is customary for one dump truck and one tractor with a hayfork to be used. When harvesting corn, a combination of one harvester and one tractor with trailer is generally adopted. Therefore, a master-slave system, which uses two vehicles, can be very useful in actual field operations.

In this paper, a method for autonomous navigation of agricultural robots under a master-slave scheme is developed. The method comprises the following elements: (i) a nonlinear controller that makes the robots track with precision the desirable trajectories, (ii) a distributed filtering scheme (Extended Information Filter) for estimating the motion characteristics of the vehicles through the fusion of measurements coming from on-board sensors, as well as measurements about the vehicles' coordinates coming from multiple position sensors (e.g. multiple GPS devices). The integrated navigation system for the agricultural vehicles also includes a path planner for generating automatically the trajectory that has to be followed by the cooperating agricultural robots, The autonomous navigation of the cooperating agricultural robots is finally implemented through state estimation-based control where the nonlinear controller uses the estimated state vector of the robots, as provided by distributed filtering, so as to generate the control signal that defines the robots speed and heading angle (see Fig. 1).

The proposed robotic system performs distributed information processing for estimating the position and motion characteristics of the vehicles. At a first stage, measurements from on board sensors are combined with measurements from multiple position sensors (e.g. GPS devices) and are initially processed by local filters to provide local state vector estimates. At a second stage, the local state estimates for the robotic vehicles are fused using a distributed filtering algorithm. Thus an aggregate state vector of the robotic harvesters is obtained (see Fig. 1). Such a filtering approach has several advantages: (i) it is fault tolerant: if a local information processing unit is subject to a fault then state estimation is still possible, (ii) the information processing scheme is scalable and can be expanded with the inclusion of more local information processing units (local filters), (iii) the bandwidth for the exchange of information between the local units and the aggregate filter remains limited since there is no transmission of raw measurements but only transmission of local state estimates and of the associated covariance matrices.

Under the assumption of a Gaussian measurement model, a solution to distributed information fusion for the robotic harvesters can be obtained with the use of distributed Kalman Filtering [2-7]. Distributed state estimation in the case of non-Gaussian models has been also studied in several other research works [8-10]. In this paper, a solution for the problem of distributed state estimation will be attempted with the use of the Extended Information Filter, which is actually an approach for fusing state estimates provided by local Extended Kalman Filters [11-12].

Another issue that has to be taken into account for the autonomous functioning of the robotic harvesters is nonlinear control for precise tracking of desirable trajectories. The paper proposes flatness-based control for steering the robot harvesters along the reference paths. Flatness-based control

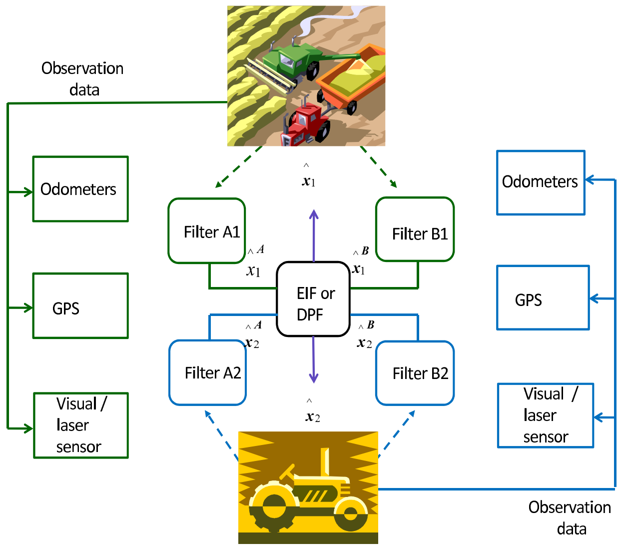


Fig. 1. Sensor fusion at the local filters for obtaining local state estimates

is currently a main direction in the design of nonlinear control systems [12]. To find out if a dynamical system is differentially flat, the following should be examined: (i) the existence of the so-called flat output, i.e. a new variable which is expressed as a function of the system's state variables. It should hold that the flat output and its derivatives should not be coupled in the form of an ordinary differential equation, (ii) the components of the system (i.e. state variables and control input) should be expressed as functions of the flat output and its derivatives [13]. Expressing all system variables as functions of the flat output and its derivatives enables transformation of the robotic vehicle model to a linearized form for which the design of the controller becomes easier.

The structure of the paper is as follows: in Section II the Extended Information Filter (Distributed Extended Kalman Filter) is studied. In Section III nonlinear control (flatness-based control) is proposed for succeeding trajectory tracking by the robotic vehicles. In Section IV simulation experiments are provided about the autonomous navigation of the robotic harvesters using the Extended Information Filter and flatness-based control. The test case is concerned with 2 autonomous tractors cooperating within a master-slave scheme. By fusing the outcome of the distributed filters with the use of the Extended Information Filter, state estimates of the robotic harvesters are obtained. These in turn are used by local nonlinear controllers for succeeding trajectory tracking. Finally in Section V concluding remarks are be provided.

II. Distributed state estimation using the Extended Information Filter

A. Kalman and Extended Kalman Filtering

In distributed filtering an aggregate state vector is produced through the fusion of the state estimates provided by local filters (e.g. KF or EKF). In the discrete-time case a dynamical system is assumed to be expressed in the form of a discrete-time state model:

$$\begin{array}{c} x(k+1) = A(k)x(k) + B(k)u(k) + w(k) \\ z(k) = Cx(k) + v(k) \end{array} \tag{1}$$

where the state $x(k)$ is a m-vector, $w(k)$ is a m-element process noise vector and A is a $m \times m$ real matrix. Moreover the output measurement $z(k)$ is a p-vector, C is an $p{\times}m$-matrix of real numbers, and $v(k)$ is the measurement noise. It is assumed that the process noise $w(k)$ and the measurement noise $v(k)$ are uncorrelated. The process and measurement noise covariance matrices are denoted as $Q(k)$ and $R(k)$, respectively. Now the problem is to estimate the state $x(k)$ based on the measurements $z(1), z(2), \cdots, z(k)$. This can be done with the use of Kalman Filtering. The discrete-time Kalman filter can be decomposed into two parts: i) time update (prediction stage), and ii) measurement update (correction stage).

measurement update:

$$\begin{array}{c} K(k) = P^-(k)C^T[C{\cdot}P^-(k)C^T + R]^{-1} \\ \hat{x}(k) = \hat{x}^-(k) + K(k)[z(k) - C\hat{x}^-(k)] \\ P(k) = P^-(k) - K(k)CP^-(k) \end{array} \tag{2}$$

time update:

$$\begin{array}{c} P^-(k+1) = A(k)P(k)A^T(k) + Q(k) \\ \hat{x}^-(k+1) = A(k)\hat{x}(k) + B(k)u(k) \end{array} \tag{3}$$

Next, the following nonlinear state-space model is considered:

$$\begin{array}{c} x(k+1) = \phi(x(k)) + L(k)u(k) + w(k) \\ z(k) = \gamma(x(k)) + v(k) \end{array} \tag{4}$$

The operators $\phi(x)$ and $\gamma(x)$ are

$$\begin{array}{c} \phi(x) = [\phi_1(x), \phi_2(x), \cdots, \phi_m(x)]^T \\ \gamma(x) = [\gamma_1(x), \gamma_2(x), \cdots, \gamma_p(x)]^T \end{array} \tag{5}$$

It is assumed that ϕ and γ are sufficiently smooth in x so that each one has a valid series Taylor expansion. Following a linearization procedure, about the current state vector estimate $\hat{x}(k)$ the linearized version of the system is obtained:

$$x(k+1) = \phi(\hat{x}(k)) + J_\phi(\hat{x}(k))[x(k) - \hat{x}(k)] + w(k),$$
$$z(k) = \gamma(\hat{x}^-(k)) + J_\gamma(\hat{x}^-(k))[x(k) - \hat{x}^-(k)] + v(k),$$

where $J_\phi(\hat{x}(k))$ and $J_\gamma(\hat{x}(k))$ are the associated Jacobian matrices of ϕ and γ respectively. Now, the EKF recursion is as follows [12]:

Measurement update. Acquire $z(k)$ and compute:

$$\begin{array}{c} K(k) = P^{-}(k)J_{\gamma}^{T}(\hat{x}^{-}(k))\cdot \\ \cdot[J_{\gamma}(\hat{x}^{-}(k))P^{-}(k)J_{\gamma}^{T}(\hat{x}^{-}(k)) + R(k)]^{-1} \\ \hat{x}(k) = \hat{x}^{-}(k) + K(k)[z(k) - \gamma(\hat{x}^{-}(k))] \\ P(k) = P^{-}(k) - K(k)J_{\gamma}(\hat{x}^{-}(k))P^{-}(k) \end{array} \quad (6)$$

Time update. Compute:

$$\begin{array}{c} P^{-}(k+1) = J_{\phi}(\hat{x}(k))P(k)J_{\phi}^{T}(\hat{x}(k)) + Q(k) \\ \hat{x}^{-}(k+1) = \phi(\hat{x}(k)) + L(k)u(k) \end{array} \quad (7)$$

B. Fusing estimations from local distributed filters

Again, the discrete-time nonlinear system of Eq. (4) is considered. The Extended Information Filter (EIF) performs fusion of the local state vector estimates which are provided by the local Extended Kalman Filters, using the *Information matrix* and the *Information state vector* [11]. The Information Matrix is the inverse of the state vector covariance matrix, and can be also associated to the Fisher Information matrix [14]. The Information state vector is the product between the Information matrix and the local state vector estimate

$$\begin{array}{c} Y(k) = P^{-1}(k) = I(k) \\ \hat{y}(k) = P^{-}(k)^{-1}\hat{x}(k) = Y(k)\hat{x}(k) \end{array} \quad (8)$$

The update equation for the Information Matrix and the Information state vector are given by

$Y(k) = P^{-}(k)^{-1} + J_{\gamma}^{T}(k)R^{-1}(k)J_{\gamma}(k) = Y^{-}(k) + I(k)$ and $\hat{y}(k) = \hat{y}^{-}(k) + J_{\gamma}^{T}R(k)^{-1}[z(k) - \gamma(x(k)) + J_{\gamma}(k)\hat{x}^{-}(k)] = \hat{y}^{-}(k) + i(k)$,

where $I(k) = J_{\gamma}^{T}(k)R(^{}k)^{-1}J_{\gamma}(k)$ is the associated information matrix and, $i(k) = J_{\gamma}^{T}(k)R(^{}k)^{-1}[(z(k) - \gamma(x(k))) + J_{\gamma}\hat{x}^{-}(k)]$ is the information state contribution. The predicted information state vector and Information matrix are obtained from

$\hat{y}^{-}(k)= P^{-}(k)^{-1}\hat{x}^{-}(k)$, and $Y^{-}(k) = P^{-}(k)^{-1} = [J_{\phi}(k)P^{-}(k)J_{\phi}(k)^{T} + Q(k)]^{-1}$.

It is assumed that an observation vector $z^{i}(k)$ is available for the N different sensor sites (e.g. GPS measurement nodes) $i = 1, 2, \cdots, N$ and each GPS node observes the vehicle according to the local observation model, expressed by $z^{i}(k) = \gamma(x(k)) + v^{i}(k),\ i = 1, 2, \cdots, N$, where the local noise vector $v^{i}(k) \sim N(0, R^{i})$ is assumed to be white Gaussian and uncorrelated between sensors. The variance of a composite observation noise vector v_k is expressed in terms of the block diagonal matrix $R(k) = diag[R(k)^{1}, \cdots, R^{N}(k)]^{T}$. The information contribution can be expressed by a linear combination of each local information state contribution i^{i} and the associated information matrix I^{i} at the i-th sensor site

$i(k) = \sum_{i=1}^{N} {J_{\gamma}^{i}}^{T}(k)R^{i}(k)^{-1}[z^{i}(k) - \gamma^{i}(x(k)) + J_{\gamma}^{i}(k)\hat{x}^{-}(k)]$, $I(k) = \sum_{i=1}^{N} {J_{\gamma}^{i}}^{T}(k)R^{i}(k)^{-1}J_{\gamma}^{i}(k)$. Thus, the update equations for fusing the local state estimates is

$\hat{y}(k) = \hat{y}^{-}(k) + \sum_{i=1}^{N} {J_{\gamma}^{i}}^{T}(k)R^{i}(k)^{-1}[z^{i}(k) - \gamma^{i}(x(k)) + J_{\gamma}^{i}(k)\hat{x}^{-}(k)]$, and $Y(k) = Y^{-}(k) + \sum_{i=1}^{N} {J_{\gamma}^{i}}^{T}(k)R^{i}(k)^{-1}J_{\gamma}^{i}(k)$.

At a second stage, in the Extended Information Filter an aggregation (master) fusion filter produces a global estimate by using the local sensor information provided by each local filter. As in the case of the Extended Kalman Filter the local filters which constitute the Extended information Filter can be written in terms of *time update* and *measurement update* equations.

Measurement update: Acquire $z(k)$ and compute

$$\begin{array}{c} Y(k) = P^{-}(k)^{-1} + J_{\gamma}^{T}(k)R(k)^{-1}J_{\gamma}(k) \text{ or} \\ Y(k) = Y^{-}(k) + I(k) \\ \text{where } I(k) = J_{\gamma}^{T}(k)R^{-1}(k)J_{\gamma}(k), \text{and} \\ \\ \hat{y}(k) = \hat{y}^{-}(k) + J_{\gamma}^{T}(k)R(k)^{-1}[z(k) - \gamma(\hat{x}(k)) + J_{\gamma}\hat{x}^{-}(k)] \\ \text{or } \hat{y}(k) = \hat{y}^{-}(k) + i(k) \end{array} \quad (9)$$

Time update: Compute:

$$\begin{array}{c} Y^{-}(k+1) = P^{-}(k+1)^{-1} = [J_{\phi}(k)P(k)J_{\phi}(k)^{T} + Q(k)]^{-1} \\ \text{and } y^{-}(k+1) = P^{-}(k+1)^{-1}\hat{x}^{-}(k+1). \end{array} \quad (10)$$

C. Calculation of the aggregate state estimation

The outputs of the local filters are treated as measurements which are fed into the aggregation fusion filter (see Fig. 1) [11]. Then each local filter is expressed by its respective error covariance and estimate in terms of information contributions and is described by

${P_{i}}^{-1}(k) = {P_{i}^{-}(k)}^{-1} + J_{\gamma}^{T}(k)R(k)^{-1}J_{\gamma}(k)\hat{x}_{i}(k) = P_{i}(k)(P_{i}^{-}(k)^{-1}\hat{x}_{i}^{-}(k)) + J_{\gamma}^{T}(k)R(k)^{-1}[z^{i}(k) - \gamma^{i}(x(k)) + J_{\gamma}^{i}(k)\hat{x}_{i}^{-}(k)]$.

The global estimate and the associated error covariance for the aggregate fusion filter can be rewritten in terms of the computed estimates and covariances from the local filters using the relations

$J_{\gamma}^{T}(k)R(k)^{-1}J_{\gamma}(k) = P_{i}(k)^{-1} - P_{i}^{-}(k)^{-1}$, and $J_{\gamma}^{T}(k)R(k)^{-1}[z^{i}(k) - \gamma^{i}(x(k)) + J_{\gamma}^{i}(k)\hat{x}^{-}(k)] = P_{i}(k)^{-1}\hat{x}_{i}(k) - P_{i}(k)^{-1}\hat{x}_{i}(k-1)$.

For the general case of N local filters $i = 1, \cdots, N$, the distributed filtering architecture is described by

$$\begin{array}{l} P(k)^{-1} = P^{-}(k)^{-1} + \sum_{i=1}^{N}[P_{i}(k)^{-1} - P_{i}^{-}(k)^{-1}] \\ \hat{x}(k) = P(k)[P^{-}(k)^{-1}\hat{x}^{-}(k) + \\ +\sum_{i=1}^{N}(P_{i}(k)^{-1}\hat{x}_{i}(k) - P_{i}^{-}(k)^{-1}\hat{x}_{i}^{-}(k))] \end{array} \quad (11)$$

The global state update equation in the above distributed filter can be written in terms of the information state vector and of the information matrix, i.e.

$$\begin{array}{c}\hat{y}(k)=\hat{y}^{-}(k)+\sum_{i=1}^{N}(\hat{y}_i(k)-\hat{y}_i^{-}(k)) \\ \hat{Y}(k)=\hat{Y}^{-}(k)+\sum_{i=1}^{N}(\hat{Y}_i(k)-\hat{Y}_i^{-}(k))\end{array} \tag{12}$$

From Eq. (11) it can be seen that if a local filter (processing station) fails, then the local covariance matrices and the local state estimates provided by the rest of the filters will enable an accurate computation of the vehicle's state vector.

III. Differential flatness for nonlinear dynamical systems

A. Definition of differentially flat systems

Each agricultural vehicle participating in the multi-vehicle system is steered along the desirable paths with the use of a flatness-based controller. The main principles of flatness-based control are as follows [13]: a finite dimensional system is considered. This can be written in the general form of an ordinary differential equation (ODE), i.e. $S_i(w,\dot{w},\ddot{w},\cdots,w^{(i)}), \quad i=1,2,\cdots,q$. The quantity w denotes the system variables (these variables are for instance the elements of the system's state vector and the control input) while $w^{(i)}$, $i=1,2,\cdots,q$ are the associated derivatives. Such a system is said to be differentially flat if there is a collection of m functions $y=(y_1,\cdots,y_m)$ of the system variables and of their time-derivatives, i.e. $y_i=\phi(w,\dot{w},\ddot{w},\cdots,w^{(\alpha_i)}),\ i=1,\cdots,m$ satisfying the following two conditions [12],[13]:

1) There does not exist any differential relation of the form $R(y,\dot{y},\cdots,y^{(\beta)})=0$ which implies that the derivatives of the flat output are not coupled in the sense of an ODE, or equivalently it can be said that the flat output is differentially independent

2) All system variables (i.e. the elements of the system's state vector w and the control input) can be expressed using only the flat output y and its time derivatives $w_i=\psi_i(y,\dot{y},\cdots,y^{(\gamma_i)}),\ i=1,\cdots,s$.

B. Controller design for agricultural robots

The kinematic model of the agricultural robot is considered. This is given by

$$\begin{array}{c}\dot{x}=vcos(\theta) \\ \dot{y}=vsin(\theta) \\ \dot{\theta}=\omega=\frac{v}{L}tan(\phi)\end{array} \tag{13}$$

where $v(t)$ is the velocity of the vehicle, L is the distance between the front and the rear wheel axis of the vehicle, θ is the angle between the transversal axis of the vehicle and axis OX, and ϕ is the angle of the steering wheel with respect to the transversal axis of the vehicle (Fig. 2). The position of such a vehicle is described by the coordinates (x,y) of the center of its rear axis and its orientation is given by the angle θ between the x-axis and the axis of the direction of the vehicle. The steering angle ϕ (or equivalently the rate of change of the vehicle's heading $\dot{\theta}=\omega$) and the speed v are considered to be the inputs of the system.

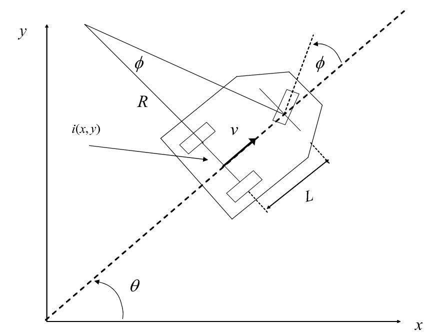


Fig. 2. The model of the autonomous agricultural vehicle (cart-like vehicle)

Flatness-based control can be used for steering the vehicle along a desirable trajectory. In the case of the autonomous vehicle of Eq. (13) the flat output is the cartesian position of the center of the wheel axis, denoted as $\eta=(x,y)$, while the other model parameters can be written as:

$$v=\pm||\dot{\eta}|| \quad \begin{pmatrix}cos(\theta)\\ sin(\theta)\end{pmatrix}=\frac{\dot{\eta}}{v} \quad tan(\phi)=ldet(\dot{\eta}\ddot{\eta})/v^3 \tag{14}$$

These formulas show simply that θ is the tangent angle of the curve and $tan(\phi)$ is the associated curvature. One then proceeds by successively differentiating the output until the input appears in a non-singular way. If the sum of the output differentiation orders equals the dimension $n+v$ of the extended state space, full input-state-output linearization is obtained. The closed-loop system is then equivalent to a set of decoupled input-output chains of integrators from u_i to η_i. The exact linearization procedure is illustrated for the unicycle model of Eq. (21). As flat output $\eta=(x,y)$ the coordinates of the center of the wheel axis is considered . Differentiation with respect to time then yields [15]

$$\dot{\eta}=\begin{pmatrix}\dot{x}\\ \dot{y}\end{pmatrix}=\begin{pmatrix}cos(\theta) & 0\\ sin(\theta) & 0\end{pmatrix}\cdot\begin{pmatrix}v\\ \omega\end{pmatrix} \tag{15}$$

showing that only v affects $\dot{\eta}$, while the angular velocity ω cannot be recovered from this first-order differential information. To proceed, one needs to add an integrator (whose state is denoted by ξ) on the linear velocity input $v=\xi$, $\dot{\xi}=\alpha\Rightarrow\dot{\eta}=\xi[cos(\theta),sin(\theta)]^T$, where α denotes the linear acceleration of the vehicle. Differentiating further one obtains

$$\begin{array}{c}\ddot{\eta}=\dot{\xi}\begin{pmatrix}cos(\theta)\\ sin(\theta)\end{pmatrix}+\xi\dot{\theta}\begin{pmatrix}sin(\theta)\\ cos(\theta)\end{pmatrix}= \\ =\begin{pmatrix}cos(\theta) & -\xi sin(\theta)\\ sin(\theta) & \xi cos(\theta)\end{pmatrix}\begin{pmatrix}\alpha\\ \omega\end{pmatrix}\end{array} \tag{16}$$

and the matrix multiplying the modified input (α, ω) is non-singular if $\xi \neq 0$. Under this assumption one defines

$$\begin{pmatrix} \alpha \\ \omega \end{pmatrix} = \begin{pmatrix} cos(\theta) & -\xi sin(\theta) \\ sin(\theta) & \xi cos(\theta) \end{pmatrix}^{-1} \cdot \begin{pmatrix} u_1 \\ u_2 \end{pmatrix} \tag{17}$$

and $\ddot{\eta}$ is denoted as

$$\ddot{\eta} = \begin{pmatrix} \ddot{\eta}_1 \\ \ddot{\eta}_2 \end{pmatrix} = \begin{pmatrix} u_1 \\ u_2 \end{pmatrix} = u \tag{18}$$

which means that the desirable linear acceleration and the desirable angular velocity can be expressed using the transformed control inputs u_1 and u_2. Then, the resulting dynamic compensator is (return to the initial control inputs v and ω)

$$\begin{matrix} \dot{\xi} = u_1 cos(\theta) + u_2 sin(\theta) \\ v = \xi \\ \omega = \frac{u_2 cos(\theta) - u_1 sin(\theta)}{\xi} \end{matrix} \tag{19}$$

Being $\xi \in R$, it is $n + v = 3 + 1 = 4$, equal to the output differentiation order in Eq. (18). In the new coordinates

$$\begin{matrix} z_1 = x \\ z_2 = y \\ z_3 = \dot{x} = \xi cos(\theta) \\ z_4 = \dot{y} = \xi sin(\theta) \end{matrix} \tag{20}$$

The extended system is thus fully linearized and described by the chains of integrators, in Eq. (18), and can be rewritten as

$$\ddot{z}_1 = u_1, \quad \ddot{z}_2 = u_2 \tag{21}$$

The dynamic compensator of Eq. (19) has a potential singularity at $\xi = v = 0$, i.e. when the vehicle is not moving, which is a case not met while executing the trajectory tracking. It is noted however, that the occurrence of such a singularity is structural for non-holonomic systems.

A nonlinear controller for output trajectory tracking, based on dynamic feedback linearization, is easily derived. Assume that the autonomous vehicle must follow a smooth trajectory $(x_d(t), y_d(t))$ which is persistent, i.e. for which the nominal velocity $v_d = (\dot{x}_d^2 + \dot{y}_d^2)^{\frac{1}{2}}$ along the trajectory never goes to zero (and thus singularities are avoided). On the equivalent and decoupled system of Eq. (21), one can easily design an exponentially stabilizing feedback for the desired trajectory, which has the form

$$\begin{matrix} u_1 = \ddot{x}_d + k_{p_1}(x_d - x) + k_{d_1}(\dot{x}_d - \dot{x}) \\ u_2 = \ddot{y}_d + k_{p_2}(y_d - y) + k_{d_2}(\dot{y}_d - \dot{y}) \end{matrix} \tag{22}$$

and which results in the following error dynamics for the closed-loop system

$$\begin{matrix} \ddot{e}_x + k_{d_1}\dot{e}_x + k_{p_1}e_x = 0 \\ \ddot{e}_y + k_{d_2}\dot{e}_y + k_{p_2}e_y = 0 \end{matrix} \tag{23}$$

where $e_x = x - x_d$ and $e_y = y - y_d$. The proportional-derivative gains are chosen as $k_{p_1} > 0$ and $k_{d_1} > 0$ for $i = 1, 2$. Knowing the control inputs u_1, u_2, for the linearized system one can calculate the control inputs v and ω applied to the vehicle, using Eq. (19). In the general case of design of flatness-based controllers, the avoidance of singularities in the proposed control law can be assured [15].

When the estimated state vector of the vehicle $[\hat{x}, \hat{y}, \hat{\theta}]^T$, as computed by the Extended Information Filter algorithm, is used in the control loop, the control input for steering the vehicle becomes

$$\begin{matrix} u_1 = \ddot{x}_d + k_{p_1}(x_d - \hat{x}) + k_{d_1}(\dot{x}_d - \dot{\hat{x}}) \\ u_2 = \ddot{y}_d + k_{p_2}(y_d - \hat{y}) + k_{d_2}(\dot{y}_d - \dot{\hat{y}}) \end{matrix} \tag{24}$$

and consequently from Eq. 19 one has

$$\begin{matrix} \dot{v} = u_1 cos(\hat{\theta}) + u_2 sin(\hat{\theta}) \\ \omega = \frac{u_2 cos(\hat{\theta}) - u_1 sin(\hat{\theta})}{v} \end{matrix} \tag{25}$$

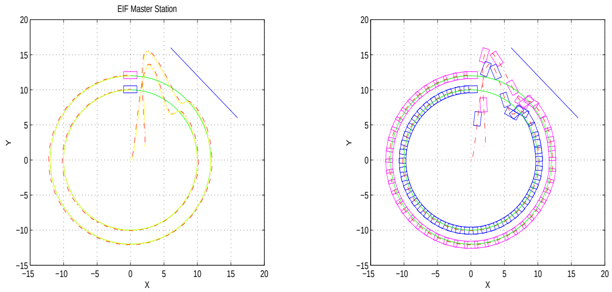
IV. Simulation tests

Master-slave cooperation of two agricultural robots was considered (see Fig. 1). The master tractor generates a reference path and the motion characteristics (velocity, acceleration, orientation) that the slave tractor has to follow. It was assumed that measurements of the xy coordinates of the vehicles could be obtained through multiple GPS units (localization of moderate accuracy), or multiple local RTK-GPS stations (localization of higher accuracy). Moreover, localization of the vehicles could be performed using measurements of their distance from a reference surface. This distance can be measured with the use of different on-board sensors, e.g. laser, sonar or vision sensors. The measurements from the GPS were combined with the distance sensor measurements and were initially processed by local filters to provide local state vector estimates. At a second stage the local state estimates for the robotic vehicles were fused using the Extended Information Filter. Using the outcome of the Extended Information Filter state estimation-based control was implemented.

Indicative results about tracking of various trajectories (e.g. reference paths followed by the vehicles to perform harvesting) with use of the Extended Information Filter are shown in Fig. 3 to Fig. 6. It can be noticed that the Extended Information Filter provides accurate estimates of the vehicle's state vector thus also resulting in efficient tracking of the reference trajectories. Finally, it is noted that the paper's approach can be applied also to various types of 4WD agricultural vehicles.

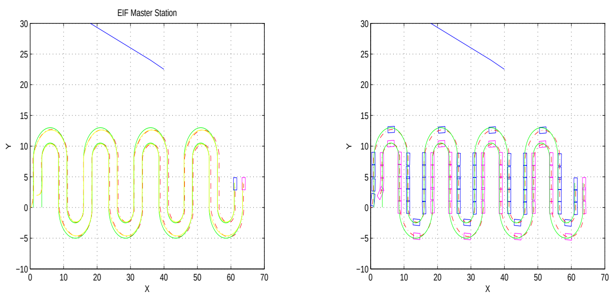
V. Conclusions

The Extended Information Filter has been introduced and applied to autonomous agricultural robots. The method is also suitable for filtering and state estimation-based control of a generic class of robotic vehicles. Thus apart from agricultural robots the method can be applied to autonomous navigation of service or surveillance robots. Two robotic vehicles were considered navigating autonomously within a master-slave cooperation scheme. Local Extended Kalman Filters provided



(a) (b)

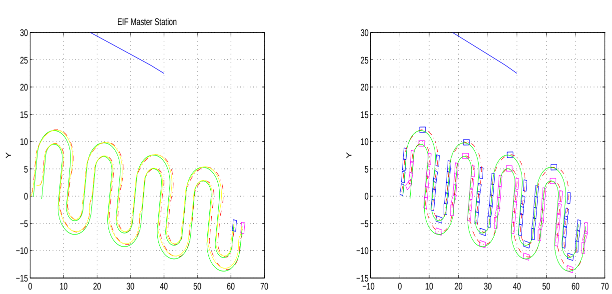
Fig. 3. Extended Information Filtering and flatness-based control for cooperating robot harvesters: (a) synchronized tracking of reference path 1 (b) position of the synchronized vehicles every 100 sampling periods



(a) (b)

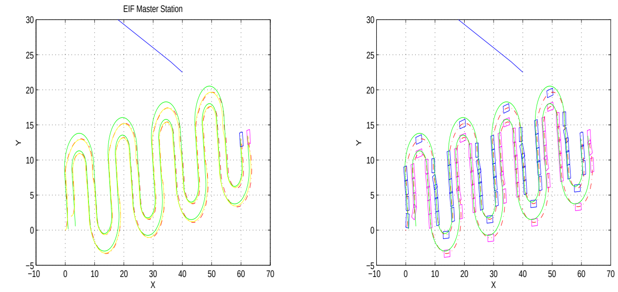
Fig. 4. Extended Information Filtering and flatness-based control for cooperating robot harvesters: (a) synchronized tracking of reference path 2 (b) position of the synchronized vehicles every 100 sampling periods

local state estimates for the vehicles which were finally fused into aggregate state estimates using the Extended Information Filter. Next, the estimated state vectors describing the motion characteristics of the vehicles were used in a nonlinear control loop which generated steering commands for guiding the vehicles along desirable trajectories. The nonlinear controller was designed according to differential flatness theory. The proposed state estimation-based control for autonomous navigation of agricultural robots was tested through simulation experiments.



(a) (b)

Fig. 5. Extended Information Filtering and flatness-based control for cooperating robot harvesters: (a) synchronized tracking of reference path 3 (b) position of the synchronized vehicles every 100 sampling periods



(a) (b)

Fig. 6. Extended Information Filtering and flatness-based control for cooperating robot harvesters: (a) synchronized tracking of reference path 4 (b) detailed motion of the synchronized vehicles

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