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Estimating future aircraft intentions using short and long term behavior modeling

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Abstract: In a scenario where two UAS can benefit from cooperation, but where one of the UAS is non-cooperative and only broadcasting very limited state information, there is a need for the second UAS to estimate the intentions of the first UAS. When the second UAS is capable of this they will be able to solve joint tasks faster even though the cooperation is only "one way". In this work we investigate a method for such an estimation. It is based on a short and a long term prediction of the intentions of the non-cooperative UAS, combined in a Kalman filter to provide a quantitative estimate of the intentions. The method is demonstrated on two helicopters semi-cooperating on covering a number of hot spots in field of crops.

1. INTRODUCTION

Cooperation between autonomous agents like robots are a challenging task and has been the focus of intense research for more than a decade. An area of particular interest is the amount of information exchange necessary to facilitate cooperation and how to handle when this communication fails. In this paper we will envision a scenario where only a very limited amount of information is flowing between the robots; this could simply be robot position acquired from a beacon or perhaps a radar.

An example of such a scenario could be a sea rescue operation where a human piloted coast guard helicopter with assistance from a autonomous UAS are searching for a missing person from a capsized boat at sea. The human pilot will draw on his experience to formulate a search pattern and the UAS will need to cooperate with the human pilot in an attempt to minimize the time to rescue, i.e. maximize the area search per time. The pilot does not communicate his intended future motion pattern to the UAS, nor will he change strategy or behavior in response to actions by the UAS. However, it would be beneficial if the UAS is still able to assist in the search simply by inferring the search pattern of the coast guard helicopter from its ADS-B beacon and using this to reduce the search time by covering some of the sea that the coast guard helicopter otherwise should have covered.

Another example is a farmer that has purchased a simple UAS to do mapping of his crop fields. After some time he purchases a newer UAS and would like them to help each other mapping the fields. The simple UAS in unable to do cooperation, but the newer UAS is capable of assisting with the mapping, simply by estimating the intentions of the older UAS from, say, ADS-B data.

To facilitate cooperation under such terms, in is necessary to be able to determine what the other part of the cooperation intends to do, i.e. infer or predict future behavior and in this paper we will focus on how to estimate and predict task driven behavior given limited motion information. This is done by developing a Bayesian estimator using a short and a long term model of the future behavior of an aircraft.

1.1 Previous Work

Cooperative UAS is fairly common in recent literature, but in virtually all cases the cooperation is based on mutual information exchange. Examples are aircraft cooperating to maximize the same objective function in a search mission by Tisdale et al. (2009), to optimize flight routes given a set of joint constraints in Vijayan et al. (2009), to traverse an urban environment without impacting obstacles and each other by Sujit and Beard (2009), or by combinatorial optimization in a vehicle routing problem in Stump and Michael (2011).

An area where intend and trajectory prediction are researched is within air traffic management (ATM) for traffic planning and conflict management focused on piloted aircrafts operating in controlled airspace (a famous example is Paielli and Erzberger (1999)). In ATM three different time scales are considered: Long term (hours) involving flight plans and schedules. Mid term (tens of minutes) involving flight plan modification by air traffic contollers. Short term (seconds to minutes) involving pilots and TCAS systems. A good example of such research is Prandini et al. (2000) where probabilistic models for short and mid term trajectory prediction are developed based on empirical inspired stochastic motion model. The models are then evaluated to determine the probability of a flight path conflict. Conflict detection is also the focus of Liu and Hwang (2010) though the development of a stochastic hybrid linear model which predicts the future trajectory of an aircraft using a combination of discrete Markov models and continuous linear models. Another example of a stochastic prediction of waypoints can be found in Rößler et al. (2006) though with a very different application.

Inspired by these approaches we will attempt to develop a short and a long (or mid) term probabilistic model and combine these in an estimator for predicting future behavior for a aircraft, piloted or autonomous.

2. BEHAVIOR ESTIMATION

In this context we will define future behavior as the visiting order of a number of waypoints and quantify it by estimating the probability of each waypoint being the next to be visited. For this task we use a Kalman filter with a state vector where elements are the probabilities for the waypoints. The state of n waypoint probabilities is

$$\boldsymbol{B} = [B_1 \ B_2 \ \ldots \ B_n]^T . \tag{1}$$

At a glance, it is somewhat unusual to have probabilities in the Kalman filter state vector. However, in fact it can simply be viewed as a number of states whos sum is constrained to 1, and there are a number of methods to handle constraints in a Kalman filter (Simon (2010)). Here, the virtual measurement of constant 1 is introduced and with a measurement model of $\sum_{i=0}^{n} B_i$.

The process model incorporates the short term probabilistic model and uses the aircraft state vector $\boldsymbol{x}$ (position, attitude, velocities) as input.

$$\dot{\boldsymbol{B}} = f(\boldsymbol{B}, \boldsymbol{x}). \tag{2}$$

The state vector must somehow be available for the estimation of operate which could, as mentioned earlier, be delivered alt least partly in the form of a beacon. If only part of the state vector is available it is possible to estimate the remaining states using a second Kalman filter.

The measurement model contains the long term model and uses the previous behavior of the aircraft – i.e. previously visited waypoints – as a measurement.

$$\boldsymbol{\zeta} = g(\boldsymbol{V}, \boldsymbol{x}). \tag{3}$$

where $\boldsymbol{\zeta}$ is the measurement vector and $\boldsymbol{V}$ is a vector of visited waypoints.

As both the measurement and the process model will be derived as linear with respect to the state vector $\boldsymbol{B}$, a standard discrete linear Kalman filter will be used. The model and measurement predict step is given as

$$\begin{aligned}
\hat{\dot{\boldsymbol{B}}}_k^- &= \boldsymbol{\Phi}_k \hat{\boldsymbol{B}}_{k-1}^+ + \boldsymbol{F}_k(\boldsymbol{u}_{k-1}) \\
\hat{\boldsymbol{B}}_k^- &= \hat{\boldsymbol{B}}_{k-1}^+ + T_s \hat{\dot{\boldsymbol{B}}}_k^- \\
\hat{\boldsymbol{\zeta}}_k &= \hat{\boldsymbol{B}}_k^-
\end{aligned}$$

where T_s is the filter sample time. The current waypoint is then simply taken as the one with the largest probability.

3. SHORT TERM MODEL

The purpose of the motion model is to map the state of the aircraft to a set of probabilities assigned to the individual waypoints depending on where the are located in relation to the motion of the aircraft – in effect a short term predictive model. It is constructed as a dynamic function of two parts; a part called probability field map to increasing the probability for waypoints near the expected future positions of the aircraft, and a part called a dissipation function for gradually reducing the probability of all waypoints such that waypoints need to stay within the future path of the helicopter to maintain a high probability.

3.1 Motion Model

To achieve the probability field map, a general predictive motion model is suggested here. We will make the assumption that when an aircraft are visiting a number of waypoints it will most often try to minimize the travel distance between them. This means that it will fly in a straight line as much as possible. Based on this, we will assume that turns are performed with a certain constant maximum angular accelerations equivalent to a bank rate maximum (Mondoloni et al. (2002) and Yoo and Devasia (2011)). The equivalent to such a turn in geometry is a clothoid or Euler spiral which has the property that its curvature is linear with respect to its arc length (Lay (2010)).

We will thus assume that for any instantaneous moment of a turning flight described by a velocity v and an angular velocity ω, the future motion of the aircraft will describe a clothoid transition curve from the circular motion ($R = \frac{v}{\omega}$) to straight flight. The Cartesian coordinates of a clothoid as a function of its arc length (ρ) is described by the Fresnel integrals

$$x = \int_0^L \cos(\rho^2)dt, \quad y = \int_0^L \sin(\rho^2)dt. \tag{4}$$

To solve these integrals a combinations of power series (for small ρ)

$$x = \sum_{n=0}^{\infty} (-1)^n \frac{\rho^{4n+1}}{(2n)!(4n+1)} \tag{5}$$

$$x = \sum_{n=0}^{\infty} (-1)^n \frac{\rho^{4n+3}}{(2n+1)!(4n+3)}, \tag{6}$$

and continued fractions (for large ρ)

$$y + ix = \sqrt{\pi/2}\frac{1+i}{2}\mathrm{erf}\left(\frac{1+i}{\sqrt{2}\rho}\right), \tag{7}$$

can be employed (Press et al. (1992)). The total arc length ρ_{max} given by

$$\rho_{max} = |\frac{\omega}{\alpha} v|, \tag{8}$$

where α is the constant angular acceleration. This parameter defines how fast the aircraft will transition to straight flight and must be determined through estimation. Note that in order to describe a transition from turning to straight, it is necessary to use the Fresnel integral solution backwards, i.e. starting from ρ_{max}. After the transition and indeed with all straight flight we will assume that the aircraft will simply continue on its course.

It should be noted it is straight forward to estimate the parameter α in the second Kalman filter together with the aircraft states using a simple zero derivative model like $\dot{\alpha} = 0$ and using the values found while turning.

3.2 Probability Field Map

To generate a probability map, a Gaussian probability function is propagated along the modeled future flight curve of the aircraft generating a higher sideways uncertainty as the curve progresses. The Gaussian as a function of curve length (ρ) and perpendicular cross distance (Δ) is given as

$$P(x_p, y_p) = e^{-\frac{(\Delta/\rho)^2}{2\sigma^2}}, \tag{9}$$

where σ is the standard deviation that defines how uncertain it is that the aircraft will follow the predicted curve. The curve length and cross distance are trivial to find

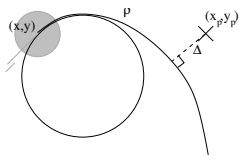

Fig. 1. The curve length ρ and cross distance Δ with respect to a waypoint.

when flying straight, but in the area of a transition curve it is more complicated. The task of finding the point on the curve closest to the point in question is not possible in closed form and a numerical search algorithm is used instead. This can be implemented very effecient and poses not problem in the overall computation of the Kalman filter.

As a further extension to the probability field map we will assume that points close to the current position of the aircraft are more likely to be visited next than points further away. This is modeled as a function decreasing with distance overlaid on the existing map. The actual shape of this function is not critical and it is here chosen as simple decreasing exponential as a function of curve distance which yields the following modified probability for a point

$$P(x_p, y_p) = e^{-\frac{(\Delta/\rho)^2}{2\sigma^2}} e^{-\rho}. \tag{10}$$

Examples of the probability field model are shown in figure 2 where the probability field for the entire plane has been calculated for different state vectors.

The short term model is then formulated as

$$\dot{\boldsymbol{B}} = \eta(\boldsymbol{\Phi}\boldsymbol{B} + \boldsymbol{P}), \tag{11}$$

where $\boldsymbol{u}$ is the process model input (in this case the state vector of the aircraft), $\boldsymbol{P}$ is a vectorized probability field map function from equation 10, τ is the dissipation function, and η is a normalizing function which ensures that $\dot{B}$ sums to zero. The dissipation function is defined as standard first order system

$$\boldsymbol{\Phi} = -\boldsymbol{I}\frac{1}{\tau}, \tag{12}$$

where $\boldsymbol{I}$ is the identity matrix and the time constant is set by τ. It should be noted that this function is linear with respect to the state B, but can be nonlinear with respect to the input.

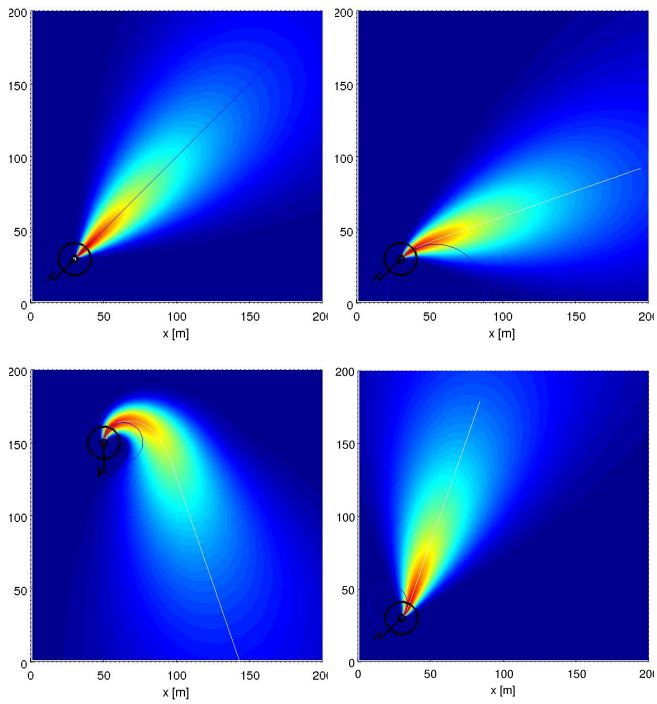

Fig. 2. Examples of the probability field model (size of helicopter is exaggerated). $\omega = [0\ -0.3\ -0.75\ 0.3]$rad/s, $v = [10\ 10\ 10\ 4]$m/s, heading= $[45\ 90\ 45\ 45]°$.

4. LONG TERM MODEL

The measurement model takes the information of which waypoints the aircraft previously have visited ($\boldsymbol{V}$) and from this attempts to predict the probability for each waypoint begin the next. This probability is then used as the measurement ($\boldsymbol{\zeta}$) for the Kalman filter which result in the measurement model matrix being the identity matrix.

This prediction is done through a set of behavior models. In the present work three behavior models are used; human, nearest neighbor, and serpentine model. They represent three fundamentally different ways of going through a set of waypoints, and each is modeled mathematically based on a set of assumptions.

Human model The human model is a description of how a human would decide the best way to visit a set of waypoints fairly evenly distributed in 2D space. While there are arguable as many ways to do this as humans, studies have shown that humans have particular tendencies which can be described fairly simple. We have decided to use a model inspired by Kong and Schunn (2007), which is based on the idea that humans tends to pick waypoints "in lumps" and "around the center of the waypoint cloud".

Nearest neighbor model This model is a greedy algorithm that picks the waypoints in the order in which they are closest to the previously visited waypoint. While this can be far from optimal (in terms of Euclidean distance) it is a simple and very easy to implement model.

Serpentine model This model makes a path with a serpentine or radiator-like look. It is a typically pattern for

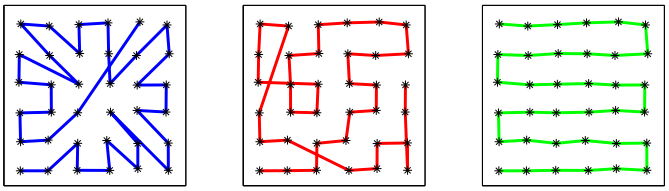

Fig. 3. A typical output from the human (blue), nearest neighbor (red), and serpentine (green) path models on the same set of 36 waypoints.

an aircraft covering an area for the purpose of search and rescue or photographic a field or similar geographical area. It is assumed that for each straight leg in the path there are at least a few waypoints, and the mathematical model is based on the idea of a prefer direction that changes regularly by 180 degrees.

Each of these models use the set of already visited waypoints to predict the probability for each of the not-yet-visited waypoints to be the next waypoint to be visited. That is, the output of these models is a vector of probabilities, and it only changes whenever a new waypoint has been visited. An arbitrator is used to determine which of the models to use. The Behavior Model Arbitrator runs each of the behavior models on the already visited waypoints to determine which of the models best explains the waypoints visited so far.

The mathematical implementation of each model as well as the Behavior Model Arbitrator is not presented in this work, but is published separately, see la Cour-Harbo (2013).

5. PREDICTION

In the case of a drop-out in the communication such that no aircraft state vector is available for a period, it is possible to reconfigure the system to function as a predictor. This means that we can attempt to use the behavior model to predict which waypoint the aircraft is heading for and then use this knowledge in a simple motion model. This prediction setup is shown in figure 4. As a motion model we will simply use the one formulated

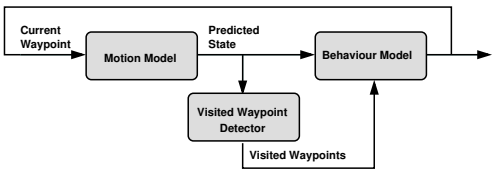

Fig. 4. One-way cooperation scheme: Predicting the next waypoint.

in section 3 and thereby let the aircraft converge on the predicted next waypoint by first pointing the aircraf towards the waypoint by means of a number of clothoids depending on which state the aircarft is coming from. When it points to the waypoint it proceeds to it at a constant velocity.

6. EXAMPLE CASE: ASETA

The specific scenario used in this paper is take from the ASETA project (Adaptive Surveying and Early treatment of crops with a Team of Autonomous vehicles, www.aseta.dk) where two small autonomous helicopters are mapping a field for weeds(Kazmi et al. (2011)). A number of possible hot-spots with weeds have previously been located in the field and the helicopters must now visit these hot-spots and capture images of each in order to map the specific clusters of weeds. The first helicopter 1 is given the task of visiting the hot-spots and it is assumed that it is unaware of the second helicopter existence. The second helicopter will attempt to assist the first helicopter by visiting some of the hot-spots such that the first helicopter does not have to. We assume that both helicopters have the complete list of hot-spots. The full estimation setup is show in in figure 5. A position and velocity is broadcasted from a beacon by the non-cooperative helicopter. This information is input to the prefilter, which estimates the current state of the helicopter as well as which waypoints have been visited. The list of visited waypoints is input to the Behavior Model Arbiter which determines which of the behavior models is the best long term prediction. The Probability Estimator is a Kalman filter using the estimated state, the visited waypoints, and the best behavior model to determine probability of each of the waypoints to be visited next.

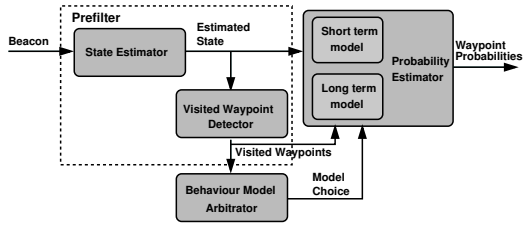

Fig. 5. One-way cooperation scheme: Estimating the current task of another helicopter.

In this scenario we will assume that a waypoint has been visited when the helicopter passed sufficiently close (i.e. less than a threshold) to it.

7. RESULTS

The cooperation scheme will be illustrated here through a simulation using the AAU HeliSim (Bisgaard (2008)) [1]. The non-cooperative helicopter is simulated as the 25 kg AAU Vario XLC platform using full helicopter dynamics and realistic sensor together with onboard flight controller, estimator, and planner. The planner is capable of delivering three times differentiable trajectories and the visiting order of the waypoints is decided using a 2-Opt TSP solver. Beacon data is take from the state-estimator at 1Hz with 15 s dropouts simulated at random points (in this case 39 s and 139 s into the simulation).

The path of the helicopter is shown in figure 6 together with beacon data and the estimated path. The waypoints are shown and it can be noted that they are numbered in the order the helicopter visits them. Furthermore, the beacon dropouts can be seen and as the cooperation scheme switches to Prediction mode it is capable propagating until the beacon is available again. The estimated heading and rate is shown in figure 7 and it is clear the the Unscented

[1] Can be downloaded at http://www.uavlab.org

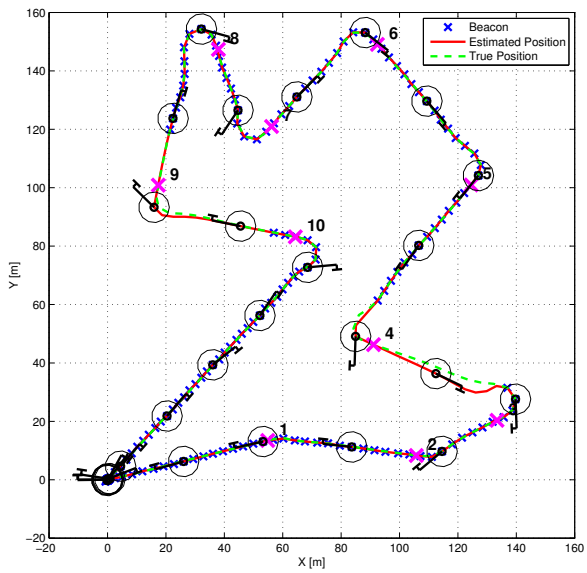

Fig. 6. The true and estimated path of the helicopter visiting the waypoints. The two beacon dropouts are visible as missing beacon measurements. Helicopter size is exaggerated.

Kalman Filter is capable of satisfactorily estimating these based only on position updates. The low-pass filtering effect of the zero-acceleration model is clearly evident on the rate estimates that lags behind the true value. The action of the prediction dynamic model is clear from both 6 and 7 where even during prediction periods the heading and rate is close to the correct value. The same

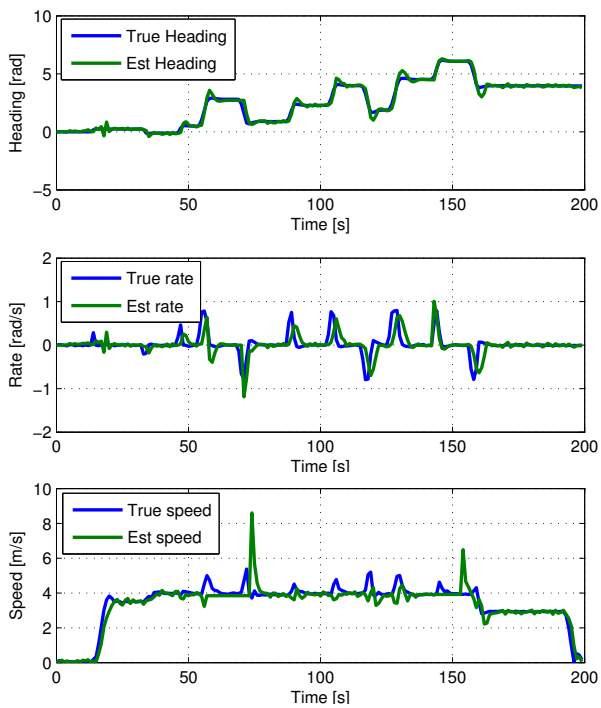

Fig. 7. Estimated and true heading, rate and speed.

lag can also be seen on the speed estimate. The estimated speed follows the true speed well, but does not follow the sudden accelerations that occurs during turns. The spikes on the speed estimates following dropout periods is the first update with a beacon that results in a relative large correction.

The output from the visited waypoint detection and probability estimator is shown in figure 8 - the model arbitrator chooses the human model as the best fitting for this order of waypoints (further results are forthcoming on the behavior modeling in la Cour-Harbo (2013)). It is clear that the probability estimator is performing well and is capable of determining the current waypoint of the helicopter. The estimated probability for all waypoints are shown in

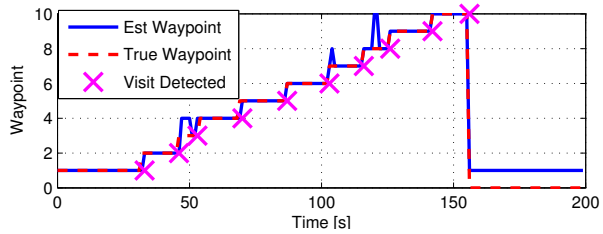

Fig. 8. Estimated and true waypoint together with detected waypoint visits.

figure 9. The probability output of the behavior model is

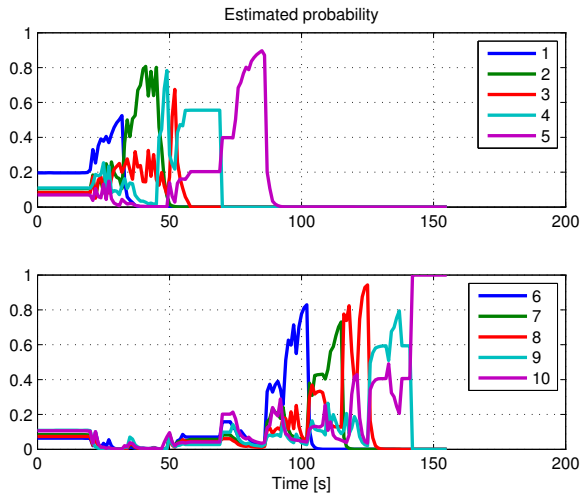

Fig. 9. Estimated probability for waypoints (Top: waypoint 1 to 5. Bottom: Waypoint 6 to 10.

shown in figure 10 and the probability field model output is shown in figure 11. The human model is a reasonable fit for the 2-Opt solved waypoint order, but an example of a discrepancy is evident after leaving waypoint 2. The human model predicts waypoint 4 while in reality the helicopter is heading to waypoint 3.

8. DISCUSSIONS AND FUTURE WORKS

8.1 Discussion

As part of a one-way cooperation scheme, an estimator to determine the intent of an aircraft which transmit only position data has been presented in this paper. This is achieved by using a Kalman filter for estimating the probability for each waypoint being the one the aircraft is heading for. The process model for this Kalman filter maps

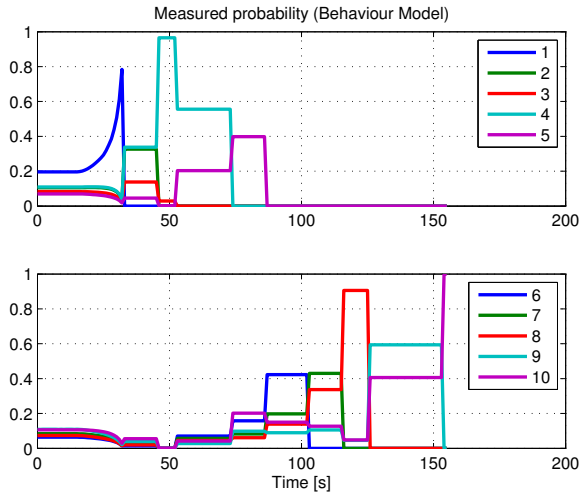

Fig. 10. Behavior model probability for waypoints (Top: waypoint 1 to 5. Bottom: Waypoint 6 to 10.

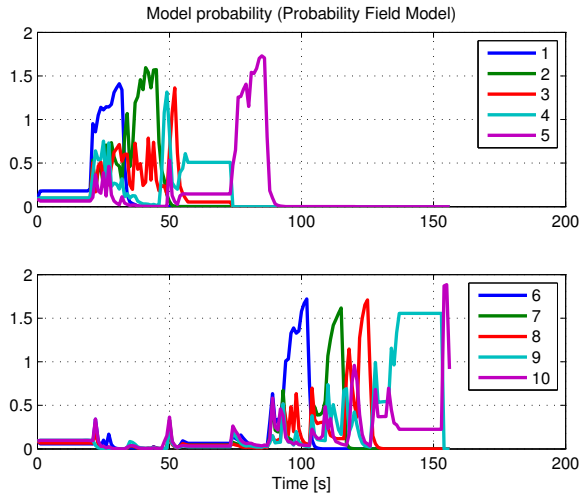

Fig. 11. Probability field model (Top: waypoint 1 to 5. Bottom: Waypoint 6 to 10.

a probability field from a propagation of the aircraft motion using clothoids and straight lines. The measurement model uses the information on which waypoints that was previously visited to determine a fitting behavior model. The operation of the scheme is demonstrated using a realistic simulated UAS flight, and it is shown that it is possible to satisfactorily estimate the next waypoint for the UAS. Furthermore, is is shown how it can be used in purely prediction. However, it should be noted that the success of the probability estimator depends very much on whether or not a good behavior model is available.

8.2 Future Works

While this paper presents a working part of the one-way cooperation scheme, several pieces are still missing from the puzzle. A more detailed work on behavior models in terms of robot cooperation will be published in a near future. Furthermore, in order for a cooperative robot to start taking active part in the task and help the non-cooperative robot, it is necessary to design a planner that can act on the information from the waypoint probability estimation. Results from this will also be published in the near future.

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