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"A Virtual Wind Sensor Based on a Particle Filter"

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A Virtual Wind Sensor Based on a Particle Filter

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Abstract

Wind sensors are essential components of any sailboat, meanwhile they are also one of its most compromised and exposed elements. This paper introduces a novel approach that allows to estimate wind direction and speed based on the application of a particle filter technique that relies on a model dynamics of the sailboat. The proposal incorporates elitism and particle re-initialization to improve filter convergence.

Extensive simulation results prove that this approach is capable of providing acceptable estimates of wind conditions at a modest computational cost.

1 Introduction

Wind sensors are key elements for articulating the control strategy of any sailboat, meanwhile they are one of the most exposed components of the ship. This problem is exacerbated in the case of autonomous sailboats where the loss or malfunctioning of a wind sensor can not be fixed or may go unnoticed for a long period of time. It is not an exaggeration to say that the wind sensor is - probably - one of the most important single points of failure in an autonomous sailboat.

The kind of wind sensor usable on board autonomous sailboats is normally conditioned by its dimensions, i.e. length-over-all or LOA. Basic solutions, frequently used on smaller vessels, have been built as custom designs based on wind-cup anemometers, most of them based on the popular AS5030 non-

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contact magnetic sensor from Austria Microsystems [1], or as just wind vanes using the MA3 analog absolute rotation encoder from US Digital [2].

The utilization of wind sensors that lack moving or rotating parts is often a big step forward in terms of robustness. Ultrasonic wind sensors belong to this type and, with a large commercial offer, are nowadays the preferred option on larger LOA vessels. Experimental wind sensors without moving parts have also been proposed with the aim of making them more resilient to adverse weather and sea conditions. A good example is the interesting thermal wind sensor design proposed by T. Barton and M. Alvira [3], where mechanical strength and small size are favored at the cost of a larger power consumption.

However, even these compact wind sensors are not immune and their placement on the top of masts and poles expose them to a significant risk of loss and, consequently, devising navigation control strategies that do not rely absolutely on the availability of a wind sensor have full sense. J. Sliwka et al. [4] propose a wind vane self steering device placed at the bow to steer the boat relative to the wind. K. Xiao et al. [5] describe a controller based on interval calculus that does not require explicit knowledge of wind direction.

In order to avoid the use of an explicit physical wind sensor on board, in this paper we explore the approach of estimating the wind direction and wind speed based on the application of a particle filter technique using the dynamic model of the sailboat, and incorporating elitism and re-initialization processes. Thus, in next section, Section 2, we introduce the particle filter technique we have applied. In Section 3, it is outlined the dynamic model and the sailboat systems equations we have utilized for applying the filter. Section 4 describes the main results we have obtained from simulated experiments to evaluate the approach. And, finally, in Section 5 we end with the conclusions we have collected.

2 Particle filters as a framework for positioning, navigation and tracking problems

Particle filters are usually known as recursive implementations of Monte Carlo based statistical signal processing techniques [6]. In problems where we are faced to estimate the state of systems governed by non-linear models and non Gaussian noise, particle filters constitute an alternative approach in real time applications solved typically with other approaches, like the use of Kalman filter techniques [7]. Moreover, considering its computational cost, they are convenient when the computational resources available at run-time are scarce and the system working rate is not very demanding. Both conditions typically found in autonomous sailboats, where the control hardware on-board is limited in terms of computational resources, and having system operating working rates in the order of seconds.

In fact, in the literature, the particle filter approach has been already applied successfully to the problem areas of positioning, navigation and tracking of moving objects [8]. A well-known problem with the particle filter approach is a degradation of performance when the dimension of the state to estimate grows. A solution for this degradation of performance is the combination of a Kalman filter approach to estimate the derivatives of the state vector, keeping the position estimated using a particle filter. All in all, in general a low dimension of 2 or 3 for the state vector of the particle filter allows to get to an operative real-time algorithm [9].

In general particle filters can be applied to systems following a non-linear model for the state vector, and a non-linear model for measurements, as expressed in equations 1 and 2.

$$x_{t+1} = f(x_t, u_t) + f_t \tag{1}$$
$$y_t = h(x_t) + e_t \tag{2}$$

Where x_t is the state vector, $f(x_t, u_t)$ is the state vector model, u_t the measurement inputs, $h(x_t)$ the model for the measurements, and f_t and e_t are respectively state vector and measurement errors. It is assumed independent distributions for f_t, e_t and x_0, with known probability densities p_{f_t}, p_{e_t} and p_{x_0}, respectively not necessarily Gaussian. When the model for the state is linear the previous equations become equations 3 and 4.

$$x_{t+1} = Ax_t + Bu_t + B_f f_t \tag{3}$$
$$y_t = h(x_t) + e_t \tag{4}$$

The particle filter approach consist of a numerical implementation to approximate the posterior distribution, $p(x_t|Y_t)$, of the state vector, applying the algorithm shown in Fig. 1 (taken from [9]).

3 Estimating wind conditions using a particle filter

Using the particle filter approach described in the former section, it is possible to estimate wind conditions, speed and direction, using a dynamic model of the sailboat. Within this approach, each particle represents an hypothesis about wind conditions and the filter will try to find the set of particles that best explains the motion of the sailboat for a short period of time, under current wind conditions.

In order to predict the motion of particles according to hypothesized wind conditions a sailboat dynamic characterization is needed. The model used in our simulations has been adapted from [10], and includes two control inputs

1. *Initialization*: Generate $x_0^i \sim p_{x_0}, i = 1, ..., N$. Each sample of the state vector is referred to as a particle.
2. *Measurement update*: Update the weights by the likelihood:

$$w_t^i = w_{t-1}^i p(y_t|x_t^i) = w_{t-1}^i p_{e_t}(y_t - h(x_t^i)), i = 1, 2, ..., N$$

and normalize to $w_t^i \leftarrow \frac{w_t^i}{\sum_i W_t^i}$. And as an approximation to

$$\hat{x}_t = \int x_t p(x_t|Y_t) dx_t$$

take

$$\hat{x}_t \approx \sum_{i=1}^{N} w_t^i x_t^i$$

3. *Re-sampling*: To make the particle population evolve, several re-sampling strategies can be applied. Two of the most commonly used are the followings:

   a. *Bayesian bootstrap*. Take N samples with replacement from the set $\{x_t^i\}_{i=1}^N$ where the probability to take sample i is w_t^i. Let $w_t^i = \frac{1}{N}$. This step is also called Sample Importance Re-sampling (SIR).
   b. *Importance sampling*. Only re-sample as above when the effective number of samples is less than a threshold N_{th},

$$N_{eff} = \frac{1}{\sum_i \left(w_t^i\right)^2} < N_{th}$$

   Here $1 \leq N_{eff} \leq N$, where the upper bound is attained when all particles have the same weight, and the lower bound when all probability mass is at one particle. The threshold can be chosen at $N_{th} = 2\frac{N}{3}$.

4. *Prediction*: Take a $f_t^i \sim p_{f_t}$ and simulate:

$$x_{t+1}^i = f(x_t^i, u_t^i) + f_t, i = 1, 2, ..., N$$

5. Let $t \leftarrow t + 1$ and iterate to step 2.

Fig. 1: Particle filter algorithm

(rudder and sail positions), two external inputs (wind direction and speed) and ten configuration parameters. As a result, the sailboat description is summarized here by the following state space equations (see the original reference for details):

$$\begin{cases} \dot{x} = v\cos(\theta) + p_1 a_{tw} \cos(\psi_{tw}) \\ \dot{y} = v\sin(\theta) + p_1 a_{tw} \sin(\psi_{tw}) \\ \dot{\theta} = \omega \\ \dot{v} = \frac{f_s \sin(\delta_s) - f_r \sin(u_1) - p_2 v^2}{p_9} \\ \dot{\omega} = \frac{f_s(p_6 - p_7\cos(\delta_s)) - p_8 f_r \cos(u_1) - p_3 \omega v}{p_{10}} \end{cases} \tag{5}$$

$$
\begin{cases}
\boldsymbol{w}_{aw} = \begin{pmatrix} a_{tw}\cos(\psi_{tw}-\theta) - v \\ a_{tw}\sin(\psi_{tw}-\theta) \end{pmatrix} \\
\psi_{aw} = atan2(\boldsymbol{w}_{aw}) \\
a_{aw} = \|\boldsymbol{w}_{aw}\| \\
\gamma = \cos(l) + \cos(\psi_{aw}) \\
l = |\delta_s| = f(u_2) \quad if \quad \gamma > 0 \\
\delta_s = \begin{cases} -arctan(\tan(\psi_{aw})) & if \quad \gamma \le 0 \\ -l sign(\sin(\psi_{aw})) & otherwise \end{cases} \\
f_s = p_4 a_{aw}\sin(\delta_s - \psi_{aw}) \\
f_r = p_5 v \sin(u_1)
\end{cases} \tag{6}
$$

Where $\dot{x}$ and $\dot{y}$ represent the horizontal velocity components in North and East directions, respectively; θ is the heading relative to the North, and $\dot{\theta}$ is the angular velocity of the sailboat; v is the tangential speed; f_s is the lift force due to the sail and f_r is the lift force on the rudder; $\boldsymbol{w}_{aw}$ is the apparent wind vector; a_{tw} and a_{aw} represent the true wind and the apparent wind speed, respectively; similarly, ψ_{tw} and ψ_{aw} are the corresponding true and apparent wind directions. Note that in these equations wind direction refers to direction of flow. In fact, if $\tilde{\psi}_{aw}$ is the apparent wind angle that would be reported by a wind sensor, i.e. the wind incidence angle, $\psi_{aw} = fmod(\tilde{\psi}_{aw} + pi, 2\pi)$. All angles are considered positive clockwise.

Regarding the model inputs, $u_1 = \delta_r$ and $u_2 = |\delta_s|$ are the control variables, where u_1 represents the rudder angle relative to boat's main axis; and u_2 is the mainsail's sheet length. l is the pretended or potential mainsail aperture, a function of the sheet length. The environmental inputs a_{tw} and ψ_{tw} represent the absolute or true wind speed and direction, respectively.

The model configuration parameters, p_i, are assumed to be known: p_1 is the drift coefficient; p_2 and p_3 represent, respectively, the tangential and angular frictions; p_4 is the sail lift; p_5 is the rudder lift; p_6, p_7 and p_8 are geometrical coefficients of the sailboat (see Fig.2); p_9 is the mass of the boat and p_{10} its mass moment of inertia.

In this work we have used the parameter set described in [10], $p_1 = 0.05$, $p_2 = 0.2$ kg/s, $p_3 = 6000$ kg·m, $p_4 = 1000$ kg/s, $p_5 = 2000$ kg/s, $p_6 = 1$ m, $p_7 = 1$ m, $p_8 = 2$ m, $p_9 = 300$ kg, $p_{10} = 10000$ kg·m^2, length over all (LOA) = 3.65 m.

Displacement vessels have their attainable speed, v, limited by its waterline length (LWL) [11] due to the motion-induced wave. The so called hull velocity, v_{hull} can be computed approximately as:

$$v_{hull}(knots) \approx 2.43\sqrt{LWL}$$

Where the LWL is given in meters. This aspect has been incorporated to the model to limit the maximum sailboat's speed.

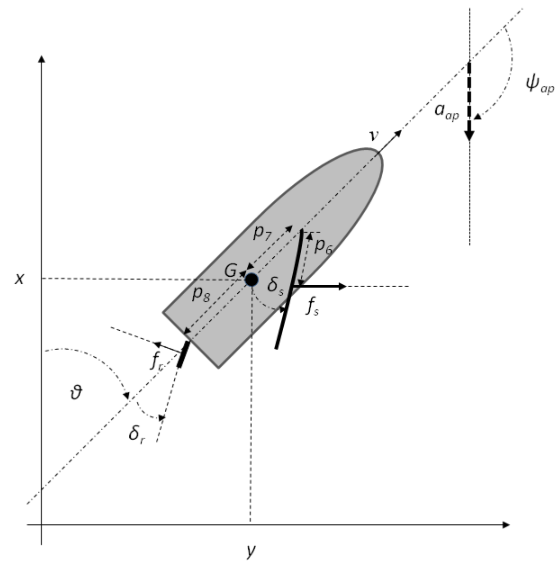

Fig. 2: Sailboat model

4 Results

A series of simulations have been performed in Matlab to test the validity of the proposed approach. The experimental setup has been defined for a short term navigation problem using a time step of 100 milliseconds (ms.) and a total simulation time of 5 minutes, as a convenient balance between the resolution of the dynamic model and the processing requirements.

Considering the limited computational resources that will be available aboard, the state dimension of the particle filter has been limited to 2: the estimation of the direction and the speed of the wind.

The environmental conditions used for testing consisted in 16 equidistant wind directions (separated by 22.5º increments) and three window speeds (1.75, 3.5 and 7 m/s), for a total of 48 test scenarios. In all simulations, both the rudder angle and the mainsail angle, have been kept constant ($\delta_r = 0$, $\delta_s = 45$).

After some preliminary analyses, a base case has been configured for the filter with 20 particles and 5 seconds of cycle time. The filter initialization of the particles selects random samples from a Uniform PDF (Probability Density Function) for the wind direction between -180º and 180º, while the wind speed is randomly sampled from a Weibull PDF with a 2 shape factor and a 10 scale value. The observation function for the particle weighting is based on the euclidean distance between the real sailboat trajectory and the one predicted according to the particle state estimation. The observation error is characterized as a Normal PDF with zero mean, 5 meters of typical deviation. The proposed scheme implements best particle elitism and sample importance re-sampling, with additive mutation processes characterized by Normal PDFs with 5 degrees and 0.2 m/s dispersion. A supplementary particle re-initialization process is applied for the 25% lower weighted ones when no filter convergence is detected.

In the following experiments, a zero mean Gaussian noise has been added to the true wind direction and speed values while simulating the sailboat trajectory, using 5 degrees and 0.5 m/s as typical deviations, respectively. Every scenario has been tested for 51 independent runs. Note that in all graphs true wind incidence angle is used in the horizontal axis.

Figures 3 and 4 show the wind estimation error analysis for the base case. Results show a median absolute direction estimation error generally below 5 degrees and a median absolute speed estimation error generally below 0.25 m/s, with only test directions around -75º and 75º degrees showing a worse result.

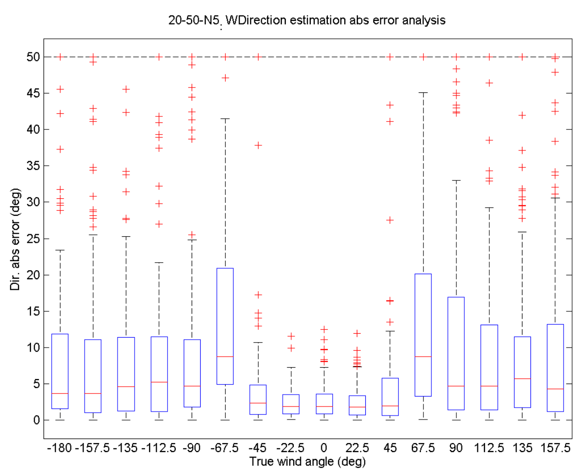

Fig. 3: Box plot for wind direction absolute errors (50 deg data limit) as a function of the different test directions

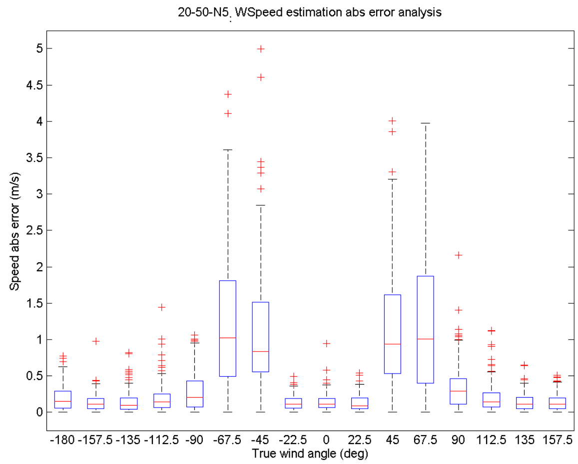

Fig. 4: Box plot for wind speed absolute errors as a function of the different test directions

Figure 5 illustrates that the worse estimation results correspond to situations where the boat shows higher variability with the wind direction. The effect of speed saturation is visible in the bottom graph.

Fig. 5: Wind estimation absolute errors and boat speed as a function of the different test directions

The base case has been compared with two alternative configurations: one with double number of particles and another with double cycle interval. Figures 6 and 7 illustrate the performance comparison between all three alternatives in terms of median and standard deviation values. The configuration using 10 seconds of cycle interval offers slightly better results in the central directions, where the boat speed is low and increasing the integration interval is positive. On the contrary, the configuration using 40 particles performs better off the central region, where the higher boat speeds demands the use of more particles in the filter. Globally, we consider these improvements are not significant enough, and the base configuration seems to be a reasonable choice.

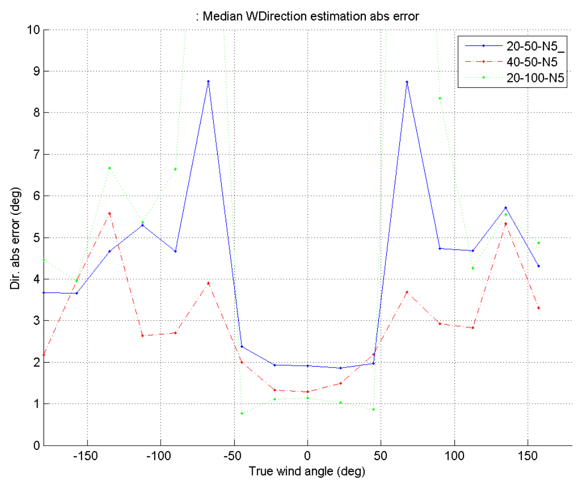

Fig. 6: Performance comparison with two alternative filter configurations: 40 particles and 10-seconds cycle - median values

In order to evaluate the effect of elitism selection, the base case simulation has been repeated deactivating this mechanism. The results, focusing in wind direction estimation error, show that elitism contributes with a global improvement of a 52.7% in the median value and a 29.1% in the standard deviation. Similarly, regarding the no-convergence re-initialization mechanism, the effect has been evaluated as a global improvement around a 19% in median value and a 13% in standard deviation.

Some extreme cases have been also tested for evaluating the filter stability. Using configurations with as low as 5 particles and noise measurement levels of 10 meters the scheme is still able to produce correct median value estimations, though the high dispersion makes them impractical for real time

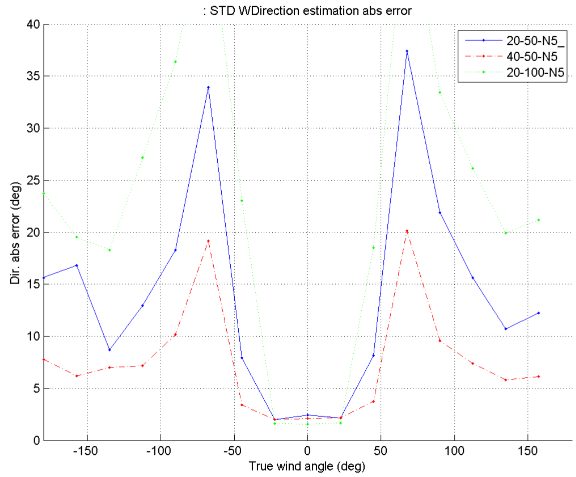

Fig. 7: Performance comparison with two alternative filter configurations: 40 particles and 10-seconds cycle - standard deviation values

operation, because a high number of wind estimations would need to be averaged to get a reliable result.

5 Conclusions

This paper has introduced a virtual wind sensor based on a particle filter, incorporating elitism and re-initialization mechanisms. The results achieved in simulation under realistic noise conditions have produced good estimates of wind direction and speed for most points of sailing. The influence of different aspects such as the number of particles and the integration interval have been analyzed, as well as the contribution of the filtering improvement mechanisms. Specially interesting, in order to implement it on the on-board microcontroller, is the fact that this approach still provide reliable estimates with small particle populations.

The primary application of this filter could be to replace the sailboat's wind sensor on board just in case it ceases to operate. But this virtual sensor could be used also to confirm wind measurements reported by the wind sensor available on board.

Future work will address more detailed simulation studies, for example, taking into account leeward and currents effect, and it will be devoted also to testing this virtual wind sensor on a real sailboat.

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