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The Identification of the Wind Parameters Based on the Interactive Multi-Models

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Abstract: The wind as a natural phenomenon would cause the derivation of the pesticide drops during the operation of agricultural unmanned aerial vehicles (UAV). In particular, the changeable wind makes it difficult for the precision agriculture. For accurate spraying of pesticide, it is necessary to estimate the real-time wind parameters to provide the correction reference for the UAV path. Most estimation algorithms are model based, and as such, serious errors can arise when the models fail to properly fit the physical wind motions. To address this problem, a robust estimation model is proposed in this paper. Considering the diversity of the wind, three elemental time-related Markov models with carefully designed parameter α are adopted in the interacting multiple model (IMM) algorithm, to accomplish the estimation of the wind parameters. Furthermore, the estimation accuracy is dependent as well on the filtering technique. In that regard, the sparse grid quadrature Kalman filter (SGQKF) is employed to comprise the computation load and high filtering accuracy. Finally, the proposed algorithm is ran using simulation tests which results demonstrate its effectiveness and superiority in tracking the wind change.

Keywords: IMM algorithm, wind parameter estimation, the Singer model, SGQKF.

1 Introduction

With the progress of agricultural modernization and the rapid development of UAV technology, the UAV spraying has been more and more applied in plant protection, which helps greatly alleviate the problems of low efficiency, high labor intensity, and pesticide poisoning in traditional operations [Hunt and Daughtry (2018); Millan, Rankine and Sanchez-Azofeifa (2020)]. During the UAV spraying, the UAV is exposed to external factors, such as the wind gusts and turbulences, which causes a deviation in the spray drift from the target plant. One way to solve the problem is by changing the flight path of the UAV to compensate for the spray deviation [Perz and Wronowski (2019)]. The information of the direction and velocity of wind is clearly very important for proper operation of the flight control system. Generally, the wind information could be obtained either from the

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weather forecast, or directly with the transducers, such as inertial sensors [Song, Luo and Meng (2018); Prudden, Fisher and Marino (2018); González-Rocha, Woolsey and Sultan (2019)], and GPS [Balmer, Muskardin and Wlach (2018)]. For measuring the wind speed, the triangulation method is commonly used, that is, the wind speed can be calculated through the airspeed obtained from the UAV-equipped pitot and the ground speed from the navigation system [Langelaan, Alley and Neidhoefer (2011); Cho, Kim, Lee et al. (2011)]. However, the coordinates transformation would couple the attitude errors, resulting in accuracy loss of the calculated wind speed. As a solution for avoiding the coupled attitude error, an anemometer is set on the ground to directly measure the wind and send in real-time, the measurement data to the computer. However, since the measurement of the transducers usually incorporates detection noise, it is critical to study the parameter estimation to extract the particularly useful information of the wind.

In literatures, wind parameter estimations were broadly addressed, and were mainly divided into two aspects, namely the wind modeling and the estimation algorithms [Chen, Wang, Liu et al. (2019)]. Conventionally, the wind models were built subject to several assumptions [Du, Wang, Yang et al. (2019)], while the estimation algorithms were developed in consideration of the research preference of the estimating accuracy and/or convergence rate. Cano [Cano (2013)] and Sikkel et al. [Sikkel, Croon, Wagter et al. (2016)] have proposed the algorithms that use a linearized-about-hover dynamic particle model to estimate the wind parameter. Petrich et al. [Petrich and Subbarao (2011)] estimated the quasi-constant wind with Kalman filter, as they were interested in the steady state of the wind. Yang et al. [Yang, Wei, Jeon et al. (2017)] used the Gaussian process regression to estimate wind fields on meteorological scales. As for the estimation algorithms, the Kalman filter and its extensions have been broadly employed in this research field [Song, Yang and Cai (2017); Wang, Luo, Zeng et al. (2019); Hajiyev, Cilden-Guler and Hacizade (2020)].

It is reasonable to assume that the UAV fly in a constant wind field during the spray. However, the natural wind is continuously changing. There are gusts and disturbances asides to the constant wind. The spraying drift can only be accurately estimated if the natural wind is approximated as accurately as possible. Neither the constant model or the traditional Markov model are necessary to depict the variability of the wind. Nevertheless, the modeling in itself has great impact on the estimation [Zhang, Deng, Liu et al. (2019)]. The proposed real-time wind estimation method is inspired by the philosophy of the interacting multi-models that could fuse different models to match the measurements with the best suitable model. In addition to the modelling, the estimation algorithms with fast convergence and good accuracy are preferred.

On this basis, this paper develops a wind estimation algorithm featuring high robustness and fast indication using the measurements of wind speed. The overall idea of the proposed algorithm is that the Markov time-dependent model is firstly established for solving time-varying parameter estimation of the wind speed. Secondly, three Markov time-dependent models with designed parameters are interacted in an IMM algorithm framework to match the wind state. The SGQKF is adopted to fulfill wind estimation, where the quadrature Kalman filter is known for its high accuracy, and the sparse grid is used to handle the computation burden. The proposed algorithm can improve the estimation accuracy of the wind parameters. It has been tested effectively with simulations and data tests.

The organization of this paper is as follows. The necessary mathematical details of the wind model using the Markov time-related model and the IMM algorithm are reviewed in Section 2. Section 3 describes the designed Markov time-related model parameters and specifics of the implementations of the proposed algorithm. Section 4 presents the numerical simulations and data tests of the wind estimating performance. Section 5 concludes the paper.

2 Preliminaries: IMM algorithm synopsis and kinematic models

In this section, the motion of the natural wind is analyzed and the elementary time-space model is built for the filtering. Also, the IMM algorithm is presented and illustrated for its benefits of adaptive tracking.

2.1 Zero-mean first-order markov model

Wind is a natural phenomenon in the continuous world. It is continuous and time-varying, and conforms to the first-order time-dependent process. That is, the wind speed $u(t)$ at a certain moment is only related to the previous moment $u(t\text{-}1)$, but not to any other time. The correlation function at the two related moments is $R_u(t)$. Applying the Wiener-Kolmogorov whitening procedure to $R_u(t)$, the wind speed variation process can be expressed by the first-order time correlation model as shown in Eq. (1). Where τ_u is the relaxation time and $w(t)$ is the white noise.

$$\dot{u}(t) = -\frac{1}{\tau_u} u(t) + w(t) \tag{1}$$

The model was first proposed by Robert A. Singer, assuming that the rate of the estimate is a zero-mean first-order Markov process. Applying discretization to Eq. (1), the discretized wind estimation model is shown in Eq. (2).

$$\boldsymbol{x}(k+1) = diag\left[\boldsymbol{F}_S(\alpha_x) \quad \boldsymbol{F}_S(\alpha_y) \quad \boldsymbol{F}_S(\alpha_z)\right]\boldsymbol{x}(k) + \boldsymbol{w}(k) \tag{2}$$

$$\boldsymbol{Q} = diag\left[\boldsymbol{q}_s \quad \boldsymbol{q}_s \quad \boldsymbol{q}_s\right] \tag{3}$$

The state vector $\boldsymbol{X}(k)$ is consist of the wind velocities in three direction $[u_x\ u_y\ u_z]^T$, $\alpha_i=1/\tau_i\,(i=x, y, z)$ is the reciprocal of the relaxation time, denoting the rate of the change of the wind velocities, the $\boldsymbol{w}(k)$ is the white noise sequence, and T is the sampling time. And the detail of system model $\boldsymbol{F}(\alpha_x)$ and the components $\boldsymbol{q}_s$ of the corresponding process noise covariance matrix $\boldsymbol{Q}$ are shown in Eq. (4).

$$\boldsymbol{F}_S(\alpha_i) = \begin{bmatrix} 1 & T & (-1+\alpha_i T + e^{-\alpha_i T})/\alpha_i^2 \\ 0 & 0 & (1-e^{-\alpha_i T})/\alpha_i \\ 0 & 0 & e^{-\alpha_i T} \end{bmatrix} \quad \boldsymbol{q}_s = \begin{bmatrix} \frac{T^4}{4} & \frac{T^3}{2} & \frac{T^2}{2} \\ \frac{T^3}{2} & \frac{T^2}{2} & T \\ \frac{T^2}{2} & T & 1 \end{bmatrix} \tag{4}$$

In this study, the wind model is built in the geodetic coordinate system, the wind speed vector is decomposed in x, y and z directions. The x direction is pointing to the east, the y direction is perpendicular to the x axis and pointing to the north, and the z direction is perpendicular to the earth level to point up.

Obviously, the Singer model does not specify the wind motion parameters, the success of this model relies on an accurate determination of the parameter α (or τ_m), which depends on how many seconds the velocity change lasts. For the variable wind field, $\tau_m \approx 60$s may stand for a lazy change of the wind speed while $\tau_m \approx 10 \sim 20$s for an evasive changing [Baringolts, Domin, Zhuk et al. (2019)]. As the speed-changing time constant τ_m increases, the Singer model reduces to the constant accelerating (CA) speed model. On the other hand, as the speed-changing time constant τ_m decreases, the Singer model reduces to the nearly constant velocity (CV) model. Consequently, for a choice of $0<\alpha T<\infty$, the Singer model corresponds to a motion in between the CV model and the CA model, but has much wider coverage than both models.

2.2 IMM algorithm

To achieve accurate estimation of wind parameters, the primary task is to establish a wind estimation model that matches with the actual wind variation process. However, the existing wind estimation models are usually based on certain assumptions about the motion of the wind, such as the constant wind speed models. Moreover, it is difficult to find a model that could cover all the real-time changes of the wind states. For systems with structures and parameters that are subject to change, multi-model estimation is one of the important methods to solve such problems. Multi-model estimation was originally proposed by filtering a set of different maneuver models separately and weighting the filter estimates to obtain the final tracking results. Based on multi-model estimation, the IMM algorithm implemented the Markov switching process of the system model through model conversion probability. Compared to the generalized pseudo-Bayesian, the IMM algorithm has the advantage of low computational complexity and high estimation accuracy, and is considered to be the most effective hybrid estimation scheme [Bilik and Tabrikian (2010)] In order to approximate and character different variations of wind speed as much as possible, the interacting multi-models are employed. The main idea is that when the object's mathematical model or the model changes are not completely determined, multiple models are designed to approximate time-varying or nonlinear processes in complex systems, so that the analyzed estimating performance could be optimal or at least near-optimal.

In the IMM approach, the state estimation at time k is computed under each possible current model using r filters, with each filter using a different combination of the previous model-conditioned estimates. One cycle of the IMM algorithm is shown in Fig. 1.

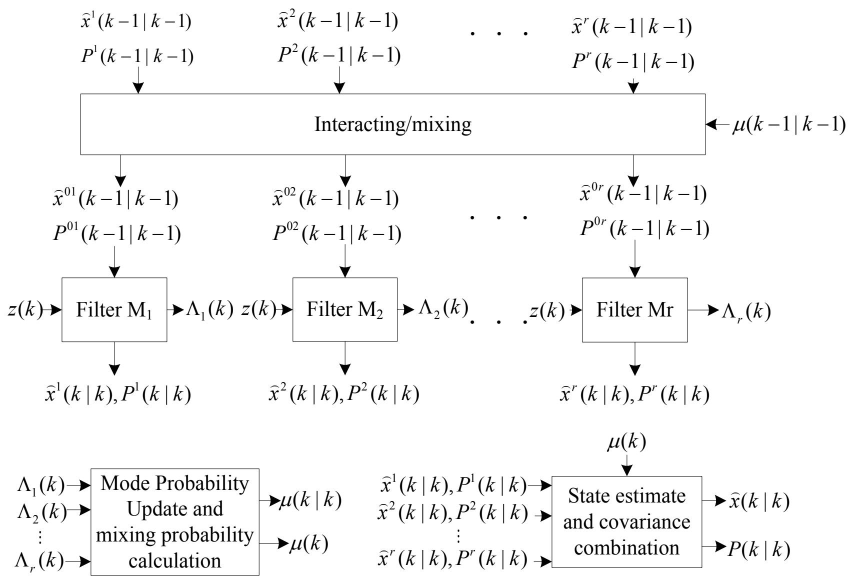


Figure 1: One cycle of IMM algorithm

In Fig. 1, $\boldsymbol{x}^j(k\text{-}1|\ k\text{-}1)$is the estimate vector at time k-1 (when k=1, it represents the initial system vector), the $\boldsymbol{x}^{0j}(k\text{-}1|k\text{-}1)$represents the jth filter's estimate input at time k-1, $\boldsymbol{P}^j(k\text{-}1|k\text{-}1)$ denotes the system covariance matrix at time k-1 (when k=1, it represents the initial system covariance) $\boldsymbol{P}^{0j}(k\text{-}1|k\text{-}1)$ symbolizes the jth filter's covariance at time k-1. The $\boldsymbol{x}(k|k)$ denotes the combined estimate and $\boldsymbol{P}(k|k)$ is the corresponding covariance. $\boldsymbol{\mu}(k|k)$ represents the mixed probabilities, and $\boldsymbol{\mu}(k)$ is a vector constituted of updated probability of mode j at time k. Λ_j is the likelihood function corresponding to filter j (j=1,…,r).

3 IMM-three-singer algorithm

To establish a robust model of the wind speed, the composition of the wind must first be analyzed. Generally, the natural wind contains four components based on the velocity profile of the wind, namely, the mean wind, the turbulence, the wind shear and gust. (1) The mean wind, also called the steady wind, is the main reference of wind speed, which is the average value in a certain time range along the height direction, which changes with time and space. It is the main part in the wind measurement. (2) The turbulence refers to continuous random pulsations superimposed on a steady wind. It is described using stochastic processes. In our research, the regularly used *Dryden* model is adopted to simulate the turbulence. (3) Wind shear denotes a change in time or space specified by the mean wind. (4) And the gust is a discrete or definite change in wind speed, which is a strong atmospheric disturbance.

According to Section 2, the key in estimating the wind speed using the Singer model is to set the appropriate time constants to characterize the intensity of speed change. Considering the possible speed changes of the wind, three sets of parameters of velocity changing conditions have been designed in this paper. The three sets of parameters are given in Tab. 1.

Table 1: Three sets of parameter for Singer model

Set	α_x	α_y	α_z
1	1/60	1/60	1/60
2	1	1	1
3	1/10	1/10	1/40

Based on the up-mentioned analysis of wind field composition, we mainly build three Singer models to response to the three features of the wind field. Set 1 is chosen to represent the steady wind, as the 1/60 of α_x, α_y and α_z means the wind speed in three directions are nearly constant. According to the world meteorological organization (WMO), gust is the positive or negative deviation of the wind speed from the average duration of no more than 2 min within the specified time. As a result, the [1/10 1/10 1/40] has been designed for Set 2, which also signify more intense horizontal change with mild vertical change of the wind speed on considering that the gust usually prefers horizontal deviation than in the vertical plane. Atmospheric turbulence can be seen the continuous random pulses of the steady wind. The engineers usually use the Dryden model and Vonkarman model to depict the turbulence in the practice. In the time domain, in order to describe the characteristics of turbulence, Set 3 is adopted for supposing that the wind velocities does great maneuvers in horizontal and vertical directions.

The proposed algorithm is called IMM-three-Singer algorithm, which involves the above three sets of Singer models to do IMM tracking. Therefore, real-time kinematics estimates of wind velocities could be obtained from the proposed algorithm.

In addition, in order to enhance the estimation accuracy of the IMM elementary filters, the SGQKF has been adopted to do the filtering. A quadrature Kalman filter (QKF) was introduced as another suboptimal, nonlinear filter. It uses the Gauss-Hermite numerical integration rule to calculate the recursive Bayesian estimation integrals and the corresponding weights under the Gaussian assumption, then the nonlinear system's statistical information can be obtained through weighted Gauss points. QKF does not require a large number of sampled particles and is more applicable for the real-time problems compared with particle filtering (PF). Like unscented Kalman filter (UKF), QKF avoids calculating the Jacobian matrix to linearize the system compared with extended Kalman filtering (EKF). With QKF, the number of the Gaussian-Hermite (GH) integrals may vary depending on the system requirements, when three GH integrals are adopted, QKF has equal accuracy as UKF; when more than three GH integrals are used, the performance is better than UKF. The framework of quadrature Kalman algorithm is shown in Fig. 2.

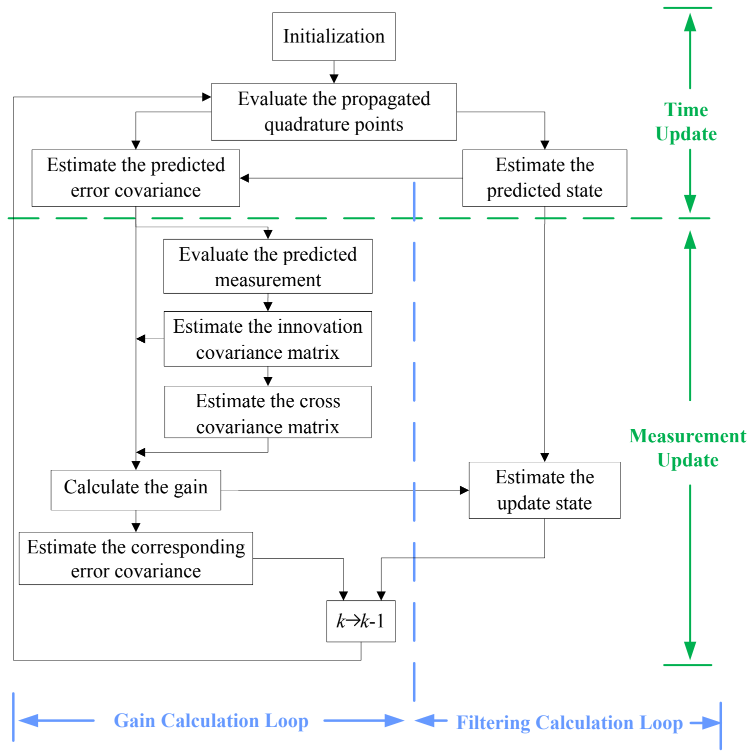


Figure 2: The framework of quadrature Kalman algorithm

Evidently, along with the increase of state dimension and GH integral, there comes an increase in computation loads. The sparse-grid method has been widely used to alleviate the curse-of-dimensionality problem in numerical integration. The original idea of the sparse-grid method was proposed by Russian mathematician Smolyak [Beck, Sangalli, Tamellini et al. (2018)]. After that, several rules were proposed, such as the trapezoidal, Clenshaw-Curtis (CC), Gauss-Patterson (GP) and Kronrod-Patterson (KP) rule. Each rule uses a special strategy to select points for numerical integration so that the number of necessary points is significantly less than that from using the direct product rule. Therefore, the SGQKF is more efficiently applied in engineering. Owing to the fact that KP rule is more adaptive to high nonlinearity, it is employed to do SGQKF in this paper.

4 Simulation

This section details numerical simulations. Firstly, setting of the simulations are described. The wind simulator for testing the algorithms has been built in three dimensions. And the proposed algorithm that the three Singer models in IMM fusion has been verified with the simulation, in order to explore the distinguishing feature of the proposed algorithm, comparative tests have been performed with common strategies of wind estimation.

4.1 The wind simulator

In order to test the effectiveness of the proposed algorithm, the natural wind must be simulated as practical as possible. In this paper, the surface wind is simulated aiming at the agricultural spraying process. On one hand, the wind environment is required suitable for the UAV spraying, for instance, it should avoid operation in strong winds. Therefore, according to the Beaufort Wind Scale, shown as Tab. 2, the 0 to 4 wind force would be selected for simulation.

Table 2: Beaufort wind scale

Wind Force	Wind Speed (m/s)	WMO Classification	Appearance of Wind Effects on Land
0	0.0-0.2	Calm	Smoke rises vertically
1	0.3-1.5	Light Air	Smoke drift indicates wind direction, still wind vanes
2	1.6-3.3	Light Breeze	Wind felt on face, leaves rustle, vanes begin to move
3	3.4-5.4	Gentle Breeze	Leaves and small twigs constantly moving, light flags extended
4	5.5-7.9	Moderate Breeze	Dust, leaves, and loose paper lifted, small tree branches move
5	8.0-10.7	Fresh Breeze	Small trees in leaf begin to sway
6	10.8-13.8	Strong Breeze	Larger tree branches moving, whistling in wires

In this paper, to be consistent with wind field composition, the wind is modeled with Simulink environment toolbox and the wind velocity including the mean wind, the gust, the turbulence and the wind shear is simulated. The output is three-dimensional wind velocity in geographic coordinate system. The established block diagram of the wind simulator is shown in Fig. 3. And the simulated output is shown in Fig. 4, in which, 3.3 m/s of Wind Force 2 has been selected to average speed of the mean wind. The wind model is constructed in geographical coordinates, x axis and y axis constitute the geographical horizontal plane, z axis is perpendicular to the horizontal plane and pointing up.

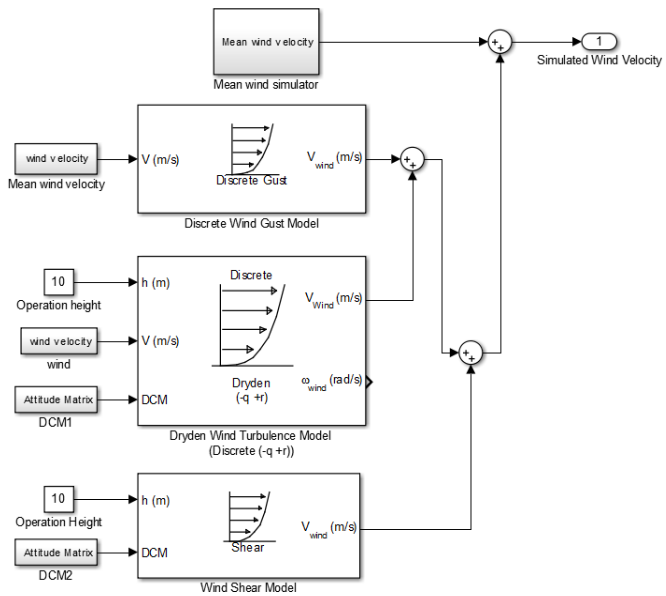


Figure 3: The wind velocity generation

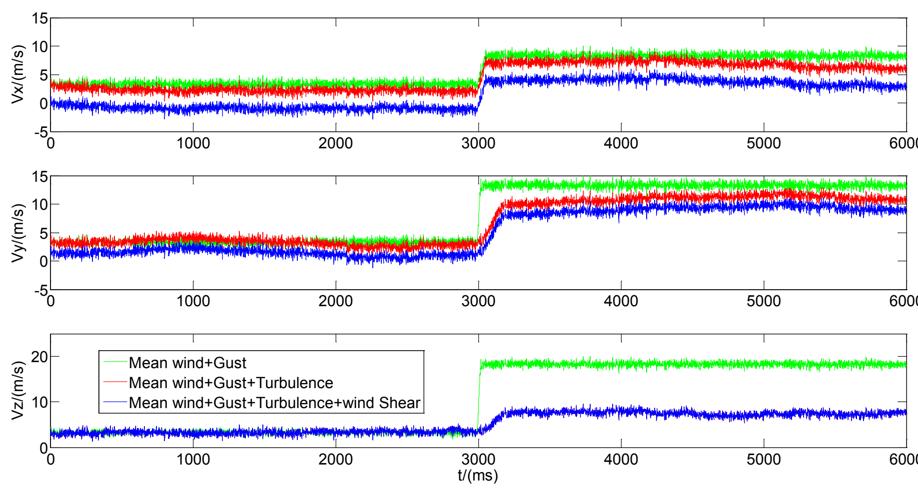
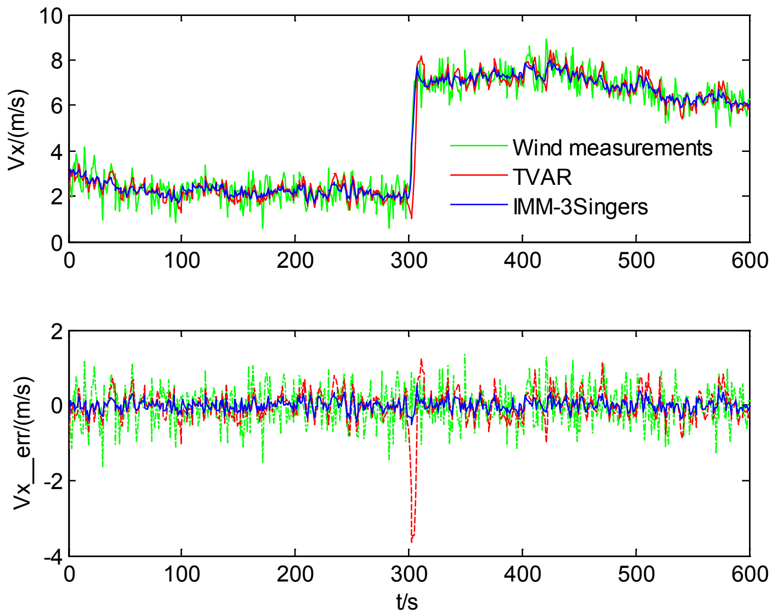


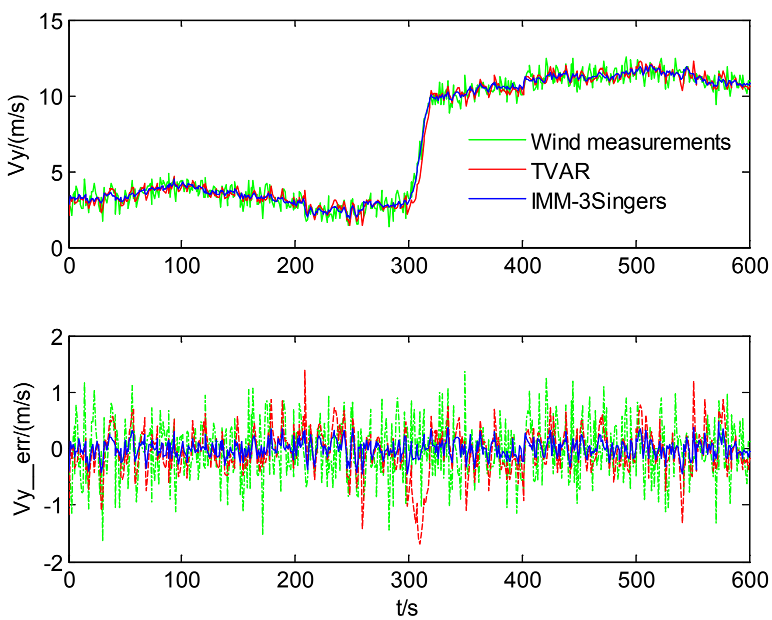
Figure 4: The wind velocities in geographic coordinates

4.2 Experimental analysis

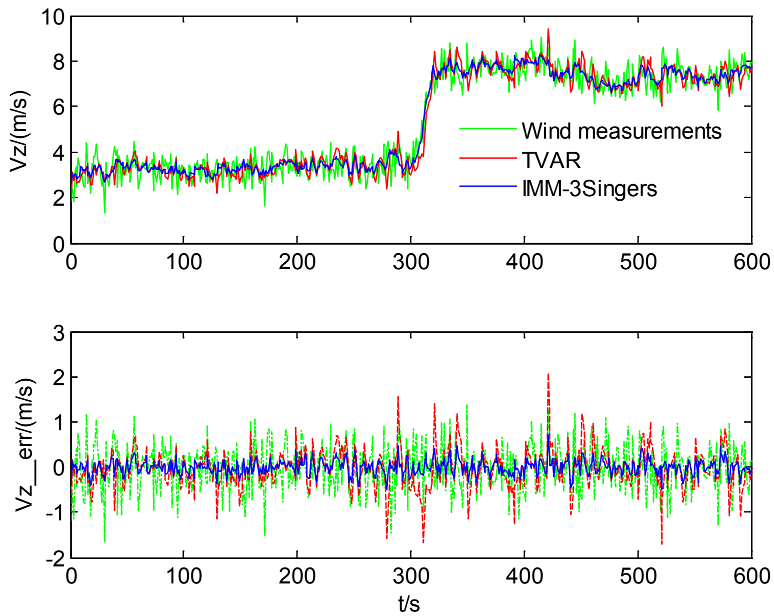
In the simulating experiments, the proposed IMM-3Singer model has been tested and compared with the frequently used the time-varying auto-regression (TVAR) in estimating the wind velocity. For the filtering scheme, IMM-3Singer uses the SGQKF, while the TVAR uses the Kalman filter. The sampling time T=0.1 s, and the experiments tested a 600 s wind data.



(a) the velocity estimation and velocity error in x direction



(b) the velocity estimation and velocity error in y direction



(c) the velocity estimation and velocity error in z direction

Figure 5: The velocity estimation of the wind

From Fig. 5, basically, both the TVAR and the proposed IMM-3Singer algorithm could track the wind. While the latter one has better accuracy as illustrated by estimation errors in three dimensions, thanks to the higher filtering capability of the SGQKF compared with the Kalman filter. Moreover, from Fig. 5(a), there is an obvious pulse in estimation error around 300 s because of the gust. Similar phenomena also arise in Fig. 5(b) and Fig. 5(c). All these pulses denote the advanced ability of IMM-3Singer in fast capturing the change of the wind.

To better reveal the principle of the IMM-3Singer, the Markov transitions of the three parameter sets are shown in Fig. 6. In which, the Singer model with parameter set 1 mainly works before 300 s as it has higher transition probability of 0.35. Comparing with Fig. 5, the of the wind state is relatively stable during this period, so that the Singer model with parameter set 1 has the highest weight as it is more consistent with the steady wind. However, from 300 s to 320 s, the transition probability of the parameter set 2 has risen to 0.7, denoting that the parameter-set 2 Singer model has been adopted for tracking the sudden changes of wind speeds, which conform to the design of parameter set 2 for gust circumstance. Besides, it is also seen that there are two peaks during 300~320 s. The first one represents the beginning of the change that is wind speed from stable state to shifting state; the other one represents the ending of the change that is wind is from shifting state back to stable state. After the gust, the wind speed state tends to be stable again, and the weight distribution of the model shifts back to the high proportion mode of set 1. The whole transition shifts demonstrate that the proposed method can find suitable combination of Singer models so as to achieve accurate estimation and fast tracking of the wind speed.

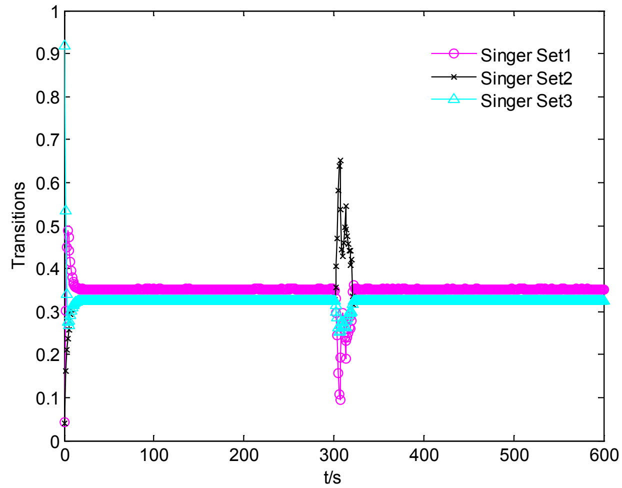


Figure 6: The mode-switching status of the IMM-3Singer

At last, with 50 times Monte Carlo simulation of the mean square error (MSE) of the velocity errors as shown in Fig. 7, IMM-3Singer demonstrates its superiority undoubtedly.

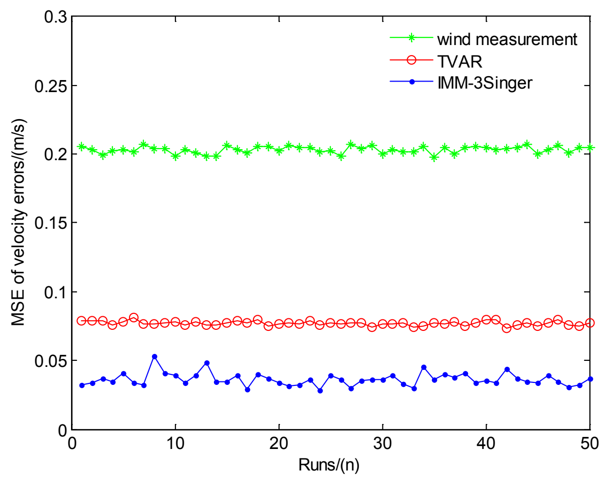


Figure 7: The Monte Carlo comparison of estimation errors

5 Conclusion

In wind parameter estimation, there are different kinds of wind with complex states, estimation algorithms with single model is hard to get accurate estimates. The IMM algorithm has been adopted for estimating the wind parameters in favor of its marked ability in dealing with uncertainty. But for IMM, the elemental models would greatly affect the tracking accuracy, because the final estimate is obtained by a weighted sum of the estimates from the sub-filters of different models, if the models are far from the physical fact, the IMM algorithm would barely achieve the expected efficiency. In order to obtain a better estimation, an improved time-related Markov model has been presented and tested experimentally in this paper. Through analysis of different types of wind, a set of Singer models with elaborative parameters are put in IMM to get the estimates of the wind velocities in geodetic coordinate. Besides, on account of the distinguished capability in filtering noise, the SGQKF has been employed to obtain better estimation to further enhance the algorithm accuracy. Eventually, the gust wind was tested with TVAR and the proposed algorithm in the numerical simulation, the results illustrated that the IMM-3Singer model could match a best model for accurately tracking the gust, and it is nearly 3s faster than the TVAR model. The 50 Monte Carlo simulations of estimation error of the wind velocities have demonstrated that the proposed algorithm outperforms the TVAR with Kalman filter in improving 50% of the estimation accuracy.

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