Acceleration for Wind Velocity Vector Estimation by Neural Network for Single Doppler LIDAR

Taro Matsuo1, Guanghao Sun1, Shouhei Kidera1, Tetsuo Kirimoto1, Hiroshi Sakamaki2, and Teruyuki Hara2
1Graduate School of Department of Informatics and Engineering, University of Electro-Communications, Tokyo, Japan
2Information Technology R&D Center, Mitsubishi Electric Corporation, Kanagawa, Japan

***Abstract* - Doppler Light-Detection-And-Ranging (LIDAR) system is an essential tool for real-time wind monitoring for aircraft taking off and landing. Single LIDAR model is preferable in terms of cost and being free from synchronization problem of multiple LIDARs. There are many studies for single LIDAR based velocity estimation. In specifying the recognition for typical air turbulences, such as tornado, microburst or gust front, the parametric approach has been introduced in our previous research. However, this method suffers from a large computational time due to solving multiple dimensional and non-linear optimization problem by particle swarm optimization (PSO). Aiming at real-time monitoring, this paper introduces neural network based optimization approach to determine the turbulence model. The results from numerical simulation demonstrate that the proposed method considerably reduces the calculation cost without sacrificing an estimation accuracy, compared with that obtained by the former PSO based method.**

***Index Terms* — Single LIDAR model, Local air turbulence estimation, Neural network.**

1. Introduction

Local air turbulence is one of the main factors which can lead to aircraft accidents in landing or taking off [1]. For a weather monitoring around an airport, Doppler Light-Detection-And-Ranging (LIDAR) comes under spotlight as long-range, high-resolution measurements of the position and radial velocity along the line-of-sight (LOS) direction. The LIDAR measures wind velocity by analyzing the scattering echo from aerosols in atmosphere, and it is, then, applicable even to fine weather case. In recent decade, while Dual-LIDAR system has been proposed [2] to reconstruct the 2-dimensional (2-D) window vectors directly, it requires accurate synchronization between them and needs more costs and tasks to maintain synchronization accuracy. According to this background, single LIDAR system is preferred. A variety of approaches for the wind vector estimation have been developed for single LIDAR, such as the velocity azimuth display (VAD) [3] and the velocity volume processing (VVP) methods [4]. The VAD assumes the uniform distribution of wind vector with the same range but different azimuth angles. Then, if there is a significant variation along the range direction, such as local air turbulence, it suffers from inaccuracy for wind vector estimation. As another approach, VVP is developed based on linear approximation of velocity distribution in local spatial area. In the case of non-linear distribution, the accuracy for this method degrades, naturally. To solve this problem, we have already proposed a parametric estimation method [5] where the mathematical model for typical air turbulences, such as tornado, microburst or gust front are introduced. However, this method requires a large computational time due to solving multiple dimensional and non-linear optimization problem through particle swarm optimization (PSO) based optimization.

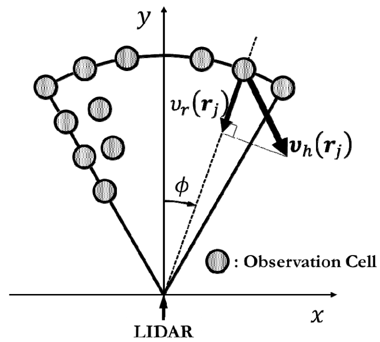

Fig. 1. System model.

To achieve more time-efficient solution, this paper introduces a neural network (NN) into a determination process of turbulence modeled in [5]. Results from numerical analysis demonstrate that the proposed method considerably reduces a required computational cost without sacrificing an accuracy.

2. System Model

This paper assumes the 2-D problem in monostatic LIDAR observation. Figure 1 shows the system model. LIDAR is located at the coordinate origin. Each location of the discrete cells (denoted as black circle in Fig. 1) is determined by range and azimuth resolution of LIDAR. $\boldsymbol{r}_j$ denotes the location of the j th discrete cell, $\boldsymbol{v}_h(\boldsymbol{r}_j)$ is a wind velocity vector with the radial velocity $v_r(\boldsymbol{r}_j)$, and ϕ is the azimuth angle. It is assumed that the horizontal wind is invariant in the observed event.

3. Conventional Methods

As mentioned in Sec.1, while there are various traditional approaches, such as the VAD and VVP methods, they must assume that the wind distribution in local spatial area should be uniformly or linearly approximated to determine the 2-D velocity field from radial velocity data. However, in the case of strong local turbulence, these methods should be discarded. To overcome such a problem, we have already proposed the parametric approach by introducing a mathematical model for typical turbulence pattern [5]. On the contrary, since this method is based on non-linear optimization scheme, which is time consuming, it is hard to achieve real-time monitoring.

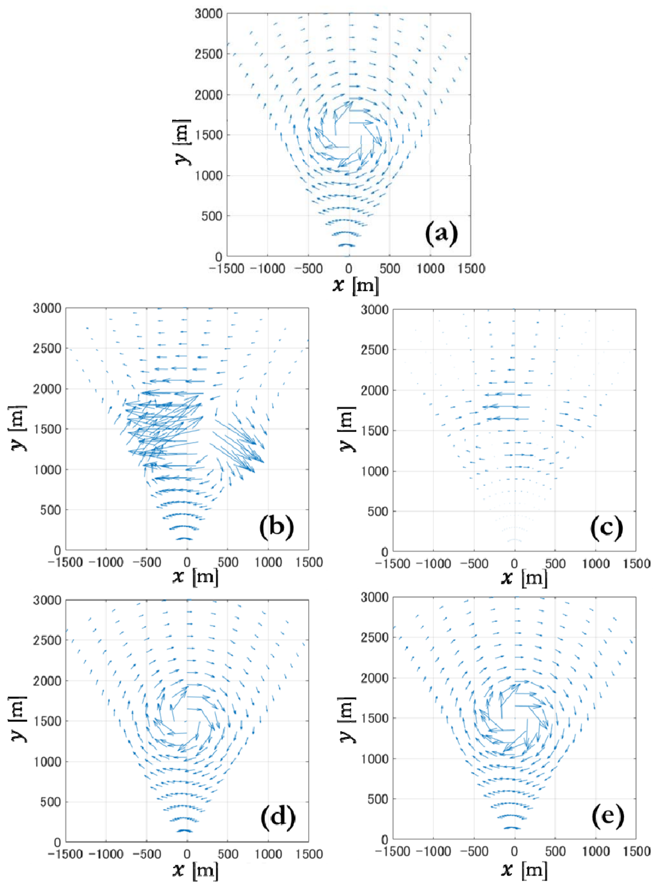

Fig. 2. Estimation results of wind velocity vector field ((a): true, (b): VAD, (c): VVP, (d): Parametric[5] and (e): Proposed).

4. Proposed Method

This section presents the methodology of the proposed method. As a solution to the aforementioned problem, a supervised machine learning approach based on NN using training datasets is adopted. Input dataset is a series of radial velocity for each discrete cell, and the turbulence model is determined through the outputs at the final layer. After the turbulence model is determined, its parameter vector in the kth turbulence model denoted as $\boldsymbol{p}_k$ are determined as;

$$\hat{\boldsymbol{p}}_k = \mathop{\arg\min}_{\boldsymbol{p}_k} \sum_{\boldsymbol{r}_j \in \Omega} \left(v_{r,k}^{\mathrm{est}}(\boldsymbol{p}_k) - v_r^{\mathrm{obs}}(\boldsymbol{r}_j) \right)^2 , \quad (1)$$

where the region Ω denotes all the observation area, $v_{r,k}^{\mathrm{est}}(\boldsymbol{p}_k)$ is a radial velocity calculated by the mathematical model for kth turbulence model denoted in [5], and $v_r^{\mathrm{obs}}(\boldsymbol{r}_j)$ is the observed one. By determining an appropriate model with NN, a redundant computational cost for assessing inappropriate model is significantly reduced.

5. Evaluation in Numerical Simulation

This section describes performance evaluation through numerical simulation. Each number of sample is 21 for range direction and 11 for azimuth direction. The range and azimuth resolutions are 150 m and 6°, at the range of $0\,\mathrm{m} \leqq |\boldsymbol{r}_j| \leqq 3000\,\mathrm{m}$ and $|\phi| \leqq 30°$, respectively. Four wind field models as uniform distribution, tornado, microburst and gust front are investigated. The NN is consisted of three layers as

TABLE I
NRMSE in Each Turbulence Model.

	Uniform Wind	Tornado	Microburst	Gust Front
VAD	6.55×10^{-3}	1.92	1.66	0.988
VVP	1.25×10^{-10}	7.45	6.15	3.42
Parametric[5]	3.10×10^{-4}	0.0927	0.0901	0.253
Proposed	4.18×10^{-4}	0.0886	0.0879	0.241

input (220 nodes), hidden (180 nodes) and output (4 nodes) layers, where the number of output nodes corresponds to the assumed turbulence models. Figure 2 shows the estimated wind vector field for each method. This figure demonstrates that the estimation errors are significantly reduced by the parametric approach and proposed methods, while the VAD and VVP suffers from a serious inaccuracy. For quantitative analysis, the normalized root mean square error (NRMSE) is introduced as

$$\mathrm{NRMSE} = \sqrt{\frac{\sum_{j=1}^{N} \left| \boldsymbol{v}_h^{\mathrm{true}}(\boldsymbol{r}_j) - \boldsymbol{v}_h^{\mathrm{est}}(\boldsymbol{r}_j) \right|^2}{\sum_{j=1}^{N} \left| \boldsymbol{v}_h^{\mathrm{true}}(\boldsymbol{r}_j) \right|^2}} , \quad (2)$$

where N denotes the number of discrete cells, $\boldsymbol{v}_h^{\mathrm{true}}(\boldsymbol{r}_j)$ is a true wind velocity vector at the jth cell, and $\boldsymbol{v}_h^{\mathrm{est}}(\boldsymbol{r}_j)$ is the estimated one, respectively. NRMSE and afternentioned computational time are all averages for 100-trials with randomly changed initial values of PSO. Table I summarizes the NRMSE for each method, and shows that the proposed method maintains almost same accuracy compared with that obtained by the parametric approach. On the contrary, the calculation time is required 273 sec for the parametric approach and 73 sec for the proposed method using Intel(R) Xeon(R) CPU E5-1620 0 @3.60GHz, where the model determination by NN requires only 0.05 sec. The proposed method achieved about 1/4 times reduction by the computational time.

6. Conclusion

This paper introduced the NN based wind field estimation method for single LIDAR model. The results of numerical simulations demonstrated that the proposed method reduces the computational time without degradation of estimation accuracy.

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