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FORECASTING HEADWIND PROFILES AND LOW LEVEL WINDSHEAR USING LIDAR VELOCITY DATA AND A CHAOTIC OSCILLATORY-BASED NEURAL NETWORK

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ABSTRACT

Two Doppler LIght Detection And Ranging (LIDAR) systems have been operated by the Hong Kong Observaotry (HKO) at the Hong Kong International Airport (HKIA) for the detection and alerting of low-level windshear to be encountered by the aircraft. The windshear alerting algorithm is based on the automatic identification of abrupt changes of headwinds along the glide paths of HKIA, which are measured by the glide-path scans of the LIDARs. To give earlier windshear alerts to the aircraft, forecasting of the headwind profiles would be required. The present paper discusses the forecast of headwinds based on the past LIDAR data and a chaotic oscillatory neural network (CONN). The LIDAR's headwind data in the previous 30 days or so are used to train the CONN, which is then used to forecast the headwind profiles in the next hour. For two selected cases as presented in the paper, the CONN forecasts successfully capture the evolution of the headwind profiles. Moreover, the use of CONN forecast to give windshear alerts is demonstrated in one sea breeze case. The forecast alerts are generally comparable with those based on the actual LIDAR observations. As such, based on the limited number of sea-breeze induced windshear episodes considered in the paper, the application of CONN to LIDAR data has the potential of forecasting the major features of the evolution of the headwind profiles.

1. INTRODUCTION

Low-level windshear, viz. abrupt headwind changes below 1600 feet or within 3 nautical miles from the runway end, could be hazardous to the landing/departing aircraft of the airport. The majority of windshear at HKIA occurs in clear-air condition, including terrain-induced airflow disturbances (70% of the pilot windshear reports) and sea breeze (20% of the reports). For the alerting of windshear, two Doppler LIDAR systems have been in operation at HKIA, each serving a particular runway of the airport.

The LIDAR-based windshear alerting algorithm is based on the detection of abrupt headwind changes along the glide paths [1]. The headwind profile along a particular glide path is first constructed by scanning the laser beam along the path itself, a specially devised scan strategy called the glide-path scan. The headwind data are then analyzed automatically in a computational algorithm to look for abrupt wind changes, also named as windshear ramps, for the issuance of windshear alerts if the headwind change exceeds a certain threshold (currently taken as 14 knots). This windshear algorithm is mainly detection-based using the actual LIDAR velocity observations.

The next development of windshear alerting services would be the forecasting of low-level windshear. In this paper, forecasting is attempted using neural network approach. Initial application of this approach has been discussed in [2]. More case studies would be discussed in the present paper. In particular, the CONN-forecast headwind profiles would be processed through the above-mentioned windshear algorithm to generate windshear alerts, which are then compared with the actual alerts based on the real LIDAR data. To the knowledge of the authors, this is the first time that neural network is used to forecast windshear based on LIDAR-measured headwind profiles.

2. BRIEF DESCRIPTION OF CONN AND ITS APPLICATION TO LIDAR DATA

The structure of CONN has been described in [2] and [3] and only a summary of the major features is given here. The input to CONN is the actual LIDAR-measured headwind data along the glide path at various distances away from the runway end. Such data are passed into the neural network, which consists of a hidden layer and an output layer. The hidden layer has two kinds of neurons with different oscillation characteristics. The parameters of the oscillators have been empirically tuned from previous case studies [2]. A schematic diagram of the neural network could be found in Figure 1.

The output data from CONN is again the headwind values at various locations along the glide path. Two glide paths would be considered in this paper, namely, landing at the north runway of HKIA from the west (i.e. 07LA) and landing at the south runway from the west (i.e. 07RA). The same set of parameters of the oscillators has been used for the neural networks as applied to these two runway corridors.

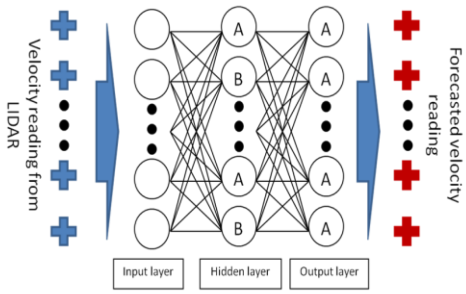

Figure 1 Structure of CONN

3. EXAMPLES OF HEADWIND FORECAST

Two cases of headwind forecast using CONN are studied here. The first is a westerly sea breeze case under background easterly winds in the daytime of 13 November 2007. Synoptically, a ridge of high pressure over southeastern coast of China brought a moderate easterly airstream to Hong Kong. With abundant sunshine, sea breeze set in over HKIA in the afternoon on that day. The LIDAR velocity imagery at about 05 UTC (1 p.m., with Hong Kong time = UTC + 8 hours) is given in Figure 2(a). The glide path of 07LA is considered for this case. A training dataset is constructed from the LIDAR velocity data recorded between 00:01:01 UTC, 13 October 2007 and 04:40:00 UTC, 13 November 2007. Forecast of headwind profiles is then made from 04:45:00 to 05:30:00 UTC, 13 November 2007. The actual 07LA headwind profiles in this forecast period is shown in Figure 2(b). A windshear ramp associated with the sea breeze front (i.e. the interface between the background easterly wind and the westerly sea breeze) could be identified at the time instance labelled as "1" in the figure, and this ramp moves further towards the airport at the latter time labelled as "2". Similar evolution of the sea breeze front is given in the CONN forecast as given in Figure 2(c).

The second case aims at testing the performance of CONN for larger-scale (mesoscale) change of the wind, i.e. the change between easterly and southwesterly winds at HKIA on 9-10 June 2007. Synoptically, a trough of low pressure persisted along the coast of southern China. The coastal area was affected by a southerly airstream. On the other hand, there was a ridge of high pressure over the southeastern part of China. The LIDAR velocity imagery captures the change of wind direction over the airport, from easterly at about 22 UTC, 9 June (Figure 2(d)) to south-southeasterly at about one hour later (Figure 2(e)). As a result, the headwind profile over 07LA changes from mostly positive (at least up to 3 nautical mile from the runway end, at time labelled "1" in Figure 2(f)) to all negative (i.e. tailwind, at time labelled "2" in the same figure). In the CONN forecast, training is made with the LIDAR data between 00:02:44 UTC, 1 May 2007 and 18:42:51 UTC, 9 June 2007, and forecast is then made from 22:11:44 to 23:11:53 UTC, 9 June. The forecast headwind profiles are shown in Figure 2(g). It could be seen that, while it is not strictly a windshear case the change from positive to negative headwinds in the forecast period is captured successfully by CONN.

In order to test the robustness of CONN relative to the other, more conventional neural networks, forecasts of headwind profiles for the above two cases have also been made using multi-layered perception (MLP) neural network. The same training sets have been employed. It turns out that the root-mean-square (r.m.s.) difference between the actual and the forecast headwind profiles is about 0.1 – 0.112 (for normalized headwind) using MLP, and the corresponding value is about 0.069 – 0.095 using CONN. As such, with the limited number of cases under study, CONN is found to have better performance over the conventional MLP neural network. More cases would be considered in the future to establish the performance of CONN relative to the other neural networks in headwind forecasts.

4. FORECASTING OF WINDSHEAR ALERTS FOR A SEA BREEZE CASE

The CONN-forecast headwind profiles have also been used to generate windshear alerts. The case under study is the windshear ramp associated with a sea breeze front in the daytime of 10 March 2006. The LIDAR velocity imagery at that time is given in Figure 3(a). The headwind profiles over 07RA are considered in the present case. The training dataset is constructed using the LIDAR velocity data between 00:05:42 UTC, 1 February 2006 and 04:28:46 UTC, 10 March 2006. The forecast is then made from 04:30:31 to 05:40:33 UTC, 10 March. The actual headwind profiles in the forecast period are given in Figure 3(b), showing the movement of the windshear ramp towards the airport and the appearance of tailwind over the whole glide path later in the period (due to the prevalence of westerly sea breeze over 07RA). This evolution of headwind profile is captured successfully by CONN (Figure 3(c)). A windshear ramp captured by the windshear alerting algorithm using the actual LIDAR data is shown in Figure 3(d). Similar windshear alerts could also be given by applying the algorithm to the CONN-forecast headwind profiles, with an example in Figure 3(e). More sea breeze cases would be considered in future studies in order to establish the performance of forecast windshear alerts based on CONN and the windshear alerting algorithm.

5. CONCLUSIONS

A sophisticated neural network, namely, CONN, is applied to LIDAR data to forecast headwind profiles to be encountered by landing aircraft at HKIA in some selected cases. In terms of the r.m.s. difference with the actual headwind data, CONN appears to have better performance in comparison with the more conventional neural network such as MLP. Moreover, for a sea breeze case, the CONN-forecast headwind profiles are input into the LIDAR-based windshear alerting algorithm to generate forecast windshear alerts, which are comparable with the alerts based on the actual LIDAR data in the forecast period. Further studies would be carried out on the performance of such forecast windshear alerts, e.g. by considering the probability of detection and the alert duration in comparison with the pilot windshear reports.

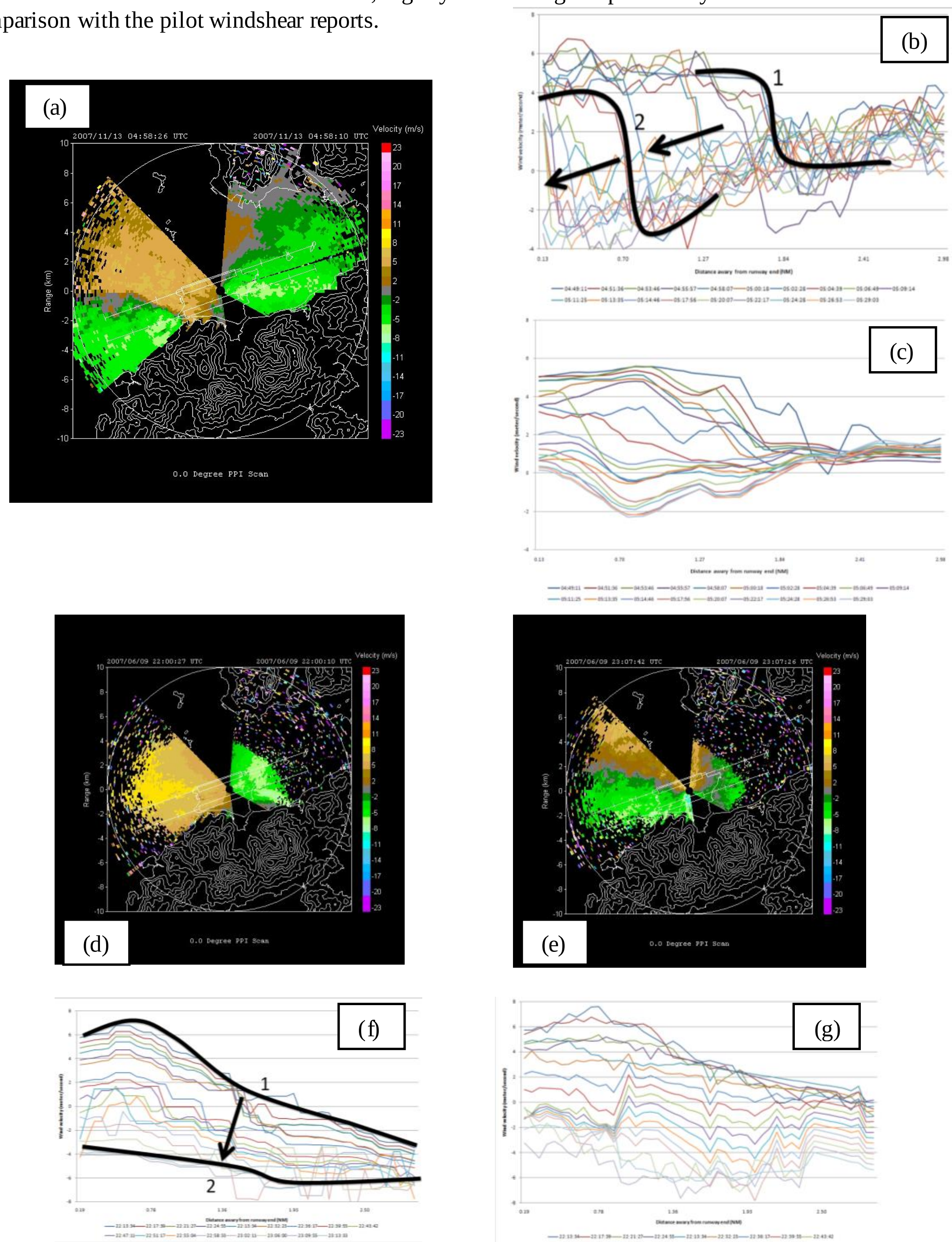

Figure 2 (a) is 0-degree conical scan imagery of the LIDAR for the sea breeze case on 13 November 2007. The headwind profiles over 07LA between 04:50 and 05:30 UTC are shown in (b) and the corresponding CONN forecast shown in (c). (d) and (e) are the 0-degree conical scan imageries of the LIDAR for the case on 9-10 June 2007, with the winds over HKIA changing from easterly to south-southwesterly. The headwind profiles over 07LA are given in (f) and the corresponding CONN forecast given in (g).

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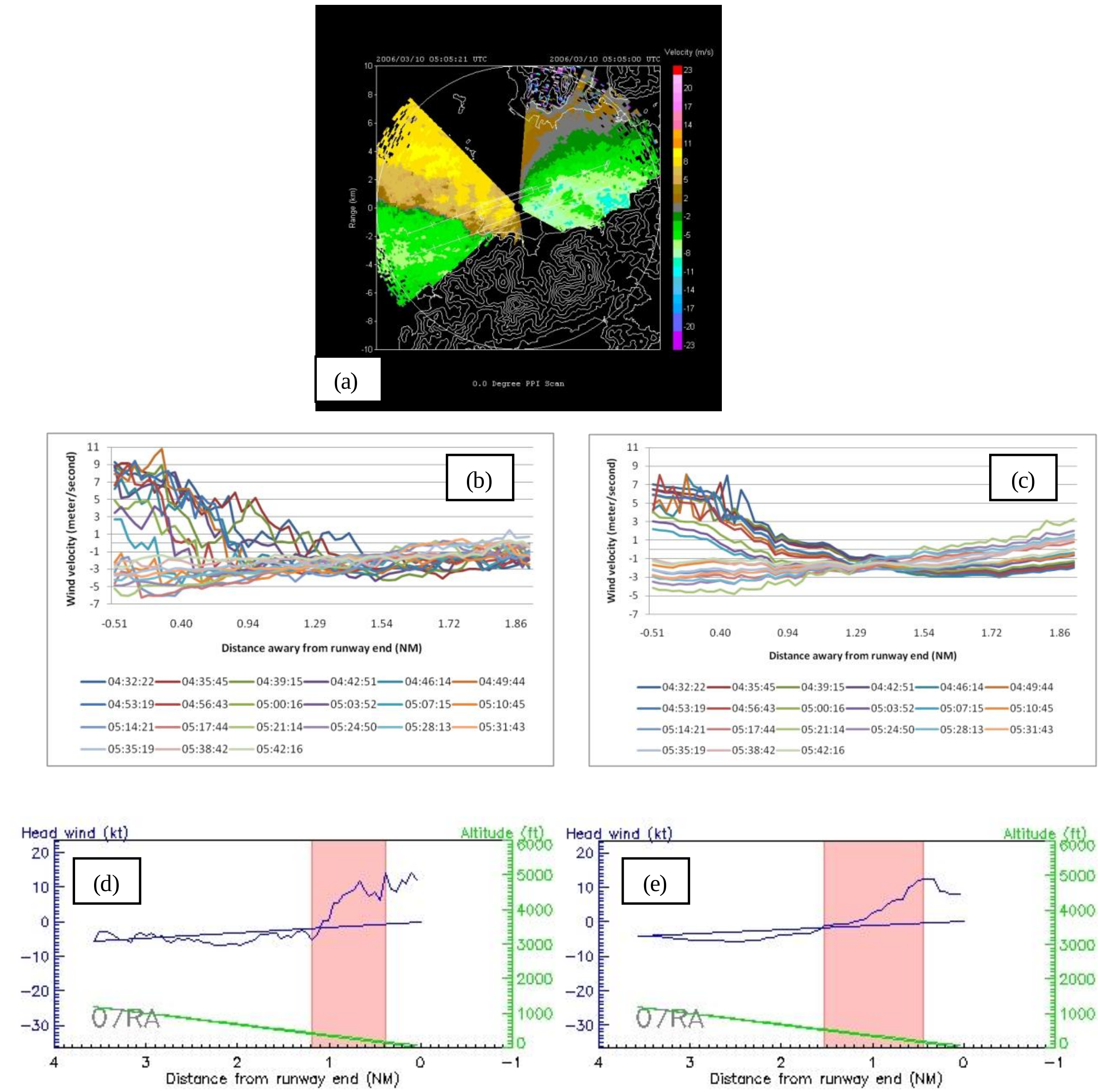

Figure 3 (a) is 0-degree conical scan imagery of the LIDAR for the sea breeze case on 10 March 2006. The headwind profiles over 07RA between 04:30 and 05:40 UTC are shown in (b) and the corresponding CONN forecast shown in (c). (d) is the headwind profile (shown in blue) over 07RA at 04:46:14 UTC, 10 March, with the windshear ramp highlighted in red. (e) is the corresponding headwind profile forecast by CONN with the windshear ramp detected by LIDAR windshear algorithm.