

Computing Aircraft Position Prediction

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Abstract: Air traffic is increasing world wide at a steady annual rate, and airport congestion is already a major issue for air traffic managers. This paper presents a model based on neural networks to predict the position of aircraft on the airport, during landing or takeoff. The same model can also be used to predict the behavior of other vehicles moving on the airport. The predictions help to detect near-collision situations earlier, giving air traffic controllers additional time to take remedial actions. The system uses the list of coordinates produced by the airport radar system, and obtains a prediction of the future position of each object. It is only necessary to store a short history of positions for each object in order to perform the estimation. This estimation has an average error comparable to the size of the airplane when the algorithm is adjusted for 20 second look ahead. The proposed model has been evaluated using data from Chicago O'Hare International Airport, which is the airport with the highest number of movements (from 2001 to 2004).

Keywords: Airport traffic management, collision avoidance, prediction models, neural networks.

INTRODUCTION

According to Civil Aviation Organization, the number of travelers is increasing at a constant rate of 5% every year [1]. Also, the number of operations (landings and takeoffs) is increasing in most airports around the world and all projections show continued growth during upcoming years.

Airport congestion raises the likelihood of having delays. In addition, the common concern about potential aircraft accidents gets even more significant. Therefore, air traffic management authorities are considering and adopting new technologies to cope with increasing traffic while simultaneously improving safety.

The safety statistics published by the International Air Transport Association show an average level of airplane accidents at about 1 per million departures (and decreasing in recent years) [2]. The absolute number of airplane accidents may grow with the increasing number of flights, but the accident rates should remain constant. This is true only when the number of accidents is independent of the congestion level. However, there are certain types of incidents that may intensify in some rapid growing airports. One such incident is the runway incursion, which involves an airplane entering a runway that has been assigned to another airplane for landing or takeoff. In this event, the fast moving airplane may potentially crash against the airplane that is entering the active runway. Another potentially dangerous situation occurs when a landing aircraft does not leave the runway on time, since landing airplanes usually approach the airport flying just a few minutes apart. Under the latter condition, the second airplane must abort the landing operation and fly over the runway to avoid a possible collision.

Many airplane accidents (80%) occur at or near airports, due to mechanical failures or human errors. Following are some examples of worst and recent accidents involving pairs of airplanes that crashed on-ground or mid-air [3]:

- On ground: Tenerife, Spain, 1977 (583 victims, worst aviation accident), Milan, Italy, 2001 (114 victims);
- Mid-air: New Delhi, India, 1996 (349 victims, worst midair collision, 3rd worst aviation accident), Überlingen, Germany, 2002 (71 victims).

Two different strategies have been developed to avoid this kind of accidents: those designed for pilots, and those designed for air traffic controllers. Pilots use on-board systems that detect or communicate with nearby aircraft. One such system is TCAS (Traffic Collision Avoidance System) launched by the FAA in 1981. On the other hand, air traffic controllers use systems that rely primarily on radar signal and analyze the positions of each target. One such system is AMASS (Airport Movement Area Safety System) developed by the FAA after the prevention of runway incursion was listed at the top of the "Most wanted transportation safety improvements", published by the NTSB (U.S. National transportation safety board) [4].

Both approaches for avoiding accidents are based on knowing the absolute positions (coordinates) of the airplanes, or their relative positions (separation distance). Then, different algorithms can be applied to decide if the condition involves any potential danger. Prediction algorithms are useful to simulate future scenarios that can be evaluated before the real situation takes place. Therefore, by adding prediction algorithms to any of the current detection systems, one provides additional time to perform corrective actions. The full potential of the proposed approach will be demonstrated if the prediction model is integrated in intelligent detections systems that make use of contextual information.

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Such intelligent systems may detect runway incursions by analyzing runway configuration and cross checking aircraft position with their expected behavior.

DESCRIPTION OF THE PREDICTION SYSTEM DESIGNED

Several prediction models can be used to estimate the value of any magnitude in the future. The algorithm presented in this paper is based on a neural network model, because previous studies demonstrated that neural networks can provide better accuracy than other models [5]. Neural networks (NN) are able to model non-linear processes accurately and are tolerant of certain degree of inaccuracy in the inputs. Both characteristics are important in the current application since airplane movement is subject to changes in speed, with significant acceleration and deceleration values; and airplane position data are imperfect due to slight non-uniform sampling frequency and errors in the analysis of reflected radar signals. Neural Networks, like any other mathematical models, require to be cautiously adjusted (trained in NN nomenclature) in order to obtain useful internal parameters. The training procedure involves executing optimization algorithms with varying convergence times that depend mainly on the complexity of the problem. However, once the neural network has been trained, the computing procedure that is performed in real-time is deterministic.

The Neural Network was originally designed as a black-box model to estimate future coordinates based on a short history of past coordinates. Two different position prediction approaches are presented in this paper (see Fig. (1)):

- **X/Y approach:** The same neural network is applied twice, one time to estimate the future X coordinate (longitude) based on the latest X values, and second time to estimate Y coordinate (latitude).
- **Bearing/distance approach:** This approach is based on estimating the direction of movement (bearing) and the distance that the target will make; then the future position is computed applying trigonometry.

The neural network is used to estimate X movement, Y movement or actual movement, using 10 seconds of past history to predict values up to 30 seconds in the future. One can feed the model with absolute X or Y coordinates to estimate the absolute coordinates in the future, but it was found more accurate to use delta values (distance made during the

last seconds) to estimate the distance that the airplane will make in the future; then the futures coordinate is computed by adding estimated distance to the current position [5]. Fig. (2) summarizes the structure of the model:

The structure selected for neural network is a Multi-Layer Perceptron (MLP), because it is efficient and easy to implement in other applications, and it demonstrated good accuracy when compared with other NNs. Delta inputs are obtained by subtracting coordinates provided by the radar system in feet. However, since the sampling period is one second, those inputs are equivalent to speed measured in feet/s.

In the X/Y approach the 10 inputs to the neural network correspond to the distances achieved during the last 10 second in the X or Y direction, and the outputs are the predictions of the distances that the airplane will make in the following 5, 10, 15, 20, 25 and 30 seconds in the X or Y direction. In the case of bearing/speed approach, the neural network uses the 10 previous real (not projected) distances to predict the distance that the airplane will have in the future. The later distance is applied according to the bearing, then it is projected over X and Y axes in order to obtain future coordinates. In this approach, the bearing is previously obtained by linear regression applied to the 10 previous positions.

EXPERIMENTAL RESULTS

The research team worked with data from some of the largest airports in the US: Boston (BOS), San Francisco (SFO), and Chicago O'Hare International Airport (ORD). The model described in this paper has been tested using data from Chicago (ORD), which is the airport with the highest number of movements from 2001 to 2004 and is second in terms of passenger traffic [6]. The log files were recorded during the summer of year 2001 and comprise the data provided by two different radar systems in operation: ASR and ASDE. Airport Surveillance Radar (ASR) has an internal sampling rate of 4 s and it is less accurate than ASDE, but has a longer range. Airport Surface Detection Equipment (ASDE) has a sampling rate of 1 s, is more accurate, and is able to track airplanes as well as ground vehicles. In general, ASDE data are more accurate (less noisy) but the behavior of the targets is more difficult to predict because this system tracks a larger range of speeds and most accelerations and decelerations while ASR usually tracks constant-speed tar-

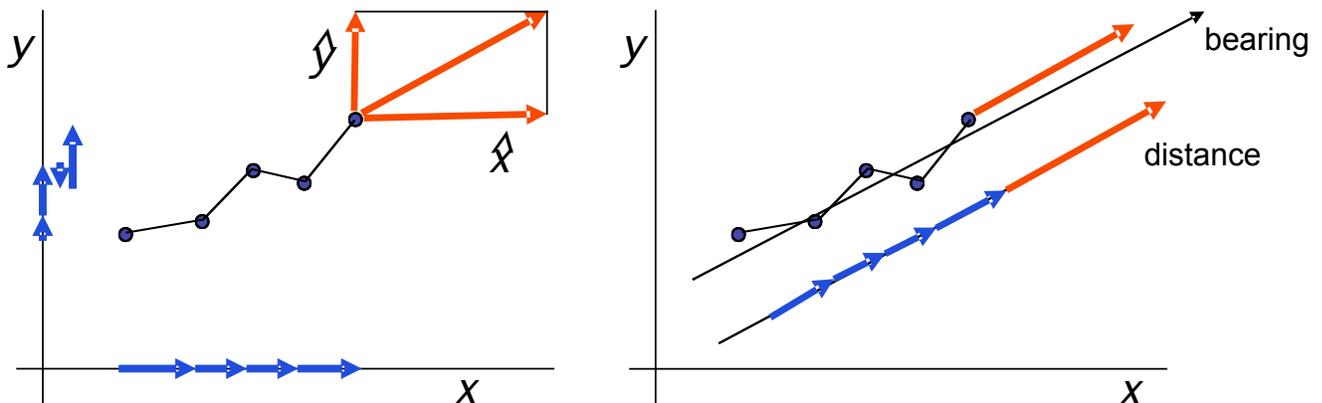


Fig. (1). Two approaches to compute future position.

gets approaching the airport. Since the two systems are so different, it was decided to make independent evaluation for each one.

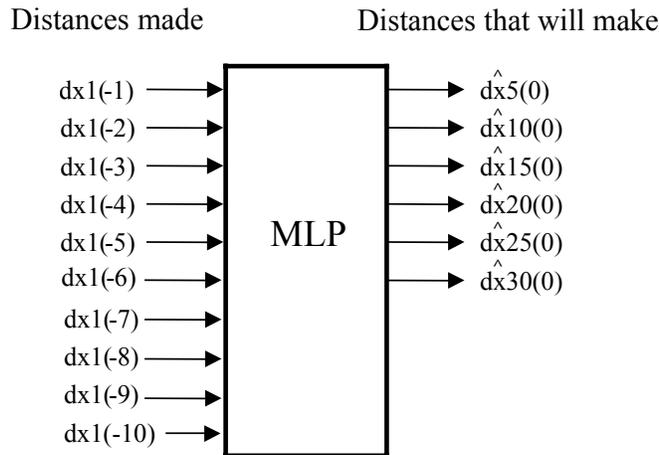


Fig. (2). Structure of NN-based model.

Positional error is computed for a given airplane at a give time as the distance from the point (x, y) predicted by the algorithm to the actual point that was found in the log file looking at later values. In order to evaluate the accuracy, the algorithms were tested using data from ORD (almost 300,000 evaluations). Two global indicators have been computed: the mean absolute error (MAE), and the normalized mean square error (MSE). The former is computed as the average of the absolute value of the difference between the real position and the estimated position. The latter is computed as the square root of the average of the squares of the distances.

MSE becomes larger than MAE if the variance of the error distances increases. If all error samples are very similar then MSE tends to be the same as MAE, but if some error levels are very large compared to the others then MSE becomes larger than MAE indicating that the estimation algorithm is less robust.

In order to compute the error of the first approach (X/Y), a neural network is used to estimate X and Y future coordinates independently, then the error is computed as the distance between the estimated coordinates and the actual values read by the radar and stores several lines below in the log files.

The second approach involves bearing estimation and movement estimation. This approach (linear regression + NN + trigonometry) is about 10 times slower than X/Y estimation (NNx + NNy).

The results shown on Tables I and II, are very similar for both approaches while using data from ASR radar but bearing/distance approach is 5% to 10% less accurate than X/Y approach for ASDE signals. In the analysis for ASR signals, most of the events involve airplanes approaching for landing, which means straight movement at high speed. For this condition, bearing is precisely identified and the results of both approaches are equivalent. On the other hand, for ASDE data, there are many events involving slow moving airplanes, sudden turns, and start/stop operations, so the overall behav-

ior is less predictable and bearing is difficult to obtain by linear regression.

Table I. X/Y Approach

	ASDE Radar		ASR Radar	
	MAE(ft)	MSE(ft)	MAE(ft)	MSE(ft)
5s	52.28	75.62	129.01	148.68
10s	165.59	220.96	167.89	200.22
15s	353.62	455.60	229.92	279.53
20s	618.04	782.94	314.55	385.00
25s	951.38	1198.83	429.19	523.20
30s	1340.35	1692.11	561.62	680.13
	MAE(m)	MSE(m)	MAE(m)	MSE(m)
5s	15.94	23.05	39.33	45.33
10s	50.48	67.37	51.19	61.04
15s	107.81	138.90	70.10	85.22
20s	188.43	238.70	95.90	117.38
25s	290.05	365.50	130.85	159.51
30s	408.64	515.89	171.23	207.36

Table II. Bearing/Distance Approach

	ASDE Radar		ASR Radar	
	MAE(ft)	MSE(ft)	MAE(ft)	MSE(ft)
5s	58.40	79.82	129.88	149.02
10s	179.04	231.02	173.23	204.52
15s	375.96	476.01	237.83	285.26
20s	651.88	821.26	321.84	389.46
25s	1001.93	1264.73	435.51	526.51
30s	1410.45	1792.76	566.76	682.96
	MAE(m)	MSE(m)	MAE(m)	MSE(m)
5s	17.80	24.34	39.60	45.43
10s	54.59	70.43	52.81	62.35
15s	114.62	145.13	72.51	86.97
20s	198.74	250.38	98.12	118.74
25s	305.47	385.59	132.78	160.52
30s	430.02	546.57	172.79	208.22

The mean error of the estimations obtained for 20 s in the future are less than 120 m while tracking with ASR; this is a very small error taking into account that the wing span of large airplanes such as B-777, B-747, B-767, A-330, A-340 or MD-11 is around 60 m, and the wing span of A-380 is 80 m. Since the radar signal may reflect in any part of the aircraft, any error in the same order of magnitude as the size of the aircraft could be considered in the same level as the

radar signal noise, that air traffic controllers are comfortable with.

CONCLUSION

A neural network model has been developed to estimate the position of airplanes up to 30s in the future. After training the model with data obtained at the airport, the system is able to predict the future position of each moving object in the airport with high accuracy; the mean error has roughly the same order of magnitude as the size of the airplane. Hence, the integration of this module in existing monitoring systems can provide air traffic controllers and pilots with valuable additional time and guidance for taking corrective action in case of imminent danger.

The proposed estimation algorithms can be used to predict position for any moving object in the airport: airplanes moving at high speed during takeoff or landing operations, airplanes moving slowly in taxi mode, or ground vehicles also moving slowly. In fact the system was evaluated using data of fast and slow moving targets that were on ground (ASDE radar data) or flying (ASR radar data).

Two different approaches for estimating position were presented. The first approach is based on estimating the future displacement in X direction and Y direction, and then adding those distances to the current position in order to obtain projections for the future. The second approach obtains the bearing by linear regression and uses the neural

network to estimate the displacement in the bearing direction. Both approaches yield similar results during approaching maneuvers, but bearing estimation is less robust for estimating on-ground movements.

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