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An Aircraft Trajectory Updating Algorithm Based on Improved Multilateration Method

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Abstract. Appropriate aircraft track data is pre-requirement for all aircraft trajectory research. However, in real life, aircraft may have no position reporting capabilities or report wrong locations and low-cost ADS-B station may offer datasets without calibration. These problems pose a challenge to air trajectory prediction and traditional localization methods like multilateration. Based on this background, we introduced an aircraft trajectory updating algorithm based on improved multilateration method. This method used datasets from randomly located and low-quality stations. It first identified stations calibrated and used them to synchronize other stations step by step. After getting calibrated location data, the author considered the aircraft trajectory as a directed graph and compute the maximum spanning tree of the graph to filter the predicted locations. They predicted nearly 70% and received 81.88954m TRMSE on the full LocaRDS datasets, and we got similar results in our research.

Keywords: multilateration, clock drift, aircraft localization, aircraft trajectory

1. Introduction

The aircraft localization is an important part of all air traffic control (ATC) systems. Accurate aircraft localization helps air traffic controllers better manage aircraft and improve the capacity of the airspace, Rapidity and accuracy are important components of Aircraft Localization[1].

Appropriate data from surveillance is pre-requirement for all aircraft localization research. It is necessary for us to improve the accuracy and robust of aircraft localization. Automatic dependent surveillance-broadcast (ADS-B) is a new technology in air traffic surveillance. Based on the information gathered in the ADS-B network, methods to locate aircraft can be applied. The most prominent example is multilateration.

Multilateration is a localization method. It determines the location of the unknown point through a distance from several known points to an unknown point. This is usually obtained by calculating the distance or relative distance of the two points by using the transmission time measured from the signal reaching time (TOA). It determines the position of the transmitter by recording the time to receive a single launch waveform at several known locations. If we know the positions of these points accurately, and their clocks are fully synchronized with the measurement is noise free, we can accurately locate the position of the transmitter by using the arrival time (TOA)[2-4].

Many classical solutions for improving aircraft localization have been proposed in the literature. Markochev proposed a grid-based localization method using the k-nearest neighbor (k-NN) algorithm. Compared with traditional multilateration (MLAT) algorithm, this method improved the accuracy of aircraft location in air traffic networks with random, unplanned deployment geometries[5]. Marady combined ADS-B datasets with MLAT datasets, and proposed a data fusion framework. Accuracy of the method in aircraft location is 49%, 49% and 13.8% better than ADS-B, multilateration and surveillance techniques that use the dynamic flight model of aircraft only for aircraft near the airport[6].

Calibration and synchronization of the receiving sensors is effectively a pre-requirement for all practical localization methods, in particular those based on TDoA measurements[7]. However, due to the ADS-B protocol is publicly developed, aircraft positioning can be collected by non-specialists through multiple Software Defined Radios (SDR), and this makes ADS-B sensitive to jamming and spoofing[8]. In recent

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years, crowdsourced flight information website such as OpenSky Network and VariFlight collect aircraft information from a large number of distributed software-defined radio-based sensors and aggregate it to display the trajectory of aircraft around the world[7]. Contray to traditional surveillance, most of the sensors are distributed randomly and majority of them are no time synchronized or calibrated. It is a challenging problem for traditional aircraft localization algorithm.

Markochev proposed an improved algorithm based on multilateration, which used data from sensors with strong clock drift or even completely broken timestamps[9]. The process of this algorithm can be described as follows: extract sensors which have been synchronized and use them to synchronize other stations step by step. Then consider the aircraft track as a directed graph and compute the maximum spanning tree of the graph to filter the predicted locations.

The remainder of this paper is organized as follows: Section 2 describes theory of improved MLAT model used for conditions with uncalibrated stations. In Section 3 the simulation experiment performed to test our model, and conclusions are presented in Section 4.

2. Improved MLAT Model and Aircraft Trajectory Reconstruction

Tradition MLAT algorithm required datasets from synchronized stations. However, it is impossible to equip all stations with GPS receivers for synchronous processing in real life, it is common for us to be confronted with a large amount of asynchronous processing data, which requires us to improve the traditional multilateration algorithm. Thus, a synchronization model was added to the algorithm.

The first part of the model is to select stations with best synchronization. The method to select them is to minimize equation below, whose input is data-sensors and data-aircraft (Table 1-2).

$$min\sum_{i,j,i\neq j}^{N}\left|d_i - d_j - \hat{v}\left(t_i - t_j + \tau_i - \tau_j\right)\right| \tag{1}$$

Where d_i and d_j are the distances from the aircraft to stations i and j, t_i and t_j are timestamps of stations i and j, τ_i and τ_j are constant clock offsets for stations i and j, and $\hat{v}$ is the effective speed of radio propagation. In many classical solutions, the speed of radio propagation is regarded as the velocity of light. However, in the condition with nanosecond precision, the difference between light and radio propagation cannot be neglected. Markochev proposed a radio wave velocity model based on theory from Purvinskis[10] and it was used in Equation (1).

What comes next is the synchronization of other stations. A station's measured time t^{means} is equal to aircraft time $t^{aircraft}$ plus time of flight (remarked as equation A). If station has drift, the equation should add drift(t). When we combined clock drift equation drift(t) with equation A, equation below can be obtained, which can be used to measure time values:

$$t^{aircraft} + \frac{D}{\hat{v}} = \frac{t^{means} - Initial - rw\left(\frac{t^{means} - b(0)}{f(0)+1}\right)}{f(0)+1} \tag{2}$$

Where $Initial$ is the initial frequency offset of the clock, $f(0)$ is frequency drift, rw represents random walk, $\hat{v}$ is radio wave velocity. From Equation (2), The model processed input stations' asynchronous data step by step. Once $t^{aircraft}$ timestamps are calculated using synchronized stations, the model other parameters can be determined, and in the end, station data optimized can be obtained[7].

Once the optimized data are obtained, locations of aircraft can be calculated independently by solving MLAT equations as follows:

$$m_i = \frac{\|\phi+\varphi_i\| - \|\phi - \varphi_j\|}{\hat{v}} + noise_{i,j} + b_{i,j} - b_j \tag{3}$$

Where $\phi = (x,y,z)^T$ represents aircraft position, $b_{i,j}$ represents the bias between station i and j, all parameters had been determined above. The Equation (3) is used for points with at least three measurements. If points have less than three measurements, Huber regression algorithm is used to fit latitude and longitude values of predicted aircraft locations as second order polynomial functions, and then use the fitted polynomials to reconstruct all locations[9].

In conclusion, the input of the model is the aircraft positioning information obtained by the ground station and the relevant information of the ground station itself. The detailed information is described in Table 1-2. The output of the model is the aircraft location information which have been corrected and its track. The whole model process can be described as follows:

The model first identifies the ground stations that have been marked as being synchronized and select several sample stations with best accuracy from them. What needs to be focused on is that these sample stations shouldn't have visible clock drift or random walk and should have combined measurements (pairs) with several other sample stations. Then it started to synchronized other stations based on sample stations step by step, when a station without calibration has been synchronized, it will be added to sample stations set to synchronize others. After all the stations have been calibrated, improved multilateration algorithm is used to determine aircraft locations, where HuberRegression and graph-based filter developed by richardalligier[12] are added to filter aircraft locations.

3. Simulation and Results

Our simulation is conducted on Ubuntu 20.04, and processor is 11th Gen Intel(R) Core(TM) i5-11400H @ 2.70GHz,2688 Mhz. The data we used in the study included aircraft positioning information and ground receiving station information, both from the OpenSky Network[11]. Among them, there are 5824610 aircraft positioning information data, and each piece of the data has 10 characteristic values. There are 716 pieces of data from the ground receiving station, and each piece of data has 6 characteristic values. Description of the dataset can be obtained from Table 1-2 for details.

Table 1: The description of data-aircraft

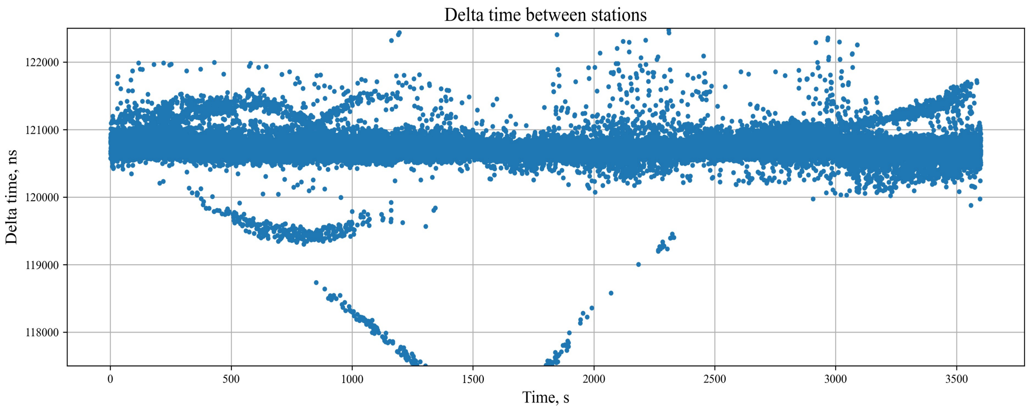
Description	***Value***
Aircraft identifier	ID 192
Unix timestamp	0.01
Aircraft latitude	37.19924 $°N$
Aircraft longitude	-5.65605 $°E$
Aircraft baroAltitude	11582.4
Aircraft geoAltitude	11635.74
Number of sensors to an aircraft	3
Nanosecond timestamps and Signal strength measurements from each of the sensors	[[402,930771796,66],[569,931012812,95], [513,61220329916.6667,70]]

Table 2: The description of data-sensors

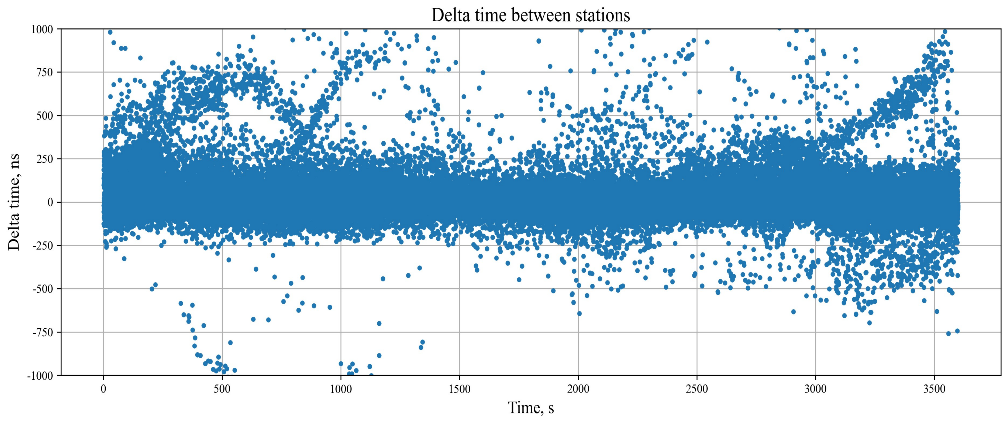
Symbol	***value***
sensor identifier	ID 1
Sensor latitude	46.68107 $°N$
Sensor longitude	7.665313 $°E$
Sensor height	680.9232
Sensor type	SBS-3
Whether is synchronized	false

We visualized the data and extracted 45 “good” stations that were marked as synchronized. In the process of data exploration and analysis, we found that some of these stations marked as synchronized had serious time offsets, which can be seen in Figure 1(a) and Figure 2(a). Since station synchronization is a continuous process, any slight deviation can affect the synchronization accuracy, we synchronized these 45 stations and selected the 35 stations with the best synchronization effect, whose distribution can be seen in Figure 3. And we listed a number of stations’ performance before and after synchronization (Figure 4 and Figure 5), it is obvious that time offsets between stations have been preferably reduced. What needs to be focused on is that station 150 has only one pair with a good station (station 14) from 35 synchronized, which is unable to update its location. To solve this problem, we added station 150 separately (use default location) instead of adding it to the best 35 stations' datasets.

In this process, we updated stations' location and optimized stations' time offsets, which had paved the way for other stations' synchronization and MLAT.

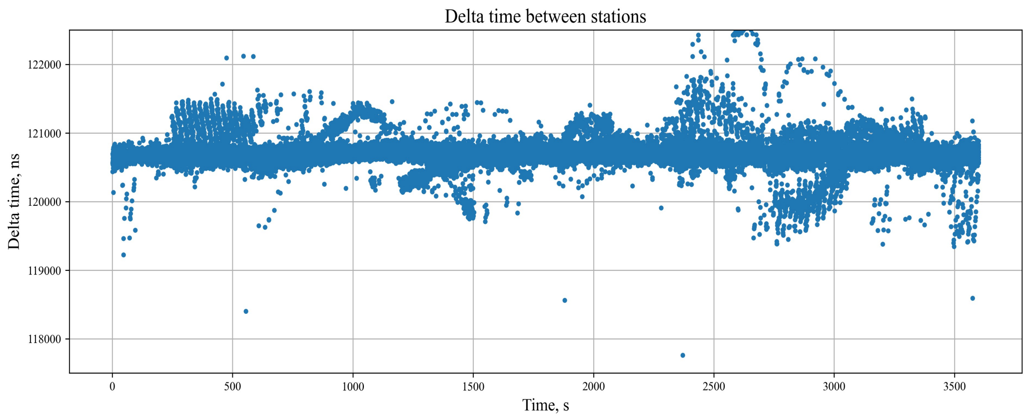


a. before synchronization, station 134 & 414
Approx Median error [m]: 36212.08098820716

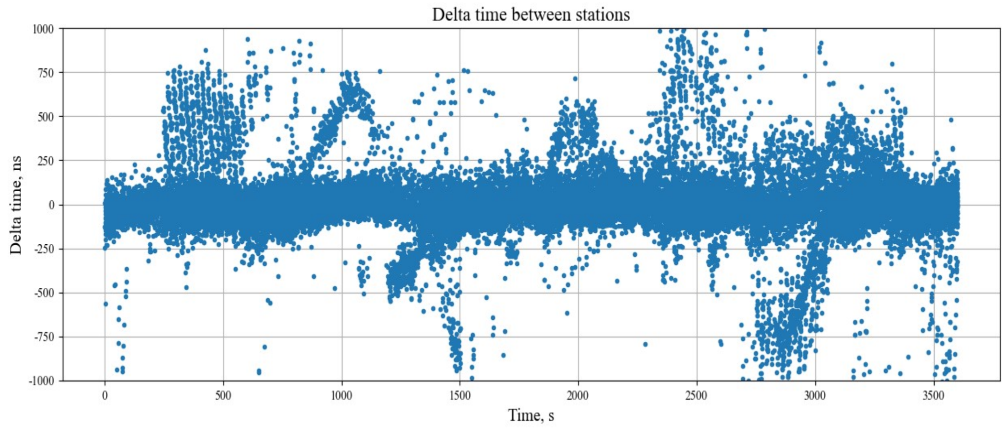


b. after synchronization, station 134 & 414
Approx Median error [m]: 18.479681784810964

Fig. 1: Delta time between station 134 & 414 before and after synchronization



a. before synchronization, station 124 & 470
Approx Median error [m]: 36205.834089741984



b. after synchronization, station 124 & 470

Approx Median error [m]: 18.448078265009826

Fig. 2: Delta time between station 124 & 470 before and after synchronization

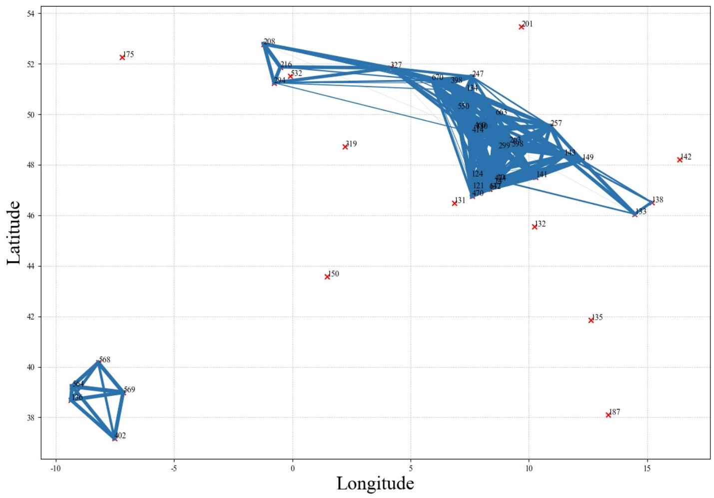


Fig. 3: Distribution of 45 station with synchronization, and best 35 stations selected from 45 them is shown with blue links.

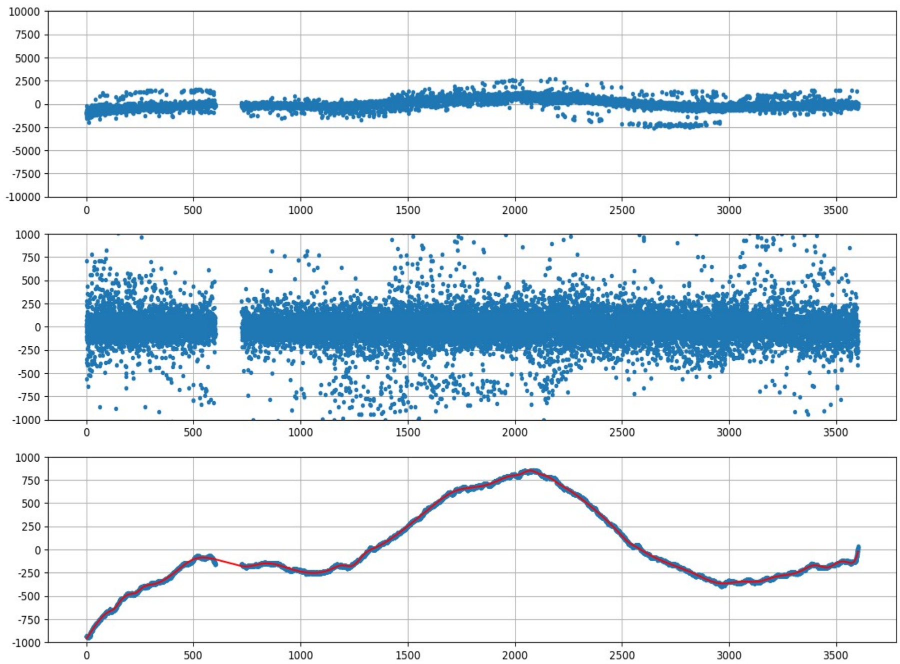


Fig. 4: Random walk of ID 455 station's clock after eliminating linear clock drift, the red solid line is a fitted cubic spline used to model this random walk. Median error is 22.96m, Max time gapis 121.5s and Delta distance is 1.238m

After synchronization of stations above, we started synchronizing from the stations closest to the 36 stations step by step. If optimization shows less than 35m median error and no large time gaps, such a station will be added to a pool of synchronized ones. Several stations optimized can be seen in Figure 5 and Figure 6.

After synchronization of all the stations, we had obtained a network of optimized stations. Based on these datasets, we were able to reconstruct the track of aircraft. When a data point has collected timestamps from at least three stations, we can use Eq. (3) to calculate the position of the target aircraft. Before the reconstruction, we need to filter outliers. In this part, the aircraft track was considered as a directed graph, we computed the maximum spanning tree of the graph to filter the predicted locations and the aircraft velocity between any two nodes did not exceed 300 m/s [7]. Finally, we predicted 71.8% points in the test dataset and compared it with true trajectory (Figure 6), achieving 81.88954m TRMSE distance.

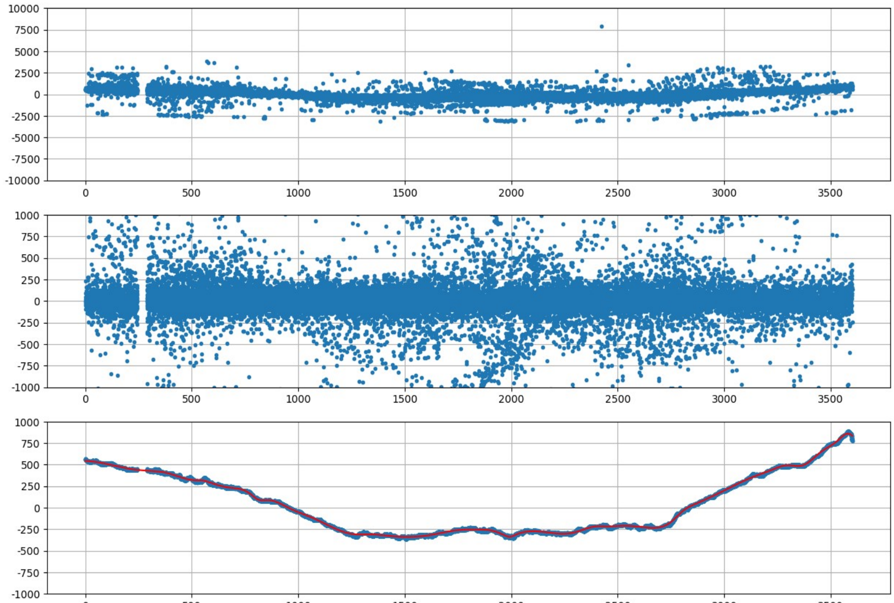


Fig. 5: Random walk of ID 678 station's clock after eliminating linear clock drift, the red solid line is a fitted cubic spline used to model this random walk. Median error is 23.76m, Max time gap is 44.73s, Delta distance is 1.514m

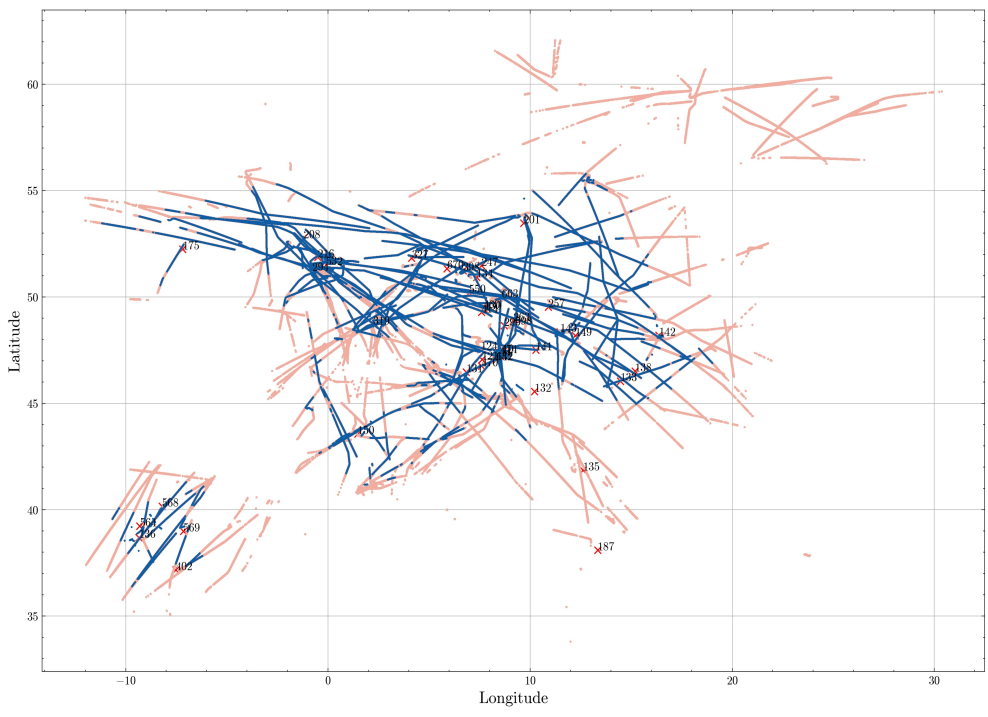


Fig. 6: Reconstructed aircraft locations (blue circles) and the ground truth (red line), and points represent the position of stations.

4. Conclusion

We introduced Sergei Markochev's novel multilateration technique based on OpenSky network datasets and received 81.88954m TRMSE on the full LocaRDS datasets correspondingly, whose results is similar to competition's 81.90m TRMSE distance. In the future, we would focus on several sections as follows: First, enhance the rapidity of synchronization and air track reconstruction. The process of the whole algorithm has taken more than ten hours, especially in the process of synchronizing all the stations. Second, graph tool is a package in air trajectory algorithm. However, if anaconda environment already contains many packages already, whose dependencies may conflict with the graph-tool dependencies[13]. We will look for algorithm optimization and adaptability to the environment and combine multilateration with machine learning or deep learning methods to improve their robustness and accuracy.

5. Acknowledgement

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