Track Data Smoothing for Air Traffic Simulation

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Abstract: The air traffic in Europe is subject of detailed research for reorganization. For a relevant research accurate simulation of different traffic categories is required. The conventional simulation techniques comprise mature models of aircraft behavior but do not include interactions between traffic objects. With trajectories corresponding to a highly complete and widespread air situation, this gap can be closed. The idea behind this way of scenario construction is to use well founded data mining techniques instead of more arbitrary constructive methods. The achieved high accuracy allows associating the complete air route topology to the trajectories. The focus of the paper is on the robust and accurate method to derive smoothed trajectories from air surveillance sensor data. The German Improved Air Defense System with up to 150 connected radars and a coverage area of 16 Million km² is used as the data source. The smoothing method presented comprises multiple evaluation paths including multi sensor tracking, sensor alignment, Kalman Smoothing, removal of outliers, fitting of Bézier type splines, subsequent segmentation-, and adaptation- cycles. The accuracy of the method described in this paper has been evaluated with a GPS recorded calibration flight with the result of a mean deviation of 80m.

1. Introduction

The air traffic research comprises economical and safety aspects. The complexity is driven by subtle relations between air traffic participants and resources like airports and airways. The most important cost drivers are flight time and capacity utilization of airports. The aim of simulations is to gain relevant information about conditions with impact on flight time and capacity utilization and the overall aim is to get a save and economically optimized concept for the air traffic.

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A possible strategy is flexibility, usage of efficient communication strategies [3]. Another strategy is based upon simulation [4], taking into account detailed 4D trajectory information and constraint driven re-planning and re-negotiation of the trajectory. Underlying strategies take into account a well balanced distribution of resource capacities to the traffic participants. A key word for this principle is Contract-of-Objectiveness (CoO) [5], the usage of mutually agreed objectives between Air Traffic Control (ATC), airlines, and airports. All strategies have the common problem to get an accurate, relevant, and complete information base with trajectory data. Various techniques exist to get trajectory data. Traditional trajectory reconstruction techniques have been developed, to be able to evaluate the performance of ATC centers [1]. Neuro-Fuzzy techniques to get trajectory information have been described in [6]. A very general method to reconstruct trajectories using opportunity targets has been presented in [7].

The intention behind the trajectory reconstruction technique described in this paper is to provide a complete set of detailed flight trajectories for all traffic categories over a large area and a long time interval. The trajectory set shall be complete in the sense that the analysis of the trajectories allows to derive relevant results about critical parameters with influence on economics and safety. The method described in this paper is implemented as a software process which uses recorded sensor data and flight plan information. The result data includes trajectories including flight attributes like transponder modes including mode S and a link to a complete joined flight plan. The flight plan contains fused contributions from up to eight ATC centers. The processing includes civil and military traffic and comprises all data available for air surveillance. A segmentation approach has been used in [1] with successful aircraft motion model recognition. The experience gained here with a huge amount of air surveillance data was, that the qualitatively best result could be achieved in a segmentation approach with the simple model of continuous turn rate and acceleration in each segment. Each experiment with specific motion model recognition resulted in a significant number of false detections and caused discontinuities in case of model switches.

1.1. Mass data handling

An important aspect is that the smoothing procedure is complete and able to handle an endless and huge stream of data. The process of trajectory reconstruction starts with recorded sensor data from up to 150 sensors. Up to 50 sensor contributions and 3000 tracks currently can be processed simultaneously. The sensors are a mix between ATC sensors and military stationary and mobile sensors. The trajectory reconstruction involves a series of subsequent processing paths. The most critical part of the processing is the simultaneous treatment of 3000 trajectories and its individual treatment after termination of the according track. In order to accomplish this, the processing must be able to store all data for the complete life time of the trajectories. The processing must be capable to handle an endless stream of data without causing a memory overflow. As soon as a trajectory has been treated, all related data must be removed. While the input data is time ordered, the order in which the result is available is according to the trajectory identifier in the sequence of trajectory termination. A peculiar effect is that if a certain result time interval smaller as the mean flight time is considered, the traffic

density has a maximum in the middle of the time interval. Near the upper and lower time limit, many trajectories are missing because they end in neighbored time intervals.

The fully automated process used for the trajectory reconstruction is also suited for online operation. In an online mode current trajectories can be compared with already known complete trajectories to come to a very precise situation prediction. Though the iterative nature of processing requires a considerable amount of processing power, with currently available multi processor hardware it is well feasible. With the trajectory information derived by such an online system, the strategies described in [3], [4], and [5] become operationally feasible on a large scale and with much broader safety reserves.

2. Data processing for trajectory reconstruction

The trajectory reconstruction is a multi path process, using recorded sensor data from a given time interval. The first path comprises multi target tracking including sensor registration. The operational tracker software is used to accomplish this path. Results of this path are aligned and correlated sets of sensor data and track messages. The next processing paths use the aligned sensor data now separated to individual trajectories. In the first path outliers are removed from the sequence of sensor data. In the second path Kalman Smoothing c.f. [2] is applied. The subsequent smoothing paths use the resulting tracks from Kalman Smoothing. The first smoothing path removes regular zigzag patterns caused by residual sensor deviations. In a next path peak kind disturbances are removed. In the next step sections are identified for spline adaptations. The sections begin and end on discrete smoothed track samples. The spline result for each section is then compared with the smoothed tracks. As soon as critical deviations occur, the section size is reduced. This section adaptation is iteratively repeated until no critical deviation remains. Details of the processing paths are described in the subsequent sections.

2.1. Multi target, multi sensor tracking

Centralized data fusion is applied to track up to 3000 targets with data from up to 50 radar sensors. Results of the tracking process are air tracks containing transponder attribute information including all available mode S categories and references to flight plans. Additional results are aligned and correlated plots. The tracks allow initializing a Kalman Smoother [2] which processes all correlated sensor data.

2.2. Removal of outliers

A set of sensor data over a longer period of time corresponding to one target is subject of the processing. The data set can contain outliers which potentially can disturb the smoothing process. A simple clustering procedure is used to identify the outliers. For the complete time ordered set of sensor data, neighborhood criteria are evaluated. Then starting with all data in separate clusters an iterative combining process is started, which puts data into the same cluster as soon as a neighborhood relation exists. The process ends if no further modification occurs.

Finally, the largest cluster and all large clusters with a certain extension are combined. With this procedure outliers, which usually occur only in small groups are removed in a reliable way.

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2.3. Kalman Smoothing

The Kalman Smoothing [2] path starts with the first track state reported from the tracking system. Then in the forward tracking path, all correlated plots are used to update the track. The backward tracking path starts with the last track state of the forward path but time reverted. In the backward path the plots are used for update in the reverted time order. During forward and backward path, the filter innovations are registered. As soon as a sufficient update frequency has been achieved, a certain percentage of the detections with the highest innovation value are marked for removal. This step helps to avoid artifacts, without the risk of loosing information.

If some detection could be marked, the forward and backward tracking is repeated without the detections marked. Finally the result of forward tracking and the time reverted result of backward tracking is added, taking into account the covariance values calculated during the tracking. The tracks resulting from Kalman Smoothing are then subject to further processing.

2.4. Kalman Smoothing track processing

Due to residual sensor alignment errors, often a regular zigzag behavior of tracks can be observed. A zigzag pattern is recognized within a subsequent set of 5 track positions. The shapes can be like the letter "W" or the letter "M," a regular up down sequence beginning either with an up or with a down. As soon as such a structure has been identified, a mean value is used instead of the individual ups and downs.

In another preparation step isolated peaks in the trajectories are reduced. As soon as the summarized path length exceeds the direct path between subsequent trajectory points by a large factor, the peak value is replaced by a mean value. The cleaned trajectories are now ready for the adaptation of Bézier type splines.

2.5. Spline construction

The term "Bézier type splines" shall not indicate that just Bézier-Splines are used. Bézier-Splines are an attractive concept to fit a smooth curve to a polygon. The sequence of track positions is given by a three dimensional polygon, but additionally the velocity vector is given and must be taken into account. The attractive property of Bézier type splines is that they are tangentially adapted to the polygon sections and that they are subject to additional tuning parameters which allow adaptation of the given path in a smooth way. The concept of Bézier-Splines is appropriate to adapt a smooth flight path in a given sector to both end conditions and to a mid term position. This shall be indicated with the term "Bézier type splines." The classical Bézier-Splines are implemented with Bernstein polynomials. For the representation of air traffic trajectories however Bernstein polynomials are inappropriate because they would lead to large modifications in the turn rate of the resulting trajectory.

The best basic shape for this kind of application is a circle because it intrinsically provides a constant turn rate with a constant speed. The application to flight trajectories additionally requires taking into account the speed. As soon as the speed changes, the concept of a constant turn rate leads to a modification of the turn radius. The tuning concept allows to take into account a mid term position and time of the trajectory.

Finally the definition data set of a segment is given by initial- and final time, position, speed, heading, and climb rate, and a mid term position and time. The data set implicitly defines a turn- and an acceleration rate. In combination with this turn rate, the start and end conditions define an initial and a final segment circle with initial and final radius and radius-orientation. (see Figure 1)

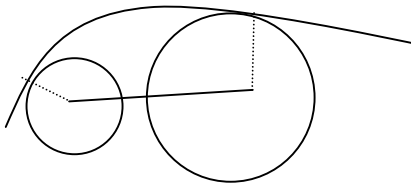

Figure 1 Initial and final segment circles

A smooth behavior with a constant turn rate now can be constructed by linear interpolation between both given parameter sets (orientation, turn radius and turn center position). But this construction is not yet adapted to the mid term position. In order to take into account the mid term position, a shape must be used, which does not influence the start and end conditions. The simplest solution of this problem is to use a symmetrical offset function for a modification of the turn radius. A shape constructed with two quarter circles and a half circle in the middle provides a continuous and differential run of the curve (see Figure 2). The only adaptation parameter is the amplitude of the radius offset. The amplitude can have a positive or a negative value.

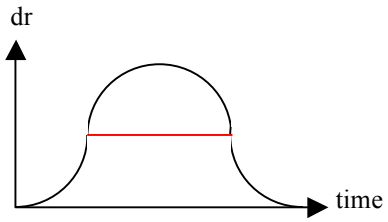

Figure 2 Radius offset for mid term adaptation

2.6. Segmentation, spline usage

In the previous paragraph spline definitions have been derived which are useable to fit a smooth trajectory run to any specific segment of the rough trajectory derived by Kalman Smoothing. But the question is where shall segments start and end? A simple strategy is to begin a new segment always after a specific time interval or as soon as there is a significant velocity change relative to the first velocity in the current segment. In most cases this works quite well, but leads to path shortcuts in cases where the track

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velocity shows gearing, i.e. if the track velocity does not accurately follow the path directions. Therefore an additional scan cycle is necessary in which the difference between smooth and rough trajectory is evaluated. As soon as the difference exceeds a certain threshold, the segment is split into two halves. This split procedure is repeated iteratively. The iteration ends with a sequence of segments with an accurate representation of the original Kalman Smoothing trajectory now by a spline controlled run. But in this stage there is a time difference of one GIADS update cycle (4.8 seconds) between segment end and start of the next segment. In a final scan the segments must be connected in a smooth way.

A simple smoothing of the connections between segments is achieved by selection of the mean values between both, the section end and the section start parameter sets. In case of large differences however, the rough values often are not precise. In this case it is better to take into account the geometrical conditions of both segments to find appropriate intermediate values for speed and heading.

3. Discussion of spline smoothing

In accordance with the intended applications of "air traffic simulation", "scenario generation for operator training", "search for alternative routing and scheduling procedures in air traffic", large data sets have been processed. The aim was to find a robust smoothing procedure applicable to all kinds of trajectories and to all detection conditions. Robust means that sensors errors are compensated to a high degree and do not lead to non-realistic trajectories.

3.1. Limitations

The spline model described in 2.5 turned out to be applicable in a limited range of segment parameters. For very small speed values and extremely small turn rates it is not applicable. In those cases it must be replaced by a linear interpolation. For heading changes > 180° and considerable speed changes peculiar paths are generated. This problem could be solved by segment splits as soon as the heading change exceeds 120° or if the speed change exceeds 30%.

The smoothing procedure described above provides basic adaptation parameters like maximum segment duration, maximum distance to Kalman Smoothing result. For the examples presented below maximum segment duration of 100 seconds and a maximum distance of 120m has been selected. In Figure 3 the Kalman Smoothing result is compared with the spline smoothing. Compared with the scale (200m) mean deviations in the range of 100m can be observed. A quantitative evaluation is given in section 4.

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Figure 3 Accuracy Limitations

The most challenging task is the application of the smoothing procedures to high agile flight paths. Figure 4 to Figure 7 show smoothing results for high manoeuvring aircraft.

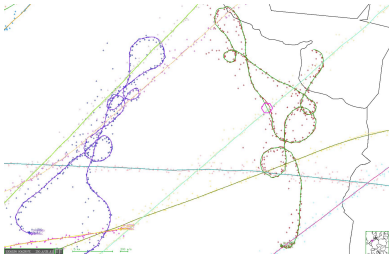

Figure 4 Manoeuvre flight pattern

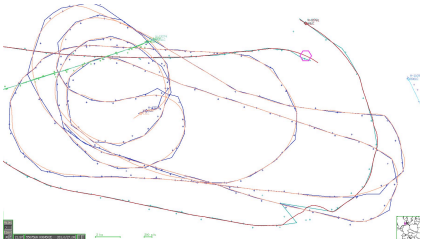

Figure 5 Low detection probability

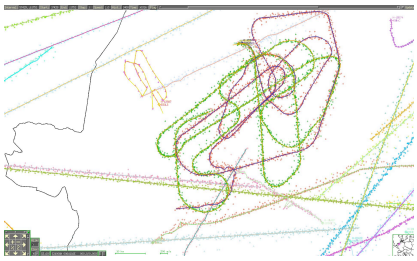

Figure 6 High manoeuvre agility

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The results displayed in Figure 4 to Figure 7 demonstrate that the trajectories gained with this method are appropriate for the training of military operators, because they allow constructing scenarios which accurately represent real flight pattern.

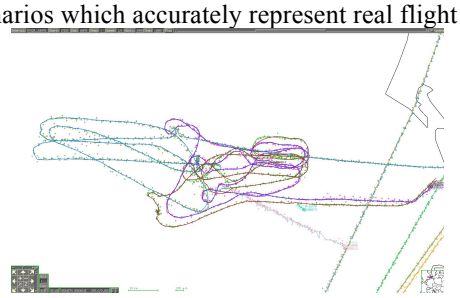

Figure 7 - Fighter Training

3.2. Result calibration

The method presented above has been evaluated with a GPS calibration flight. Figure 8 shows the calibration flight which has been used for accuracy determination. With a special computer program the reconstructed trajectory and the GPS recording has been synchronised in time and then compared with a time resolution of 4 seconds. For the time synchronisation the first ten sample points have been used to calculate the optimal time shift.

With the computer program, the longitudinal and lateral distance between the GPS position and the trajectory position has been evaluated. The numbers in Figure 8, Figure 9, and Figure 10 represent the lateral distance. The green color of the numbers indicates a distance below 100m, yellow indicates a distance below 250m, and red signals a distance above 250m. The overall evaluation result of this flight has been a linear mean value of 60m and a root mean square value of 80m. The calibration flight shows a quite high manoeuvre activity. Therefore we expect to achieve an even better accuracy in representative mean air traffic situations.

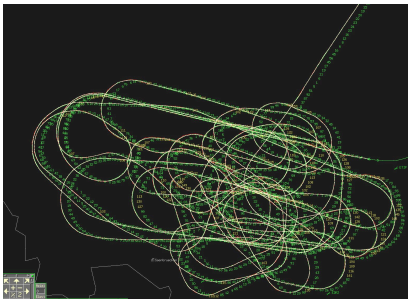

Figure 8 Calibration Flight of 2.5 hours duration

Another important accuracy aspect is the stability, defined by occurring deviations between subsequent trajectory points. Due to the spline adaptation, a very good stability has been achieved, as shown in the figures 3-10.

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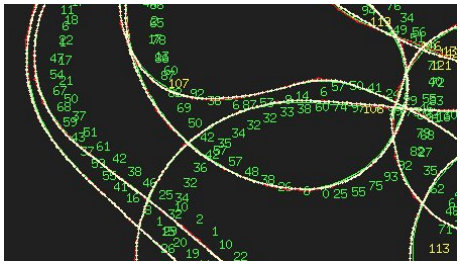

Figure 9 Trajectory, calibration flight distance evaluation

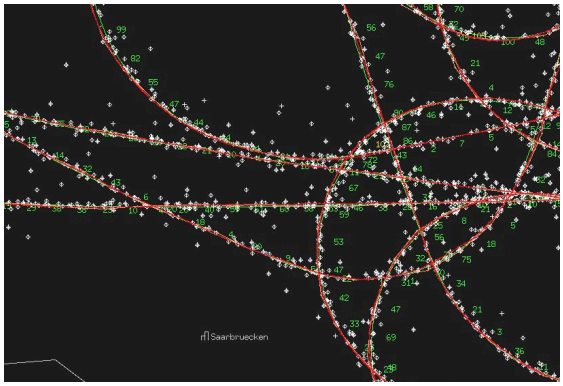

Figure 10 Calibration flight and sensor data

In the following text three typical applications for trajectory data sets are discussed, which are now possible due to the high accuracy and high stability of the data.

3.3. Scenario handling for operator training

The data derived from the smoothing procedure represents live trajectories with a high accuracy and contains all track attributes from the live scenario. The usability for operator training however requires that the trajectories easily can be modified. One possible concept is during the training simulation a takeover procedure by a flight simulator. This means, that upon selection the flight simulator can be initialized with the trajectory state and then overwrites the trajectory.

Another modification strategy is possible by the usage of the segment representation of the trajectories. An according tool allows to select a specific segment and to modify segment parameter. Guided by the cursor movement, the tool always calculates the resulting trajectory run and modifies the current segment and neighboured segments.

The tool for manual segment adaptation additionally provides the capability to a further accuracy enhancement. If required, the given trajectory shape iteratively can be adapted towards a smaller mean deviation to the sensor data.

3.4. Life sensor calibration

An important application of data sets with reconstructed life trajectories is the calibration of sensors. The air picture recording is continuously available. In accordance with sensor test campaigns, the recorded data can be filtered in time and space in order to reconstruct all trajectories, potentially visible to the sensor. The high trajectory data accuracy allows to evaluate a broad spectrum of sensors including optical, infrared, radar sensors, multilateration sensors and Doppler detecting sensors.

3.5. Air traffic optimization

Starting with the current traffic situation, modifications can be specified with techniques like those proposed for operator training. In order to be able to assess the modifications, tools are required to evaluate the economic and safety quality of the modified scenario.

4. Discussion of processing results

All figures show the reconstructed trajectory with a sample time of 1 second, the result of Kalman Smoothing with a sample time of 4.8 seconds and the sensor data.

The figures show live data processing results beginning with a detailed view (

Figure 11 - Kalman smoothing versus analytical smoothing) up to a complete view of the traffic over middle Europe during half an hour (Figure 15.) The figures show plot positions, the result of Kalman Smoothing and the reconstructed trajectories.

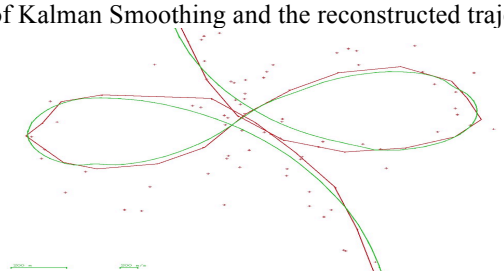

Figure 11 - Kalman smoothing versus analytical smoothing

Figure 11 - Kalman smoothing versus analytical smoothing impressively demonstrates with a nice small scale maneuver the performance of the algorithms. The red lines follow the tracking path of the Kalman Smoothing result with time steps of 4.8 seconds. The green line represents the path of the reconstructed trajectory with an update frequency of 1 second. Figure 12 shows reconstructed trajectories of 500 seconds duration in larger context. In order to demonstrate the scaling, the blue arrow points to the detail shown in

Figure 11 - Kalman smoothing versus analytical smoothing.

The green line scale graph on the left bottom part of the figures shows the scaling of 200m in

Figure 11 - Kalman smoothing versus analytical smoothing versus 10km in Figure 12.

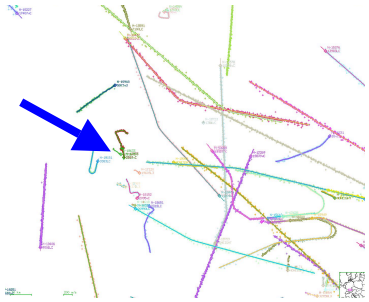

Figure 12 Larger Scale Smoothing Result

Figure 13 Different Traffic Categories

The results for different traffic categories are shown in Figure 13. This figure shows extremely straight trajectories of high and fast aircraft, trajectories of maneuvering aircraft, and some aircraft detected by primary radar only. The primary radar detections are displayed as crosses ("+"). The figure shows speed and heading of the trajectories and the Kalman Smoothing result as a small line segment in accordance with the scaling (200m/s). Figure 13 also shows the limits of the procedure in accordance to the limited detection accuracy (c.f. trajectory in the upper left part).

The third dimension of the aircraft movement is shown in Figure 14. In a scale from zero up to about 35000 feet the figures shows a good match between radar detections and the reconstructed trajectory path.

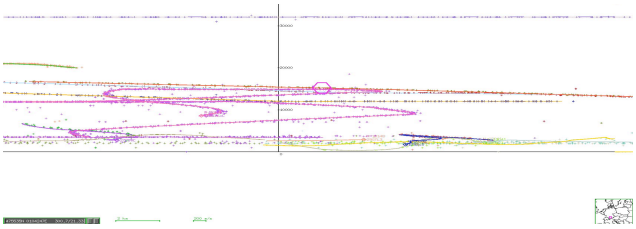

Figure 14 Trajectory height profile

Figure 15 finally shows half an hour of air traffic over Central Europe. Though, the large scale hardly allows focusing on details, it shows that the trajectories are smooth and surrounded by detections.

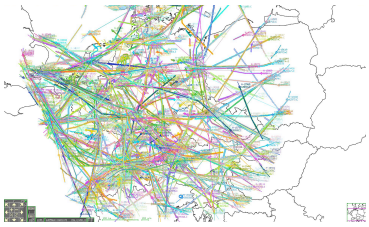

Figure 15 Half an hour of air traffic

This shows that the process is complete, handles all kinds of trajectories, and always follows the path given by the detections. The figures have been generated with a high capacity air surveillance display and analysis tool, which also has been used for detailed performance analysis during development of the method. In this view with the capability to increase the level of detail in time and space it is straight forward to detect weak points in the smoothing procedure where the trajectory is not corresponding to the detections or does not represent a possible flight path.
Finally, the complete system including sensors can be evaluated with GPS recordings of reference flights.

5. Conclusion

With the method described above, a procedure is available to generate detailed and accurate air traffic trajectory data from radar sensor data. The processing chain includes multi sensor tracking, Kalman Smoothing, and iterative adaptation of Bézier type splines. The numerical evaluation of a calibration flight shows that mean accuracies better than 80m can be achieved in areas with good radar coverage even in cases with high maneuvers.

The method is appropriate to reconstruct trajectories from different aircraft categories including highly maneuvering military aircraft, low level targets like helicopters, and targets detected by primary radar only. Due to the high completeness of the traffic representation and the available large coverage area and large time scale the set of trajectories is appropriate to investigate critical air traffic parameters, e.g. any type of conflicts.

The combination of trajectory-, transponder-, and flight-plan-data provides an excellent base for air traffic simulation. A key aspect is, that the high absolute accuracy and the extremely high stability allows to to evaluate the trajectory topology in terms of waypoints defined by the associated flight plan.

In combination with the sensor data a detailed error analysis and if required a further increase of accuracy is possible.

The trajectory data also can be used to evaluate tracking and sensor capabilities and to prepare relevant scenarios for operator training including the training for military operators for the control of highly maneuverable aircrafts.

The trajectory generation is a fully automated process using recorded sensor data from up to 150 radar sensors. It can be extended to cover an even larger area and to include additional radar sensors or as an example ADS-B transponder messages or data from Multilateration sensors (ASTERIX category 20.)

With this method a huge amount of data can be processed, analyzed, and converted to data formats required for specific research. The method continuously can be applied to the available data streams and has the realistic potential to comprise the sensor data for the complete European air traffic. The capability to process an endless data stream allows systematic investigation of long time effects. Statistical properties of cyclic traffic processes and as an example waiting queue dynamics can be learned up to the required level of detail. Relevant correlations and dependencies can be studied in simulations with a mix of original traffic and modified trajectories.

Final conclusion is that the trajectory generation method applied to the GIADS sensor data stream has the potential to play an important role in projects like the project SESAR of Euro control, with the aim to find a new order for the European air traffic.

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