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Feature Extraction from Trajectory Data for the Identification of Holding and Point Merge Patterns

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ABSTRACT

One of the most critical phases of a flight is the approach phase, conducted within the Terminal Maneuvering Area (TMA). In this phase, multiple aircraft converge toward the same airport (or nearby airports) within a constrained airspace, resulting in high traffic density and workload for controllers. This work aims to show that it is possible to detect relevant flight patterns in terminal airspace, focusing on holdings and point merge procedures. The results can be used to indicate that there is an imbalance in the terminal area and that there are flow management inefficiencies, for example. They can also support post-operations by providing a performance analysis of the TMA, thereby generating valuable data for improved flow management. The proposed algorithm processes trajectory data with the aim of identifying critical points, those possibly associated with holding patterns and point merge procedures, through a multi-step analysis that includes the representation of distance to the aerodrome, signal smoothing, detection of stationary intervals, and analysis of the zeros of the gradient function. The results include the application of the methodology to real flight trajectory data for arrivals at SBGR, where it is possible to observe that key trajectory points were successfully identified by the proposed algorithm.

Keywords: Feature Extraction, Holding Pattern, Point Merge System, Pattern Recognition, Air Traffic Management.

GENERATIVE AI USAGE STATEMENT

The authors declare that the use of generative AI tools was limited to technical support activities, without compromising the originality, analysis, or conclusions presented in the work. All information obtained through these tools was carefully evaluated and integrated into the study, ensuring methodological rigor and academic integrity. The tool ChatGPT was used to assist in text review.

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1 INTRODUCTION

Terminal Maneuvering Areas (TMAs) represent one of the most critical and complex portions of the airspace structure, due to the high density of traffic, limited maneuvering space, and the need to ensure safety, efficiency, and environmental sustainability. As global air traffic demand continues to rise, especially in busy metropolitan areas, the ability to systematically identify operational patterns becomes increasingly relevant to support strategic and tactical air traffic management (ATM) decisions. Among the most prominent of these patterns are holding maneuvers and the execution of full arcs in Point Merge procedures, both commonly applied to manage arrival flows under constrained capacity conditions, according to ICAO (2020a).

ICAO (2017a) defines Point Merge as an RNAV-based arrival procedure which uses a sequencing technique based on time/distance flown on predefined arcs before direct routing to a common merge point. Frequent execution of full arcs and holding procedures may indicate capacity imbalances, flow management inefficiencies, or sector overload, which can impact fuel efficiency, generate airborne delays, and compromise overall network performance. ICAO (2017b) highlights that these patterns serve as valuable indicators of operational stress in terminal environments and are critical for the implementation of effective Air Traffic Flow Management (ATFM) strategies.

Despite their operational relevance, the systematic detection of these patterns remains a challenge, particularly when dealing with large-scale surveillance data such as ADS-B or radar tracks. Currently, it is difficult to process trajectory data at scale or to extract meaningful behavior classification in a timely and reliable manner. For this reason, a notable gap identified in the literature concerns the development of trajectory preprocessing methodologies capable of extracting only the most relevant points, thereby reducing computational cost and improving the efficiency of subsequent analysis. To address this gap, there is a growing need for automated trajectory processing methods, aligned with the objectives of the ICAO Global Air Navigation Plan (GANP), particularly in support of system-wide performance monitoring, network resilience, and airspace design optimization, according to ICAO (2020b).

This paper proposes a trajectory preprocessing algorithm aimed at the feature extraction of relevant flight patterns in terminal airspace, with a particular focus on the detection of holdings and full-arc execution in Point Merge procedures. The proposed method processes radar-derived trajectory data through a sequence of signal transformations,including distance function modeling, noise reduction, stationary interval stabilization, and derivative analysis, to extract critical points that characterize aircraft behavior. The resulting insights can support post-operational analysis, performance-based airspace monitoring, and the development of advanced ATFM strategies in line with ICAO's Aviation System Block Upgrades (ASBU) framework, based on ICAO (2023).

2 LITERATURE REVIEW

A holding maneuver is an air traffic control procedure in which an aircraft follows a predetermined elliptical pattern while awaiting clearance for further navigation or descent. Holding is typically used in terminal areas to manage sequencing during periods of high traffic volume, congestion, or operational delays due to weather or runway availability. The procedure is defined by an initial fix, inbound and outbound legs, and standard or non-standard turns, and is critical for maintaining separation and system capacity. The use of holdings can increase the complexity of air traffic control service, generate environmental impact through additional fuel consumption, saturate airspace control sectors, and thus propagate the impact to adjacent sectors. ICAO (2006) defines a holding pattern as a predetermined maneuver which keeps an aircraft within a specified airspace while awaiting further clearance from air traffic control.

The Point Merge system is a Performance-Based Navigation (PBN) arrival procedure designed to optimize sequencing by routing aircraft along predefined RNAV arcs converging at a common merge point. This concept reduces controller workload and improves predictability, as stated in ICAO (2013).

According to Basora et al. (2019), detecting anomalies or events is a complex process with several methods and techniques and with substantial dependence on the aim that one wishes to achieve. This area has become relevant for research, especially when using large datasets from critical systems, such as aviation, as highlighted by Pimentel et al. (2014). Basora et al. (2019) present a survey of advanced methods for anomaly detection applied to the aviation area using data-driven techniques and listed 16 techniques, classified into five areas: distance-based, ensemble-based, statistical, domain-based and reconstruction-based. In recent studies, Basora et al. (2019) and Olive et al. (2020) added to the data-driven techniques list the following techniques: Neural Networks (recurrent and convolutional), Autoencoders, Generative Models, and Temporal Logic Learning Models. They conclude that data-driven approaches are challenging due to the large volume of data, its heterogeneity and high dimensionality, as well as the temporality of operations. Olive et al. (2020) analyze rule-based methods for detecting events in trajectories and conclude that rule-based methods are simpler to explain and can present consistent results. However, many parameters need to be adjusted, which is an implementation challenge because it requires well-grounded operational knowledge. Olive et al. (2020) also argue that using rules-based methods may seem attractive to identify in-flight holdings. However, they showed the false positives and negative cases that can be found with these techniques.

Another line of work is a machine learning holding predictor developed by Dhief et al. (2023). Using estimated flight velocity components at each trajectory point, they employed a Kalman filter-based algorithm to detect speed variations during holding maneuvers, which can be seen as a data-driven approach. This approach has the disadvantage that another speed variation can maintain the seam pattern and the holding speed. While machine learning solutions generally discover patterns by adjusting feature weights based on data, a potential drawback of this approach is the lack of transparency regarding how the weights are determined. Alternatively, a rule-based method would require an explanation of all parameters to make an accurate identification. Data-driven or rule-based approaches can be employed in event or anomaly recognition in trajectory data. However, the accuracy and robustness of each implementation must be evaluated in the specific case and without confirmation bias, as stated in Olive and Basora (2020). In this work, a rule-based method was designed, implemented, and validated for detecting holdings in trajectory data, The decision to use this approach was based on the fact that a rule-based approach is more straightforward to understand, and that the number of false positives, listed by Olive et al. (2020), in commercial aviation is reduced. Table 1 summarizes the literature review by comparing the main related works.

Table 1: Comparison of Main Related Works.

Reference	Approach Type	Technique Summary	Advantages	Disadvantages
Olive and Basora (2020)	Rule-Based (Explained logic)	Designed and validated a rule-based method for detecting holdings in trajectory data.	Simple and interpretable; Transparent decisions; Effective for commercial aviation holdings	Limited generalizability; Requires strong operational understanding; Not adaptive to novel cases
Olive et al. (2020)	Rule-Based	Analyzed rule-based methods for detecting events in flight trajectories.	Easy to implement; Good consistency; Operationally grounded	Many parameters to tune; Risk of false positives/negatives; Needs domain expertise
Dhief et al. (2023)	Data-Driven (ML + Kalman Filter)	Used estimated flight velocity and Kalman filter to detect holding via speed changes.	Automatically detects speed patterns; Less dependent on predefined rules	Can confuse other speed changes with holdings; Black-box nature of ML; Less explainable
Basora et al. (2019)	Data-Driven (Survey of ML / Statistical Techniques)	Comprehensive survey of 16 anomaly detection techniques applied to aviation.	Broad method landscape; Covers advanced ML (e.g., NN, Autoencoders); Highlights applicability	Complex implementations; High data demands; Difficult interpretability; Sensitive to noise

3 METHODOLOGY

The objective of this section is to describe the algorithm developed for extracting potential key points to identify holding trajectories and the arc of the point merge.

3.1 Experimental Data

To conduct the experiments, trajectories constructed from surveillance radar data were used, with sampling rate of $4s$, of flights bound for Guarulhos. Guarulhos was chosen because it is the only Brazilian airport with a Point Merge System. The terminal area was simplified for the analysis, being defined as a cylinder with a radius of $100NM$ around the aerodrome. This simplification is common in regulatory bodies such as ICAO and DECEA and was therefore adopted in this study. Figure 1 presents the trajectory segments used.

3.2 Holding and Point Merge Trajectory Feature Extraction Algorithm

The objective of the algorithm is to identify critical points, which can identify the occurrence of holdings and point merge trajectories, from radar data. Figure 2 presents at a high level the steps of the algorithm and the result for each of the steps.

The first step of the algorithm consists of Trajectory Processing, which constructs flight trajectories bound for SBGR from radar data, grouping the points by callsign and cutting them at the $100NM$ around the aerodrome. The second step, called the Distance Function, represents the trajectory as a signal of distance to the aerodrome as a function of the time remaining until landing. For each point on the trajectory, the distance to the aerodrome is calculated, using the time to landing as the time axis (x). This makes it possible to clearly identify the approach and departure profiles of each flight in relation to the aerodrome.

The third step consists of smoothing the curves obtained in the second step. To achieve this, the Savitzky-Golay filter was applied, which smooths the curve while preserving its local features, such as peaks, valleys, and trends. This filter fits low-order polynomials to moving windows of points in the time series using linear regression. Unlike other smoothing

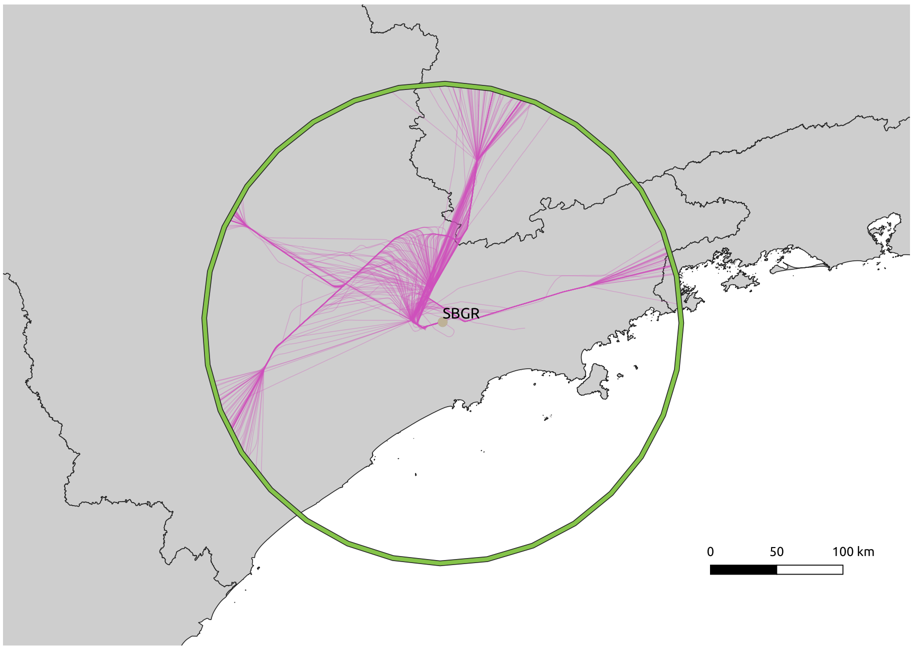

Figure 1: Examples of trajectory data for flights destined for SBGR used in this study.

methods, such as simple moving averages, the Savitzky-Golay filter is particularly effective in maintaining the shape and structure of the original curve, which is important for trajectory analysis and the identification of subtle approach and divergence patterns.

The fourth step was named the Stationary Interval Stabilization Filter, aimed at enhancing the stable segments of the distance curves. In this step, an algorithm was developed to stabilize stationary intervals in a signal while preserving continuity in cases of small variations. The algorithm processes the input curve point by point, comparing each value with its predecessor. If the absolute difference between them exceeds a threshold defined empirically, the new value is recorded in the filtered signal. Otherwise, the previous value is retained, promoting interval stabilization. This approach helps reduce noise and low-amplitude oscillations, allowing for a more consistent analysis of aircraft trajectories.

The result of the fourth step aims to highlight intervals in which the distance to the aerodrome remains stable, that is, there is neither approach nor divergence of the aircraft. Geometrically, these segments correspond to regions of the curve where the derivative is zero. Based on this, the fifth step was named Differentiation, consisting of calculating the derivative of the curve resulting from the previous step. The objective is to represent the aircraft's movement pattern around the zero value: negative derivative values indicate divergence from the aerodrome, positive values indicate approach, and values equal to zero represent distance stability.

The sixth and final step of the algorithm was named $f(x) = 0$, and its objective is to identify the critical points of the trajectory, that is, the zeros of the function. To achieve this, the geographical points corresponding to the intersections of the derivative curve with the x-axis were located, that is, where the derivative is zero. These points indicate transitions between approach and divergence and are therefore candidates to represent holding patterns or point merge procedures.

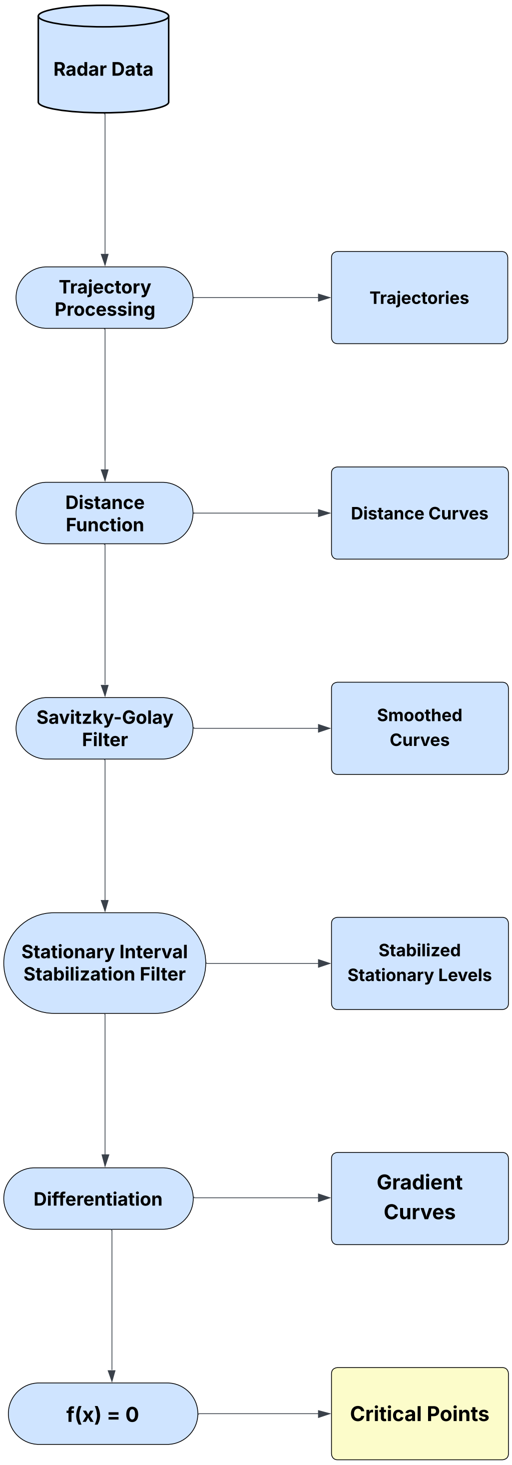

Figure 2: Diagram of the steps of the algorithm developed for features extraction from flight trajectories.

4 RESULTS AND DISCUSSIONS

This section presents the results corresponding to each step of the algorithm described in the methodology. To facilitate the understanding of the complete process, all steps are illustrated using a single flight trajectory.

Figure 3.a shows a trajectory destined for SBGR aerodrome, resulting from the Trajectory Processing step. This trajectory was selected because it contains typical patterns of holding maneuvers and full-arc execution of the Point Merge. Figure 3.b presents the representation of the same trajectory as a distance-to-landing curve over the remaining time to landing, corresponding to the Distance Function step. In this curve, characteristic patterns associated with holding and point merge maneuvers can already be observed. Between time instants 1000 and 1750, for example, a holding pattern is noticeable, in which the aircraft repeatedly approaches and moves away from the aerodrome. Between time instants 650 and 1000, the distance to the aerodrome remains nearly constant, which is consistent with point merge behavior.

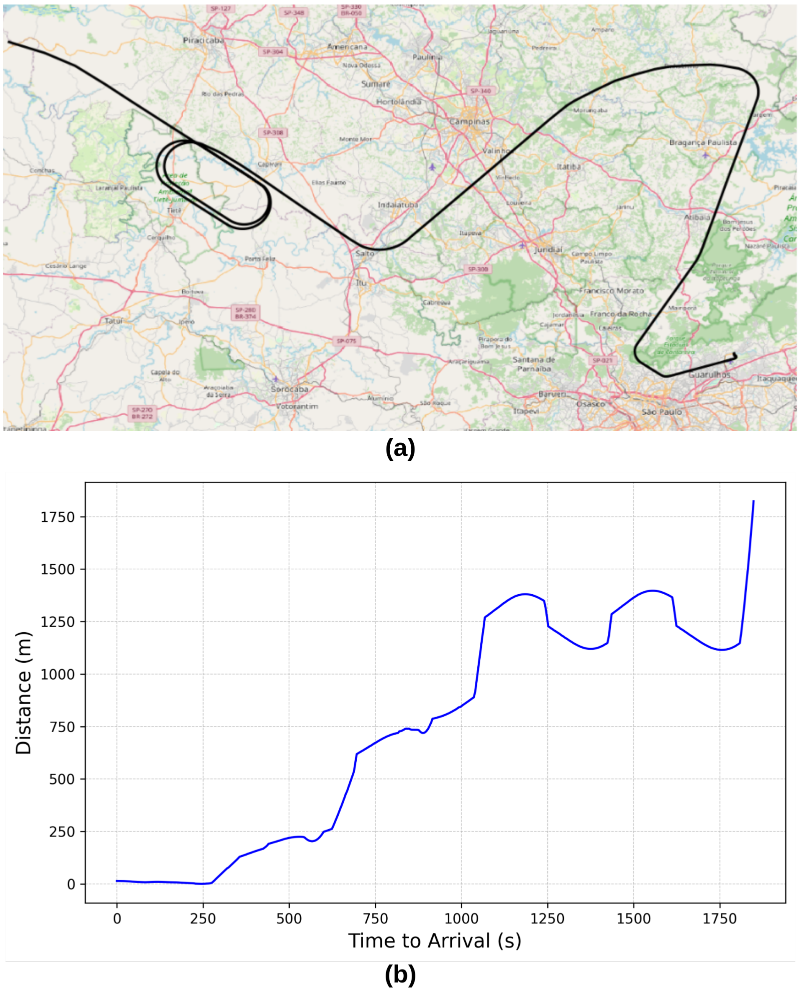

Figure 3: (a) Flight Trajectory and (b) Distance Representation of Trajectory.

In the next step, the distance curve was smoothed using the Savitzky-Golay filter. Figure 4 shows the result of this smoothing. It can be observed that small fluctuations, possibly associated with radar inaccuracies, were eliminated, resulting in a smoother curve without compromising the relevant characteristics of the original signal.

The subsequent steps are presented in Figure 5. Figure 5.a shows the result of applying the Stationary Interval Stabilization Filter. It can be seen that the low-variability periods,

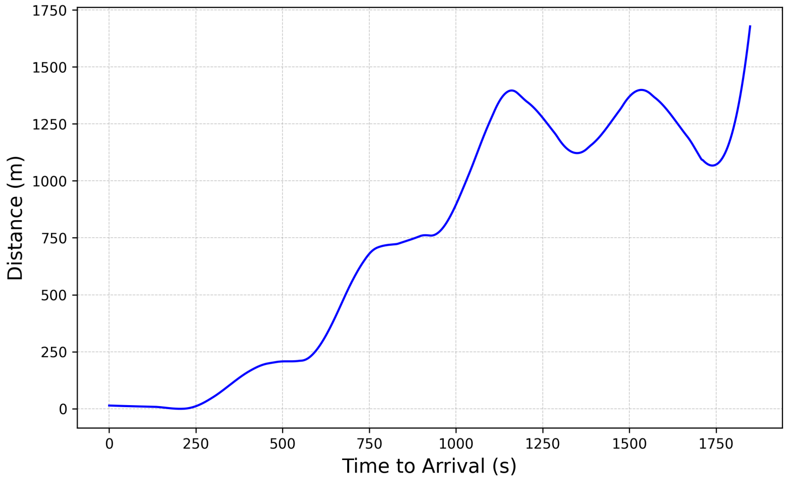

Figure 4: Distance curve smoothed by the Savitzky-Golay filter.

typical of point merge arcs and the initial and final points of holding pattern ellipses, were stabilized, which facilitates the automatic identification of these patterns.

Figure 5.b presents the results of the Differentiation and $f(x) = 0$ steps. The derivative of the distance curve makes it possible to identify the moments when the aircraft's relative approach speed to the aerodrome approaches zero, that is, $v \to 0$. The points where $f(x) = 0$ are illustrated in red in Figure 5.b.

Finally, Figure 5.c shows the location of the critical points directly over the original trajectory. There is a clear coherence between these points and the segments of operational interest, suggesting that the algorithm was effective in identifying relevant segments: holding patterns and point merge execution.

5 CONCLUSION

This paper presented a trajectory preprocessing algorithm designed to identify critical points in terminal airspace operations, with an emphasis on holding patterns and full-arc executions of Point Merge procedures. The method relies on a structured sequence of signal transformations to highlight relevant behavior changes along aircraft trajectories based on radar data. The results demonstrate that the proposed approach is effective in extracting key trajectory features. By revealing patterns such as prolonged holding or systematic use of point merge arcs, the algorithm provides valuable insights for post-operational analysis, performance monitoring, and the development of advanced ATFM strategies.

As future work, it is proposed to carry out a trajectory labeling step to determine for each sample of the dataset if it is a holding pattern or point merge or other. This process enables the training of supervised machine learning models capable of automatically classifying the occurrence of holding maneuvers and the use of Point Merge procedures, based on the data processed by the proposed algorithm. Alternatively, unsupervised learning techniques (such as DBSCAN and K-Means) could be applied to cluster trajectories after preprocessing, allowing for the exploratory identification of distinct behavioral patterns.

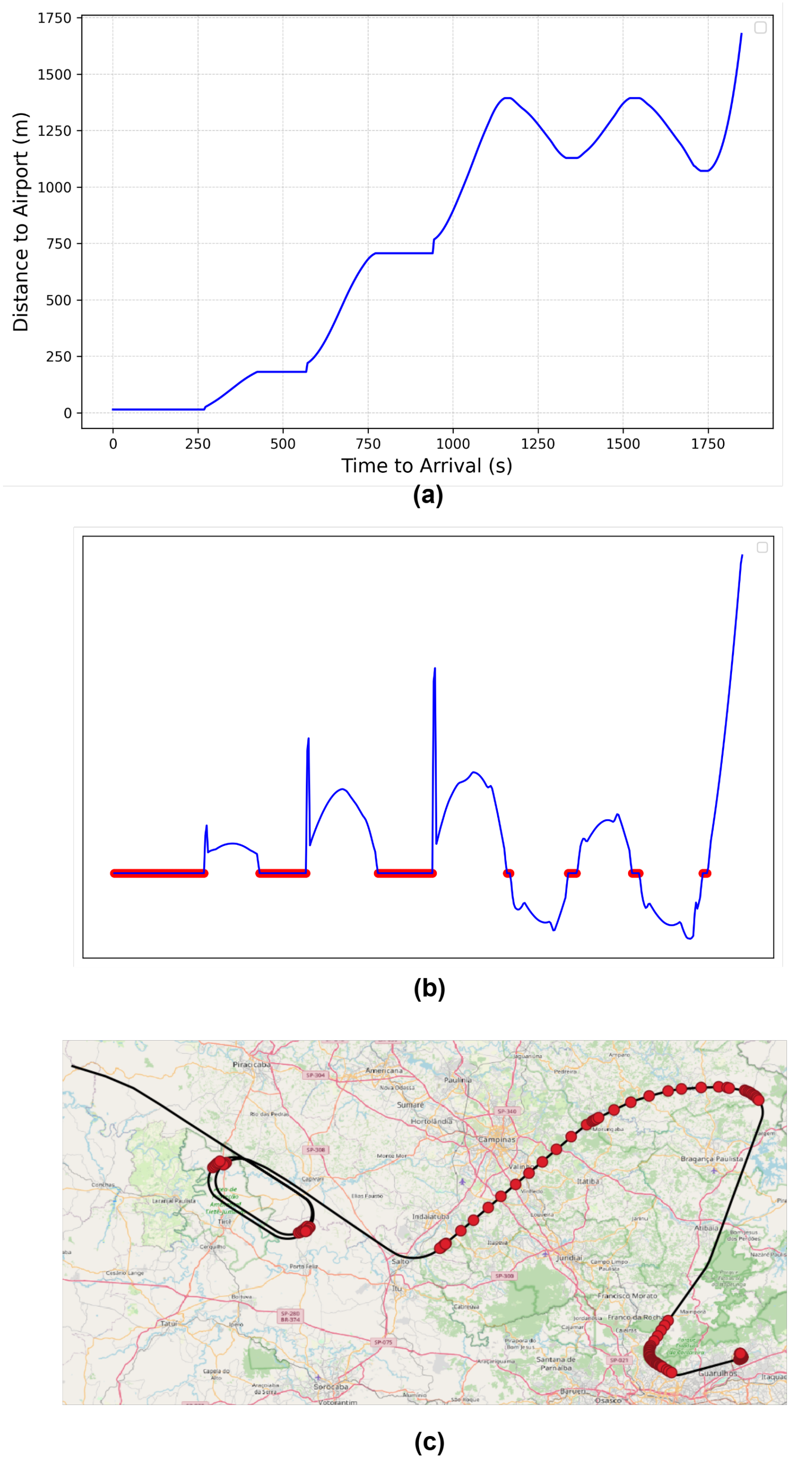

Figure 5: (a) Result of Stationary Stabilization Filter, (b) Differentiation and Critical Points Identification, and (c) Visualization of the candidate Critical Points (red dots) in the original trajectory.

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