

Contrastive Learning-Based Air Traffic Trajectory Representation: A Case Study on Incheon International Airport

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ABSTRACT

Air traffic trajectory recognition has become an interest in response to the airspace modernization. Similar to time series data, trajectory can be analyzed using representation learning. However, research on trajectory is less explored compared to other time series data. This paper introduces a machine learning-based approach to learning trajectory representations, which enhances performance in downstream recognition tasks. This contrastive representation learning framework is demonstrated on public unlabeled air traffic surveillance data. Using the contrastive objective, the model learns to maximize the agreement in representation for similar subseries, defined by the unchanged track, while distinguishing them from globally sampled negatives. The model uses sliding window encoding to transform the trajectories into more generalizable semantic terms, resulting in scalability for incomplete trajectories. The clusterability of the embeddings was compared with the clustering of the corresponding raw trajectories. The results suggest that analysis using the learned representation generates more elaborative clusters from a comprehensive point of view for both arrival and departure air traffic data.

Keywords: Contrastive Learning; Air Traffic Management; Representation Learning; Time Series Analysis; Trajectory Clustering

Nomenclature

D	= Discriminator function
Enc	= Encoder function
E, E'	= Number of features, Encoding size
η	= Size of reference sub-series
N	= Number of samples
p	= p-value
r, θ	= Polar positional components (radius, bearing)
S, S'	= Number of measurements (Number of timestamp), Encoding length

t	= Timestamp
t_p, t_n	= Centroid of sub series (Positive, Negative)
u_x, u_y, u_z	= Directional cosine vector components
w	= Encoding window size
x, y, z	= Cartesian positional components in ENU coordinates
X	= Trajectory array
x_t, x_p, x_n, x_{ref}	= Subseries (Anchor, Positive, Negative, Reference)
z	= Encoded subseries
z_t, z_p, z_n	= Encoded sub series (Anchor, Positive, Negative)
Z	= Encoded trajectory array
δ	= Sliding gap
μ, σ	= Mean, Standard deviation

1 Introduction

Trajectory-based operations (TBO) have become interested in airspace modernization to enhance the safety and capability of the strategic air traffic flow management system. The autonomous operation has been developed to flexibly manage large high-dimensional trajectory data. As a part of the system, air traffic trajectory recognition has been a topic of interest in the air traffic management community, especially for a metropolitan airport with a high-density traffic flow and complex air traffic pattern. Although flight procedures exists as the designated flight pattern published by the authority, the air traffic controller may assign direct instruction or advice on the deviation from the standard courses, causing a challenge to identify the non-standard trajectories. The artificial intelligence model has successfully extracted useful information from the time series to learn the pattern.

Nowadays, a massive amount of aircraft trajectory data can be obtained from a publicly available data source, such as the collected Automatic Dependent Surveillance–Broadcast (ADS-B) signal recorded by surveillance facilities. The publicly available ADS-B data contain the information on aircraft's identifications, positions, velocities, headings, and the time of broadcasting, and the data can be reorganized and preprocessed into the time-series of positional information, the trajectory of a specific aircraft; however, the data are usually unlabeled. Therefore, to characterize the information from the massive amount of unlabeled trajectory data, various clustering algorithms have been widely applied to provide groups of similar trajectories.

The trajectories as time series are usually rich in information, complex, and highly dimensional; transforming them into a more generalizable representation can enhance the performance of downstream tasks such as classification and clustering. Unsupervised contrastive representation learning is successful in many applications, yet contrastive learning on time series data was less popular than vision and natural language processing. Although many real-world time series, such as sound waves, electromagnetic signals, medical signals, human activity data, etc., have been demonstrated in recent works, the trajectory data of moving vehicles still needs to be explored. This paper proposes an unsupervised contrastive representation learning model for air traffic trajectory data, exploiting the nature of air traffic trajectories. The proposed technique uses contrastive learning that aims to pull together, in the feature space, the representations of the sub-trajectories within the determinable time boundary and push away the representations of the sub-trajectories outside this region. Using the unlabeled data, the paper further demonstrates the clusterability of the embeddings compared to the raw trajectory data to show that implementing downstream clustering tasks on the embeddings provides separability among the ambiguous clusters.

2 Related Works

Earlier works on learning-based trajectory representation predominantly use autoencoder architecture. The autoencoder architecture consists of the encoder attached to the decoder, and they are trained simultaneously to reconstruct the original inputs. In this manner, the learned representation usually refers to the meaningful latent space between the encoder and decoder. Prior works [1, 2] utilized the autoencoder architectures for trajectory feature learning to reduce the computational burden in trajectory clustering by compressing the information in trajectories into meaningful latent space. The trajectory variational autoencoder (TrajVAE) has been proposed for a more complex model in [3]. Although the VAE is built mainly for trajectory generation, the architecture extracts meaningful information from the original trajectory. By applying the masking strategy in Traj-MAE [4], the masked autoencoder can be utilized to predict future trajectory state, which is beneficial for collision prediction of vehicles. The deep trajectory clustering in [5] does not incorporate only the reconstruction loss function for trajectory feature learning but also enforced the clustering loss to ensure the separation of the latent space representation.

The goal of contrastive learning is to perform optimization in the embedding space such that the embedding of similar samples from the positive set is put together in the feature space closer to the anchor sample. In contrast, embeddings of dissimilar samples from the negative set are pushed away from the anchor and positive set [6–8]. In this manner, contrastive learning has been recognized as a powerful self-supervised learning technique, especially for vision [8–11], and natural language processing [12–14]. On the other hand, time series were less studied and even less on the trajectories of moving objects compared to other types of time series signals.

Contrastive learning has become popular in representation learning because the time series are often highly oscillated or too complex to be reconstructed. Therefore, the more complex the time series, the more challenging it is to fit the autoencoder, and the learned latent space could underrepresent the original time series. Contrastive Predictive Coding (CPC) [15] maximizes the mutual information between the encoded representation of subseries using InfoNCE loss. The technique attaches an autoregressive model to the encoder. It maximizes the agreement between the future subseries’ latent space and the prediction of them using the information encoded from the previous subseries. The work in [16] demonstrates the Unsupervised Scalable Representation Learning that applies to the set of time series with unequal length. The positive samples are selected randomly within the reference region using uniformly random distribution while letting the negative be the subseries outside the interested series. The encoder is trained with the time-based triplet loss, ensuring the similarity of positive subseries and distinguishability from negative subseries. Temporal neighborhood coding (TNC) [17] determines the positive region within a sample by exploiting the local stationarity of the time series. The positive and negative sets are defined within a series without accessing others. The TNC framework was built with the encoder and the discriminator; they are trained simultaneously by encouraging the discriminator output to be the same for the positive and oppositely for the negative sets. The TNC loss applies a debias parameter to ensure the encoder’s contrastive learning objective using the discriminator’s decision. Some literature augments the raw input data to obtain different data with identical contexts. Representation learning via Temporal and Contextual Contrasting (TS-TCC) [18] is one of many successful works. This method demonstrated the weak and strong augmentation of the original time series. It maximizes the similarity between these two augmentations while distinguishing them from all other series. The Bilinear Temporal-Spectral Fusion (BTSF) [19] demonstration shows that dropout can be used as an augmentation process. Moreover, the work considered the spectral domain of time series by combining the encoded product of time and the spectral domain into the bilinear feature map; hence, it was successful for medical signals. This paper proposes a contrasting representation of learning for air traffic trajectory as they are rarely explored in prior literature.

3 Methodology

This paper proposes an unsupervised contrastive representation learning technique for the aircraft trajectory data within the airport terminal area. The methods are explained in detail in the section. The implementation includes aircraft trajectory dataset preparation, the model training pipeline construction, and the experiments.

3.1 Dataset Preparation

The experiments in this paper were done using the publicly available historical Automatic Dependent Surveillance–Broadcast (ADS-B) data recorded in the OpenSky database [20], considering the area within 150 kilometers circumstancing the Incheon international airport (ICAO airport code: RKSI). The trajectory data in this paper was recorded between 2018 and 2023. Since the Incheon International Airport shares some operational fixes with the Gimpo International Airport, the trajectories not belonging to the arrival and departure of the Incheon International Airport were filtered out. Besides, trajectories that are too short, too long, and incomplete were filtered out to clean the data.

The important tracking information in an ADS-B state vector includes broadcasting time, icao24 code, latitude, longitude, velocity, heading, vertical speed, call sign, on-ground indication, barometric altitude, geometric altitude, etc. The barometric altitude was selected as a vertical position state as it is published in the Aeronautical Information Publications (AIPs) for the aircraft operator to comply. Therefore, the latitude, longitude, and barometric altitude were transformed into the Cartesian position x , y , and z in the ENU (East-North-Up) coordinates, the local tangent plane coordinates, centered at the Incheon International Airport. Since the ADS-B state vector may not be recorded in consistent time interval, the trajectory data were resampled and interpolated to fill in the missing data points. Then, the outlier states were removed, and the Savitzky-Golay filter was applied to smooth the trajectory data. Finally, the filtered trajectories were unified in step length by linear interpolation.

After obtaining the Cartesian position in x , y , and z stacked along the time steps, t , the heading and flight path are also valuable features that describe the shape of the trajectory. Moreover, when an aircraft maintains the course, it conducts a particular assigned procedure; the positional states within this period are parts of the procedural track. The directional cosine vectors were calculated for each consecutive position to describe the heading and the flight path angle. The directional vector is a vital element for the proposed method in this paper, as it will exploit the unchanged angles to determine similar samples for the learning model. Furthermore, to make the input features more expressive, the cylindrical coordinates are sometimes preferred for air-traffic management; therefore, the lateral radius, r , and bearing angle, θ , were calculated for each lateral points x , and y in the trajectories. These features provide the context of how far the aircraft is from the airport and which angular sector it is located. The dataset was normalized within $[-1, 1]$ using the max-absolute scaler.

The trajectory data for Incheon International Airport is generally imbalanced because both arrival and departure flights are densely distributed in the south and southeast of the airport. With this characteristic, the undersampling was done on the southbound and southeastbound trajectories, creating a balanced dataset of trajectories bound from the west, northeast, southeast, and south of the airport. Each arrival and departure flight data consists of a 5000-time series of aircraft trajectory states without labels, partitioned into 2,500 training samples and 2,500 clusterability testing samples. Each sample has 1000 measurements with eight features, including three directional features from the directional cosine vector of the flight path u_x , u_y , u_z , and five positional features from three Cartesian elements x , y , z and cylindrical elements, r , and θ . A separate raw trajectory dataset was prepared for comparative clustering. This dataset contains the original Cartesian positions in x , y , and z and consists of 1,000 measurements.

3.2 Training Pipeline

This paper introduces the method for contrastive representation learning, exploiting the behavior of air-traffic trajectories. With this setting, it is crucial to set the boundary of sampling in such a way that the positive samples are similar and distinguishable from the negative samples. For N samples of time series, let a multivariate time series denoted as X having a dimension of $E \times S$, while E is denoted as the number of features and S is the sequence length. Pre-encoded subseries are denoted as x centering at the sampled time $t \in [\frac{w}{2}, S - \frac{w}{2}]$, comprise the states in the time window $[t - \frac{w}{2}, t + \frac{w}{2}]$.

The statistical tests have been proven to be an efficient method to set the boundary of the region of positive reference for time series [17]. As the sampling procedure in this paper exploits the unchanged direction during aircraft flying, the distribution in the directional features should have a constant trend with low variance within a window. Therefore, the statistical tests can be applied to test whether the distribution of the anchor time window x_t and the region of reference x_{ref} are indifferently normally distributed. The framework employs the two-sample t-test for means and two-sample Levene's test for variances. To test the indifference in means and variances, the null hypotheses in testing are $H_{o,t-test} : \mu_t = \mu_{ref}$, and $H_{o,Levene} : \sigma_t^2 = \sigma_{ref}^2$. To combine the p-values from two statistical tests, Fisher's method was applied to calculate $p_{combined} = 1 - F(-2(\ln(p_{t-test}) + \ln(p_{levene}))) / 4$. The centering time t is first sampled for a trajectory sample $X_i, i \in [1, N]$, creating an anchor subseries x_t of window size w .

To construct the positive set, the region of reference x_{ref} is repeatedly tested by the combined test; in each test, the size of x_{ref} increases until the test returns the p-value, indicating the difference in two distributions. The maximum size of the reference region is denoted as η . The assumption was made similarly to [17] in which the signals closer to the anchor subseries in time are more similar to the centroid. For this assumption, the positive sampling modeled by Gaussian distribution was applied. The centroid of positive samples has Gaussian distribution $t_p \sim \mathcal{N}(t, \eta)$, and the positive subseries x_p comprise the states in the time windows $[t_p - \frac{w}{2}, t_p + \frac{w}{2}]$.

On the other hand, another assumption was made for negative samples that the context of positive does not exist in different time series samples, even though there might be some, similar to the negative-sampling word-embedding method [16, 21]. Thus, the negative subseries are randomly selected from other trajectories. Two uniform distributions are applied. First, the candidate trajectories were randomly selected from the dataset X , excluding X_i denoted as the subset $X \setminus \{X_i\}$ by allowing duplicates to be sampled. Then, the time centroids of negative set t_n are sampled from the uniform distribution $t_n \sim U(\frac{w}{2}, S - \frac{w}{2})$. Note that both candidate trajectories sampling and negative centroids sampling were conducted using the same sample size. The negative set can now be constructed by matching the candidate trajectories to the centroids; as the results, x_n comprise the states in the time windows $[t_n - \frac{w}{2}, t_n + \frac{w}{2}]$ of the time series $X_j \in X \setminus \{X_i\}$, while $i, j \in [1, N]$. Fig 1 visualizes the positive and negative sampling.

The representation, z of any subseries x , are obtained from the differentiable encoder model; $z = \text{Enc}(x)$. The anchor, positive, and negative subseries representations are denoted as z_t, z_p , and z_n , respectively. The framework utilized the Transformer encoder model presented in [22]. In the encoder's architecture, the linear projection layer expands the feature dimensions of subseries x for more expressiveness; then, the class token c as learnable parameters are appended as the first-time element. After passing the inputs to the transformer encoder, the class token is extracted and mapped to the encoding size E' as the representation z . The architecture of the Transformer encoder used in this paper is illustrated in Fig 2. According to the assumption of the negative sampling method stated that some samples in the negative set are the positive samples; to encourage the similarity of z_t and z_p , and distinguishability of z_t and z_n , the TNC loss [17] were implemented, for it has been proven to be robust for bias sampling in the Positive-Unlabeled (PU) learning. The original TNC loss function was modified according to the sampling procedures, and the loss function used in this framework is expressed in equation (1). The w parameter represents the probability of having positive samples in the negative set.

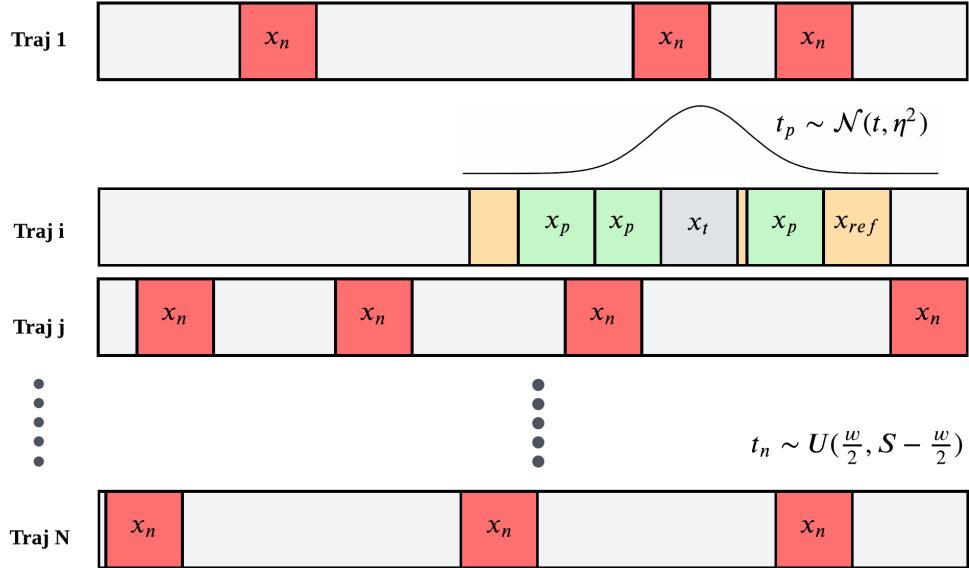


Fig. 1 Sampling visualization for x_{ref} , x_p , and x_n

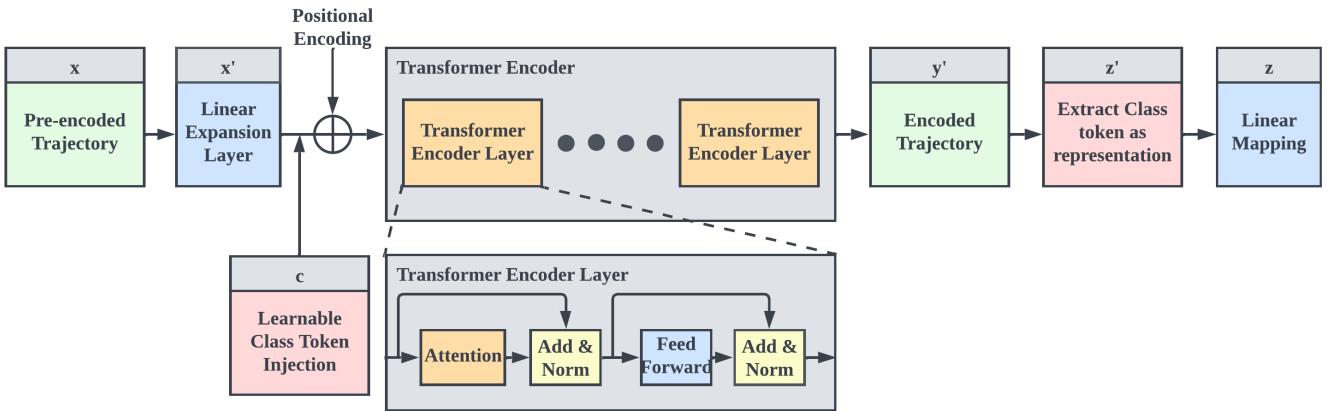


Fig. 2 Architecture of Transformer Encoder used in trajectory representation learning

$$\mathcal{L} = -\mathbb{E}_{x_t \sim X} [\mathbb{E}_{x_p \sim x_{ref}} [\log D(z_t, z_p)] + \mathbb{E}_{x_n \sim X_j \setminus \{X_i\}} [(1-w) \log(1 - D(z_t, z_n)) + w \log D(z_t, z_n)]] \quad (1)$$

A Discriminator is employed to approximate the probability of a representation, z is the same as the anchor representation z_t ; the sigmoid output of the discriminator is denoted as $D(z_t, z)$. For the architecture, the discriminator in this framework is a simple multi-headed binary classifier that returns 1 when z_t and z are the same and returns 0 when z_t and z are different. The encoder and the discriminator jointly learn to optimize the loss function in equation 1 using the newly sampled anchor sample x_t positive samples x_p , and negative samples x_n in each training epoch. After the training, the discriminator will not be used; only the encoder will be used to transform the original subtrajectory into representation.

For this paper's trajectory data, the window size was set at $w = 20$ measurements; the linear projection layer expands eight features to the dimension of 64. The transformer encoder has three layers; each consists of single head attention and 256 units in the feed-forward layer with 0.1 drop rate. The token mapping layer transforms 64 elements of the token into the encoding size of 32. There are five revisiting times for training for a single time series sample. Since the trajectory data significantly rely on in-batch negatives, the sampling size for both positive and negative sets is 1000 samples.

3.3 Experiments

Contrastive representation learning typically aims to obtain a better performance on the downstream tasks, generally referring to classification and clustering. However, since the experimental dataset is unlabeled, the analysis of representation learning performance was done by testing the clusterability of the encoded data. According to the framework architecture, the encoder transforms the sub-trajectories into representation vectors; the whole trajectory can be encoded using sliding windows. For the time $t \in [\frac{w}{2}, S - \frac{w}{2}]$ with adjustable sliding gaps δ . The encoded trajectories have the dimension of $E' \times S'$, while E' is adjustable encoding size, and S' is encoding length following equation (2). For example, the experiment throughout this paper set the sliding gap at $\delta = 5$; the encoding length, $S' = 200$.

$$S' = \left\lfloor \frac{(S - \frac{w}{2}) - \frac{w}{2}}{\delta} \right\rfloor + 1 + 2 \left(\frac{w}{2 \times \delta} \right) \quad (2)$$

The clustering experiment compared the clusterability between the raw trajectories and encoded data. The Hierarchical Density-Based Spatial Clustering of Applications with Noise (HDBSCAN) [23] was selected in this experiment, for it can identify clusters of various shapes and densities without requiring the number of clusters to be specified. Moreover, unlike DBSCAN, which requires the epsilon parameter to specify the radius of the neighborhood around each sample, HDBSCAN does not require such a parameter to be set as such radius is automatically determined. The distance metric between two samples in HDBSCAN is measured using Dynamic Time Warping (DTW) [24]. The DTW was employed for both since raw 3-dimensional trajectory data and encoded trajectories have temporal dynamics. Unlike point-to-point Euclidean distance, DTW uses dynamic programming to approximate the best-aligned point pairing to calculate the distance between two temporal sequences. After obtaining the cluster assignments, the Silhouette scores were calculated for every cluster the HDBSCAN algorithm can group. The higher scores indicate that the object is well-matched with its cluster and poorly matched to the neighboring cluster. The clustering results were visualized using t-SNE, which produced 2-dimensional scatter plots to illustrate the groupings of similar samples, along with grouped trajectories plots for comprehensible view. The framework was implemented using Python 3.11 and Pytorch 2.0.1, trained on a machine with NVIDIA GeForce RTX 4090 GPU. The testing data analysis was done with benchmarking and comprehensive plotting of the clusters.

4 Results and Discussion

This section elaborates on the encoded trajectories' characteristics, supported by illustrative examples. It then presents the clusterability results of the encoded trajectories with the experiment setting discussed in the previous section. Further discussion and analysis of these results are also provided.

4.1 Encoded Trajectory

With the window size $w = 20$ and sliding gap $\delta = 5$, the encoded trajectories Z are two-dimensional arrays, having the extent of 200×32 . Sliding through the windows of x_t over the time step, each column with 32 elements is the embedded z_t , representing a sliding window x_t with the size of 20×8 . All trajectories were encoded and standardized and stored for use in the clustering experiment. As illustrated in Fig 3, the embeddings capture the states within each sliding window. In a broader context, these embeddings collectively represent the temporal dynamics of the entire trajectory. A smaller sliding gap can also capture the transition when the aircraft changes its course, thereby providing a better representation of the trajectory's continuous nature; consequently, it takes a longer inference time for encoding. As illustrated in Figure 3, the encoded representations of eastbound and westbound trajectories show distinct patterns. Moreover, the embeddings during the landing phase on different runways are clearly distinct. Local positive sampling encourages the agreement within the reference

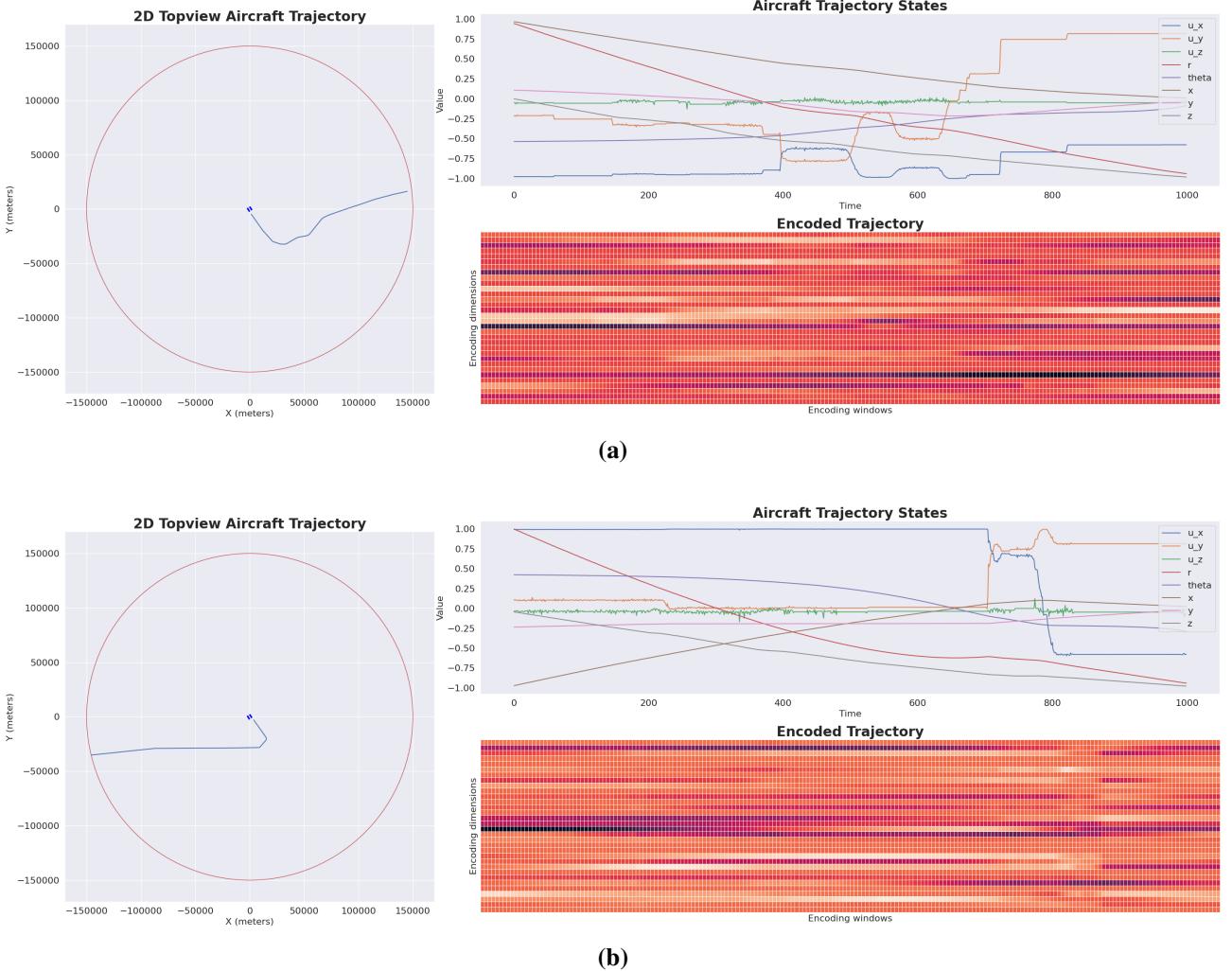


Fig. 3 Example Trajectory Plots with Trajectory states and Encoded Trajectory. (a) shows the eastbound trajectory, and (b) shows the westbound trajectory.

part of individual trajectories. On the other hand, global negative sampling increases the dissimilarity between representations across different trajectories, resulting in the unique representation of patterns regardless of their physical closeness.

4.2 Clusterability

The clusterability experiment was conducted on both raw trajectory and encoded trajectory, as well as departure and arrival scenarios. The raw 3-dimensional trajectory dataset contains 1000 measurements, the same size as the trajectory states dataset; however, to reduce the computational time for the DTW distance calculation, the raw trajectory was downsampled to 250 measurements while retaining most of the vital information. The results obtained using HDBSCAN with Dynamic Time Warping (DTW) distance are as follows: 2-dimensional t-SNE visualization of clusters, individual plots for separated trajectories, and the average silhouette score for each group.

4.2.1 Arrival data analysis

Refers to Appendix A.1, Table 1 shows the Silhouette scores for arrival trajectories analysis. Comprehensive visualizations, including t-SNE and individual cluster trajectory plots, are presented in Fig. 4. The raw trajectories effectively separate the trajectories that are different in early approach patterns. For example, as evident in the clusters pair 6-7 and 9-10, the trajectories in each pair have different

entry points and later have a similar pattern; they are separated into two clusters. Nevertheless, using raw trajectories poorly differentiates the landed runways. This is because, in the Euclidean space, the distance between runways is closer than between entry points. In contrast, as seen in Fig. 4c and Fig. 4a, HDBSCAN clustering using the encoded data provides more apparent separations. In these separated clusters, the clusters pair 1-2, 7-11, 9-10, and 12-13 obtained by the encoded data represent the distinctly situated runways for the reason that in the latent space, the representation does not represent the physical position; however, they represent the piece of information setting apart from their negatives. The clustering on the encoded data effectively separates the overlapping clusters. The lower Silhouette scores for the encoded data could be the results from the global negative sampling that encourage the model to distinguish, from the anchor sample, the positive samples within the negative set. This technique may cause some trajectories to be outliers, even if they could be considered a cluster member.

4.2.2 Departure data analysis

Using the same metrics as the arrival trajectories, in Appendix A.2, the Silhouette scores for departure trajectory analysis are presented in Table 2, while Fig. 5 provides the t-SNE visualization and separately plots the trajectories grouped in the clusters. According to Fig. 5c and Fig. 5a, the using encoded trajectory performs more effectively on clustering, observable from a better clusters separation in t-SNE space comparing the t-SNE representation of the raw trajectory. This is because, with enough generalization ability, contrastive learning can group similar trajectories, although some subseries identical to them are sampled in the negative set. HDBSCAN generated 8 clusters for the raw departure trajectory data, and the algorithm does not separate the cluster of distinct runways due to the mentioned characteristic of raw trajectories in Euclidean space. Although the parameter of minimum samples per cluster can be adjusted lower to obtain the fine-grained group, the number of samples considered as noise consequently increase. On the other hand, HDBSCAN generates more detailed clusters on the encoded data. In addition, the algorithm can recognize detailed departure patterns, for it can differentiate almost all patterns available in the dataset with few noise samples. Similar to the clustering on the encoded arrival data, the clusters of trajectories departed on different runways are well clustered for the same separability advantage as this occurred for the arrival dataset. The results in the comprehensive view for encoded data are visually better than those using raw trajectories, even though the Silhouette scores are lower. Same as the results from arrival data, the data groups together in t-SNE space, but it might be internally distant measured by DTW.

4.3 Discussion

Both analyses suggest that using the encoded trajectory data for downstream clustering tasks results in more fine-grained groups because the contrastive representation learning encourages the local neighboring subseries similarity and ensures distinction from the global negatives. The encoder was trained to set apart the subseries close to Euclidean space to be distant in feature space. Thus, encoding the trajectory into a representation transforms the raw trajectory into a semantic view, eliminating conflicts or biases from directly using distance measures on time-series features of different scales and allowing points that are physically close but operationally different to be distinguishable in the feature space. As a result, the HDBSCAN on the encoded data can differentiate the points close together in physical space such as runways. However, the Silhouette scores are lower for experiments on encoded data than those on raw trajectories. Global negative sampling might be responsible for this issue because the optimization also sets apart the positive samples within the negative set. To solve this problem further, fine-tuning for the loss function's weight parameter and model architecture search should be performed. Moreover, the results in this paper also rely on the performance of the clustering algorithm; therefore, fine-tuning the hyperparameters or changing the clustering algorithm could output differently. As the results of departure data and arrival data reflect different behaviors, experimenting on other datasets could provide additional insights into the adaptability and generalizability of the method proposed in this paper.

5 Conclusion

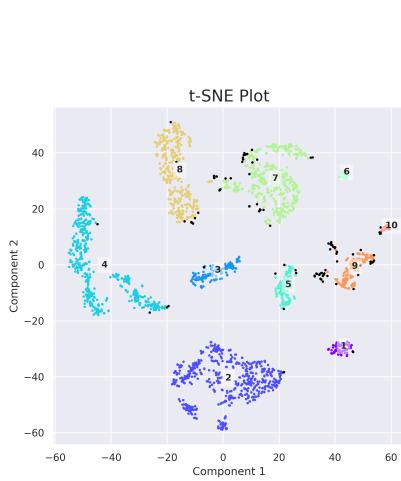
This paper aims to construct a contrastive learning model specifically for trajectory data to facilitate downstream tasks like classification and clustering. The experimental data in this paper is collected from a publicly available ADS-B data source. The unlabeled dataset consists of arrival and departure trajectories circumstancing the Incheon International Airport. The learning framework applied statistical t-tests and Levene’s test to the directional features to test the identical distribution along the aircraft’s track and determine the region of the unchanged flight path. The model was trained to encourage the similarity along the positive reference time and ensure its distinction from the globally sampled negatives. The model transforms the trajectory into a sequence of feature representations, enabling the downstream algorithm to analyze the data samples semantically. In addition, the model’s encoding process utilizes sliding windows applicable to trajectories of varying lengths or incomplete by converting them into shorter sequences that can be evaluated using DTW or other time series distances. The lower Silhouette scores are evidence of setting apart the positive samples, resulting in a more considerable distance. However, the results on HDBSCAN show more clusters in well-separated visualization on the encoded testing data, emphasizing the distinguishability and familiarization of the trained encoder, further reflecting that the stationarity of the path direction can be used as the local context for trajectory data. In future works, the fine-tuning of hyperparameters and the architecture search could be performed to obtain better results. Other clustering performance indices, such as the Davies-Bouldin score (DBI) or the Adjusted Rand score (ARI) with labels, can also be measured to confirm the results better. Finding the most appropriate algorithm could be challenging because the results are sensitive to the clustering algorithm. Furthermore, since the method in this paper determines the reference period from single time series samples, testing positivity across the samples is recommended for future works. The authors present this method as a preliminary step to encourage further studies on various trajectory datasets, learning models, and architectures to demonstrate further the versatility and broad applicability of contrastive learning for trajectory representation.

Appendix

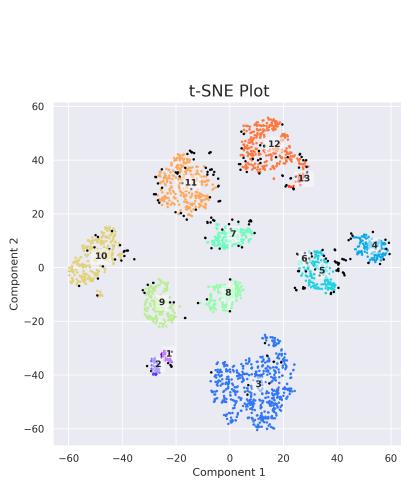
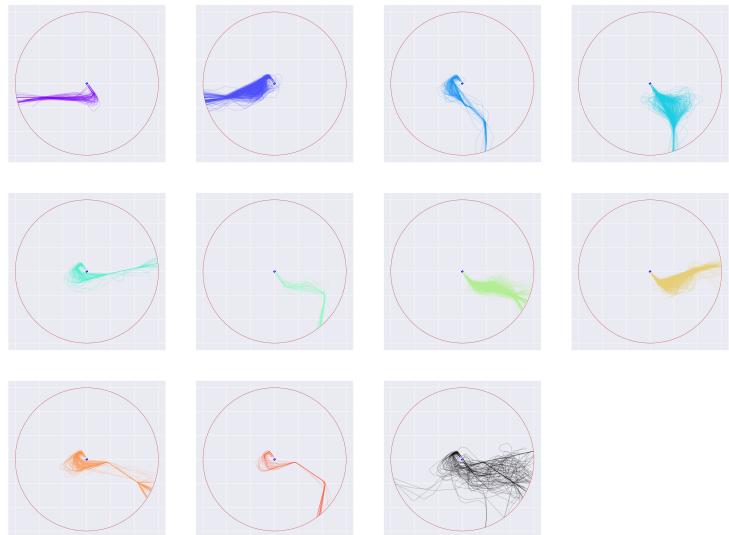
A.1 Experimental Results: Arrival Traffic Data

Table 1 Cluster Silhouette Scores for Arrival Trajectories: Raw and Encoded

(a) Arrival Raw Trajectories		(b) Arrival Encoded Trajectories	
Metric	Silhouette Score	Metric	Silhouette Score
Overall Score	0.5846	Overall Score	0.1680
No Noise Score	0.6311	No Noise Score	0.2084
Noise Samples	102	Noise Samples	229
Cluster -1	-0.5086	Cluster -1	-0.2329
Cluster 0	0.7588	Cluster 0	0.2376
Cluster 1	0.7172	Cluster 1	0.2319
Cluster 2	0.7495	Cluster 2	0.2137
Cluster 3	0.5667	Cluster 3	0.2325
Cluster 4	0.6721	Cluster 4	0.1412
Cluster 5	0.6582	Cluster 5	0.2430
Cluster 6	0.5712	Cluster 6	0.1879
Cluster 7	0.5925	Cluster 7	0.2789
Cluster 8	0.5529	Cluster 8	0.2968
Cluster 9	0.6745	Cluster 9	0.2174
		Cluster 10	0.1689
		Cluster 11	0.1613
		Cluster 12	0.3010



(a)



(c)

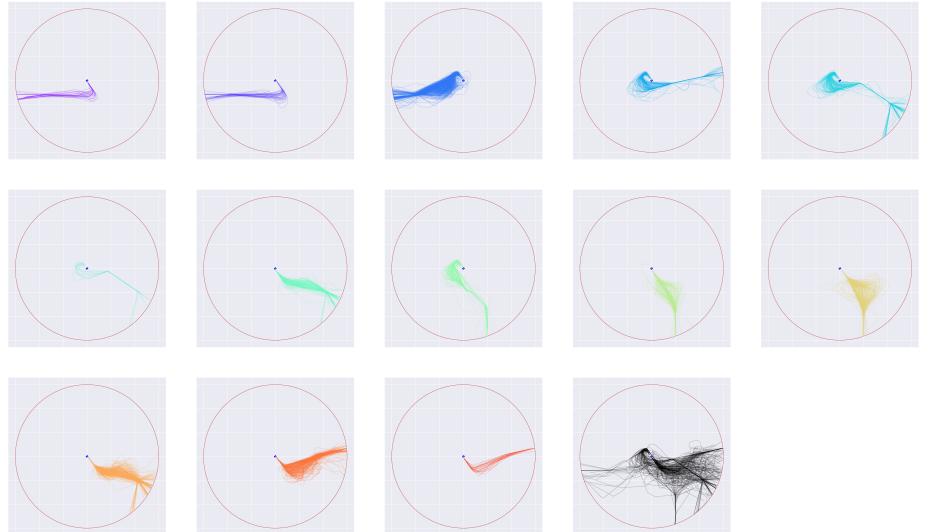
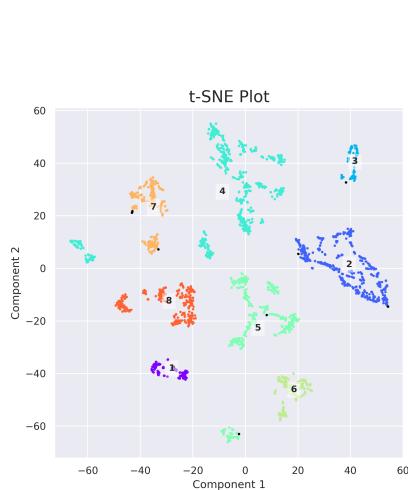


Fig. 4 Comprehensive Visualization of Trajectory Clustering: (a) t-SNE plot illustrating the clusters separation of raw trajectories, (b) Individual clustering of raw trajectories, (c) t-SNE plot illustrating the clusters separation of encoded trajectories, and (d) Individual clustering of encoded trajectories.

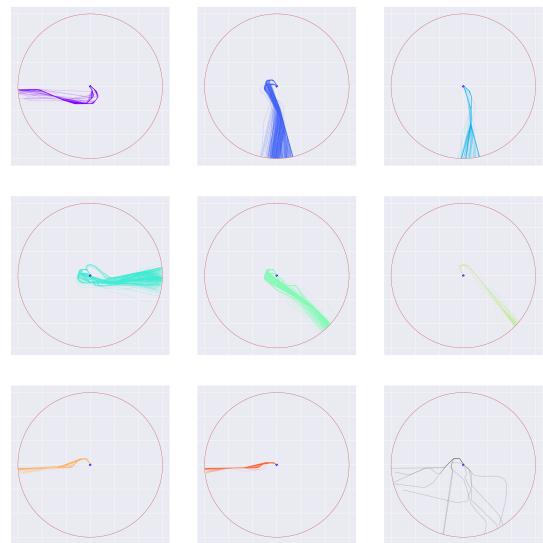
A.2 Experimental Results: Departure Traffic Data

Table 2 Cluster Silhouette Scores for Departure Trajectories: Raw and Encoded

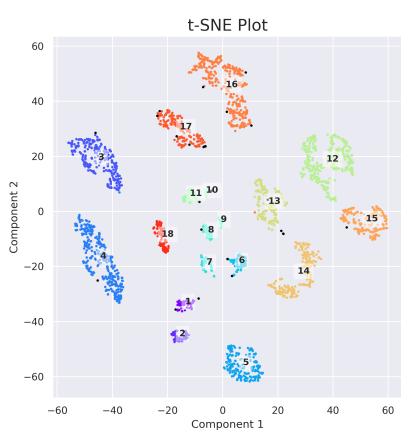
(a) Departure Raw Trajectories		(b) Departure Encoded Trajectories	
Metric	Silhouette Score	Metric	Silhouette Score
Overall Score	0.5927	Overall Score	0.2073
No Noise Score	0.5985	No Noise Score	0.2123
Noise Samples	11	Noise Samples	27
Cluster -1	-0.7041	Cluster -1	-0.2550
Cluster 0	0.7628	Cluster 0	0.2968
Cluster 1	0.4533	Cluster 1	0.4028
Cluster 2	0.6040	Cluster 2	0.1706
Cluster 3	0.7285	Cluster 3	0.2290
Cluster 4	0.5460	Cluster 4	0.3770
Cluster 5	0.9148	Cluster 5	0.3373
Cluster 6	0.4432	Cluster 6	0.1408
Cluster 7	0.4962	Cluster 7	0.3608
		Cluster 8	0.4113
		Cluster 9	0.3277
		Cluster 10	0.4423
		Cluster 11	0.1448
		Cluster 12	0.1622
		Cluster 13	0.1817
		Cluster 14	0.1114
		Cluster 15	0.1346
		Cluster 16	0.1877
		Cluster 17	0.3355



(a)



(b)



(c)



(d)

Fig. 5 Comprehensive Visualization of Trajectory Clustering for Departures: (a) t-SNE plot illustrating the clusters separation of raw departure trajectories, (b) Individual clustering of raw departure trajectories, (c) t-SNE plot illustrating the clusters separation of encoded departure trajectories, and (d) Individual clustering of encoded departure trajectories.

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