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Deep motion-aware representation learning for vehicle trajectory analysis

B. Swarna Jyothi *
S. K. Mouleeswaran †
Department of Computer Science and Engineering
Dayananda Sagar University
Bangalore 562112
Karnataka
India

M. Suleman Basha §
Department of Computer Science & Engineering (Data Science)
Rajeev Gandhi Memorial College of Engineering & Technology (Autonomous)
Nandyal 518501
Andhra Pradesh
India

Abstract

Identifying vehicle trajectories from video surveillance is an essential task in modern traffic management systems to prevent accidents and reduce congestion. Detecting cluster structures in trajectory paths is crucial for distinguishing between normal and abnormal vehicle behaviours. Traditional visual clustering approaches, such as Visual Assessment of cluster Tendency (VAT) and improved VAT (iVAT), are effective for visualizing cluster patterns but are limited in capturing complex motion characteristics due to inadequate feature representation. To address this limitation, this paper proposes a novel Deep Motion-Aware Trajectory iVAT (DMAT-iVAT) framework that integrates motion-enhanced trajectory modelling with deep learning-based feature extraction. The proposed method augments trajectory data with velocity and acceleration information to capture rich spatio-temporal dynamics, followed by representation learning using a Bidirectional Long Short-Term Memory (BiLSTM) network with an attention mechanism. The learned embeddings are then analyzed using iVAT to reveal cluster tendencies more effectively. Experimental results on benchmark video trajectory datasets demonstrate that the proposed DMAT-iVAT framework

* *E-mail:* **badimela1508@gmail.com (Corresponding Author)**
† *E-mail:* **meetmoulee@gmail.com**
§ *E-mail:* **suleman.ndl@gmail.com**

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significantly improves cluster structure visualization and discrimination compared to conventional VAT-based methods.

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1. Introduction

Clustering is a very popular machine learning method for classification problems that operates without supervision and can be used to group similar objects or trajectories in video surveillance systems. To understand how past cluster information affects cluster quality, detecting cluster tendency (CT) is essential. Bezdek and Hathaway [1] recently reported improvements in visual assessment of cluster tendency, Havens and Bezdek [3] reported on further enhancements to visual assessment of cluster tendency, and Basha, Mouleeswaran, and Prasad [4] reported on the use of a visual assessment of the quality of clusters. The fundamental VAT approaches are effective for small datasets; however, they impede the detection of CT in larger datasets. The methodologies of BigVAT and sVAT have been established in Hu [14] for the identification of CT in extensive datasets. Basha et al. [15]. Introduced a time-efficient and scalable VAT EMST method, which produces the Euclidean minimum spanning tree (EMST) edge with an efficient k-d tree data structure. The k-d tree represents data points in a k-dimensional space and is classified as a space-partitioning data structure. This method cannot evaluate clusters for video surveillance data due to the dynamic nature of video frame streaming. Gloaguen et al. [8] reported that existing methods for extracting features from moving objects require considerable computational time to process their trajectories. A deep learning model combining CNN and LSTM is used to extract meaningful features from object trajectories in video surveillance data. Since trajectory data naturally exhibit path-like patterns, iVAT is employed to reveal and evaluate their cluster structures effectively. Compared to other methods, iVAT is better suited for analysing trajectory-based clusters. Figure 1 presents the workflow of the proposed trajectory-based analysis framework, Kumar et al. [7] proposed a scalable trajectory-clustering method for identifying meaningful movement patterns and clusters in vehicle-trajectory data Raw trajectories are filtered to only include those with at least five time instances with noise removed. The velocity and acceleration features are then extracted to describe the motion and to identify normal and abnormal motion.

The processed trajectories are subsequently passed to the Deep Feature Embedding module, the core component of the framework, which consists of three key parts.

1. Attention Pooling highlights the most important parts of a trajectory by assigning higher weights to key time steps.

2. The Projection Layer reduces high-dimensional motion features into a compact, meaningful representation.
3. Feature Normalisation standardises the learned features, improving numerical stability and similarity measurements.

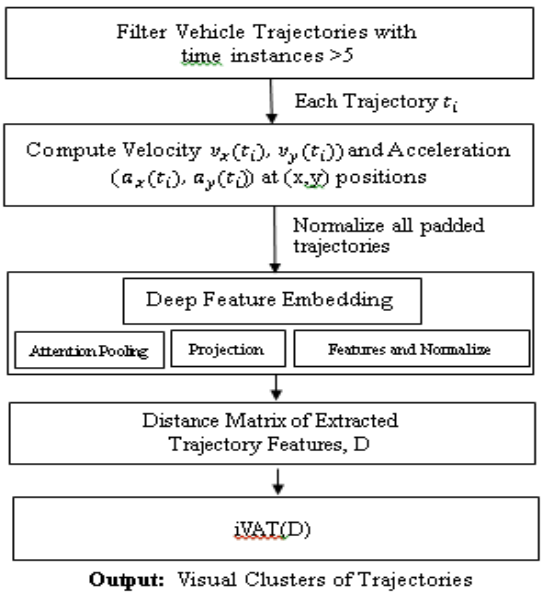


Figure 1
Flow of Work for Proposed frameowrk

Rathore et al. [2] used the extracted trajectory features to construct a distance matrix, denoted by (Dis), for clustering. The iVAT algorithm reorganizes this matrix to reveal cluster structures more clearly in Xie et al. [5]. By combining motion features, deep learning, and iVAT visualization, the framework effectively identifies meaningful and abnormal movement patterns. The following sections discuss the literature review, the proposed method, the experimental results, and the conclusions.

2. Literature Study

Before clustering, data exploration can be used to identify possible cluster structures. Bezdek and Hathaway [1] introduced the Visual Assessment of Cluster Tendency (VAT) method is one of the methods for visually identifying clusters using distance-based similarities, represented as dark or grey blocks along the diagonal. The Table 1 summarizes some related studies of work.

Table 1
Summary of Existing Methods

Reference Paper	Methods / Techniques – Results	Limitations
Bezdek and Hathaway [1] proposed work	VAT (Visual Assessment of Cluster Tendency): Effectively visualizes and identifies natural cluster structures within a dataset.	Works well for regular clusters but struggles to clearly identify complex or path-shaped cluster patterns.
Nordahl et al. [13]	FensiVAT: A fast and scalable method that efficiently identifies cluster structures in large, high-dimensional datasets.	Scalable and fast, but may lose accuracy and struggles to capture complex spatio-temporal patterns in trajectory data.
Mahdi, Hosny, and Elhenawy [11] introduced the method in for the assessment of big data clusters assessment	ClusiVAT: Efficiently identifies cluster structures and estimates the number of clusters in large-scale datasets.	Works best with numerical data and may inaccurately estimate clusters in complex trajectory or path-based datasets.
Havens and Bezdek [3] developed the improved visual technique	iVAT (Improved VAT): Provides clearer visualization of cluster structures and is especially effective for identifying complex, path-shaped clusters.	The method struggles with complex data patterns, and its performance can decrease as the dataset size grows, limiting scalability.

Shkaberina et al. [12] and Zhang et al. [6] studied aVAT and SpecVAT, respectively, for discovering underlying cluster structures. To detect irregular clusters and path-shaped clusters, Havens and Bezdek [3] came up with iVAT. Datta et al. [10] and Nordahl et al. [13] introduced extensions for scalability and trajectory analysis respectively while Kumar et al. [7] proposed extensions for scalability and trajectory analysis. However, it is still difficult to process complex and continually changing surveillance-trajectory data.

3. Proposed Methodology

The Deep Motion-Aware Trajectory iVAT (DMAT-iVAT) algorithm is a trajectory data modelling algorithm based on motion dynamics, deep learning-based feature extraction, and cluster tendency analysis. It maps raw trajectories into meaningful feature embedding's and identifies underlying cluster structures using iVAT, as illustrated in Algorithm 1.

Algorithm 1: Deep Motion-Aware Trajectory iVAT (DMAT-iVAT)

Input:

$T = \{t_i\}_{i=1}^{N}, t_i = \{(x_t, y_t)\}_{t=1}^{L_i}$

Output:

$F \in \mathbb{R}^{N \times d}, R \in \mathbb{R}^{N \times N}$

Methodology:

1. **Filter Trajectories**

   Remove all $t_i$such that: $L_i < 5$

2. **Construct Motion-Enhanced Trajectory**

   For each trajectory $t_i$and time step $t, (x_t, y_t)$

   // First-order difference in trajectory

   $v_x(t) = x_{t+1} - x_t, v_y(t) = y_{t+1} - y_t$// Second-order difference in trajectory:

   $a_x(t) = v_x(t+1) - v_x(t), a_y(t) = v_y(t+1) - v_y(t)$ Boundary handling:

   $v_x(L_i) = 0,\ v_y(L_i) = 0 a_x(L_i - 1) = 0,\ a_y(L_i - 1) = 0$

   $\tilde{t}_i(t) = (x_t,\ y_t,\ v_x(t),\ v_y(t),\ a_x(t),\ a_y(t))$

3. **Sequence Normalization**

   //Compute:

   $L_{max} = \max_i L_i$// Pad all trajectories to L_{max}:

   $X \in \mathbb{R}^{N \times L_{max} \times 6}$// Normalize

   $X \in \{0,1\}^{N \times L_{max}}$

4. **Deep Feature Embedding**

   For each X_i, Encode sequence:

   $H_i = BiLSTM(X_i)$//Attention pooling:

   $h_i = \sum_{t=1}^{L_i} \alpha_t H_i(t)$//Projection:

   $f_i = W h_i + b$//Form feature matrix:

   $F = [f_1, f_2, \ldots, f_N]^T$//Normalize:

   $F \leftarrow \dfrac{F - \mu}{\sigma}$

5. **Distance Matrix Computation and iVAT Reordering**

   $D(i,j) = 1 - \frac{F_i \cdot F_j}{\|F_i\| \|F_j\|}$//Initialize:

   $J_1 = 0, K = \{1,2, \ldots, N-1\}$//For $r = 2$ to N:

   $J_r = arg\min_{k \in K} D(k, J_{r-1})$//Construct reordered matrix:

   $R(r,c) = D(J_r, J_c)$

   $I = Image(R)$ Return F, I

In Step 1, Input trajectories are filtered according to their length; very short length trajectories ($L_i < 5$) are removed because they do not provide enough motion information. This guarantees a more reliable analysis in the next steps.

In Step 2, the trajectories of objects are used to determine their velocity and acceleration, which are displayed as motion features. In Step 3, the lengths

of the trajectories are normalized by adding padding and masking, to ensure that they are fed into the learning algorithm consistently. A BiLSTM network with an attention mechanism is trained to extract patterns in the temporal and motion spaces from the trajectories in Step 4. The extracted features are then scaled and combined to form a feature matrix. Elementary feature vectors are extracted and calculated in Step 5, leading to a pairwise distance matrix, which is reorganized by the iVAT algorithm to discover a natural cluster structure. This facilitates understanding and recognizing similar trajectory groups through clear clusters.

4. Experimental Results and Analysis

The experiments were conducted using the open-source QMUL Junction Dataset provided by Queen Mary University of London [16]. The object trajectories were extracted after preprocessing and classified into four labelled trajectory categories. Sample frames that depict objects' movement patterns are shown in Figure 2.

The trajectories of various moving objects are shown in Figure 3, coloured differently. The x-axis is the horizontal position of objects in an observation area, and the y-axis is the vertical position of objects in an observation area. Sampled points along the path are indicated.



Figure 2

The sample video frames for the trajectory paths of objects (vehicles) – Trajectory Paths Labels: Left-Right, Right-Left, Top-Bottom, Bottom-Top

Overlapping and intersecting trajectories indicate where overlapping movement happens and where interactions may occur. This visualization displays movement patterns, trajectory diversity, and trend direction, enabling analysis of movement behavior and trend clustering. To compare the clustering tendency of the proposed iVAT with BB-VAT, k-d VAT, and tkd-VAT, cosine dissimilarity is used, and the comparison is shown in Figure 4.

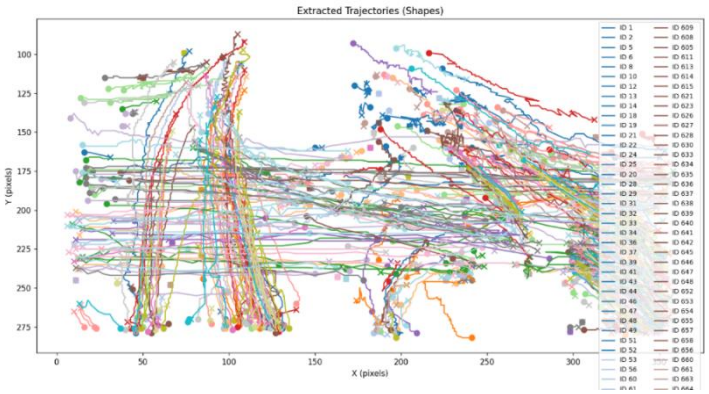


Figure 3
Detected Trajectory Paths of the Objects

The iVAT visualization also shows distinct block-like structures and very strong clusters. BB-VAT, however, is noisy, whereas k-d VAT and tkd-VAT provide little information about overall cluster relationships. Nukala, Sri, and Prasad [9] showed that iVAT is able to reveal cluster structures at the global level, especially in high dimensional data where cosine distance was used.

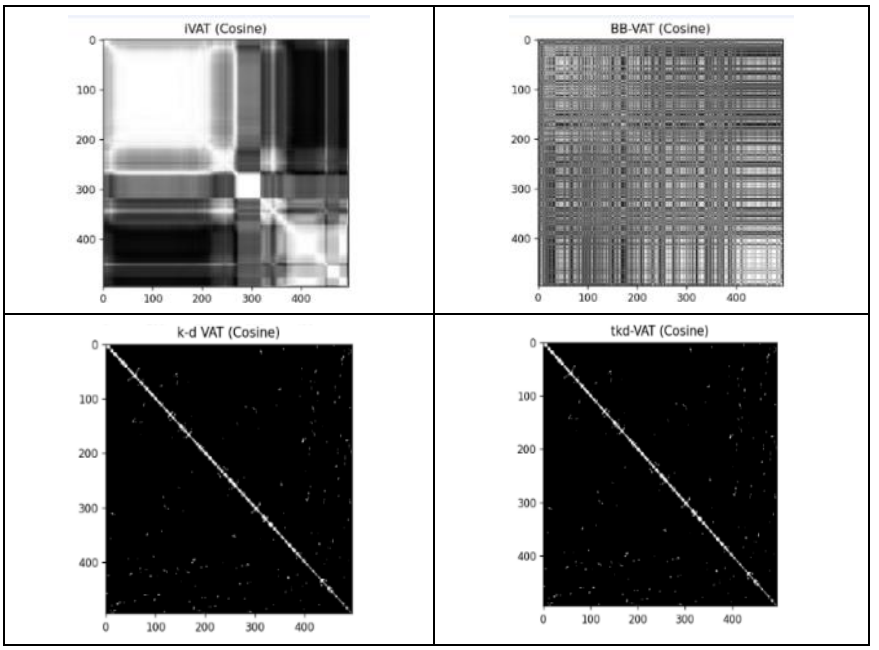


Figure 4
Visual Assessment of Clusters Using Deep Embedded Features

Table 2
Comparative Clustering Performance of DMAT-iVAT and Existing Methods

Methods	ACC	NMI	Precision	Recall	F-Score
DMAT-iVAT	96.42	0.91	95.84	96.10	95.97
BB-VAT	92.18	0.84	91.50	91.92	91.71
tkdVAT	89.76	0.80	88.94	89.21	89.07
iVAT	86.34	0.74	85.62	86.05	85.83
ClusiVAT	90.87	0.82	90.11	90.43	90.27
FensiVAT	88.95	0.78	88.20	88.61	88.40

As shown in Table 2, the DMAT-iVAT representation is the most informative for identifying possible cluster formation in the data. The recombined dissimilarity matrix also provides a better idea of the intrinsic clusters than BB-VAT and k-d VAT, due to their higher noise levels. However, tkd-VAT and kd-VAT prove to be too sparse in nature to show clear boundaries of the clusters in the real world.

5. Conclusion and Scope of the Work

The proposed deep trajectory-based iVAT framework combines deep feature extraction with the improved Visual Assessment of Tendency (iVAT) algorithm to evaluate cluster structures in video trajectory data. Experimental results on benchmark datasets demonstrate its ability to effectively identify cluster patterns and distinguish normal trajectories from abnormal ones. Compared with other VAT-based methods, iVAT produces clearer, more interpretable cluster structures in the dissimilarity matrix, making the tendency toward clustering easier to detect. In contrast, BB-VAT produces noisy visualisations, while k-d VAT and tkd-VAT often yield sparse patterns that make cluster identification difficult. These findings highlight the effectiveness of the proposed approach for trajectory analysis. Future work will focus on developing online and incremental versions for real-time video stream processing.

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