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APPLIED RESEARCH

Detecting of Robotic Imitation of Human on-the-Website Activity With Advanced Vector Analysis and Fractional Derivatives

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ABSTRACT This paper introduces a novel approach for the detection of automated entities in online environments through the analysis of mouse dynamics. Leveraging fractional derivatives and vector cross products, our methodology scrutinizes the intricate patterns embedded in mouse movements. Fractional derivatives capture the non-integer order dynamics, while vector cross products reveal deviations from expected trajectories. The combination of these advanced mathematical tools offers a unique perspective on distinguishing between human and bot behaviors. We present experimental results showcasing the efficacy of our approach in various scenarios, demonstrating its potential in the realm of cybersecurity and online integrity. Our findings contribute to the evolving landscape of bot detection methodologies, emphasizing the importance of incorporating mathematical rigor in the analysis of digital behavior.

INDEX TERMS Bot detection, human-bot interaction, clusterization, feature engineering, feature interaction.

I. INTRODUCTION

Bots are automated programs designed for the efficient execution of repetitive tasks at maximum speed [1]. However, malicious bots pose significant risks to network users, causing substantial damage and creating potential threats in the online environment [2].

Recently, the issue of bots mimicking human behavior [3] has become particularly relevant. Cybercriminals actively employ technologies that enable bots to emulate human actions and interactions online [4]. This imitation complicates the detection of malicious bots, as they become more sophisticated in distinguishing from human behavior. In the context of government programs, the threat of such imitation can lead to data manipulation [5], disinformation [6], and other forms of cyberattacks [7], emphasizing the importance of developing effective methods to protect against such technological threats.

In various scientific literature, the significance of bot detection is emphasized, as bots, prevalent on the modern internet, pose a serious threat, influencing diverse aspects from data falsification in online advertising to large-scale attacks for harvesting user accounts. In [8] propose a non-intrusive stress measurement method through routine computer mouse operations, utilizing a simple model capturing muscle stiffness during movement. The study [9] investigates cursor trajectories of motion-impaired and non-disabled users to enhance our understanding of impaired movement, revealing distinctions such as increased pausing frequency and duration The pivotal focus of work [10] lies in proposing a semi-supervised method for effectively distinguishing between bots and legitimate users on social

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networks. Study [11] describes the uniqueness of this system lies in its utilization of fine-grained, point-by-point angle-based metrics of mouse movements, which prove distinctive across individuals and independent of computing platforms The article [12] discusses the advantages of detecting bots using mouse dynamics. Thesis [13] describes the distinction between "good" bots, which are permitted and utilized for specific tasks such as web indexing by search engines, and "bad" bots, which scrape data without permission, potentially leading to issues like skewed analytics and misuse of information. Paper [14] underscores the issue of malicious bots, posing a serious threat and introduces an innovative approach, leveraging deep learning and a new representation method based on mouse dynamics. Crucial point of the study [15] lies in the evolution of mouse dynamics as a biometric, particularly in web bot detection. The key focus of the paper [16] is the introduction of the SapiMouse dataset, designed for training and evaluating systems in user authentication and bot detection based on mouse dynamics. Article [17] highlights the central theme of creating an end-to-end deep framework designed for detecting bots through computer mouse movements. The paper [18] introduces ReMouse, a unique real-world mouse dynamics dataset, offering insight into combating session-replay bots, a challenging issue in domains frequented by the same genuine users

Kinematics pertains to the study of object motion without considering the reasons behind this movement [19], and in this case, the object is the mouse used for user input. Typically, quantities such as velocity and acceleration are used to describe motion. Fractional derivatives [20] in the context of kinematics may include, for example, fractional derivatives of velocity or acceleration over time [21]. Since fractional derivatives can cover non-integer degrees, they can be useful for capturing more complex aspects of motion. When applied to the analysis of mouse movement, fractional derivatives can help identify trajectory features that might be overlooked when using only integer derivatives. For instance, fractional derivatives can highlight changes in speed or acceleration over small time intervals, which may be crucial for detecting unusual or bot-specific movement patterns [22].

In the scope of our research, we went beyond limiting ourselves to the second derivative and extended the analysis to derivatives up to the sixth order. This includes derivatives of higher orders, such as the third, fourth, fifth, and sixth derivatives.

Jerk (Je) [23], sometimes referred to as jolt [24], is the third derivative over time of position $\vec{j}(t) = \frac{\mathrm{d}^3 \vec{x}}{\mathrm{d}t^3}$ and represents the change in acceleration over time. The absence of jerk in acceleration is essentially a manifestation of a static load. Jerk, on the other hand, is the sensation derived from alterations in force; it manifests as either an ascending or descending force acting on the body [25]. The analysis of jerk is crucial for understanding how these long-dwell mechanisms generate intermittent motions with delay and a holding position of the output member [26].

Snap (S) [27], also referred to as jounce [28], represents the fourth derivative of the position vector concerning time $\vec{s}(t) = \frac{\mathrm{d}^4 \vec{x}}{\mathrm{d}t^4}$. Alternatively, it signifies the rate of change of jerk with respect to time. In other terms, it can be expressed as the second derivative of acceleration or the third derivative of velocity. Snap is analyzed to comprehend its impact on the kinematic performance of mechanisms with long dwell times, where higher-order time derivatives become essential for a complete description of their motion [26].

Crackle (C) [29] is the kinematic parameter $\vec{c}(t) = \frac{\mathrm{d}^5 \vec{x}}{\mathrm{d}t^5}$ corresponds the fifth derivative of the position vector with respect to time. For example, crackle represents a higher-order kinematic parameter derived from the Doppler radar measurements, specifically denoting the time derivative of snap, and is identified as a potential indicator of cognitive impairment during the sit-to-stand movement in elderly individuals [30].

Pop (P) $\vec{p}(t) = \frac{\mathrm{d}^6 \vec{x}}{\mathrm{d}t^6}$ is the term that occasionally used to describe the sixth derivative of the position vector concerning time [31].

The study [32] primarily focuses on assessing the impact of mouse device configurations on mouse dynamics metrics through statistical evaluation. In contrast, our study takes an approach by employing trajectory classification techniques and analyzing time derivatives of mouse movements. Its objective is to identify distinct user behavior patterns, specifically targeting the differentiation between ordinary users, clickers, and human mimic bots.

The aim of this study is to employ two types of metafetures: trajectory classification approach, utilizing vector cross product with trajectory length and session time, and time derivatives up to the sixth order, including fractional derivatives of semi-integer order. Through this unique perspective, we seek to identify a clustering model for user trajectories that effectively distinguishes ordinary users from clickers and human mimic bots.

II. RELATED WORKS

When considering mimetic robotic systems observed in the context of mouse movement, it's important to acknowledge the various approaches that have been proposed. Some studies focus on employing statistical methods to analyze mouse movement patterns [32], [33]. Other research endeavors focus on utilizing mouse temporal dynamics features, such as velocity [34], acceleration [35], jerk [36], snap [37]. Other research endeavors apply machine learning techniques for mouse movement clusterization. Work [38] introduces a novel approach to mouse trajectory analysis through trajectory clustering, surpassing the limitations of aggregation-based trajectory analyses. Paper [39] presents a dynamic approach combining trajectory simplification and clustering to address visual clutter in confined spaces like soccer pitches. Certain approaches concentrate on analyzing temporal characteristics of mouse movement, such as click frequency [40] and duration [41]. Several studies have suggested the utilization of biometric methods [11], [42] for mouse movement analysis. Additionally, some research endeavors aim to combine various approaches [43], [44]. Consequently, currently developed approaches do not fully explore all possible patterns of mouse trajectory movement by creating new meta-features such as fractional derivatives for highly effective analysis of non-human mouse movement, addressing the gap in knowledge that this paper seeks to close.

III. METHODOLOGY

Drawing insights from the dataset on user trajectories obtained from the e-commerce platform, we conducted an analysis of mouse movements. This involved an examination of keystroke and mouse dynamics, allowing us to distinguish distinct behavioral patterns for humans and bots. For the analysis of mouse movement in the experiment, data were utilized containing records for each user session in a sequential format $x_i, y_i, t_i, \ldots$, where x_i, y_i represent the coordinates of the mouse position at time t_i. Time values t_i were measured in milliseconds since January 1, 1970 (Unix format). Each session had a varying number of coordinate entries and included information about the session's creation time.

Initially, velocities, accelerations, and session times were computed for each record. Subsequently, the pattern of mouse movement was investigated using the cross product of vectors.

One of the primary tools employed was Python [45], renowned for its flexibility and robust data analysis libraries. Specifically, for processing and analyzing mouse trajectory data, the Pandas [46] library was used for handling tabular data, NumPy [47] for array-based computations, and Matplotlib [48] for result visualization.

For more complex operations, such as computing fractional derivatives of mouse trajectories, the SciPy [49] library was employed. SciPy offers a wide array of scientific computing functions, including support for differentiation operations.

A. UTILIZATION OF VECTOR CROSS PRODUCT FORMULA

The application of the vector cross product formula in this context is associated with determining the collinearity of three consecutive points (coordinates). The vector cross product formula provides a method to check whether three points lie on the same line in a two-dimensional space.

For three points $A(x_1, y_1)$, $B(x_2, y_2)$, and $C(x_3, y_3)$, vectors AB and AC are represented as:

$$AB = \langle x_2 - x_1, y_2 - y_1 \rangle, \quad AC = \langle x_3 - x_1, y_3 - y_1 \rangle$$

The cross product of vectors is calculated as:

$$\begin{aligned} \mathit{Cross\ Product} = (AB \times AC) &= (x_2 - x_1)(y_3 - y_1) \\ &\quad - (y_2 - y_1)(x_3 - x_1) \end{aligned}$$

If the points lie on the same line, the cross product is zero. Otherwise, it is non-zero. Therefore, the vector cross product formula allows determining whether a set of points forms a line. A value close to zero (considering the threshold value straight_line_threshold) may indicate straight-line movement. Clicker bots (Fig. 1c), commonly employed for automated actions online, exhibit distinctive trajectories easily identifiable through vector cross product analysis of their movement lines. This enables efficient recognition of such bots by analyzing deviations in mouse positions beyond typical user movements (Fig. 1ab).

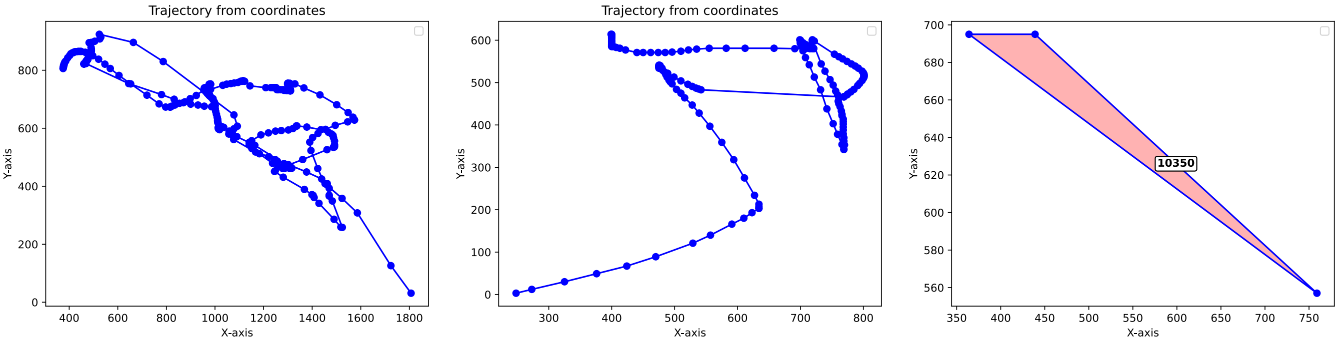
If two lines emanating from the same point exhibit a significantly large value in their cross product, it suggests a sudden deviation in the mouse's position amid seemingly regular user movements, indicating a potential human mimic bot. This distinct pattern (Fig. 2) suggests the presence of a human mimic bot, as the trajectory reflects characteristics that deviate from typical user behavior.

Data on mouse movements were captured using user activity monitoring methods, with coordinates recorded at equidistant time intervals. The results revealed that a key characteristic of such users is the large distance between mouse coordinates on the computer screen. This pattern is observed in users who mimic the behavior of real people but employ mechanical methods for moving the computer mouse. We hypothesize this because it is unlikely for a human to move their mouse over distances significantly greater than the average distance between coordinates of the same user. It is speculated that the reason for the occurrence of this pattern in human mimics may be an attempt to deceive behavior analytics systems and overcome limitations in estimating the speed and accuracy of mouse movements inherent to real users. To better discern this pattern, vector multiplication of adjacent vectors was conducted. Analyzing such vector-related features can enhance the detection of bots striving to mimic human interactions on digital platforms. Analyzing such vector-related features can contribute to the effective detection of bots attempting to emulate human interaction on digital platforms.

B. UTILIZATION OF FRACTIONAL DERIVATIVES

For a more in-depth analysis, we incorporate fractional derivatives of semi-integer order in our study, allowing for a nuanced examination of temporal dynamics. Fractional derivatives [21] serve as a mathematical tool that generalizes the concept of derivatives to non-integer orders. In physics, they find applications in modeling complex phenomena where changes cannot be adequately described by ordinary differential equations. For instance, fractional derivatives are employed in describing diffusion in porous media [50], relaxation in intricate systems [51], and analyzing nonlinear phenomena like fractal structures [52]. Their application allows for a more precise consideration of nonlinear and non-uniform processes, making them a powerful tool in physical modeling.

We will refer to the derivative of order 0.5 as **half-velocity (hV)**, the derivative of order 1.5 as **half-acceleration (hA)**,



a) b) c)

FIGURE 1. The coordinates of mouse trajectories along the X and Y axes: a), b) - trajectories of human, c) - clicker.

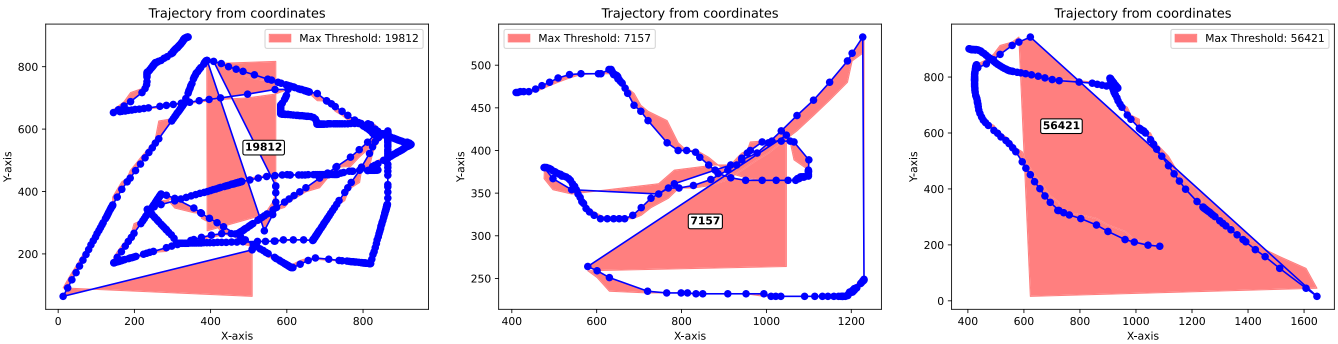


FIGURE 2. Trajectories of human mimic bots with area which filled between two lines with maximum vector cross product (examples).

and order 2.5 as **half-jerk (hJe)**. Also we introduce the terms **half-snap (hS)**, **half-crackle (hC)**, and **half-pop (hP)** to denote derivatives of orders 4.5, 4.5, and 5.5, respectively. These terms extend the concept of snap, crackle, and pop, commonly used for the fourth, fifth, and sixth derivatives of displacement in the context of motion analysis.

These terms are defined by the following formulas:

$$\vec{\tilde{v}}(t) = \mathrm{D}^{1/2}\vec{x} = \frac{\mathrm{d}^{0.5}\vec{x}}{\mathrm{d}\,t^{0.5}} \tag{1}$$

$$\vec{\tilde{a}}(t) = \mathrm{D}^{3/2}\vec{x} = \frac{\mathrm{d}^{1.5}\vec{x}}{\mathrm{d}\,t^{1.5}} \tag{2}$$

$$\vec{\tilde{j}}(t) = \mathrm{D}^{5/2}\vec{x} = \frac{\mathrm{d}^{2.5}\vec{x}}{\mathrm{d}\,t^{2.5}} \tag{3}$$

$$\vec{\tilde{c}}(t) = \mathrm{D}^{7/2}\vec{x} = \frac{\mathrm{d}^{3.5}\vec{x}}{\mathrm{d}\,t^{3.5}} \tag{4}$$

$$\vec{\tilde{s}}(t) = \mathrm{D}^{9/2}\vec{x} = \frac{\mathrm{d}^{4.5}\vec{x}}{\mathrm{d}\,t^{4.5}} \tag{5}$$

$$\vec{\tilde{p}}(t) = \mathrm{D}^{11/2}\vec{x} = \frac{\mathrm{d}^{5.5}\vec{x}}{\mathrm{d}\,t^{5.5}} \tag{6}$$

The fractional derivative of a signal $f(t)$ of order q is defined as follows:

$$D^q f(t) = \frac{1}{\Gamma(n-q)}\frac{d^n}{dt^n}\int_0^t (t-\tau)^{n-q-1} f(\tau)\,d\tau$$

where $\Gamma(n)$ is the gamma function and n is the nearest integer greater than or equal to q. This fractional derivative provides insight into the rate of change of the signal with respect to time, capturing more nuanced aspects of the mouse movement.

To interpret the fractional derivatives, a computational approach was implemented using Python. The function takes a signal and an order as input and returns the fractional derivative of the signal. It involves the following steps:

1) It initializes variables for the length of the signal (`n`) and an array representing time (`t`).
2) Finds local maxima indices in the signal using SciPy's `argrelextrema` function [53], [54].
3) Creates an interpolator using cubic interpolation between identified extrema.
4) Interpolates the signal at all time points using the created interpolator.
5) Calculates the fractional derivative using cumulative trapezoidal integration up to each time point.
6) Normalizes the calculated fractional derivative values using the gamma function.
7) Returns the resulting array containing the fractional derivative of the input signal.

In essence, the code numerically computes the fractional derivative, a useful operation for extracting nuanced features

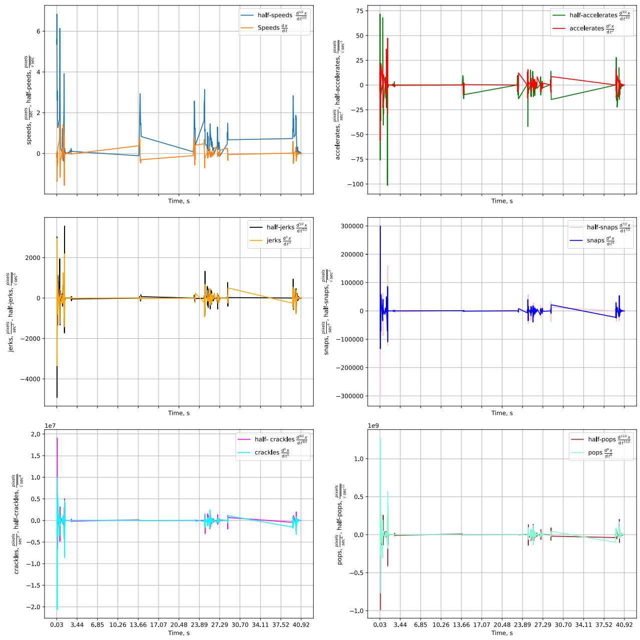


FIGURE 3. Temporal derivatives including fractional of computer mouse position: A comprehensive visualization for a single session.

from a signal, such as those relevant to the analysis of mouse movement patterns.

All motion patterns, accompanied by the specified fractional derivatives for a particular trajectory, are illustrated in Fig. 3. Each subfigure in the diagram portrays the distinctive characteristics of motion, capturing the nuances revealed by various fractional derivatives, including half-velocities, half-accelerations, half-jerks, half-snaps, half-crackles, and half-pops. The comprehensive depiction aims to provide a visual representation of the intricate features embedded within the trajectory dynamics.

Upon closer examination of the figure, intriguing nuances and distinctions between integer and fractional derivatives become apparent. For instance, on segments where the derivative is increasing, the corresponding half-derivative exhibits a decrease. Additionally, at points of inflection, the values of the half-derivative are significantly larger than those of the derivative. Moreover, as the order of the derivative increases, the maximum values of the derivative decrease, despite the heightened values at inflection points, demonstrating a unique interplay of features across various orders of derivatives.

In pivot points where the trajectory changes direction, the distinctions between integer and half-integer derivatives become particularly evident. Half-integer derivatives exhibit higher values in these turning points since they account for additional dynamics associated with changes in the movement direction. Simultaneously, integer derivatives, which fail to capture fine details in these points, may demonstrate less pronounced characteristics.

For instance, the half-derivative may emphasize intensive changes in velocity or acceleration at turning points, which could be crucial in analyzing motions in terms of their dynamism and maneuverability. Meanwhile, integer derivatives, focusing on average values, might overlook these aspects and show less pronounced peaks in these points. This indicates that the use of half-integer derivatives can enrich the motion analysis by capturing additional aspects related to turns in the trajectory.

C. PIPELINE

The experimental pipeline involved a comprehensive analysis of temporal coordinate data from user sessions. For each coordinate sequence $(x_i, \ y_i)$ with corresponding timestamps, numerical derivatives were calculated over time, including integer orders (velocity, acceleration, jerk, snap, crackle, pop) and fractional orders starting from 0.5 (half-velocity, half-acceleration, etc.).

For each user session, the average values of these derivatives were computed, generating 12 new meta-features in addition to standard ones (trajectory length, session duration, session clicker status, and the number of coordinates in the trajectory).

Subsequently, user trajectories were compared with their clustering, averaging metrics across all trajectory-related meta-features for each specific user. Results indicated that dimensionality reduction did not alter the 3D t-SNE distribution pattern but facilitated transitioning from a dataset of 15,000 trajectories to one of 2,146 users with characteristic metrics.

Next, an experiment was conducted to determine optimal clustering parameters using four algorithms: DBSCAN, Kmeans, GMM, Agglomerative, with variations in the number of clusters from 3 to 10. The optimal algorithms were found to be Kmeans, GMM, and Agglomerative with variations in clusters from 3 to 6.

The goal of the experiment was to assess the impact of new meta-features on user clustering characteristics. The sum of all unique non-repeating combinations of 12 elements ($n = 12$), taken for all possible meta-features k from 1 to 12, can be expressed as:

$$S = \sum_{k=1}^{12} \binom{12}{k}$$

Due to the unknown interplay of these meta-features, 4,095 unique combinations of 12 these features were explored, resulting in $4,095 \times 3 \times 4 = 49,140$ experiments. To identify the best pipeline. Models were compared using metrics such as Silhouette [55], [56], Davies Bouldin Index [57], [58], and Calinski Harabasz Index [59], [60].

IV. RESULTS

Heatmap of correlations among the averaged characteristics of time derivatives, including fractional derivatives, for our analyzed dataset is presented in Fig. 5. Notably, the least

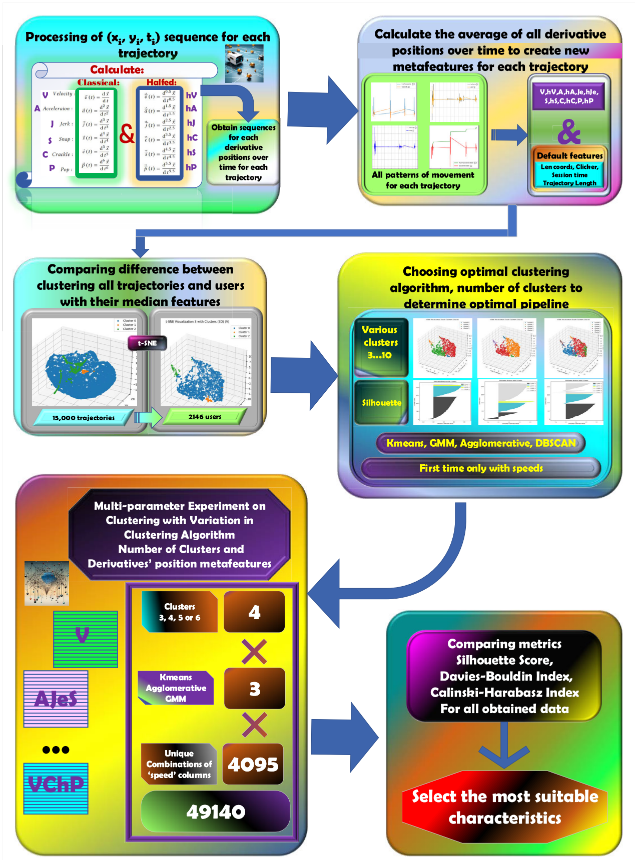


FIGURE 4. Experiment Pipeline Overview: A Sequential Journey Through Data Calculation, Processing, and Analysis.

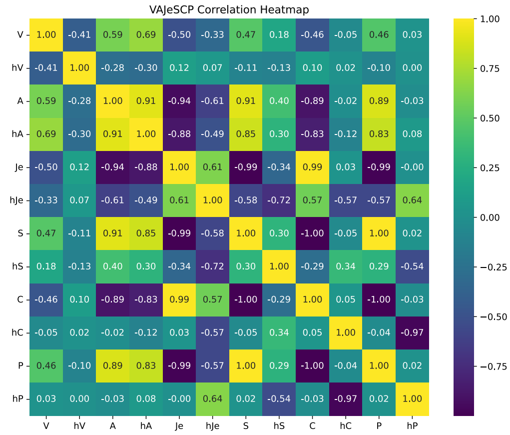


FIGURE 5. Heatmap depicting the average Temporal Derivatives meta-features across various sessions.

correlated features with all others are the characteristics of half-speed (hV), half-Crackle (hC), and half-Pop (hP). Conversely, the features that exhibit the highest correlations across the board are acceleration (A), half-acceleration (hA), and Jerk (Je). This intriguing pattern suggests a unique relationship between these motion descriptors, wherein the former set may capture distinct aspects of motion independent of others, while the latter set tends to co-vary more consistently. Possible explanations for such behavior could be rooted in the intrinsic nature of motion dynamics, where certain characteristics align closely, while others manifest greater independence. The observed correlations provide valuable insights into the interplay between different motion features, offering a foundation for more nuanced interpretations of trajectory dynamics.

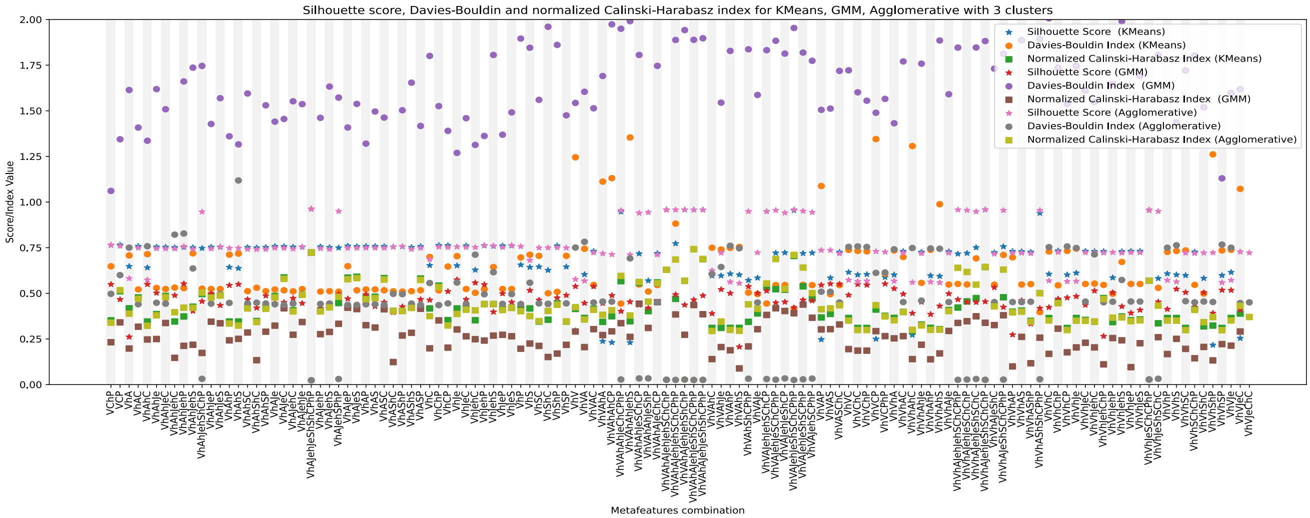
It is important to note that while these correlation patterns were observed within our specific dataset, their generalization to other datasets may vary. The characteristics of motion dynamics are inherently influenced by diverse factors, including the context of data collection, user demographics, and specific tasks involved. Therefore, caution should be exercised when extrapolating these findings to different datasets, as the underlying dynamics of human behavior and interaction with digital interfaces can significantly differ. Further research across diverse datasets is essential to ascertain the robustness and generalizability of these correlation patterns in various contexts.

In our study, we employed a comprehensive set of evaluation metrics, including Silhouette Score and Davies-Bouldin Index, to assess the quality of the obtained clusterings from KMeans, GMM, and Agglomerative algorithms. Silhouette Score, providing a measure of cohesion and separation within clusters, allowed us to quantify the appropriateness of the clustering solutions. Simultaneously, Davies-Bouldin Index, assessing the compactness and separation between clusters, offered valuable insights into the performance of each algorithm in capturing distinct and well-separated groupings. By leveraging these metrics, we gained a nuanced understanding of the clustering outcomes, enabling a rigorous comparison and selection of the most suitable algorithm for our specific dataset and clustering requirements.

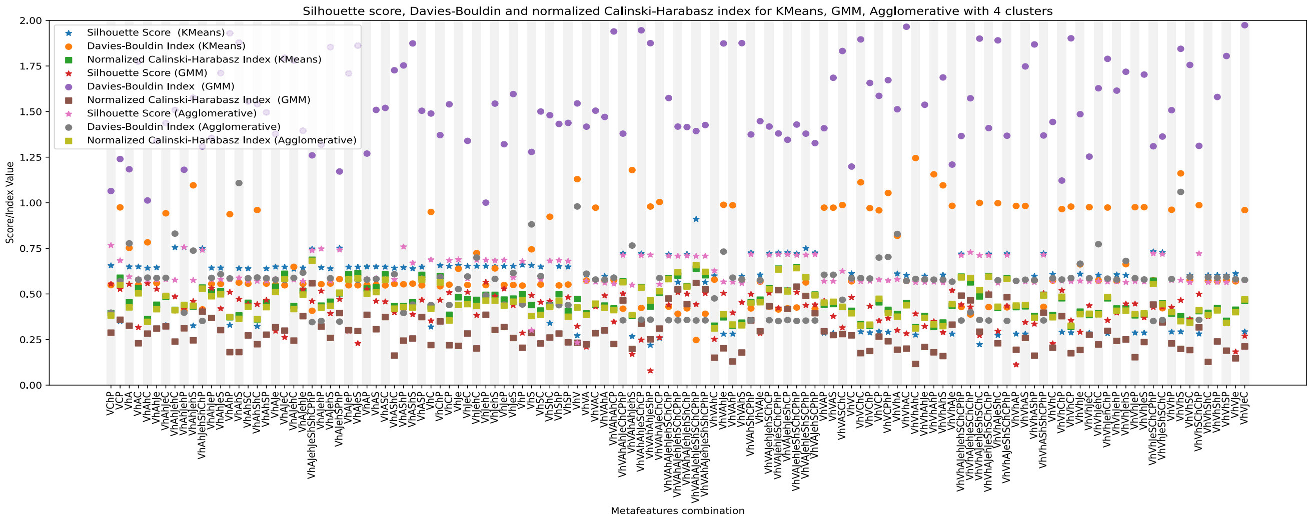
Comparative analysis of metrics of clustering algorithms for 3, 4 and 5 clusters are shown on Fig. 6 respectively for 125 randomly selected dataset with diffrent combinations of meta-features. including KMeans, GMM, and Agglomerative, focused on the evaluation metrics for three and four clusters, as these configurations reveal common trends. Notably, GMM exhibited inferior clustering performance with elevated Davies-Bouldin Index scores. Silhouette Scores demonstrated moderate consistency around 0.79 for KMeans and Agglomerative with three clusters, declining to 0.75 with four clusters and 0.7 with five clusters. This trend is more apparent with three clusters and diminishes with increasing clusters. The reliance on Silhouette Score as a similarity metric may not consistently yield optimal clustering, as high Silhouette Scores can result from grouping all points into one cluster and isolating outliers in another, which may not align with true cluster patterns.

To select optimal clustering models, the following approach was employed:

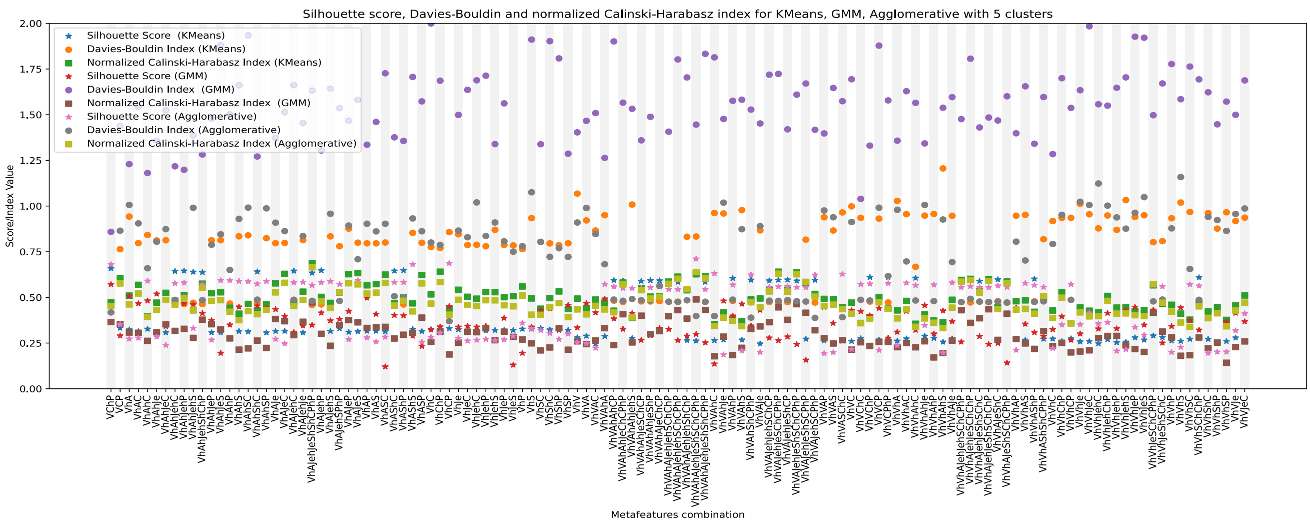
1) **Silhouette Score:** Models were filtered based on Silhouette Score, considering models with scores



a) 3 clusters



b) 4 clusters



b) 5 clusters

FIGURE 6. Comparative analysis of clustering algorithms KMeans, GMM and Agglomerative: evaluation metrics for different algorithms with diffrent number of clusters.

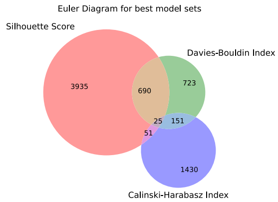


FIGURE 7. **Euler diagrams of number of best scores for obtained models.**

exceeding 80% of the maximum Silhouette Score across all models.

2) **Davies-Bouldin Index:** Models were filtered based on Davies-Bouldin Index, considering models with indices less than 165% of the minimum Davies-Bouldin Index across all models.
3) **Calinski-Harabasz Index:** Models were filtered based on Calinski-Harabasz Index, considering models with indices exceeding 75% of the maximum Calinski-Harabasz Index across all models.

Subsequently, an analysis of intersections among these models was conducted, forming three new sets: `res_12`, `res_13`, and `res_23`. Each of these sets represents models that simultaneously meet different combinations of criteria. `res_12` includes models that satisfy thresholds for both Silhouette Score and Davies-Bouldin Index, `res_12` comprises models that satisfy the specified thresholds for both Silhouette Score and Calinski-Harabasz Index, and `res_23` includes models that satisfy the criteria for Davies-Bouldin Index and Calinski-Harabasz Index simultaneously.

Fig. 7 illustrates Euler diagrams intersections of sets based on selected clustering metrics. The sizes of each region represent the number of models meeting specific criteria. The sets include models with high Silhouette Score (red area), low Davies-Bouldin Index (green area), and high Calinski-Harabasz Index (purple area). The intersections highlight models that simultaneously satisfy combinations of these criteria.

For the final evaluation of the selected models, a visual analysis was performed using 2D and 3D t-SNE maps. The distribution of users across different cluster counts was examined, and statistics related to meta-features for each of the selected models were analyzed. This approach aided in identifying optimal models that exhibit the best characteristics across various clustering quality metrics.

V. DISCUSSION

The stability of the 3D t-SNE [61] distribution pattern despite dimensionality reduction can be attributed to the preservation of essential geometric relationships among trajectories in lower-dimensional spaces. The reduction process maintains the relative distances and arrangements of trajectories, emphasizing the dominant structural features within the dataset. This allows for a more concise representation of the user trajectories while retaining the key characteristics that define their clustering. The transition from a larger dataset of individual trajectories to a more compact representation of user clusters is facilitated by this preservation of essential geometric relationships, enabling effective analysis of characteristic metrics for distinct user groups.

The process of selecting an appropriate clustering model based on metrics may not always lead to a clear interpretation of the obtained clusters. Specifically, interpreting clusters becomes more challenging as the number of classes increases. A lower number of classes often facilitates the interpretation of created meta-features for each cluster. However, it is crucial to consider the adaptability of clustering to correlated features, as similar features can significantly impact the clustering results.

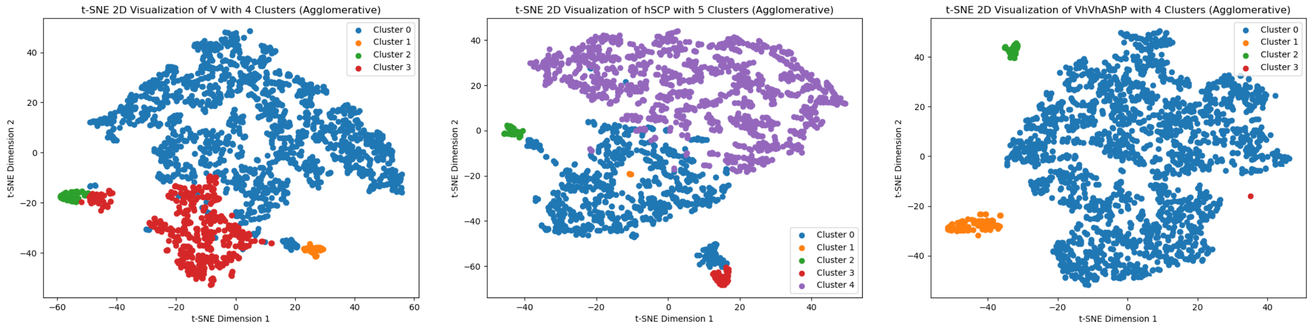
In the context of correlated features, it is essential to note that closely related features may influence the clustering outcome, leading to the formation of clusters that represent similar aspects of the data. As the number of correlated features increases, the risk of collapsing the entire dataset into a single cluster becomes more pronounced. Additionally, outliers may be highlighted as individual clusters, especially when clustering with six or seven meta-features.

Despite low silhouette and Davies-Bouldin Index metrics, there are instances where the clustering model demonstrates good interpretability. The visual examination of 2D and 3D [62], [63] cluster maps proves instrumental in identifying and understanding the distinct clusters. For example, outliers might appear as isolated points within the main cluster on a 2D map but could be situated far away from the main cluster on a 3D map. Such visualizations help uncover nuances that may not be captured by traditional clustering metrics, emphasizing the importance of incorporating visual inspection in the evaluation process.

Fig. 8 shows 2D t-SNE maps the distribution of clusters for 3 various clustering models. Each point on the map represents a users' trajectories, and the proximity of points indicates similarity in the feature space. The distinctive spatial arrangement reveals the clustering patterns produced by different models, providing valuable insights into the separation and cohesion of user trajectories based on the chosen meta-features and clustering algorithms.

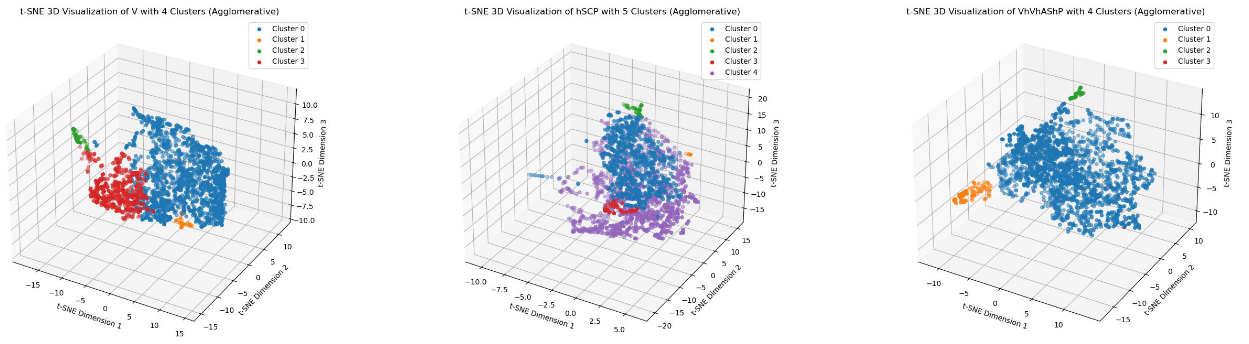
Fig. 9 is the 3D t-SNE (of the corresponding 2D maps) offer a three-dimensional perspective of the clustering results obtained from different models. Each point in the 3D space represents a user trajectory, and the spatial configuration reflects the model's ability to separate trajectories based on the chosen meta-features. The three-dimensional visualization enhances our understanding of the cluster distribution, providing a comprehensive view of the clustering patterns and relationships among users' trajectories.

Continuing with the analysis, when incorporating only `Velocity` (V) as an additional meta-feature, the agglomerative clustering model with 4 clusters identified distinct user types among 2,146 individuals. Specifically, it categorized 1,616 and 451 users as regular users, differing only in the average session duration–5 minutes and 4 hours, respectively.



a) b) c)

FIGURE 8. **2D t-SNE maps of users' trajectories for dataset with additional features: a)** `V` **b)** `hSCP` **c)** `VhVhAShP` **with 4, 5 and 4 clusters respectively.**



a) b) c)

FIGURE 9. **3D t-SNE maps of users' trajectories for dataset with additional features: a)** `V` **b)** `hSCP` **c)** `VhVhAShP` **with 4, 5 and 4 clusters respectively.**

TABLE 1. **Cluster evaluation metrics.**

Combination	Clusters	Type	Silhouette	Davies-Bouldin	Normalized Calinski-Harabasz
V	4	Agglomerative	0.76	0.53	0.48
hSCP	5	Agglomerative	0.78	0.39	0.41
VhVhAShP	4	Agglomerative	0.8	0.48	0.35

This distinction highlighted users who briefly accessed the system and those who spent a significant part of the working day within the system. Further categorization revealed 47 users exhibiting a high Clicker index and very short session times, on the order of fractions of a second. Remarkably, these users had an average session count of around 14, indicating frequent but extremely brief interactions. Additionally, the model identified 32 users with a significantly high session count, approximately 30 sessions per user. Interestingly, within this group, there was a small fraction of Clickers. This comprehensive analysis showcases how the inclusion of specific meta-features, such as velocity, refines the clustering outcomes and provides detailed insights into diverse user behavior patterns.

Expanding the analysis to include the combination of `half-Snap, Crackle, Pop` (`hSCP`), utilizing the Agglomerative model with 5 clusters, results in the following distribution of users across clusters: 1258, 810, 43, 32, 3. Remarkably, the same set of 32 users was identified in the Clicker category. The majority–1258 and 810 users–were characterized as 5-minute and 4-hour diligent users, respectively. Additionally, the 3 remaining users exhibited an intriguing pattern, featuring exceptionally long trajectories (approximately 6000 pixels, similar to regular 5-minute users) combined with extremely brief system interaction times (around 1 second) and notably high values of the `half-Snap` metric. This unique group showcases the ability of the model to identify outliers and uncover distinctive behavioral patterns within the user population. Moreover, it is noteworthy that the average number of sessions for users within this group is approximately 10. But clicker value is 0.

In the case of the `Velocity`, `half-Velocity`, `half-Accelerate`, `Snap`, `half-Pop`(`VhVhAShP`) combination with the Agglomerative model featuring 5 clusters, the distribution among user clusters reveals 2029 users in the normal category, 31 identified as clickers, and 84 representing a blend of clickers and regular users. Additionally, there is one user each characterized by short session times and long trajectories. This detailed breakdown exemplifies the ability of the clustering model to differentiate among user behaviors, shedding light on distinct usage patterns.

Index metrics for these models are shown in Tab. 1. When considering the balance of these indices, one can obtain the most optimal models.

VI. CONCLUSION

In conclusion, while clustering metrics provide valuable quantitative insights, the interpretability of clustering models depends on various factors, including the number of classes, adaptability to correlated features, and the effectiveness of visualizations in capturing the underlying structure of the data. A holistic approach, considering both quantitative metrics and visual explorations, enhances the understanding of complex clustering results. This becomes particularly crucial when extending the analysis to cluster users based on mouse trajectories using combinations of new meta-features, such as derivatives up to the 6th order and their corresponding fractional derivatives. The incorporation of these advanced meta-features not only deepens the analysis but also introduces intricate patterns into the clustering process. By synergizing quantitative assessments with visual representations, our approach strives to unravel the latent structures in user trajectories, providing a more nuanced interpretation of the clustering outcomes. This nuanced understanding, rooted in both metrics and visualizations, is pivotal for discerning meaningful user behavior patterns and optimizing the efficacy of trajectory-based clustering algorithms.

Future directions for this work could include exploring additional features or algorithms to further enhance the analysis of mouse trajectory data. For example, exploring the integration of machine learning techniques, such as optimizing hyperparameters of clustering or classification algorithms using genetic programming, could enhance the accuracy and effectiveness of analyzing mouse trajectory data. Additionally, expanding the scope of the study to include a broader range of applications beyond web maps, such as gaming interfaces or virtual reality environments, could offer valuable insights into human-computer interaction dynamics. Furthermore, integrating real-time processing capabilities into the analysis pipeline could enable the development of interactive systems for immediate feedback and decision-making based on mouse trajectory data. Finally, collaborating with experts in related fields, such as cognitive psychology or human-computer interaction, could provide interdisciplinary perspectives and lead to innovative advancements in understanding and utilizing mouse movement behavior.

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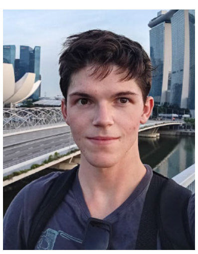

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