E3S Web of Conferences **351**, 01042 (2022) https://doi.org/10.1051/e3sconf/202235101042
ICIES'22

Clustering analysis of human navigation trajectories in a visuospatial memory locomotor task using K-Means and hierarchical agglomerative clustering

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Abstract. Throughout this study, we employed unsupervised machine learning clustering algorithms, namely K-Means [1] and hierarchical agglomerative clustering (HAC) [2], to explore human locomotion and wayfinding using a VR Magic Carpet (VMC) [3], a table test version known as the Corsi Block Tapping task (CBT) [4]. This variation was carried out in the context of a virtual reality experimental setup. The participants were required to memorize a sequence of target positions projected on the rug and walk to each target figuring in the displayed sequence. the participant's trajectory was collected and analyzed from a kinematic perspective. An earlier study [5] identified three different categories, but the classification remained ambiguous, implying that they include both kinds of individuals (normal and patients with cognitive spatial impairments). On this basis, we utilized K-Means and HAC to distinguish the navigation behavior of patients from normal individuals, emphasizing the most important discrepancies and then delving deeper to gain more insights.

1. Introduction:

Neuropsychological assessments (NPAs) are often used to identify cognitive impairments (CIs) [6]. Researchers from a variety of fields, including mathematics [7-10], robotics [11-14], neuropsychology [15], and computer science [16], are interested in researching visuospatial memory locomotion and NPAs associated with it to develop a stereotypical model of human navigational behavior.

Robotics engineers and academics identified that the development of human trajectory during goal-oriented locomotion is stereometric and kinematically prototypical [12,13]. Moreover, Mathematicians are mainly focusing on the geometrical element of human locomotor activity, considering the organization and the management, as well as the necessity to integrate various types of actions and perceptions [8].

Machine learning [16] and artificial intelligence [17] spurred the search for classifiers to recognize patterns in human navigation. As in this paper, we focus mainly on using K-Means [1] and (HAC) [2] to analyze the VR Magic Carpet TM [3,18] output and dig further into the many classes acquired via an early kinematic participant-based data analysis [5].

2. Materials and methods

2.1 Spatial memory locomotor neuropsychological assessment (SMLNP)

Numerous SMLNPs paradigms have been developed [18] and applied in a variety of studies, ranging from establishing the relationship between critical components of human navigation, such as spatial representation, goal-directed navigation, learning, and spatial performance enhancement [19] to determining what, how, and which part of the brain contributes to navigational information processing [20].

2.1.1 The Virtual Carpet ™

The walking Corsi test (WTC) [21] was created by following the identical instructions as the CBT but changing the table to a room (3m 2.5m) and the blocks to tiles (30cmx30cm), with the participant walking rather than tapping. Furthermore, the magic carpet replaced the task administrator's vocal instructions by flashing the tiles to display the sequence. VR was included in the WCT through the construction of a Blender environment, which concluded in the founding of the VMC in Unity3D, motivated by technological innovations and the demand to record the subject while passing the test.

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 https://doi.org/10.1051/e3sconf/202235101042

2.2 Experimental setup and data acquisition

The experimental setup includes two laptop computers, a multimedia projector and HTC Vive hardware The first computer is linked to a video projector which displays floor tiles One is connected to an HTC Vive headset The HTC Vive kit includes two SteamVR controllers as well as two SteamVR base stations for monitoring movement in the play area

After installing SteamVR software on a laptop linked to the HTC Vive the play area and a few calibrations were changed the experiment is then launched by starting the environment built by Unity. Using Euler angles, we were able to calculate the center of the VR detecting area and the rotation of a first controller attached to the head and a second controller connected to the waist. The 3-dimensional data were collected using the SteamVR tracking software and the OpenXR API, allowing the device to be quickly connected to Unity3D.

Additionally, Unity c scripts were developed to extract geographical data from Unity3D. The data was kept in text files called session data, which reveal the order in which the participant participated. We also recorded the tile coordinates as JSON files. The HTC Vive calibration's adjustments were mirrored in each file.

2.3 Experimental Data

Dr. Bernard Cohen's pilot test provided the experimental data, and the assessment was carried out in line with the Helsinki Declaration. The protocol was accepted by the Paris University ethics committee [20]. Each of the twenty-two individuals was assessed individually. The experiment resulted in no neurological or cognitive impairments. To eliminate a priori bias, all personal information, from population to pathologic features, was deleted from the study. Participants' anonymized data is collected. Details are also left out to improve data accessibility and to allow for additional in-depth analysis on the subject.

2.4 Visual replication

We created a Unity environment that graphically emulated participant action to recreate what transpired utilizing data collected during the various VR-Magic Carpet Sessions. This assisted us in learning how to isolate critical components for our inquiry from a kinematic standpoint. In this simulation, we represented the participant as two spheres, one blue representing head motion and the other red representing waist movement and rotation. Considering the use of the calibration JSON files, we additionally included the tiles as they were put throughout the clinical trial. We created animation by lighting the tile in red as the person passes by, and we plotted the head and waist trajectories. We also looked into updating the frames in Unity so that we could analyze the speed, rotation, and acceleration during the experiment. Aside from that, we considered two points of view, one orthogonal as indicated in Fig1 and the other as a first player viewpoint to be entirely placing the emphasis and studying the subject behavior from her or his point of view.

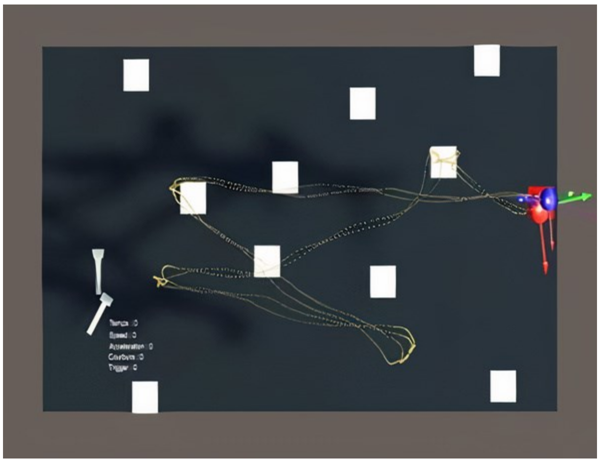

Fig. 1. visual replication of a session using Unity

2.5 Data Preprocessing

Utilizing "Pandas, NumPy" a Python data analysis and processing tool. We consolidated the data structure to prevent incompatibilities across file types. Additionally, a local target identification technique was developed to collect information about the time spent within the targets. the primary function of the algorithm is to ascertain if the participant has visited the goal.

Additionally, we added extra kinematic variables to aid in the study, which was conducted using considerable calculation.

As mentioned in the experimental data description, the session files were recorded at a sampling rate close to 1 kHz, which accounted for the great sensitivity of the different sensors. Therefore, we considered filtering and thresholding techniques, which made our dataset more consistent.

We aggregated our data using Microsoft SSIS and shifted the focus to participant-based analysis rather than session-based analysis. The data aggregation process produced a dataset including two primary columns for our analysis: the participant's average speed including the nullification and the decrease of speed when the participant visits a target and the participant's average time spent near recognized tiles (targets) across all sessions.

2.6 K-Means: Unsupervised Machine Learning

We find that our dataset lacks categorical data after completing the data preparation. As a result, using an unsupervised machine learning clustering method, such as Kmeans clustering, is a viable option that is simple to comprehend and apply, scalable for large data sets, and assures convergence. For the implementation, we used "Scikit-learn," a Python machine learning package.

2.6.1 The algorithm

As mentioned in [1]. "Let X = {xi}, i = 1,..., n represent the collection of n d-dimensional points to be clustered into a collection of K clusters. C = {c_k, k = 1, K} K-means algorithm [14] discovers a partition that minimizes the squared error between a cluster's empirical mean and its points. Let μ_k be the mean of cluster c_k. The squared error between μ_k and the points in cluster c_k is defined as

$$J(ck) = \sum xi \in ck \parallel xi - \mu k \parallel^2 \quad (1)$$

K-means purpose is to minimize the total of the squared errors across all K clusters."

$$J(C) = \sum_{k=1}^{K} \sum xi \in ck \parallel xi - \mu k \parallel^2 \quad (2)$$

The following are the major steps of the K-means algorithm:

1. Given an initial partition of K clusters, repeat the second and third stages until the clusters settle.

2. Create a new partition by allocating each point to the cluster that has the shortest distance between it and the cluster center.

3. Find new cluster centers.

2.6.2 Parameters of K-means

For the K-means method, the user must supply three parameters: the number of clusters K, cluster initiation, and distance metric.

2.6.3 Identifying the number of clusters K using HAC

HAC, another unsupervised machine learning method was used. While K-Means is utilized for clustering, we found that the HCA can determine the number of clusters without being specified in the parameters [15]. The obvious issue is why HAC is not utilized for clustering; it is employed as a clustering technique, but solely for comparison reasons at this early stage of the research. The main problem is that the performance and type of data (which may come from a huge number of clinical trials performed in different places) prevent us from categorizing it as non-spherical [22].

3. Results:

Using the K Means (figure 2) and HAC (figure 3) analysis, this study identified four distinct clusters. Despite being prepared to categorize people into three groups based on earlier data analysis [4] we were unable to separate those who did not fit into any of the categories. We stress that the created clusters are based on significant data that resulted in aggregate variables; in other words, we lay a larger weight on the participant's average speed and average time spent near identified tile targets throughout all sessions. Furthermore, the two measures employed may be regarded as valid predictors of differences in human navigational behavior between control and patient groups. These results have attracted the attention of neuroscientists, who think they will aid in the development of profiles based on clustering research, particularly when additional factors are included.

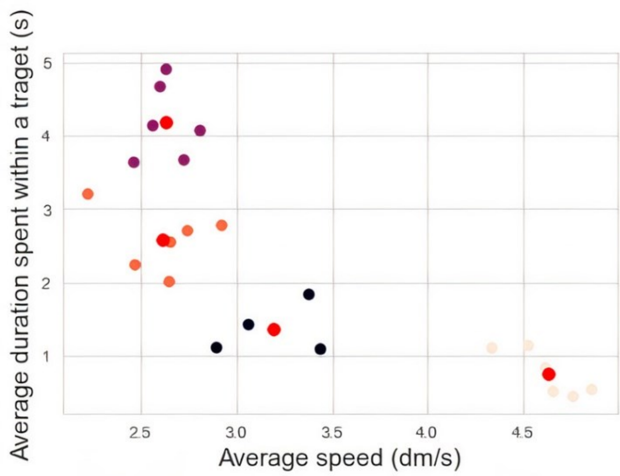

Fig. 2. K-Means clusters, indicating the difference between different groups of participants

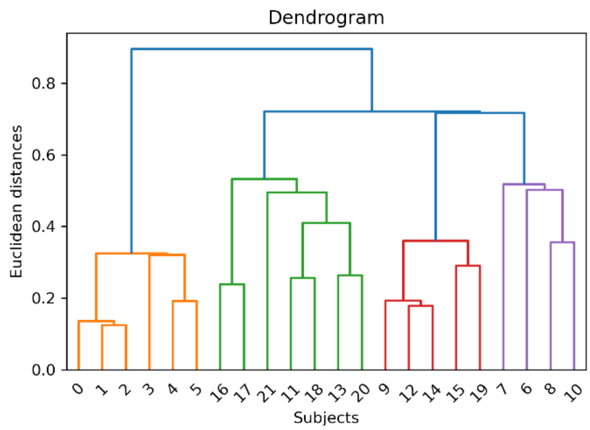

Fig. 3. HAC dendrogram, indicating the difference between different groups of participants

4. Discussion:

While in earlier research [4], we were able to create groups and characterize in broad strokes the various behaviors of individuals who completed the VR Magic Carpet using a kinematic method. The goal of this paper was to verify the prior analytical findings as well as to dig further into the unclear classes that included participants from both groups.

This is a broad method that will supplement other behavioral data analyses. However, providing criteria and describing classifiers that define human navigation behavior may be tremendously beneficial, especially as the sequence lengthens or incorporates mental rotations, etc. This instrument was not included in any of the previous research on these assessments. It is also worth considering it for young children, and the elderly since it will be insightful in assessing learning or functional recovery during rehabilitation.

5. Conclusion:

The current study is part of an ongoing effort to describe human behavior in a complex visuospatial assessment intended to assess memory and navigation skills. The goal is to include a new analytics method into the decoding of neuropsychological tests, allowing neuropsychologists to use machine learning applications. Furthermore, the primary aim is to provide a methodological approach that can be used to model and conceive human navigation behavior utilizing diverse machine learning and artificial intelligence methods and algorithms.

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