Static Data Visualization by ”Vibration and IMU Sensing Human Activity Dataset” example

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***Abstract*—Human daily activities are multifaceted, reflecting the dynamic nature of our lives in diverse living environments. This study delves into the ”Vibration and IMU Sensing Human Activity Dataset,” a rich source of fine-grained human daily activity data. The dataset integrates infrastructure vibration sensors and an on-wrist Inertial Measurement Unit (IMU) sensor, providing a holistic perspective on human behavior in real-world settings. The primary objective is to leverage advanced data visualization techniques to uncover hidden patterns within the dataset, shedding light on the intricacies of human activities and contributing to a deeper understanding of behavior and interactions in living spaces.**

***Index Terms*—Vibration sensors, IMU sensor, Fine-grained activity data, Real-world settings, Data visualization techniques,**

I. Introduction

Human daily activities are intricate and varied, reflecting the dynamic nature of our lives within diverse living environments. Understanding these activities at a detailed level can provide valuable insights into behavioral patterns and trends. In this context, our study delves into a rich dataset, the ”Vibration and IMU Sensing Human Activity Dataset” comprising fine-grained human daily activity data. This dataset captures the nuances of daily life through infrastructure vibration sensors and an on-wrist Inertial Measurement Unit (IMU) sensor. The integration of these sensors offers a comprehensive perspective on human behavior in real-world settings. The primary objective of our project is to leverage advanced data visualization techniques to uncover hidden patterns within this dataset, shedding light on the intricacies of human activities. By exploring this unique dataset, we aim to contribute to a deeper understanding of human behavior and interactions within their living spaces [1].

II. Materials & Methods

A. Data Collection

The ”Vibration and IMU Sensing Human Activity Dataset” presents a detailed exploration of human daily activities, encompassing data collected from six individuals across two domestic homes. Twelve sub-datasets are meticulously crafted, denoted by the combination of ”p” for person and ”l” for location. The dataset comprises eleven columns, with ten of them representing sensor readings. Notably, vibration sensors are strategically placed on the Living Area floor and table, as well as the Studying Area floor and desk. Additionally, three-axis accelerometer and gyroscope readings from the on-wrist IMU sensor provide further insights into movement and orientation. It is imperative to highlight that all signals are zero-meaned, ensuring consistency in the dataset. The vibration sensors operate at an approximate sampling rate of 6500Hz, while the IMU sensors maintain an original sampling rate of around 235Hz. Version 2 of the dataset introduces extracted features from both IMU and vibration data, enhancing its richness and analytical potential. These features, detailed in the associated literature, enable a more profound exploration of human activities and their underlying dynamics.

Activity	Activity type	Activity index
Working	Keyboard typing	1
	Using mouse	2
	Handwriting	3
Cooking	Cutting vegetables	4
	Stir-frying vegetables	5
Vacuuming	Using vacuum to vacuum floor	8
Cleaning	Wiping the table	6
	Sweeping floor	7
	Open and close drawer	9

TABLE I
Activities and corresponding indices.

B. Methods

Our analytical approach included a precise series of operations, performed using the Python programming language and facilitated by the **pandas**, **numpy**, **matplotlib.pyplot**, and **seaborn** libraries. The ”Vibration and IMU Sensing Human Activity Dataset” consisting of distinct activities labeled for cleaning, cooking, vacuuming, and working, underwent a detailed exploration to unveil underlying patterns and trends. Our analytical approach involved several key phases, each characterized by distinct operations and methodologies.

1) Data Preprocessing: To ensure uniformity and facilitate meaningful comparisons, each activity dataset underwent a comprehensive preprocessing phase. The dataset was structured into a consistent format using the predefined column labels (shown in the table II-B1), including categories for location-specific vibration sensor readings and IMU signals from accelerometers and gyroscopes. The signals were zero-meaned, aligning with the dataset specifications.

2) Temporal Alignment and Time Series Conversion: Given the variation in sampling rates between vibration sensors and IMU signals, a critical step involved aligning these signals in time. The IMU signal, originally sampled at approximately 235Hz, was up-sampled to 6500Hz and time-aligned with the vibration signal. Further, to enhance temporal resolution and simplify meaningful time-based analyses, a time series conversion was applied, yielding time-stamped data indexed at intervals corresponding to the up-sampled rate.

3) Visualization Techniques: A set of powerful visualization techniques was employed to gain insights into the temporal dynamics of human activities. Time series plots were generated for key locations and activities, showcasing the variations in sensor readings over time. Each plot provided a detailed view of the vibrations in specific areas, contributing to a nuanced understanding of activity patterns.

4) Descriptive Statistics and Diversity of Activities: Descriptive statistics, such as mean, standard deviation, and skewness, were meticulously computed to capture key characteristics of sensor readings within the "Vibration and IMU Sensing Human Activity Dataset." Given that the dataset is zero-meaned, the mean does not provide significant discriminatory information. Therefore, our focus was primarily on the standard deviation, which highlights the spread or variability of the data. This choice aligns with the nature of zero-meaned data, where the mean is intentionally centered around zero, rendering it less informative for characterizing central tendencies. To gain a more comprehensive understanding of the dataset's diversity, a series of subplots dedicated to specific location and activity combinations were visualized. This visual exploration provided nuanced insights into the variability of sensor readings across diverse activities and living environments.

5) Exploration of Non-Linear Sensor Data: It's noteworthy that our sensor data exhibit non-linear characteristics. Consequently, traditional correlation coefficients and heatmaps, which assume linearity, may not fully capture the intricate relationships present in the dataset. To address this, our analysis focused specifically on the linear components of the data, namely the "Accelerometer X," "Accelerometer Y," "Accelerometer Z," "Gyroscope X," "Gyroscope Y," and "Gyroscope Z" columns. The utilization of scatter plots and heatmaps in this context aimed at uncovering linear correlations and intensity patterns between these features. This targeted approach was chosen to align with the inherent non-linearity of the broader sensor dataset, ensuring that the exploration of relationships was meaningful and tailored to the nature of the available data.

III. Results

The culmination of our rigorous analytical journey unfolds in the results section, where we unveil the intricate tapestry of human activities embedded in the "Vibration and IMU Sensing Human Activity Dataset." Through a multifaceted lens, we leverage a repertoire of visualization techniques and statistical analyses to shed light on the temporal dynamics, spatial correlations, and variability within the dataset. This comprehensive exploration encompasses time-series plots that trace the ebb and flow of sensor readings over time, heatmaps that illuminate spatial correlations, 3D scatterplots that offer a multi-dimensional perspective on relationships, and a tabulated summary of standard deviation values capturing the variability across distinct activities. Each facet of our results aims to provide a detailed and nuanced portrayal of the diverse human activities captured by the sensors, offering insights that transcend the boundaries of conventional analyses. The following sections delve into the specifics of each visualization, unraveling the rich narrative woven by the interplay of sensors and human behavior in varying living environments.

A. Time-series visualization

In the domain of temporal exploration, our analysis harnesses the nuanced granularity inherent in time series plots, revealing an intricate tapestry of human activities intricately integrated into the "Vibration and IMU Sensing Human Activity Dataset". Each plot, a carefully crafted visual narrative, offers a dynamic portrayal of sensor readings evolving over time. The depth of this exploration is magnified through a structured arrangement of subplots, strategically organized to provide multifaceted insights.

In each row of subplots, we delve into distinct areas marked by "Activity label", "Category label", "Living Area floor", "Living Area table", "Studying Area floor", and "Studying Area desk". The richness of this arrangement allows for a comparative analysis, explaining variations across diverse locations. Simultaneously, each column of subplots corresponds to a specific area, capturing the essence of sensor responses within a singular spatial context across different activities.

Crucially, the significance of each individual plot is underscored by its dedication to a specific activity type. For cooking activities, the plots unravel the sensor dynamics during "Cutting vegetables" and "Stir-frying vegetables." Cleaning activities manifest through the lens of "Wiping the table", "Sweeping floor", and "Open and close drawer". The vacuuming domain is encapsulated in the singular activity "Using vacuum to vacuum floor", while the working activities are dissected into the keystrokes of "Keyboard typing", the intricacies of "Using mouse", and the artistry of "Handwriting". Additionally, a dedicated plot captures the essence of "None Activity" (with Activity index = 10), providing a baseline for periods devoid of specific predefined activities. All of those information are captured also in the table II-B1.

This systematic arrangement and categorization, encompassing both spatial and activity-centric perspectives, illustrate the intricacies of human behavior within diverse living environments. The interpretive depth of these time series plots is further enhanced by their alignment with the categorical legends, elucidating the intricate dance between activities, locations, and sensor responses.

The time-series plots dedicated to working activity types (figure 1) provide a detailed canvas for unraveling the sensor dynamics inherent in activities such as "Keyboard typing,"

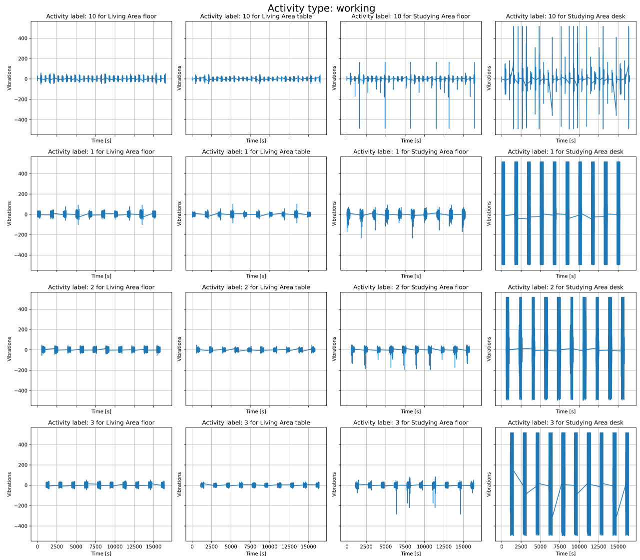

Fig. 1. Time-series plots for working activity types.

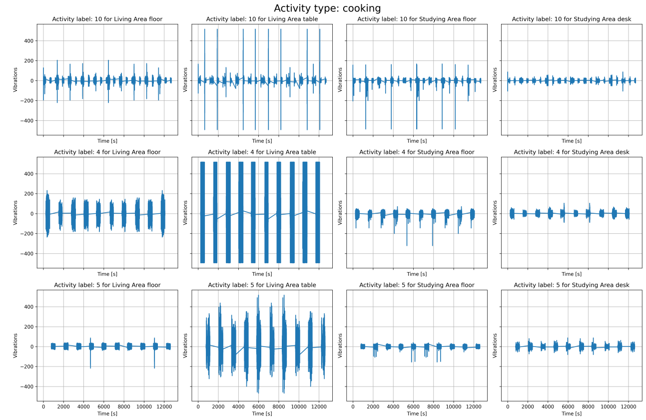

Fig. 2. Time-series plots for cooking activity types.

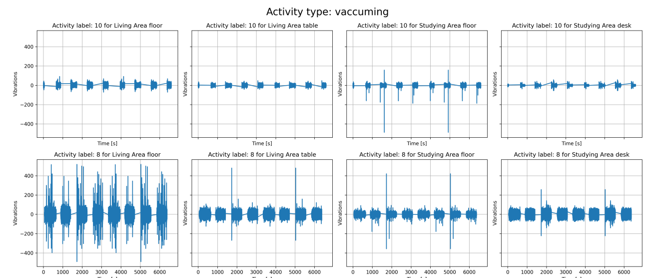

Fig. 3. Time-series plots for vacuuming activity type.

"Using mouse," and "Handwriting." Focused specifically on the Studying Area desk, these plots spotlight notable patterns and deviations in vibration readings, presenting a nuanced view of human behaviors within the context of work-related activities. Intriguingly, the plots reveal consistently high deviations in vibrations, particularly pronounced during activities conducted at the Studying Area desk. This heightened amplitude, observed across all working activity types, suggests a robust and regular pattern of sensor responses. However, a particularly perplexing observation emerges during periods labeled as "Non Activity." Contrary to expectations, the Studying Area desk exhibits elevated vibrations, prompting inquiries into the nature of these occurrences. The juxtaposition of Non-Activity and elevated vibrations raises the possibility of environmental noise or potentially unlabeled activities occurring during the examination period. Further investigation into the Studying Area floor reveals subtle deviations in vibration readings. These minor variations could be indicative of resonance effects, wherein vibrations from the Studying Area desk propagate to the floor. This resonant behavior, while more subdued than the pronounced deviations in the desk, introduces an additional layer of complexity to the sensor readings within the Studying Area.

Examining the time-series plots for cooking activities (presented in figure 2), particularly "Cutting vegetables" and "Stir-frying vegetables", reveals distinct vibrational dynamics. Notably, during Non-Activity periods, both high and subdued vibrations are observed, warranting exploration into potential surrounding influences or unaccounted-for activities. For "Cutting vegetables", the Living Area table exhibits consistently high vibrations, suggesting a strong association with this culinary task. In contrast, the Living Area floor shows smaller vibrations, likely resonating from the table's activity. During "Stir-frying vegetables", the Living Area table displays fluctuating vibrations, distinct from the constant amplitude during cutting. Minimal deviations are observed in the Living Area floor, highlighting the differential impact of stir-frying on sensor responses in different locations. Surprisingly, deviations in Non-Activity periods are evident across all locations, even when the culinary activities occur outside the Studying Area. This prompts consideration of potential environmental factors or unlabeled activities influencing sensor readings in diverse living spaces.

The exploration of time-series plots for the "Using vacuum to vacuum floor" activity unveils distinctive vibrational patterns associated with vacuuming (figure 3). Notably, irregular fluctuations are observed in the Living Area floor, suggesting dynamic sensor responses during the vacuuming process. It's essential to note that while singular fluctuations are discernible in all other locations, these deviations are relatively small. Consequently, drawing definitive conclusions from these singular fluctuations requires cautious consideration of their magnitude and potential significance.

Exploring the time-series plots for cleaning activities - figure 4 - including "Open and close drawer", "Sweeping floor", and "Wiping the table", reveals distinct vibrational dynamics associated with each task. For "Open and close drawer", the Living Area table exhibits high and constant vibrations, emphasizing a strong association with this cleaning activity. In the Living Area floor, medium-level vibrations, though not as constant, are noticeable. This suggests differential sensor responses to drawer activity in distinct locations. In contrast,

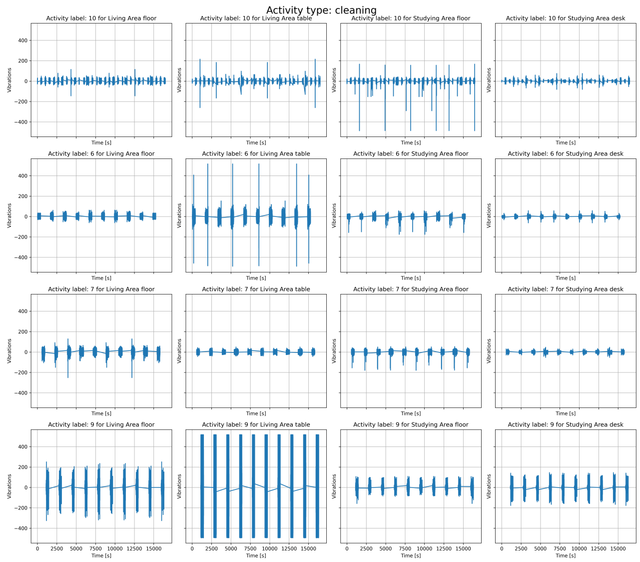

Fig. 4. Time-series plots for cleaning activity types.

Living Area floor	Living Area table	Studying Area floor	Studying Area desk	Activity label
9.265654	7.510727	10.062416	**292.007385**	keyboard_typing
8.020540	6.125157	7.252144	**83.531624**	using_mouse
7.848457	5.807913	7.225295	**164.831529**	handwriting
18.049720	**172.982615**	8.203118	8.942607	cutting_vegetables
8.581456	**45.836577**	6.524534	7.016378	stir_frying
9.490547	19.590079	8.402424	5.337126	wiping_table
10.438754	7.346718	7.978726	4.939710	sweeping_floor
30.234854	17.476399	10.707846	18.659598	vacuuming
19.552274	**259.097459**	10.513025	14.945652	open_close_drawer

TABLE II
STANDARD DEVIATION FOR VIBRATION IN VARIOUS AREAS.

”Sweeping floor” manifests as very small vibrations in each area, emphasizing the subtlety of sensor responses during this particular cleaning task. For ”Wiping the table”, a single, high deviation is observed in the Living Area table, while other locations exhibit very small vibrations. This distinct pattern implies unique sensor dynamics associated with table-wiping, potentially influenced by surface characteristics or cleaning techniques. Surprisingly - as before - during Non-Activity periods, there is a singular high deviation observed in the Living Area table. This unanticipated observation raises questions about potential environmental noise or unlabeled activities during periods of presumed inactivity.

B. Standard Deviation Analysis

W decided to delve into the descriptive statistics and standard deviation analysis of the ”Vibration and IMU Sensing Human Activity Dataset”. The tables presents standard deviation values for various sensor readings across different living areas (table II) and activities (table III). Notably, the highest standard deviation (std) for keyboard typing (292.01) is observed in the Studying Area desk, emphasizing its significance in detecting typing-related vibrations. Similar trends are observed for using mouse (83.53) and handwriting (164.83), indicating the potential of vibrational analysis in discerning specific tasks based on location. Cooking activities, such as cutting vegetables and stir frying, exhibit elevated std values, suggesting a pronounced impact on the surrounding environment. Vacuuming, while displaying a noticeable std, falls short of the intensity observed in cooking-related tasks. Cleaning activities, however, present mixed results, with open close drawer showing substantial vibrations, while wiping table and sweeping floor provide inconclusive evidence.

Accelerometer X	Accelerometer Y	Accelerometer Z	Gyroscope X	Gyroscope Y	Gyroscope Z	Activity label
0.044054	0.084313	0.087655	19.935021	7.985573	6.315592	keyboard_typing
0.111166	0.115628	0.063846	13.833263	8.426346	35.234981	using_mouse
0.059687	0.143208	0.089650	28.648616	8.649801	7.984709	handwriting
0.229901	0.220285	0.406800	23.222063	21.297361	10.473101	cutting_vegetables
0.205108	0.329783	0.261723	52.352010	34.829597	24.133552	stir_frying
0.351843	0.860951	0.301248	**91.520756**	16.878301	**100.523353**	wiping_table
0.149029	0.202208	0.229737	21.859935	32.087592	23.784563	sweeping_floor
0.086709	0.141699	0.157646	16.871502	18.376826	19.023220	vacuuming
0.088967	0.159636	0.121683	32.685212	9.766497	16.830539	open_close_drawer

TABLE III
STANDARD DEVIATION FOR ACCELEROMETER AND GYROSCOPE DATA.

For the activity of wiping table, the accelerometer and gyroscope readings suggest a distinctive vibrational pattern associated with the act of wiping a table. The elevated accelerometer readings, particularly in the X and Z axes, imply dynamic movements, while the gyroscope values indicate rotational motion, potentially corresponding to the wiping motion. In examining additional activities, sweeping floor (23.78) reveals notable vibrations, although their specific implications remain unclear. Vacuuming (19.02) exhibits discernible vibrations, shedding light on the characteristic movements associated with this activity. The open close drawer task (16.83) demonstrates significant vibrations, aligning with the expected physical motions involved in opening and closing drawers. It is noteworthy that certain activities, such as working, may lack distinctive vibrations based on the provided values, necessitating further analysis to elucidate their significance in the context of specific tasks.

C. 3D movement scatter plots

3D movement was picked up using a gyroscope and an accelerometer. In this analysis, focus was put on activities connected the most with specific observed patterns.

In figure 5 presented are gyroscope sensor scatter plots for cleaning activities, specifically corresponding to four distinct tasks: None Activity (Label 10), Wiping Table (Label 6), Sweeping the Floor (Label 7), and Opening/Closing Drawers (Label 9). The scatter plot for None Activity serves as a baseline, revealing dispersed points indicative of inactivity or environmental noise. Conversely, the Wiping Table and Sweeping the Floor scatter plots exhibit scattered patterns, highlighting the dynamic and varied hand movements associated with these activities. Notably, the dispersion in the Wiping Table plot underscores its energetic and expansive gestures, while the Sweeping the Floor plot emphasizes broad hand movements. In contrast, the scatter plot for Opening/Closing Drawers displays a tighter cluster of points, indicative of controlled and precise hand movements associated with this activity. The observed variations in dispersion offer a comprehensive visualization of the distinct hand movement patterns associated with each activity, providing valuable insights into the physical dynamics of daily tasks.

The accelerometer data focus was on working activities, as specific patterns were observed there. The four subplots

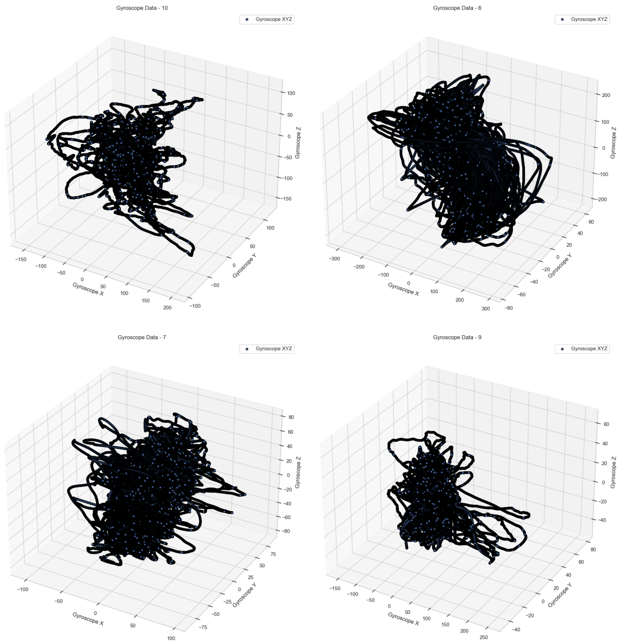

Fig. 5. 3D scatter plot of gyroscope readings during cleaning.

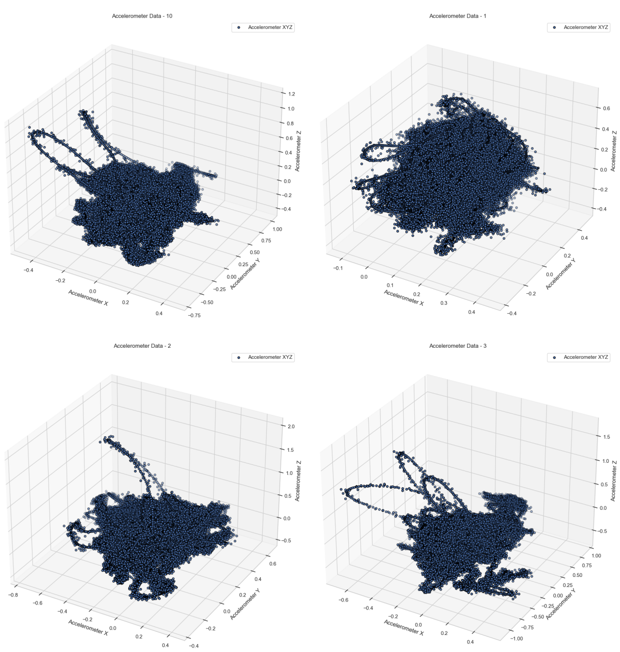

Fig. 6. 3D scatter plot of accelerometer readings during working activities.

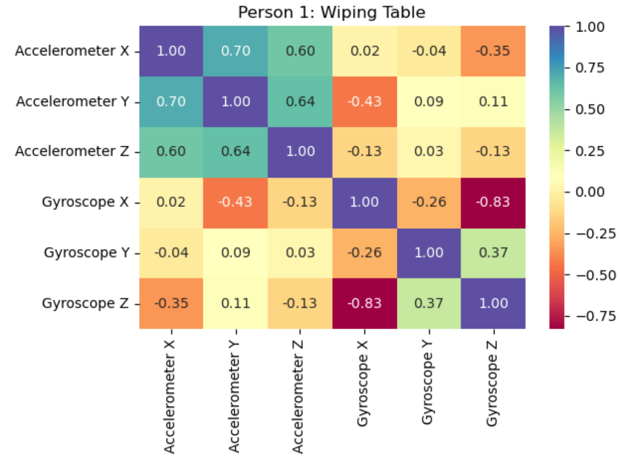

Fig. 7. Correlation heatmap for accelerometer and gyroscope axis data (Wiping Table).

in figure 6 correspond to specific activities connected with working — None Activity (Label 10), Keyboard Typing (Label 1), Using Mouse (Label 2), and Handwriting (Label 3). The scatter plots illustrate the inherent characteristics of hand movements during each activity. The "None Activity" subplot is depicting minimal hand movement across all axes, as it has been said before, may be noise or an unknown activity, not described by any label. In contrast, the Keyboard Typing subplot manifests a dispersed distribution, indicative of varied hand gestures occurring in all directions. Transitioning to Using Mouse, the plot reveals a concentration of movement primarily within two axes, suggestive of the stable, sliding hand motion associated with mouse usage. Similarly, the Handwriting subplot echoes this pattern, emphasizing predominant movement in two axes while occasionally exhibiting shifts in the third axis, aligning with the lifting of the hand during handwriting. This observation contributes valuable insights into the nuanced dynamics of hand movements during distinct activities, as discerned through accelerometer data.

D. Correlation Heatmaps

Through the utilization of heatmaps, we aim to visually capture the intensity patterns and correlations across these sensor dimensions. Each cell in the matrix indicates the Pearson correlation coefficient between pairs of variables, which include three axes (X, Y, Z) of an accelerometer and a gyroscope.

The heatmap shown in the figure 7 represents a correlation matrix for sensor data captured from a person performing the activity of wiping a table. We may observe that there is a strong positive correlation between the X and Y axes of the accelerometer (0.70), suggesting that these axes' movements are linked during the wiping activity. The accelerometer's Z-axis also shows moderate positive correlation with the X (0.60) and Y (0.64) axes, indicating that vertical motion is somewhat associated with horizontal movements during wiping. Notably, there is a strong negative correlation between

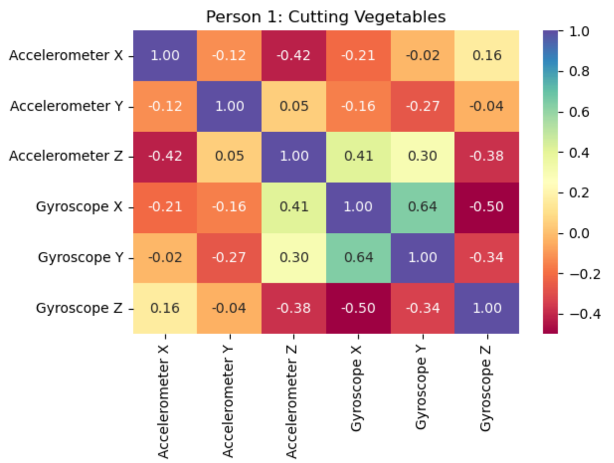

Fig. 8. Correlation heatmap for accelerometer and gyroscope axis data (Cutting Vegetables).

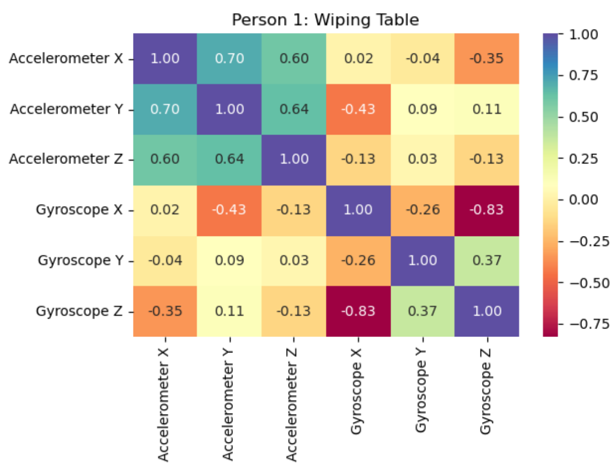

Fig. 9. Correlation heatmap for accelerometer and gyroscope axis data (Vacuuming).

the gyroscope's Y and Z axes (-0.83), implying an inverse relationship between rotational movements around these axes. By analyzing heatmap presented in figure 8, we may notice some strong positive correlation - the strongest positive correlation is observed between the gyroscope measurements on the X and Y axes (0.64), suggesting that these two motions are related and tend to increase or decrease together during the activity of cutting vegetables. However, there is also a moderate negative correlation between the accelerometer's Z-axis and the gyroscope's Z-axis (-0.38), indicating that as the acceleration in the Z-axis increases, the rotational motion around the Z-axis tends to decrease, and vice versa. In figure 9 there is no significant correlation between the accelerometer and gyroscope readings along the same axes, as indicated by the near-zero correlation coefficients in those cells (-0.04 for X, -0.03 for Y, and -0.14 for Z). The strongest negative correlation is between the accelerometer's Y and Z measurements (-0.44), suggesting a possible inverse linear relationship during the activity of vacuuming. The gyroscope's X and Y readings show a notable negative correlation (-0.50), which might be indicative of the dynamics of rotational motion captured during the vacuuming activity. Positive correlations are observed within the accelerometer readings (X-Z: 0.21) and gyroscope readings (Y-Z: 0.62), which may highlight inherent relationships in the movement patterns.

In all of the heatmaps, we can observe strong correlations among the Gyroscope measurements. Different activities exhibit distinct correlations between the gyroscope axes, likely attributable to variations in hand positions and usage demands during these activities. The heatmaps lead us to the conclusion that, generally, when we rotate our hands along one axis, we also tend to rotate them along the other axes. This shouldn't be surprising, as humans, when engaged in activities requiring hand movements, naturally rotate their hands in all three directions. It would be unnatural and uncomfortable for a person to rotate their hands along only one axis at a time while performing an activity.

IV. Discussion

Our exploration of the "Vibration and IMU Sensing Human Activity Dataset" through advanced data visualization and analysis techniques has provided valuable insights into the intricacies of human daily activities. This study contributes to the growing body of research aimed at understanding human behavior in real-world settings, with potential applications in fields such as healthcare, smart environments, and human-computer interaction. Future work may involve further refinement of analytical techniques, exploration of additional features, and the development of predictive models based on the dataset.

References

[1] Z. Hu, Y. Zhang, and S. Pan, "Vibration and IMU Sensing Human Activity Dataset" Zenodo, May 04, 2022. doi: 10.5281/zenodo.7058383.