

Defining The Pattern of the Thai Osteoarthritis Movement Data Model

Sira Saklertwilai¹, Wisan Tangwongcharoen²

¹Master student, School of computer science, Faculty of science, King Mongkut's Institute of Technology Ladkrabang, Bangkok, Thailand. E-mail: 60605087@kmitl.ac.th

²Assistant Professor School of computer science, Faculty of science, King Mongkut's Institute of Technology Ladkrabang, Bangkok, Thailand. E-mail: wisan.ta@kmitl.ac.th

Abstracts: This study proposed an algorithm to identify the patterns of Thai osteoarthritis, a condition that has seen an increase in prevalence in recent years, significantly affecting patients' quality of life and mobility. We aimed to define the data patterns for analysis. For data collection, we employed a Razor-IMU sensor and a WIFI transmitter, allowing testers to independently perform full-range knee motions. Data collection was categorized into two groups: healthy and unhealthy. Our goal was to categorize the data and establish criteria for pattern classification. Once the patterns and criteria were established, our objective was to validate movement models for both normal individuals and osteoarthritis patients. To achieve this, we conducted statistical hypothesis testing to verify the accuracy of the data. This testing comprised three main steps: first, evaluating the accuracy of data collection and data cleaning. Second, assessing the precision of converting data from linear to angular format, including degree coordinates selection. The last, Evaluating the accuracy of data sorting and grouping using Louvain clustering. The researcher thoroughly scrutinized each step to confirm the results. Each step demonstrated an accuracy test As Thailand transitions into an aging society, the prevalence of osteoarthritis is increasing due to the natural deterioration of the body. This deterioration can be decelerated by avoiding risky behaviors. Osteoarthritis significantly impacts patients' physical and mental well-being, making it a critical health concern. The objective of this research is to develop movement prototypes for both normal individuals and osteoarthritis patients by leveraging computer knowledge. This includes data collection with motion sensor devices, enhancing data quality using data mining techniques such as data cleaning and data transformation into suitable formats, and grouping of data. Additionally, the study seeks to validate the accuracy of the algorithm using statistical hypothesis testing methods and graph pattern detection. Based on the experimental results, an accuracy rate of 97% was achieved, demonstrating a high level of reliability. This prototype can be applied in treatment analysis, monitoring treatment outcomes, and even injury prevention. Furthermore, the dataset can serve as a model for the Thai population and can be expanded to accommodate larger datasets.

Keywords: Hypothesis Testing, T-Test, Onetail Testing, Pattern Searching, Osteoarthritis, Data Model.

1 INTRODUCTION

The general population data of Thailand in 2022[1]-[2] revealed that a population survey found the percentage of the elderly population to be approximately 26.51% out of a total population of 66.09 million people in Thailand. This means that there are approximately 18 million elderly people in the total population. The elderly group will experience significant physical and health changes, affecting the cardiovascular system, nervous system, and bone and joint system. Most of the diseases found are chronic and require continuous care. They also significantly impact the lifestyle of the elderly. A major health problem for the elderly is osteoarthritis, which has the most severe impact on illness and service provision. Without appropriate treatment and behavior, people with severe knee osteoarthritis will experience more severe abnormalities, leading to pain and deformation of the knee joint, resulting in abnormal walking. This causes suffering both physically and mentally because osteoarthritis is a chronic disease that takes a long time to heal. When a patient develops abnormal symptoms, knee surgery is often necessary to completely cure osteoarthritis, which is expensive and requires physical therapy for the patient to return to a normal life. For this reason, researchers wanted to focus on preventing osteoarthritis, reducing the severity of the disease, and recognizing the status of knee joints in at-risk groups. They aimed to achieve this by creating a prototype of knee joint movement for disease diagnosis. If people at risk of developing the disease can use proactive treatment methods, such as exercises to increase joint strength, increase the range of motion in the knee joint, and maintain body weight within specified limits, it will be possible to prevent and reduce the chance of osteoarthritis. [3]-[5] To create a prototype of knee joint movement, computer knowledge was applied to achieve the desired results. This process began by collecting data from both normal and abnormal movements using motion sensors. The obtained

movement data underwent preprocessing to eliminate noise and optimize it into a proper format. Clusters were generated using the Louvain clustering method to create data prototypes. This multi-step data prototyping process was subject to rigorous testing, including generating linear graphs, transforming data into polar coordinates, and using Louvain data clustering. T-tests were applied in one-tail testing to verify the accuracy of the knee motion data model.

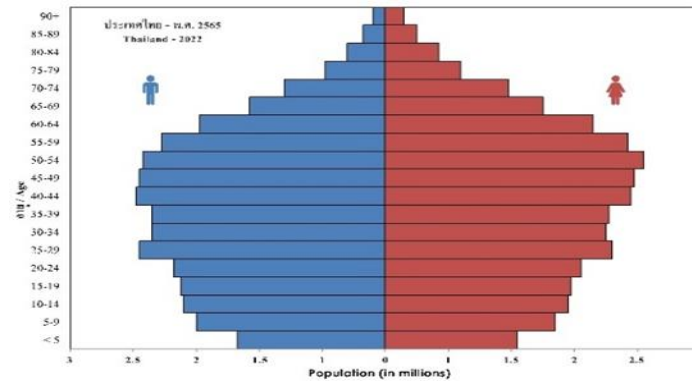


Figure 1. Thailand population pyramid of year 2022[2].

2 KNEE JOINT MECHANISM

In the knee's movement, a joint called "Synovial joints" is the hinge joint. The hinge joint's function is to provide flexion and extension, which are essential functions of the human mechanism. They support the huge force a whole body with added power to do activity. This bone functions found in three parts: elbows, ankles, and knees. Knee's movement is called "Screw home mechanism" because the joint moves like a screw. When the knee locks, knee joint extension takes over to support the human's whole-body weight. This movement is safer than knee flexion. When the knee bend, the knee joint unlocks for movement. The knee joint is covered with ligament and muscle for lubrication. If the cartilage degenerates due to heavy weight support or overuse, the knees will not move freely and extremely painful during movement. This is the main cause of osteoarthritis symptoms.[9]-[13]

3 POLAR COORDINATE SYSTEM

The coordinate system in geometry is used to locate points in a plane. This theory finds wide application in fields such as land surveying and map-making. There are two primary systems: the standard Cartesian system and polar coordinates. Polar coordinates describe the relationship between an angle and radius in two dimensions. The system defines a point, denoted as P, which serves as the origin. An ordered pair is formed by specifying both the radius and the angle. The angle can range from 0 degrees to 270 degrees, a value obtained through the motion sensor. We convert the polar coordinates into the Cartesian system to create graphs. In the Cartesian system, ordered pairs are represented by X and Y. [14]-[16]

4 LOUVAIN CLUSTERING

Louvain Clustering is a technique for detecting network communities. It identifies the density of groups by utilizing greedy algorithms. This clustering method calculates the optimal data for modularity, which is a value that falls within the range of -0.5 to 1. A low modularity value, such as -0.5, implies a lack of clustering. Conversely, an almost 1 modularity value indicates a high level of clustering. [17],[19]

5 HYPOTHESIS TESTING

Hypothesis testing involves taking the results of the research process and revising the theory, related concepts, and research. The researcher conducts research to predict the answer to the research question and to test whether the initially proposed predictions are suitable for addressing the research problem or not. In the scientific hypothesis testing process, conclusions are drawn using relevant statistical knowledge to determine whether the parameters of interest align with the expected outcomes or not. There are following step:

- a) Set hypothesis both null hypothesis as H_0 and alternative hypothesis as H_1
- b) Set confident value to commit or rejected H_0
- c) Select and calculate statistic value of population
- d) Calculate critical value
- e) Translation and conclusions[20],[21]

5.1 T-Test Independent

A statistical method used in hypothesis testing involves comparing the mean of a sample data within the same group of the population or comparing means between two sample data groups, which may have a relationship or be independent. The sample selection should be random, drawn from a population with a normal distribution, and with a known population variance. There are three primary types of T-testing.

- One-Sample test
- Paired Sample T-Test
- Independent T-Test

One-sample T-Test comparison is commonly used in scientific research. Researchers set criteria and conduct tests to determine whether the results adhere to the established criteria or not. This testing is straightforward and uncomplicated, with the selected sample size typically not exceeding 30 people, and variance calculation can be done whether the variance is known or unknown.

This type of hypothesis testing has the following conditions:

- Sample data not exceeding 30 data
- Value of the variable is independent.
- Cannot calculate variance of the sample.
- Randomize the sample data is the normal distribution[21]-[24]

factors of the testing was illustrated as Figure 2.

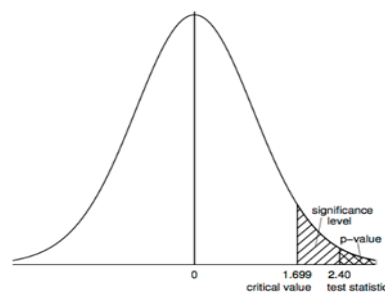


Figure 2. Factors of the one-tailed test [25].

5.2 Graph Matching

Graph matching is a method used to calculate similarity between graphs. The characteristics of a graph are commonly referred to as structural information in various fields, including computer vision and pattern recognition. In the area of study, it's often assumed that the comparison is made between a data graph and a model graph. Inexact graph matching pertains to matching problems when exact matching is not possible, for example, when the number of vertices in the two graphs differs. In the case of attributed graphs, the features for comparison include the numbers of vertices and edges. Even if these numbers are the same, the matching can still be only inexact. Graph edit distance is one of the similarity measures proposed for graph matching. The distance value represents the similarity of the data. Popular methods for calculating this distance include Euclidean, Manhattan, or averaging [26],[27]

6 RESEARCH METHODOLOGY

We began by collecting data from participants, aged 50 and 60, who had been diagnosed with osteoarthritis or had normal knees, using our research equipment. The equipment included a motion sensor and a Wi-Fi transmitter, allowing participants to move independently. An exercise training program was stored in the database as a user profile. The leg lifting data underwent preprocessing, involving the calibration of proper angles and the generation of linear graphs, illustrating the range of motion of the leg. These linear graphs were selected based on their optimal performance time. However, the linear graphs did not clearly differentiate between normal and abnormal patterns.

Subsequently, we transformed the cutoff data into polar coordinates to achieve graph density. Although we were able to detect differences in patterns between the normal cases and patients with osteoarthritis through density, it was challenging to establish specific criteria to distinguish between normal and abnormal patterns. To address this, we attempted to identify patterns in the data using a data clustering method. All data were input and processed using the Louvain clustering technique via the Orange Canvas data mining tool, which displayed the data clusters as a scatter plot. The clustering method aided in establishing criteria for defining normal and abnormal patterns. In the final step, researchers sought to validate the algorithm through statistical hypothesis testing. We utilized one-sample T-tests and graph matching techniques, selecting proven techniques based on the data characteristics.

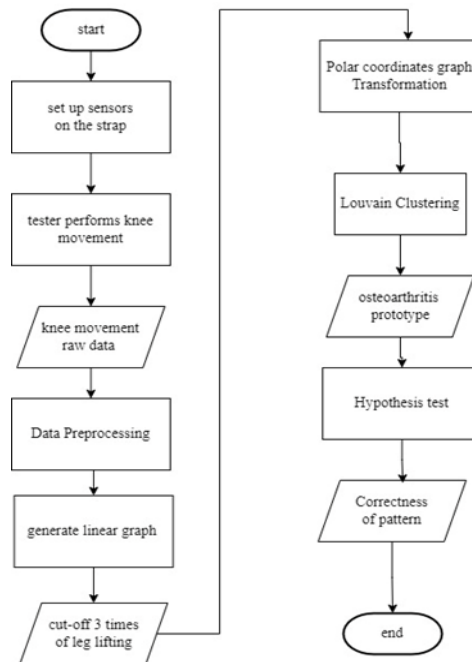


Figure 3. Proposed study methodology.

6.1 Data Gathering Via Razor-Imu

We used motion sensors, specifically the 9 Degrees of Freedom-Razor IMU M0, which includes an accelerometer for measuring acceleration and a gyroscope for tracking rotation angles. The valid angle measurement range falls between -180 and 180 degrees. Motion angle data was transmitted via Wi-Fi signal using the ESP8266 Wi-Fi module. Data were collected from a developed training program. This application was designed for training purposes and data collection, storing the tester's data on a tablet. The data was recorded at a frequency of 50 motion angle data records transmitted every second. The motion sensor was attached using straps to fix the position of motion sensor at calf of the tester. Set-up the motion sensor shown in Figure 4(a) and how to attach sensor with tester shown in Figure 4(b) and (c).

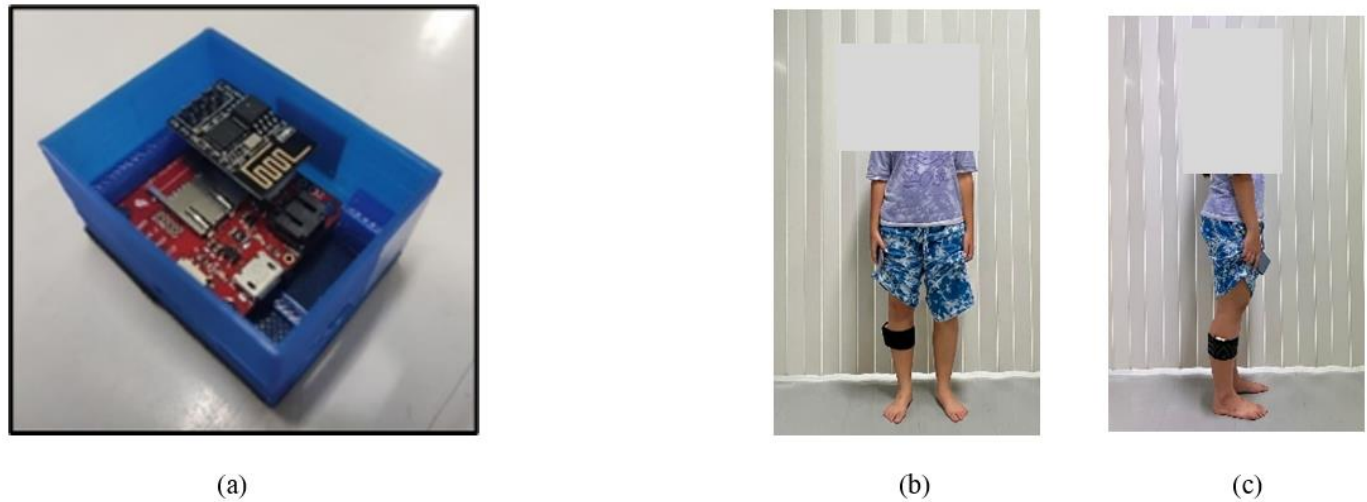


Figure 4. (a) Setting up motion sensor (b) the tester with sensor setup front side (c) the tester with sensor setup lateral side [14]

6.2 Implementing The Linear Graphs

After gathering the raw data as data files, the initial raw data consisted of angles within the range suitable for sensor movement detection. Subsequently, the raw data was calibrated to the actual performing angles. The new data range represents the angles between the reference and polar coordinate systems. This data preprocessing step involved as equation (1)

$$a' = \text{mod}((a_i + 180), 360) \tag{1}$$

When a' is new angle data

mod is modulation expression.

a is the raw data

i is order of data

Before calibration, the data exhibited swings to the highest angles and abrupt drops to the lowest points, as depicted in the red circle in the Figure.5 This form of data was bad to calculate accurately and did not offer a clear range for segmenting into three optimize data waves. The segmented or cut-off data is presented in the Figure.6

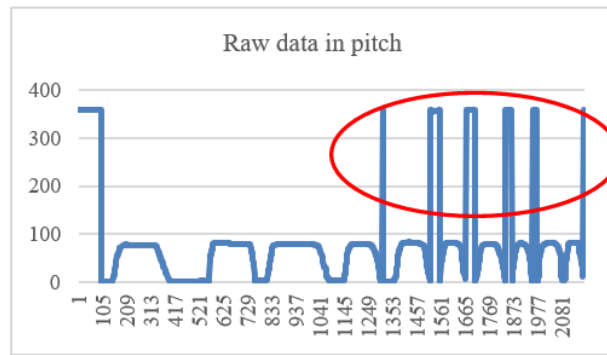


Figure 5. Raw linear graphs

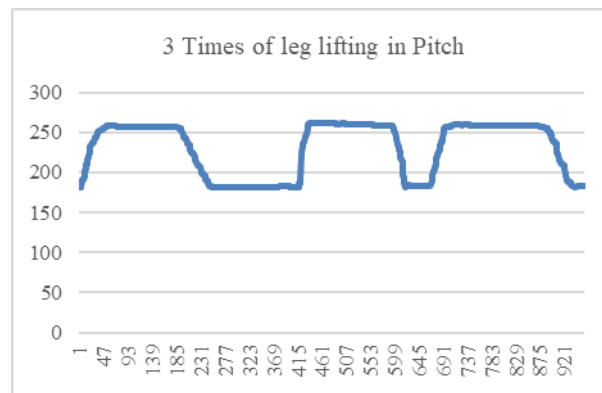


Figure 6. Calibrated linear graphs of leg lifting.

6.3 Polar Coordinate Graphs Transformation

Gaining data density which be transformed linear graph into polar equation form, which allows the data to be displayed density in terms of axial displacement angles. Data transformation in this step is accomplished using polar coordinate equations as equation (2) and (3)

$$x = r \cos \theta \tag{2}$$

$$y = r \sin \theta \tag{3}$$

When r is radius

θ is angle.

x is data in x axis

y is data in Y axis

6.4 Pattern Generated Using Louvain Clustering

Since the polar coordinate graph displayed the density and distribution of angle movement, we aimed to group this density based on similarity. We employed the Louvain clustering method for this purpose because it can effectively capture groups within the data and interpret them as patterns, providing valuable criteria.

7 ALGORITHM PROVING

This section explained how the research methodology was validated, referencing Figure.3 in the previous method. To validate the prototype, we implemented three steps based on the results:

- Proving the linear graphs,

- Confirming the polar coordinate graphs, and validating the criteria of the clusters

7.1 Implementing T-Test with The Linear Graphs

Checking the average of both the sample and population is crucial to represent the data accurately. It allows us to assess the accuracy of the data collected and the effectiveness of the data cleaning process at a 90% confidence level. This process determines the accuracy of all three axes of the sample data. The reason for this is that the researcher needs to utilize data from each axis as a reference. Without conducting these tests, the researcher won't be able to select data accurately and calculate all three axes.

This stage of testing employs a multiple-sample t-test to calculate the data average and determine the representativeness of the data as equation (4)

$$t = \frac{\bar{x} - \mu_0}{s/\sqrt{n}} \tag{4}$$

When \bar{x} is average score of the sample

μ_0 is average score of the all data as pitch axis = 232.77, yaw axis = 77.44, and roll axis = 288.61

s is standard deviation of the sample

n is total number of population as equal 30

calculate df value as equation (5)

$$df = n - 1 \tag{5}$$

when received df value, then open t-score table and got the T-value of the data. And set H_0 and H_1 as equation (6) and (7)

$$H_0: \mu = 1.321 \tag{6}$$

$$H_1: \mu > 1.321 \tag{7}$$

7.2 Implementing Pattern Analysis with Polar-Coordinate Graphs

This section explained how to analyze the results of the data to proof movement patterns and algorithm, encompassing both normal and abnormal patterns of individuals. The algorithm to prove as shown in Figure 7.

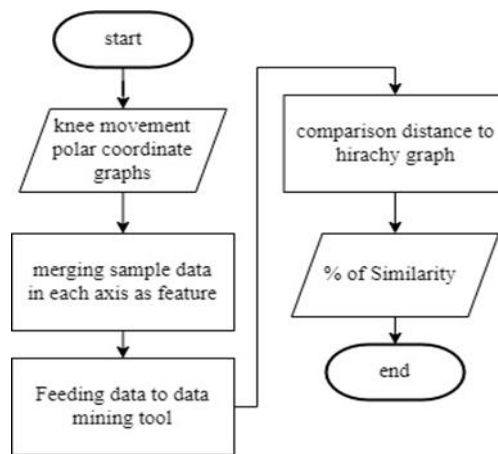


Figure 7. Implementation percent of similarity

We calculate graph matching. Sample comparison distance as shown is Figure.8

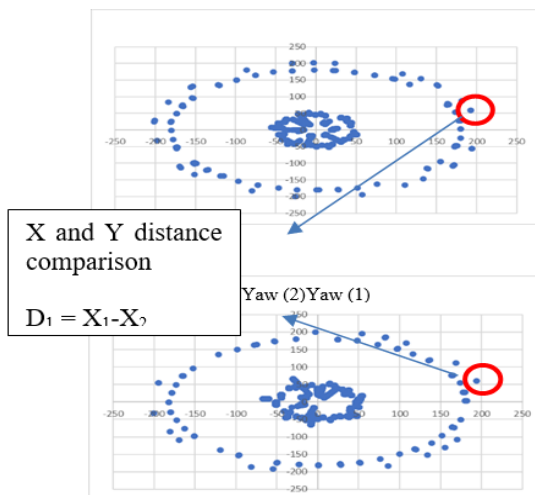


Figure 8. Gathering X and Y from graph to distance comparison

When the results of the matching data are obtained, the distances between each pair of data are compared. Similarity matches are placed into a matrix table, and the distance values in the matrix are used to create a graph for assessing the level of data similarity. This approach is necessary due to the unequal amounts of movement data for each person, resulting in only a rough comparison.

7.3 Hypothetical Testing of Louvain Clustering

The researcher chose to group the data based on the characteristics of the data groups by converting the data into a polar form to test for differences between normal and abnormal movement patterns. The Louvain Clustering method revealed that groups of normal individuals have fewer data clusters that can be categorized by Louvain Clustering and are easier to distinguish compared to abnormal individuals. We use orange canvas version 3.35 which data mining tool clustering data as shown in Figure. 9

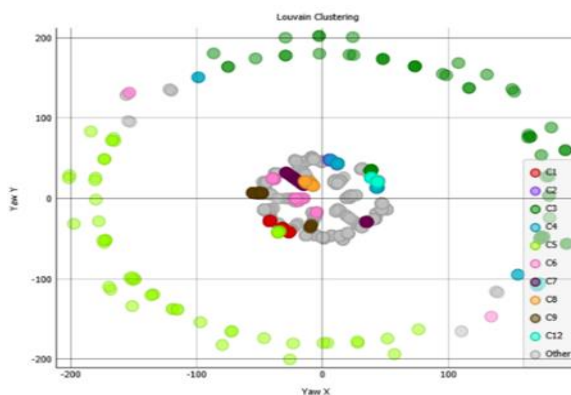


Figure 9. Example cluster result of Louvain clustering

8 EXPERIMENTAL RESULTS OF PATTERN PROTOTYPE

This section presents the results of generating patterns. We display them separately in linear graphs, the angle movement of the polar coordinate graph, and cluster groups.

8.1 Linear Graphs Pattern

This section presents the experimental results and discusses them. The tester's raw data was converted into linear graphs to depict the data's behavior. We defined the patterns of the data and segmented the data for the injured part across three axes were illustrated as in Figure. 10

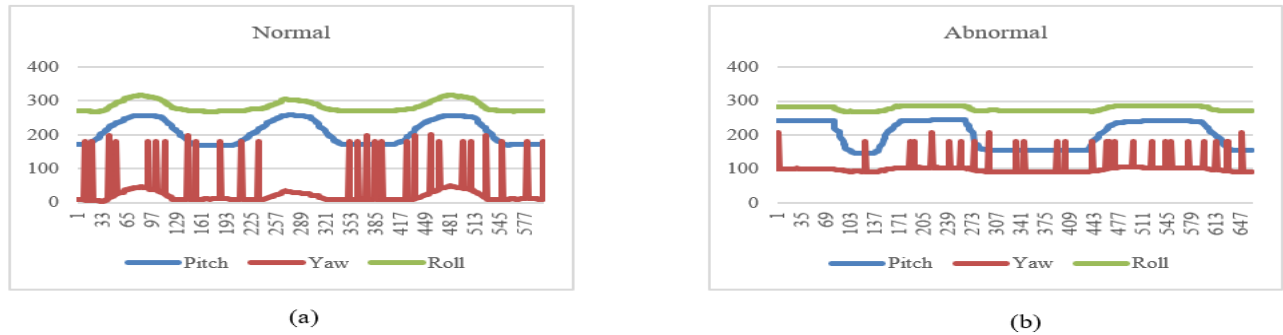


Figure 10. (a) Linear graph in 3 axes of the normal pattern (b) Linear graph in 3 axes of the abnormal pattern

Data generated from the tester's leg lifts were illustrated, with a cut-off range for normal and abnormal cases. In the pitch axis, normal data ranged from 0° to 180°, in the yaw axis from 180° to 250°, and in the roll axis from 270° to 317°. Abnormal data in the pitch axis ranged from 100° to 207°, in the yaw axis from 180° to 243°, and in the roll axis from 270° to 280°. Comparing the linear graphs revealed variations in the angles of performance on each axis. As a result, it was challenging to determine whether the patterns and ranges were close. For this reason, we chose to transform the data into polar coordinates to capture the patterns based on density.

8.2 Polar Coordinates Pattern

The cut-off data was transformed into a polar coordinate system. The radius represents the angle at which the tester is working over a period of seconds, starting from 1 until the end of the data. These graph results show that the healthy pattern is denser than the unhealthy pattern, primarily because a healthy tester can lift with consistency. In cases where the unhealthy tester performed at a slower pace than the healthy tester, the frequency of data collection was higher. The strength of the polar coordinate graphs lies in their ability to increase data density when the tester performs at the same angle, causing the data points to overlap. This heightened density can be observed in the data plots. When comparing the two patterns, the differences are clearly visible in the pitch and yaw axes. Healthy patterns are displayed in Figure 11, while the unhealthy pattern is shown in Figure 12.

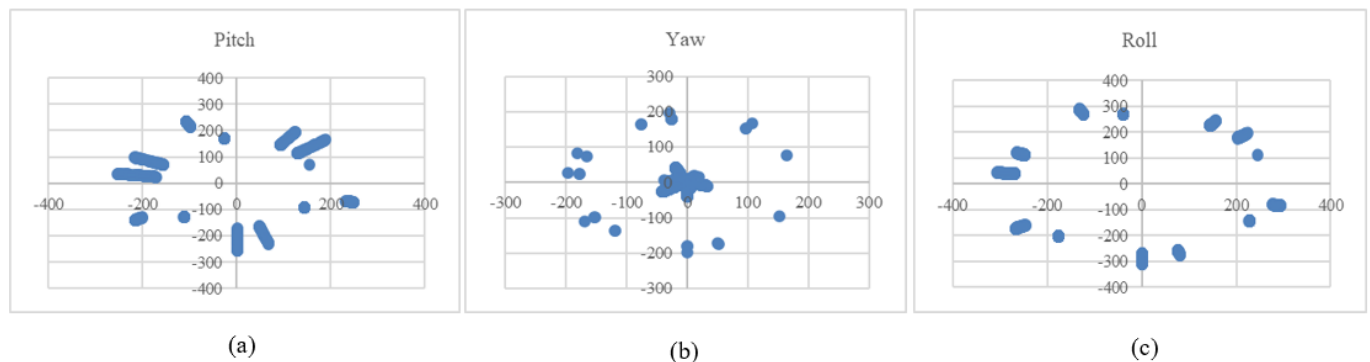


Figure 11. Healthy pattern (a) Polar Coordinate graph in Pitch (b) Polar Coordinate graph in Yaw (c) Polar Coordinate graph in Roll

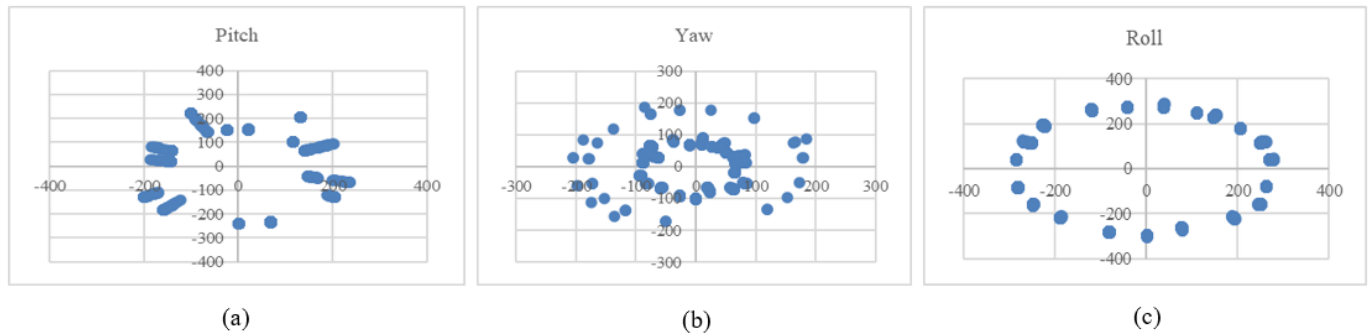


Figure 12. Unhealthy pattern (a) Polar Coordinate graph in Pitch (b) Polar Coordinate graph in Yaw (c) Polar Coordinate graph in Roll

8.3 Cluster Group of Louvain Clustering Pattern

This section presents the experimental results of clustering polar coordinate graphs using the Louvain clustering method. Another popular clustering methodology is employed to capture density as groups. We established the k-nearest distance by calculating the average distance from the lowest angle to the highest angle at which the tester performed, resulting in a value of 70. The results of the healthy pattern show that Louvain Clustering gain the cluster is good and see edge of the data by order paired of angles, because polar coordinated graphs were reduced noise before clustering process. In pitch axis gained group of clusters 7 clusters. In yaw axis gained group of clusters 8 clusters. And In roll axis gained group of clusters 6 clusters. The healthy pattern cannot detect noise as shown in Figure 13. The unhealthy pattern were shown in Figure 14.

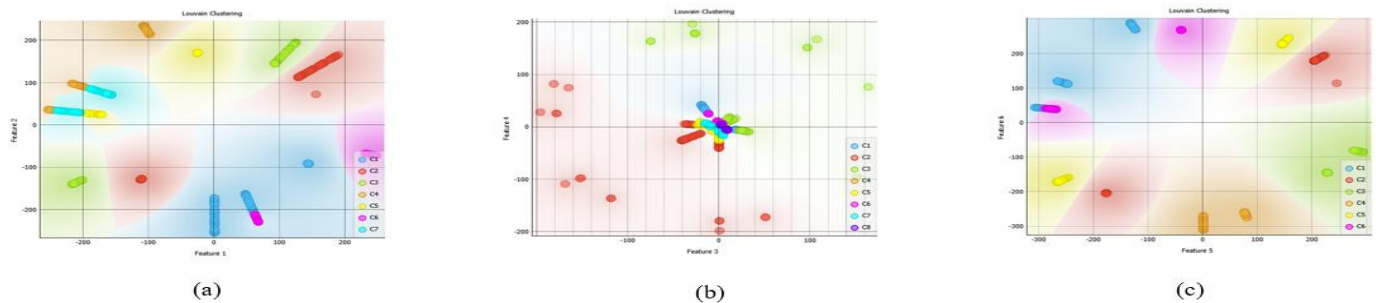


Figure 13. Healthy pattern (a) Groups of cluster in Pitch (b) Groups of cluster in Yaw (c) Groups of cluster in Roll

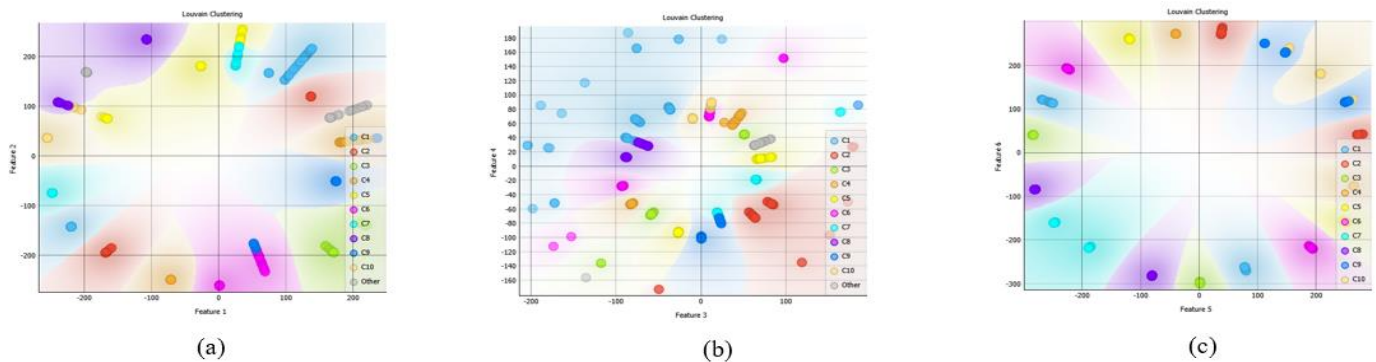


Figure 14. Unhealthy pattern (a) Groups of cluster in Pitch (b) Groups of cluster in Yaw (c) Groups of cluster in Roll

As shown in Fig.14, the Louvain Clustering grouped the data of unhealthy patterns into 11 clusters each in the pitch and yaw axes, while the roll axis yielded 10 clusters. These experimental results indicate that the unhealthy pattern has a higher number of clusters compared to the healthy pattern. In some axes, data were detected as noise, primarily because the unhealthy pattern exhibits higher density than the healthy pattern.

9 EXPERIMENTAL RESULTS OF HYPOTHESIS TESTING

9.1 Result of Hypothesis Testing of Linear Graphs

There were 30 sample groups of knee joint movement in this test and it was shown as Table I and II.

Table I. Data Information The Linear Graph

Sample no.	\bar{X} pitch	\bar{X} yaw	\bar{X} roll	s pitch	s yaw	s roll
SAMPLE1	235.18	48.56	300.54	30.33	30.20	16.51
SAMPLE2	237.26	48.99	302.26	31.33	30.64	17.60
SAMPLE3	244.41	50.69	304.88	27.70	30.51	16.34
SAMPLE4	246.21	51.03	305.09	27.78	30.18	16.65
SAMPLE5	236.91	51.53	303.54	27.54	29.45	17.90
SAMPLE6	220.49	36.19	286.97	33.47	27.74	19.26
SAMPLE7	239.04	52.36	305.98	33.75	31.86	23.28
SAMPLE8	208.48	25.82	283.79	34.81	36.55	15.96
SAMPLE9	212.72	23.13	283.99	35.28	28.51	14.88
SAMPLE10	212.11	27.46	286.51	34.68	35.63	17.08
SAMPLE11	222.07	311.59	237.83	23.65	35.87	33.91
SAMPLE12	241.22	51.34	299.98	32.34	28.67	21.93
SAMPLE13	243.53	57.02	307.07	31.88	28.08	21.05
SAMPLE14	244.32	57.00	307.07	31.87	28.94	20.82
SAMPLE15	244.06	57.95	306.39	31.22	32.07	20.89
SAMPLE16	243.24	56.58	304.59	31.76	31.45	21.35
SAMPLE17	241.98	58.67	306.74	32.11	31.77	23.29
SAMPLE18	242.35	58.26	307.54	31.14	29.42	22.18
SAMPLE19	238.99	59.36	306.27	33.62	33.21	23.76
SAMPLE20	225.93	62.85	299.62	27.30	38.18	31.27
SAMPLE21	225.25	62.50	299.22	27.82	38.08	31.30
SAMPLE22	231.30	271.55	262.61	27.55	134.37	19.57
SAMPLE23	233.55	290.65	261.34	26.63	118.64	18.84
SAMPLE24	231.82	63.40	212.80	30.33	54.70	120.48
SAMPLE25	229.20	61.36	224.59	30.44	55.22	113.07
SAMPLE26	225.78	59.71	235.83	33.22	52.55	106.54
SAMPLE27	224.19	66.85	293.12	27.12	35.86	55.83
SAMPLE28	233.80	66.01	306.92	18.76	34.04	27.33
SAMPLE29	233.19	67.57	307.18	18.71	35.94	28.37
SAMPLE30	234.51	67.29	307.98	17.72	33.80	25.07

Table II: μ score of the linear graph.

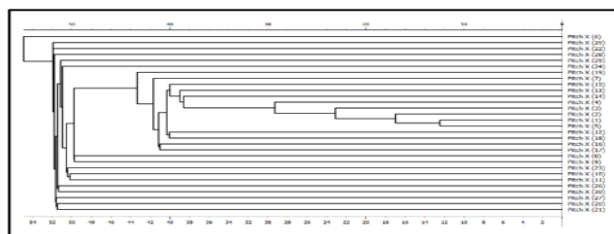
Sample no.	pitch	yaw	roll
SAMPLE1	0.434523183	-5.238881806	3.957968239
SAMPLE2	0.784757373	-5.085535294	4.24775523
SAMPLE3	2.302295095	-4.802814626	5.45445641
SAMPLE4	2.648971004	-4.792733	5.422084434
SAMPLE5	0.822720646	-4.819873075	4.568528751
SAMPLE6	-2.0099836	-8.143558631	-0.465717667
SAMPLE7	1.017972622	-4.311829118	4.087318495
SAMPLE8	-3.821515669	-7.735795754	-1.653923652
SAMPLE9	-3.112631912	-10.43557541	-1.700782863
SAMPLE10	-3.262239587	-7.683918151	-0.672457045
SAMPLE11	-2.478388993	35.75709672	-8.20155434
SAMPLE12	1.431595883	-4.988131726	2.841464642
SAMPLE13	1.84815644	-3.984341132	4.803474923
SAMPLE14	1.985672267	-3.869471478	4.857143104
SAMPLE15	1.981023358	-3.328393797	4.663056464

SAMPLE16	1.805666761	-3.633005627	4.101343173
SAMPLE17	1.570901377	-3.236390124	4.265097707
SAMPLE18	1.684809957	-3.571148549	4.674555415
SAMPLE19	1.013361566	-2.981973287	4.072292298
SAMPLE20	-1.373133616	-2.093941702	1.929707683
SAMPLE21	-1.480723504	-2.149192726	1.857077881
SAMPLE22	-0.291944589	7.912250308	-7.276489127
SAMPLE23	0.159989665	9.842808624	-7.926211157
SAMPLE24	-0.172305822	-1.405953181	-3.44640476
SAMPLE25	-0.641461635	-1.595061631	-3.100988679
SAMPLE26	-1.152025295	-1.848113781	-2.713394681
SAMPLE27	-1.733154083	-1.617434163	0.442542776
SAMPLE28	0.302241074	-1.838905333	3.669030643
SAMPLE29	0.123626787	-1.504154395	3.584560619
SAMPLE30	0.537273758	-1.645066479	4.231946597

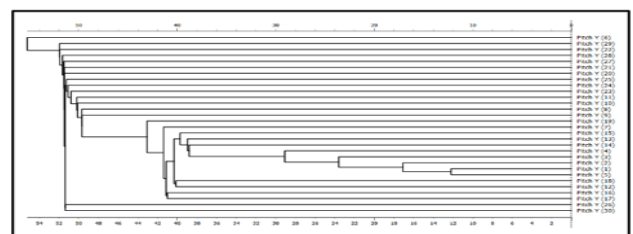
Based on the experimental results of t-testing at a confidence level of 90%, the percentage accuracy in the pitch axis was 70%, in the yaw axis was 90%, and in the roll axis was 36.67%. This suggests that the data in the pitch and yaw axes can be utilized to create prototypes of movements for both normal individuals and people with osteoarthritis.

9.2 Result of Pattern Comparison

Data each axis would process to distance matrix 30*30 to compare every paired and matching to hierarchy level. Based on hierarchy level to derive percent of similarity by interval as shown in Table III.

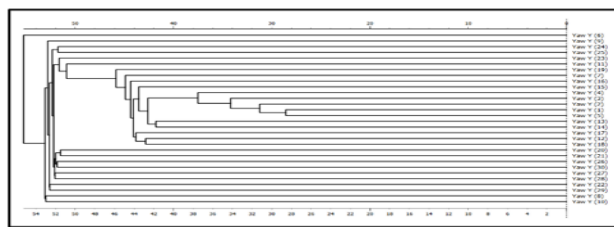


(a)

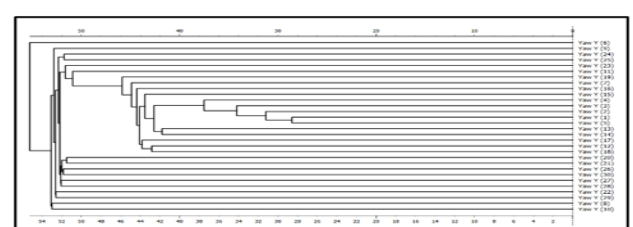


(b)

Figure 15. Distance comparison (a) x in pitch axis (b) y in pitch axis



(a)



(b)

Figure 16. Distance comparison (a) x in yaw axis (b) y in yaw axis

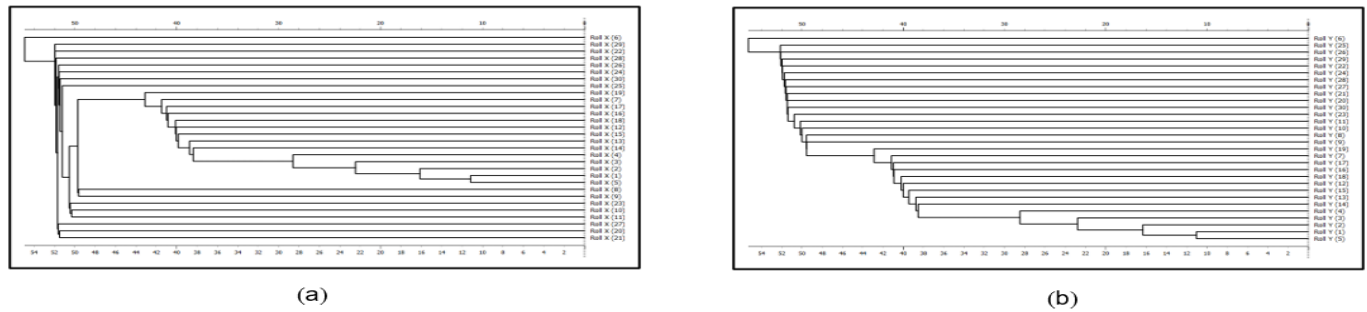


Figure 17. Distance comparison (a) x in roll axis (b) y in pitch axis (c) z in roll axis

Table III. Percent of Similarity Score of The Polar Coordinate Graphs

Similarity	Pitch X	Pitch Y	Yaw X	Yaw Y	Roll X	Roll Y
62-42	80.00	60.00	86.67	86.67	63.33	70.00
41-21	13.33	33.33	13.33	13.33	26.67	16.67
20-0	6.67	6.67	0	0	10.00	13.33

From graph similarity test in Table III shown data on each axis categorizes the results into three levels. The most similar will get the score closer to 62, the closer the distance matching. Since pattern checking involves both the X-axis and Y-axis coordinates, we conducted a similarity average, resulting in the following findings:

In the pitch axis, with a similarity score range of 62-42, the average similarity was 70%. In the pitch axis, with a similarity score range of 41-21, the average similarity was 30%. In the pitch axis, with a similarity score range of 20-0, the average similarity was 6.67%.

In the yaw axis, with a similarity score range of 62-42, the average similarity was 86.67%. In the yaw axis, with a similarity score range of 41-21, the average similarity was 13.33%. In the yaw axis, with a similarity score range of 20-0, the average similarity was 0%.

In the roll axis, with a similarity score range of 62-42, the average similarity was 66.67%. On the roll axis, with a similarity score range of 41-21, the average similarity was 21.67%. On the roll axis, with a similarity score range of 20-0, the average similarity was 11.67%.

Results of examining data clusters in Louvain clustering of the normal data will gain 6-10 clusters. For the abnormal data will gain more than 15 clusters. After comparison revealed percent of correctness 97%. From corrective result confirm that this algorithm to generate prototype is highly performance and extended to the larger population.

CONCLUSION

This research focused on studying osteoarthritis movements while bending and stretching the knee in a sitting position to define movement patterns. Testers performed leg lifts three times to allow the knee joint full extension and flexion. During knee extension, testers also held their legs and counted from 1 to 10 to assess muscle strength. Each knee movement was promptly transmitted to the program on a tablet. The data collected in three axes include raw data in pitch, yaw, and roll. From this raw data, we created linear graphs to gain insights into the movement behavior of both the osteoarthritis group and the normal group. After understanding the data's characteristics, we performed data preprocessing and refined the data to select the best-performing values. The data range was then transformed into polar coordinate graphs to visualize density and distribution. We aimed to choose an appropriate algorithm for defining patterns. These polar coordinate graphs were subsequently fed into Louvain clustering. Louvain Clustering effectively grouped the data into clusters based on the actual angle. The number of clusters

helped define patterns for both healthy and unhealthy individuals.

Proving the accuracy of the algorithm and prototype is based on hypothesis testing, spanning from knee movement methods to the data cleaning process. It is evident that the Yaw and Pitch axes exhibit high accuracy and reliability, aligning with the observed kicking direction and the rhythm of the tester's movements. The data transformation algorithm also demonstrates reliability, as seen in the similarity between data from all axes and the leg kick patterns of normal individuals, even with varying angular distributions. Throughout the Louvain clustering process, it becomes apparent that this method correctly groups and distinguishes patterns within the data. Interestingly, normal individuals provide fewer data points compared to those with abnormalities due to the lower frequency of information. The testing results confirm the effectiveness of this separation method, making it a reliable tool for analyzing movement patterns within more extensive datasets.

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