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Fuzzy Assessment Model for Functional Impairments in Human Locomotion

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Abstract : *Neurological disorders affect the human locomotion system. The effect of neurological disorders can be decreased significantly by an efficient rehabilitation. In this paper, a new methodology has been proposed to analyze and classify joint angles of Ankle, Knee, and Hip in three dimensions (3D). Fuzzy assessment model has been developed based on fuzzy granulation and fuzzy similarity. Using joint angles data of healthy subjects and patients, experiments have been performed to show how effectively the developed system work. A physician on our team evaluated the experimental results. Kappa statistics has been used to evaluate the system results. The kappa coefficients show excellent agreement between the decision of the physician and the developed system. The proposed system serves as an assessment tool in the rehabilitation process to detect and evaluate abnormality in human movement. Physicians and clinicians benefit from this tool in the diagnosis and assessment of functional impairments in human locomotion system. As well as prescribe treatment and measure the outcome of therapy for patients with neurological disorders.*

Keywords: *Granule, Fuzzy Inference System, Human Locomotion, Joint Angles, Fuzzy Assessment Model*

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I. Introduction

According to World Health Organization (WHO), 12% of total deaths are attributable to neurological disorders [1]. To alleviate the severity of neurological disorders, an effective rehabilitation can be useful. WHO defines rehabilitation as "an active process by which those affected by injury or disease achieve a full recovery or, if a full recovery is not possible, realize their optimal physical, mental and social potential and are integrated into their most appropriate environment" [2]. The rehabilitation process, Rehab-CYCLE [3], involves four activities: assessment, assignment, intervention and evaluation. An effective neurorehabilitation is based on the involvement of expert and multidisciplinary assessment, realistic and goal-oriented programs, and evaluation of the impact on the patient's rehabilitation achievements [2].

Gait analysis is considered an essential tool in the rehabilitation process It offers quantitative assessment of disorder and benefits treatment prescription [4]. Clinical gait analysis can be used to diagnose disorders, assess severity, monitor improvement, and predict outcome of intervention [5, 6, 7]. Gait analysis usually comprises dynamic kinematics, kinetics, and muscles activity, i.e. electromyography (EMG). The kinematic variables include displacements, joint angles, velocities, and accelerations. Joint angles of the lower limb have minimal variability among normal subjects and offers a powerful tool in diagnosing abnormalities [8].

Several research work and studies explored various techniques to represent and classify gait data. Recently, machine learning techniques have been used widely [9-15]. This method demonstrated a high ability to represent and model complex patterns and non-linear relationships in the gait data. Fuzzy logic algorithms have been investigated and applied in previous work [16-22]. Research findings revealed that FL can be used efficiently to develop an automated system provides an objective and quantitative classification and assessment of gait impairments. The advantages of FL are: simplicity to implement, reduction of massive gait data, representing non-linear relationships, and providing quantitative analysis.

The rest of this paper is organized as follows: Section 2 describes the Fuzzy assessment model, including Fuzzy granulation algorithm and the developed work. The experiments and result analysis are presented in Sections 3. Section 4 shows the conclusion.

II. Fuzzy Assessment Model

2.1 Fuzzy Information Granules and Similarity

Zadeh [23] defined granulation as "Granulation of an object A results in a collection of granules of A, with a granule being a clump of objects (or points) which are drawn together by indistinguishability, similarity, proximity or functionality". Granular computing (GrC) comprises theory, techniques, and tools to solve problems using granules, i.e. classes, clusters, or groups. Where, granules can be fuzzy or crisp [23-25].

Fuzzy Information granule can be formed for a collection of data within the granulation window W using one of the types of fuzzy set, e.g. triangular, Gaussian, parabolic, etc. However, such information granule A, i.e. fuzzy set, should be experimentally valid, contains adequate experimental data, as well as specific enough [26-28]. The size of granulation window W can be adjusted experimentally to compromise both specificity and generality requirements. Figure 1 shows the design of fuzzy information granule A of type Gaussian membership function with mean and variance as parameters

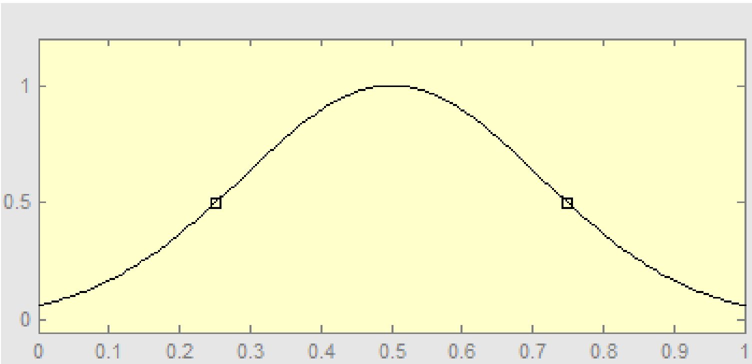

Fig.1. The design of fuzzy information granule A, i.e. fuzzy set, of type Gaussian membership function with mean and variance as parameters.

Fuzzy granulation methodology has been used for gait analysis and assessment in previous work [23,29]. The proposed methodology consists of three main processing phases; rescaling, building granules, and then calculating similarity.

Rescaling: Rescaling is performed to reduce the effect of the variability between subjects, e.g. walking speeds and physiological variability, as well as, the variability between experiments, e.g. sensors placement. It consists rescaling both the stride time and the signal amplitude of joint angles as follows:

$$\acute{x}(t) = \frac{x(t) - \underline{x}}{\overline{x} - \underline{x}}$$

where, $\acute{x}(t)$ is the scaled signal, $x(t)$ is the original signal, $\underline{x}$ is the minimum and $\overline{x}$ is the mean of original data.

Fuzzy granules: Given a data series

$$X = \{x_1, x_2, \dots, x_n\}$$

X can be divided into *k* segments of size *wsize*, the number of data points within granule window, as

$$W = \{x_1, x_2, \dots, x_k\}$$

For each segment, a granule g_i is established and represented by the mean and the standard deviation of the segment. Then a series of *p* granules G can be built as

$$G = \{g_1, g_2, \dots, g_p\}$$

Fuzzy similarity: A comparison between two fuzzy granules, fuzzy sets, can be evaluated using fuzzy similarity method as illustrated in the following equation.

$$\mu_{ref} \times \mu_{test} = \frac{\mu_{ref} \wedge \mu_{test}}{\mu_{ref} \vee \mu_{test}} = \frac{\min(\mu_{ref}(x, y), \mu_{test}(x, y))}{\max(\mu_{ref}(x, y), \mu_{test}(x, y))}$$

Where, $\mu_{ref} \times \mu_{test}$ is the degree of similarity between two the fuzzy granules, reference and test. $\times$ is a fuzzy cross-correlation operator, $\wedge$ (min) is a fuzzy logic intersection, $\vee$ (max) is a fuzzy logic union.

2.2 The Developed System

The developed system is shown in Figure 2 for Training stage and Figure 3 for Testing Stage.

2.4.1 Training Stage

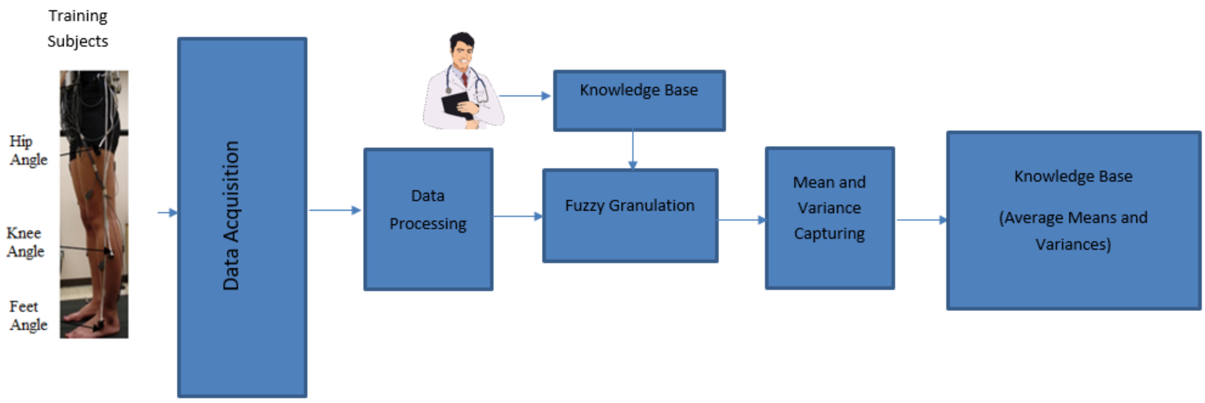

Fig.2. Training Block Diagram

2.4.2 Testing Stage

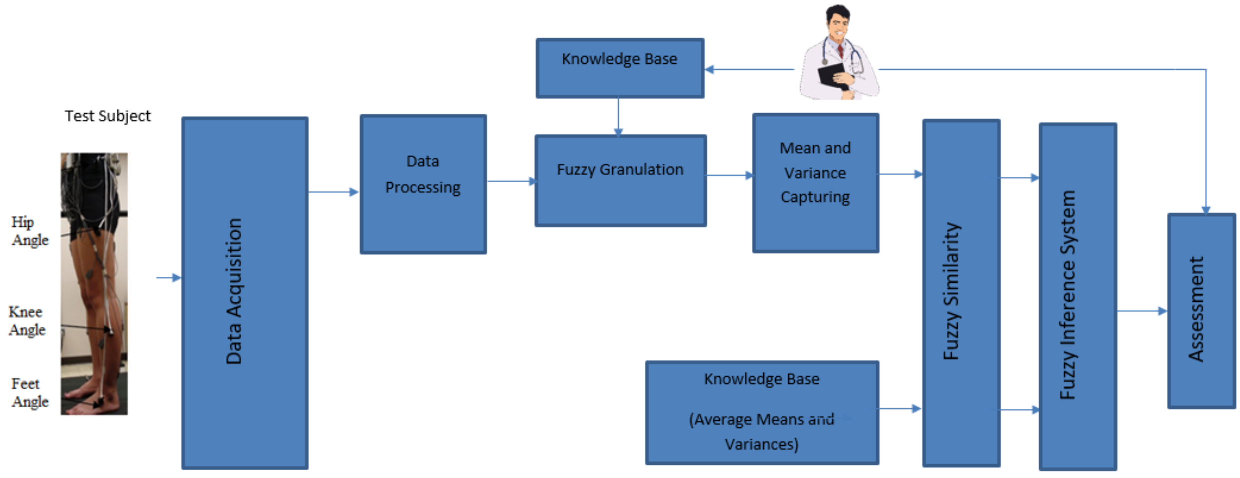

Fig.3. Testing Block Diagram

The reasoning is based on fuzzy logic. The structure of the Assistant System includes four components: Fuzzifier, Inference Engine, Knowledge Base, and Defuzzifier. The Fuzzifier translates crisp inputs into fuzzy values. The Inference Engine is the part that controls the process of deriving conclusions. It applies a fuzzy reasoning mechanism to obtain a fuzzy output using rules and the fuzzy values. The Knowledge Base contains a set of fuzzy IF-THEN rules and a set of membership functions of fuzzy sets. These rules represent the knowledge that the PA possesses. The Defuzzifier coverts the fuzzy output into a crisp value that best represents the out fuzzy set. The Defuzzifier uses the center of gravity scheme. The implication methods used in the proposed system are min (minimum), which truncates the individual output fuzzy sets, and max (maximum), which scales the resulted output fuzzy sets. The input to the implication process is a single number given by antecedent.

The input and output variables will be defined in order to be used by the Fuzzy Inference Engine, and each variable is fuzzified by input fuzzy sets. The fuzzy sets used in fuzzifying the Input and Output variables are shown in Table 1. Bell fuzzy sets are specified by three parameters a, b and c while the Gaussian fuzzy set is specified by two parameters a and b and trapezoidal fuzzy set is specified by four parameters a, b, c, and d.

TABLE 1: DEFINITIONS OF FUZZY SETS USED IN THE PROPOSED SYSTEM

Fuzzy Set Type	Fuzzy Set Definition
Trapezoidal	$\mu_{Trap}(x) = \begin{cases} 0, & a < x \\ -\frac{1}{b-a}(a-x), & a \le x \le b \\ \frac{1}{d-c}(d-x), & c \le x \le d \\ 0, & d < x \end{cases}$
Bell	$\mu_B(x) = \frac{1}{1+\left\lvert\frac{a-x}{b}\right\rvert^{2c}} \quad , \quad c > 0$
Gaussian	$\mu_G(x) = \mathrm{e}^{-\frac{(a-x)^2}{2b^2}}$

The mean and variance Similarities are defined by the following membership functions: Extremely Low, Very Low, Low, Medium, High, Very-High, Extremely High. The output of the fuzzy variable, the Overall Similarity, is defined by four membership functions low (L), Medium (M), and High (H). The centroid method is used for defuzzification. Mean similarity, Variance similarity and Overall Similarity are represented by Gaussian membership functions (Figure 4, Figure 5 and Figure 6).

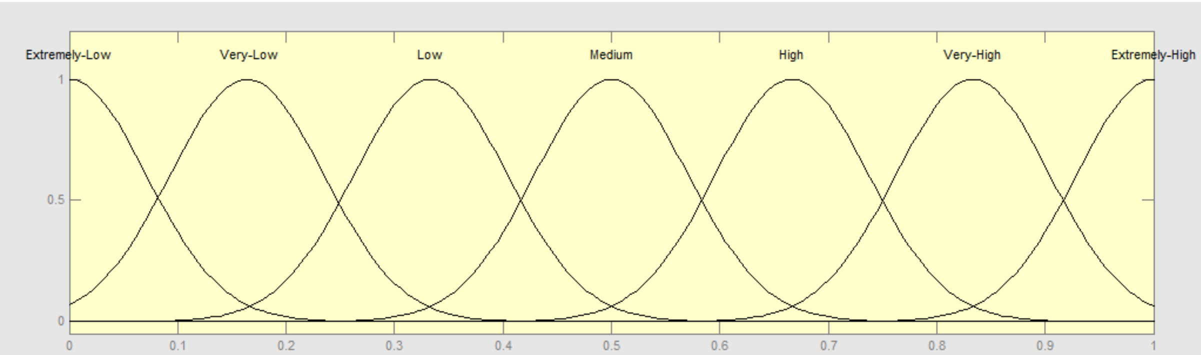

Fig.4. Fuzzy sets for mean similarity

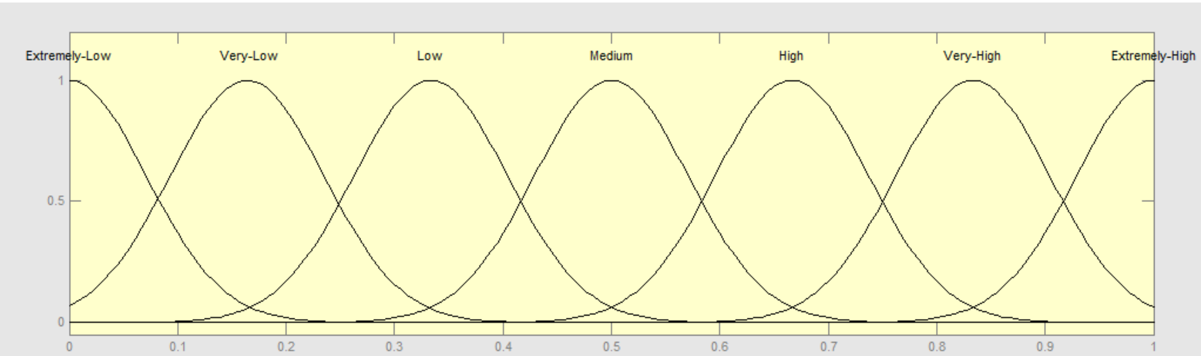

Fig.5. Fuzzy sets for variance similarity

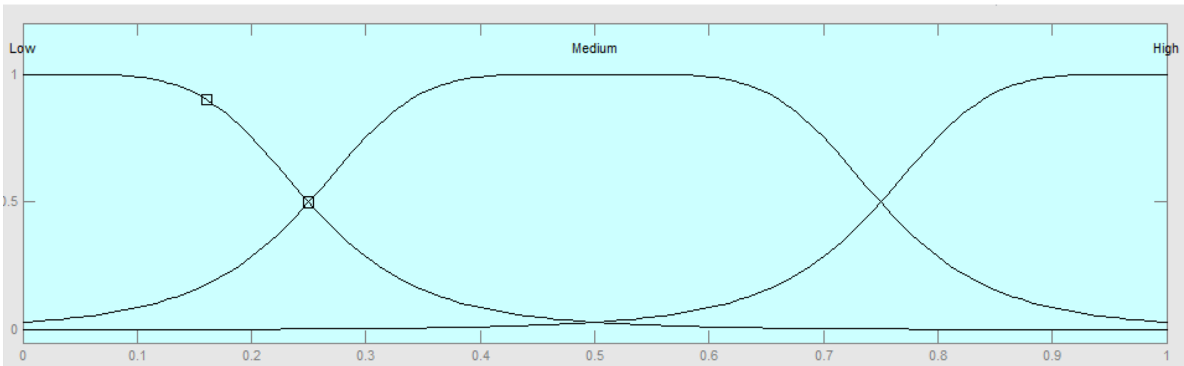

Fig.6. Fuzzy Sets for the overall similarity

Here are some of the if- then rules used by the fuzzy inference system

- If Mean Similarity is *Extremely Low* and Variance Similarity is *Extremely Low* the Overall Similarity is *Low*
- If Mean Similarity is *Extremely Low* and Variance Similarity is *Low* the Overall Similarity is *Medium*
- If Mean Similarity is *Extremely High* and Variance Similarity is *Extremely High* the overall similarity is *High*

In this design, the following settings have been used: The Min-Max fuzzy inference and the centroid defuzzifier.

III. Experiments and Results

3.1 Subjects

All experiments were performed in our previous work [29]. Healthy subjects were recruited from the University of Texas at El Paso (UTEP) and patients were recruited from the hospitals and rehabilitation clinics (Paul L. Foster School of Medicine at Texas Tech University Health Sciences Center and MENTIS Neuro Rehabilitation). In this paper, twenty healthy subjects were used to represent the reference, 12 males and 8 females. Table2 illustrates the anthropometric data for all healthy subjects.

The analysis of joint angles data was applied and tested for three abnormal patients with different disorders: First patient suffers from hemiplegic cerebral palsy and had treatment in the form of foot surgery. Second patient suffers from relapsing remitting multiple sclerosis. Third patient suffers from congenital dislocation of left hip and the right limb is lower than left one by 2 cm. Table 3 illustrates the anthropometric data for all abnormal subjects.

3.2 Data Acquisition

This paper used the joint angles of the lower extremity of human body; ankle, knee and hip joints for both right and left sides. Figure 7 shows the experimental setup and data acquisition. Both joint angles and GRFs data were captured at 100 Hz sampling rate while subject walk naturally on the instrumented treadmill for three minutes.

TABLE 2: ANTHROPOMETRIC DATA FOR 20 HEALTHY SUBJECTS.

Subject	Gender (M/F)	Age (years)	BMI (kg/m^2)	Speed (m/s)
1	F	25	22.10	1.0
2	F	20	22.32	1.0
3	F	27	22.43	1.0
4	F	20	15.55	0.81
5	F	25	22.81	0.85
6	F	23	22.11	1.0
7	F	20	24.06	0.95
8	F	40	22.77	1.2
9	M	32	24.41	1.2
10	M	38	29.07	1.0
11	M	23	21.69	0.99
12	M	24	20.55	1.0
13	M	31	28.83	1.0
14	M	26	24.91	1.2
15	M	26	27.60	1.0
16	M	19	23.78	1.15
17	M	22	26.35	1.05
18	M	24	26.20	1.0
19	M	25	27.10	1.1
20	M	20	22.12	1.0
Mean±std		25±4.49	23.72±3.26	1.03±0.10

Body mass index (BMI) = weight (kg)/(height(m)) ^{2}

TABLE 3: ANTHROPOMETRIC DATA FOR 3 ABNORMAL SUBJECTS.

Subject	Gender (M/F)	Age (years)	BMI (kg/m^2)	Speed (m/s)
1	F	18	17.39	0.70
2	F	49	22.94	0.81
3	F	22	22.02	0.90

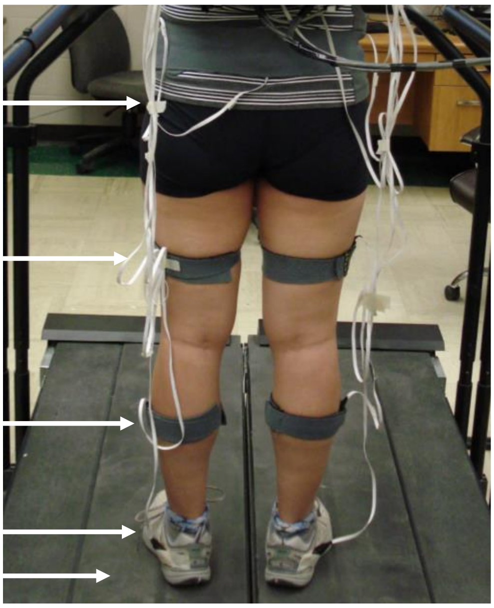

Fig.7. Experimental setup and data acquisition. Joint angles and GRFs data were captured at 100 Hz.

3.3 Experimental Results

The proposed methodology was tested and evaluated using two subject groups: 20 healthy subjects were recruited to establish the reference fuzzy rule-base. A fuzzy rule-based system was developed to provide the joint angles of Ankle, Knee and Hip.

Two fuzzy sets were developed to represent 3D joint angles.

$$x \in X, \qquad X = \{Ankle_X \; Ankle_Y \; Ankle_Z \; Knee_X \; Knee_Y \; Knee_Z \;\; Hip_X \; Hip_Y \; Hip_Z\}$$
$$y \in Y, \qquad Y = \{Gr_1 \;\; Gr_2 \;\; Gr_3 \;\; Gr_4 \;\; Gr_5 \;\; Gr_6 \;\; Gr_7 \;\; Gr_8 \;\; Gr_9 \;\; Gr_{10}\}$$

Where each *Gr* represents a fuzzy granule with mean and standard deviation using Gaussian membership function.

The fuzzy relational matrix is obtained using the membership function described as

$$P(x,y) = \mu_p(x,y) = \frac{1}{n}\sum_{i=1}^{n} \mu(i)$$

where $\mu_p(x,y)$ depicts the membership function, *n* is the number of data samples in a fuzzy set, and $\mu(i)$ is the value of the membership function. The membership function $\mu_p(x,y)$ represents the mean and standard deviation of the data samples of joint angle for each granule. The reference rule-based matrix $P_{ref}(x,y)$ was established to represent the joint angle of healthy subjects, whilst the test matrix $P_{test}(x,y)$ was established to represent the joint angle of patients. The fuzzy similarity between $P_{ref}(x,y)$ and $P_{test}(x,y)$ was determined. Table 4 and Table 5 exhibit the mean and the standard deviation of the rule-based matrices, $P_{ref}(x,y)$ for all 20 healthy reference subjects.

TABLE 4: THE MEAN FOR ALL HEALTHY SUBJECTS.

Granulaes	Ankle_X	Ankle_Y	Ankle_Z	Knee_X	Knee_Y	Knee_Z	Hip_X	Hip_Y	Hip_Z
1	22.63328	6.940647	9.815186	0.740749	5.984871	2.840048	1.614482	20.69982	3.952072
2	13.85691	9.36083	12.3758	2.430784	14.18364	0.584119	0.577859	15.6318	6.237221
3	10.92613	15.05905	10.7789	3.774074	12.73121	0.862095	0.59217	9.027245	4.631974
4	9.096829	18.33752	9.471998	4.797335	9.805905	0.187736	2.107128	4.491744	3.17874
5	7.565355	21.21599	8.087399	6.141736	9.206124	0.695413	2.080676	1.261567	2.546977
6	7.291614	21.60887	4.875538	8.922651	19.49495	0.544471	3.16578	0.686716	1.337104
7	2.408242	6.108521	0.673649	13.37827	47.08164	3.711921	8.978832	8.875718	0.199913
8	3.045415	4.976455	2.128802	14.11304	64.6321	3.760987	9.37836	21.37789	1.123647
9	14.42647	11.58515	5.954661	8.362626	47.92978	9.266215	5.510721	27.93314	7.216399
10	27.12282	10.98181	10.4544	1.516273	10.50442	5.778418	3.145245	25.12342	4.987505

TABLE 5: THE STANDARD DEVIATION FOR ALL HEALTHY SUBJECTS.

Granulaes	Ankle_X	Ankle_Y	Ankle_Z	Knee_X	Knee_Y	Knee_Z	Hip_X	Hip_Y	Hip_Z
1	4.179617	2.225749	0.579139	0.507114	3.750808	0.755727	0.178486	1.202612	0.70072
2	1.370369	2.439158	0.636302	0.511279	0.749603	0.327889	0.458376	2.071229	0.358651
3	0.606495	1.156761	0.336229	0.35384	0.911271	0.378926	0.50361	1.690398	0.553433
4	0.521789	0.897263	0.340601	0.294523	0.771404	0.185342	0.284331	1.133871	0.205498
5	0.333079	0.866893	0.641768	0.554376	0.902891	0.185636	0.205973	0.794516	0.405284
6	0.409774	1.82338	1.532289	1.259341	5.888229	0.688972	1.149816	0.854792	0.440733
7	2.093076	5.805785	0.575483	1.046951	9.555265	0.610116	1.728156	3.922808	0.142646
8	2.488194	3.04692	0.418844	0.870568	1.433029	1.300735	1.197968	3.257362	1.154783
9	4.153138	0.766587	1.699231	2.306491	9.797849	1.213738	0.884287	0.705054	1.575719
10	2.908763	0.28638	0.715629	1.51206	10.30601	2.095256	0.762906	2.023651	1.923425

Table 6 and Table 7 exhibit the mean and the standard deviation of the rule-based matrices, $P_{test}(x,y)$ for one selected patient.

TABLE 6: THE MEAN FOR A TEST SUBJECT.

Granulaes	Ankle_X	Ankle_Y	Ankle_Z	Knee_X	Knee_Y	Knee_Z	Hip_X	Hip_Y	Hip_Z
1	4.356108	6.044144	9.036641	12.5235	7.406666	10.36443	6.207975	31.57822	8.022157
2	0.566777	6.932463	6.041611	7.689864	14.05209	9.589763	2.186151	26.3736	2.350331
3	0.152859	12.11284	2.269715	7.423286	12.29336	10.79869	0.392358	17.67529	1.555869
4	0.03671	14.10993	0.458315	8.052794	6.981057	10.4079	1.055037	11.02769	2.347615
5	0.121723	15.96797	0.055302	8.765877	1.593343	10.36766	2.462247	5.299733	3.361318
6	2.298926	20.57287	2.068178	7.50852	2.889965	9.631385	4.002362	0.74017	3.909261
7	9.644911	17.4522	6.213323	3.425637	22.84708	8.659209	7.365271	4.340107	7.082089
8	11.62873	1.726422	4.867162	0.477077	55.60321	12.051	11.9019	21.41574	9.553732
9	10.81838	3.83863	5.209755	3.853975	61.96157	9.282655	9.964428	35.28898	8.66519
10	7.211708	8.671237	8.413123	13.224	35.04962	1.678123	8.679505	38.55191	4.179356

TABLE 7: THE STANDARD DEVIATION FOR A TEST SUBJECT.

Granulaes	Ankle_X	Ankle_Y	Ankle_Z	Knee_X	Knee_Y	Knee_Z	Hip_X	Hip_Y	Hip_Z
1	1.491257	2.079412	0.252297	1.647277	2.002471	1.333609	1.117949	1.68829	0.638967
2	0.212414	2.487619	2.552101	0.956568	1.951786	0.623572	0.789698	2.109702	2.200417
3	0.139766	0.795367	0.76737	0.247921	1.526161	0.274763	0.41939	2.429768	0.613001
4	0.027567	0.490719	0.34538	0.094458	1.75305	0.375906	0.363548	1.822418	0.774663
5	0.130514	0.758375	0.064864	0.237014	1.348234	0.447778	0.511288	1.727948	0.373296
6	1.508126	1.802189	1.403899	1.06136	2.691235	0.067222	0.429182	0.777101	0.931482
7	2.271335	4.867654	0.642152	1.161695	9.819439	0.534284	1.805975	3.678276	0.63252
8	0.372935	2.219596	0.649896	0.499347	7.717478	1.758857	0.502401	5.406532	0.92537
9	0.808318	1.698507	1.01059	2.640967	3.893749	3.818935	0.618515	2.959156	1.991187
10	1.023357	0.975827	0.52347	2.216482	11.66722	1.69958	0.30838	1.215825	0.90214

A comparison between the reference and test subjects was achieved using Fuzzy similarity algorithm. Table 8 and Table 9 show the mean and the standard deviation similarity between $P_{ref}(x,y)$ and $P_{test}(x,y)$ for healthy reference subjects and abnormal test subject respectively and the grade of similarity between them.

TABLE 8: FUZZY SIMILARITY BETWEEN MEAN OF HEALTHY SUBJECTS AND A TEST SUBJECT.

Granulaes	Ankle_X	Ankle_Y	Ankle_Z	Knee_X	Knee_Y	Knee_Z	Hip_X	Hip_Y	Hip_Z
1	0.192465	0.870833	0.920679	0.059149	0.808038	0.274019	0.260066	0.65551	0.492645
2	0.040902	0.740582	0.488179	0.316102	0.990725	0.060911	0.264327	0.592706	0.376823
3	0.01399	0.804356	0.21057	0.50841	0.965608	0.079833	0.662576	0.510727	0.335898
4	0.004035	0.769457	0.048386	0.595735	0.711924	0.018038	0.500699	0.407315	0.738536
5	0.016089	0.752639	0.006838	0.700641	0.173074	0.067075	0.845031	0.238043	0.757731
6	0.315284	0.952057	0.424195	0.841512	0.148242	0.056531	0.790978	0.927781	0.342035
7	0.24969	0.350014	0.10842	0.25606	0.485265	0.428667	0.820293	0.488987	0.028228
8	0.261887	0.346918	0.437381	0.033804	0.860303	0.312089	0.787972	0.998233	0.117613
9	0.749898	0.331341	0.874904	0.460857	0.77354	0.998229	0.553039	0.791554	0.832803
10	0.265891	0.7896	0.804745	0.114661	0.299701	0.290412	0.362376	0.651678	0.837965

TABLE 9: FUZZY SIMILARITY BETWEEN STANDARD DEVIATION OF HEALTHY SUBJECTS AND A TEST SUBJECT.

Granulaes	Ankle_X	Ankle_Y	Ankle_Z	Knee_X	Knee_Y	Knee_Z	Hip_X	Hip_Y	Hip_Z
1	0.356793	0.934253	0.435641	0.30785	0.533877	0.566678	0.159654	0.712325	0.911873
2	0.155005	0.980519	0.249325	0.534493	0.38406	0.525824	0.580445	0.981764	0.162992
3	0.230448	0.687581	0.438158	0.70066	0.5971	0.72511	0.832768	0.695704	0.902826
4	0.052832	0.546906	0.986164	0.320716	0.440035	0.493053	0.7821	0.622179	0.265274
5	0.39184	0.87482	0.101071	0.427532	0.669684	0.414571	0.40285	0.459803	0.921073
6	0.271711	0.988378	0.916211	0.842791	0.457053	0.097568	0.373262	0.90911	0.473153
7	0.921518	0.838414	0.89618	0.901227	0.973097	0.875709	0.95691	0.937664	0.225519
8	0.149882	0.728472	0.644479	0.573587	0.185686	0.739534	0.419378	0.602487	0.801337
9	0.194628	0.45133	0.594734	0.873351	0.397409	0.317821	0.69945	0.238262	0.791347
10	0.351818	0.293474	0.731482	0.682189	0.88333	0.811156	0.404218	0.600808	0.469028

The overall similarity of the mean and standard deviation between $P_{ref}(x,y)$ and $P_{test}(x,y)$ was calculated using Fuzzy inference system explained in section 2. Table 10 shows the overall similarity grades.

TABLE 10: OVERALL SIMILARITY GRADES BETWEEN HEALTHY SUBJECTS AND A TEST SUBJECT.

Granulaes	Ankle_X	Ankle_Y	Ankle_Z	Knee_X	Knee_Y	Knee_Z	Hip_X	Hip_Y	Hip_Z
1	0.41663	0.867968	0.565431	0.166415	0.673357	0.341263	0.460212	0.58478	0.660122
2	0.118408	0.824504	0.346952	0.547272	0.496405	0.411921	0.377927	0.731562	0.509585
3	0.351215	0.569733	0.318903	0.584703	0.622149	0.285968	0.594437	0.522998	0.505832
4	0.232177	0.600813	0.637602	0.384809	0.421449	0.199792	0.709088	0.554288	0.520301
5	0.312303	0.764381	0.219799	0.64111	0.536677	0.460476	0.662773	0.374628	0.814421
6	0.248813	0.842899	0.460675	0.800232	0.211217	0.137029	0.53762	0.940561	0.380317
7	0.551942	0.55568	0.372576	0.48583	0.752055	0.441095	0.857302	0.527243	0.214551
8	0.316867	0.468989	0.467665	0.51056	0.411176	0.677626	0.57402	0.564915	0.372075
9	0.595552	0.535535	0.577819	0.715721	0.527799	0.49363	0.627856	0.664489	0.657702
10	0.476946	0.375315	0.81958	0.451285	0.661124	0.66615	0.486246	0.567713	0.486971

The aggregated joint angle similarity between the referenced joint angles of healthy subjects and the selected patient is calculated as a linear combination of the corresponding sub granules joint angle similarities. The aggregated angle of ankle, Knee and Hip Similarity is computed as the following:

$$Joint\ Angle\ Similarity\ = \sum_{i=1}^{10} w_i \times granule\ similarity\ _i$$

$$where \qquad \sum_{i=1}^{10} w_i = 1$$

The weights control the importance of the sub joint angle similarities. In case of equally importance, the weights will have the value 1/10.

The final similarity value is represented by 3 levels whose values are labeled as: *Level 1* = “Normal,” *Level 2* = “Close to normal,” and *Level 3* = “Abnormal”.

Table 11 shows the classification of the test subject for all joint angles. Where,

- *Level 1*: score from 0.75 to 1 represents “Normal”.
- *Level 2*: score from 0.0.6 to 0.75 represents “Close to normal”.
- *Level 3*: score from 0.00 to 0.6 represents “Abnormal”.

TABLE 11: CLASSIFICATION ACCORDING TO SIMILARITY OF A TEST SUBJECT.

	Similarity Measurement	Classification
Ankle_X	0.362085	Abnormal
Ankle_Y	0.640582	Close to normal
Ankle_Z	0.4787	Abnormal
Knee_X	0.528794	Abnormal
Knee_Y	0.531341	Abnormal
Knee_Z	0.411495	Abnormal
Hip_X	0.588748	Abnormal
Hip_Y	0.603318	Close to normal
Hip_Z	0.512188	Abnormal

The physician checked whether the patient is similar to the index patient or not. Then the physician assigned the similarity in a numerical score between 1 and 3 to show the strength of similarity. Where 1 = 'Low Similarity,' 2 = 'Moderate Similarity,' and 3 = 'High Similarity.' The similarity results generated by the physicians are shown in Table 12.

TABLE 12: CLASSIFICATION OF PHYSICIAN ACCORDING TO SIMILARITY OF A TEST SUBJECT.

	Similarity Level	**Classification**
Ankle_X	1	Abnormal
Ankle_Y	2	Close to normal
Ankle_Z	1	Abnormal
Knee_X	1	Abnormal
Knee_Y	1	Abnormal
Knee_Z	1	Abnormal
Hip_X	2	Close to normal
Hip_Y	2	Close to normal
Hip_Z	1	Abnormal

3.4 Result Analysis

This section examines the agreement between the scores generated by the developed algorithm and those by the physicians. In this research, we used Kappa statistic to give the agreement between physicians and the system. A Kappa score ranges between 1 which shows full agreement and 0 which shows no agreement. In the literature there is no consensus about the interpretation of Kappa. There is excellent agreement if the Kappa coefficient is greater than 0.75, poor agreement for Kappa coefficient less than 0.4, and fair to good agreement for kappa coefficient between 0.40 and 0.75 as shown in Table 13.

Table 14 summarizes the number of matches between the decision of the system and the physicians.

TABLE 13. INTERPRETATION OF KAPPA.

Kappa	**Agreement**
< 0.45	Poor Agreement
0.45 - 0.75	Fair Agreement
> 0.75	Excellent Agreement

TABLE 14.CONFUSION MATRIX OF SYSTEM BY PHYSICIAN

		Physician			
	Frequency	**1**	**2**	**3**	**Total**
Developed System	**1**	6	1	0	7
	2	0	2	0	2
	3	0	0	0	0
	Total	6	3	0	9

The estimate of agreements is as follows: Kappa = 0.7573 for physician and the developed system. These coefficients suggest excellent agreement between the system and the physicians. The asymptotic standard error (ASE) is also computed, as well as 95% confidence bounds. Those values are computed using Weighted Kappa which considers disagreement close to the diagonals less heavily than disagreement further away from the diagonals. The simple Kappa is also provided. The results of these two methods are shown in Table 15.

TABLE 15. KAPPA STATISTICS BETWEEN PHYSICIAN VS. DEVELOPED SYSTEM.

Kappa Statistics between Physician 1 vs. MAS System

Statistic	Value	ASE	95% Confidence Limits	
Simple Kappa	0.7573	0.2425	0.2425	1
Weighted Kappa	**0.7573**	0.2474	0.2425	1

In view of these results, a quantitative assessment of the neurological state of the subject can be evaluated. This algorithm may serve as an assessment tool for clinician and doctors to gain substantial insight into the neurological state of joint angle and evaluate the outcomes of surgery and/or therapy. This study demonstrates an efficient method of joint angle characterization utilizing wearable sensors through building and comparing the reference rule-base of healthy subjects with an input rule-base of impaired subjects using a fuzzy similarity algorithm.

IV. Conclusion

In this paper, fuzzy assessment model has been developed to analyze and classify three joint angles in 3D, Ankle, Knee, and Hip. Fuzzy granulation and Fuzzy similarity algorithms were implemented in the system. Experiments were performed and a comparison between healthy subjects and patients were achieved. The results were evaluated by a physician and Kappa statistics were used and demonstrated an excellent agreement between the physician and the developed system.

The proposed system has a potential application in the rehabilitation process. It presents an automated tool to detect and evaluate abnormality in human movement. Physicians and clinicians benefit from this tool in the diagnosis and assessment of functional impairments in human locomotion.

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