Fuzzy-Rough based Decision System for Gait adopting Instance Selection

Abhishek Jhawar*, Chee Seng Chan*, Dorothy Monekosso† and Paolo Remagnino‡
*Centre of Image and Signal Processing, Faculty of Computer Science and Information Technology
University of Malaya, 50603 Kuala Lumpur, Malaysia
Email: {abhishek.jhawar;cs.chan}@um.edu.my
†AET, School of Computing, Leeds Beckett University, Leeds , UK
Email: d.n.monekosso@leedsbeckett.ac.uk
‡Robot Vision Team, Faculty of Science, Engineering and Computing, Kingston University, London, UK
Email: p.remagnino@kingston.ac.uk

***Abstract*—A fuzzy rough set theory based gait decision system is presented for diagnosis of fall risk. Distracted walking is investigated. Gait cycles of thirty young participants were monitored while they walked across a walkway at a self-selected pace and also while being distracted by performing a task alongside walking. Results shows distracted walking being similar to impaired walking of an elderly person. The aim is to adopt instance selection methods to eliminate redundant or noisy sample from training data thus preventing the system from detecting erroneous gait patterns or deviations. Decision systems have great potential in medical informatics to serve as diagnostic tools. Results show that instance selection improves the efficacy of various classifiers in detecting distracted gait. The model is capable of assessing gait based on the easily obtainable features and categorizing them in terms of fall risk. This will help to identify individuals at risk in fall prevention management.**

I. Introduction

Falls are a common cause for injury and account for over one million emergency room cases each year across the globe. The medical cost of falls is estimated at 70 billion dollars each year. The lasting effects of a fall are wide ranging, and includes personal, social and economic effects [16]. Falls occur in all population groups but older adults are a group more prone to falling due to a combination of factors. With the boom in the aging population, falls is becoming more threatening than ever. Apart from the aging community, another emerging cause of falls is 'Distracted walking'. This has seen a rapid increase in recent years with the use of mobile technology, such as smart phone, while on the move in public areas such as roads; having divided attention most of the time. The National Safety Council has now officially stated 'distracted walking' as a separate category in its injury report.

Walking is a key measure of a person's mobility. Walking may seem autonomous but is not a completely automated task. It requires cognitive, executive and motor abilities [22]. Coordinating multiple tasks such as using a mobile device while walking down a busy public street requires the brain to continuously allocate and re-allocate the required attention to each task at hand. With constant shuffling between the primary and secondary task, the selective attention allocation meets irrelevant distractors, leading to deterioration of control transfer [5]. Not much data on cognitive processes during walking is available, due to the difficulty to assess neuronal activity [6]. Studies have shed light on distracted driving [18] but distracted walking is yet to be well explored.

The causes of falls can be intrinsic dealing with one's individual body or extrinsic as in one's environment. Surroundings and physical wellness of a person determine the risk of falling. Fall risk increases as the number of factors accumulates. Fall risk factors can arise from lack of fitness, attention or some medical condition. A fall can be an indicator of weakness in lower extremity, strain in balance, poor gait, improper vision or cognitive load. Identifying and analyzing risk factors are part of a fall prevention management. Fall prevention can be approached strategically by first identifying people at high risk of falling and then following it up by pinpointing individual factors via detailed assessment. The identified risk factors can then be intervened and managed to reduce the fall risk.

Gait patterns are indicator of fall risks. Human gait patterns was analyzed by [19] but only limited to three subjects whereas [10] evaluated gait for hemaphlic conditions. Logistic regression was used by [14] to predict fall risk in the geriatric patients while Hidden Markov model was used in [13] for gait analysis. A recent study [11] looks at the changes in gait pattern during distraction but the tasks involved are challenge completion tasks. This paper presents work on the distortion produced in the gait, resulting from reduced attention while casually walking. The primary spatial and temporal features are extracted and used in decision making system for fall risk arising from distraction. Set theory with fuzzy rough concept is employed with instance selection to reduce irrelevant samples from training. In particular, instance selection uses the spread measure rather than the range to incorporate the inconstancy of gait.

II. Distracted Gait Analysis

Gait analysis forms a crucial part in any fall risk assessment. Gait is the term used to describe the way one walks or moves. Being bipedal is a marked trait of human [20]. Walking and running are characterized by different gait. Here, we recap the gait cycle and it phases during walking as seen in Fig.1.

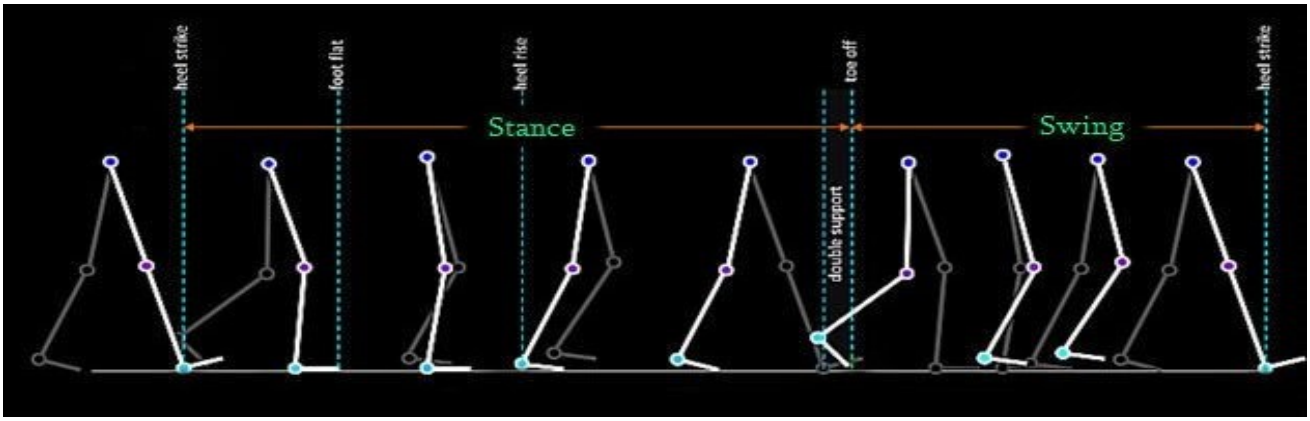

Fig. 1: Gait cycle and its phases during walking

A. Gait Recap

Walking is a continuous sequence of steps. Each step propels the entire body in the direction of motion. Two continuous steps is representative of a stride and is refereed to as a gait cycle. The pattern of gait is repetitive and cyclic in nature [12]. It begins when a foot touches the ground and continues till the same foot comes in contact to the ground again. A complete gait cycle can be split in two phases: stance phase and swing phase. Stance phase is seen to last for approximately 60% of the gait cycle and the remaining 40% makes up the swing phase. Stance phase begins with the heel strike of a limb and ends with its toe off movement whereas swing phase outsets with the toe off of the limb and terminates at the heel strike.

The heel making initial contact with the ground is termed as heel strike and is the beginning of stance phase. This is followed by foot flat where the foot is entirely flat on the ground plane ready to take on the load of the entire body. Heel rise follows where the heel leaves the ground, shifting the body weight to the other limb. The stance phase ends with toe off movement where the toe leaves the ground propelling the body forward and entering the swing phase. Double support is the time when both the limbs are in contact to the ground and the body transits from stance to swing phase.

B. Data Collection

For the data collection, thirty young healthy participants were recruited and consent sought to record their gait while walking under two different conditions. The data was collected with a video-based motion capture system. Reflective markers were attached to the person's body to assist the motion cameras to gather the lower limb movements. The areas of interest were the heel, toe, knee and hip. All participants were familiar with technology and had ample experience of using smart devices in everyday life. In a controlled environment with the motion capture system, each participant walked across a walkway.

Each subject's gait was recorded as he/she walked to and fro across the walkway at their regular pace. Soon after, each participant was sent a set of questions via electronic mail. They had to respond back using their smartphones, while continuing to walk. They were free to search the internet for the answers. No restrictions were in place except one and that is to be in locomotion. The subject had to walk across the walkway while responding back as standing still was not allowed. The motion capture system was used to record this walk as well. Every participant rated their comfort of smart device usage while walking on a scale of 1 to 10.

C. Distortion Caused

Distraction means any cognitive task not relevant to walking. A cognitive task interferes with attention allocation regime as it has high requirements for information processing [9]. The person needs to compensate for the simultaneous execution of secondary tasks. A controlled environment with sufficient measures do not reveal the extent of risk. Risk of falling is expected to be more pronounced in real environment.

The discrepancies in gait of individuals arising due to distraction was seen to be worrisome. Geriatrics found some of the distracted walking data very similar to that of an elderly with impaired walking. In the typical scenario of today's world where usage of smartdevices while walking is habitual [3], distraction among commuters is on the rise. Safety is compromised and even gait is impaired.

The reflective markers used in data collection provided the position of the joints over time. Gradient descent method was used to detect steps. The gait obtained from the participants casual walk is referred here as 'Normal Gait' or NG. The recording of the walk while responding back gives the 'Distracted Gait' or DG. Over 1300 gait cycles were analyzed. The avg. timeframe for gait in NG was clocked as 1.07 sec and 1.27 sec for DG. The gait cycle was seen to be divided into 63% stance phase and 37% in both cases but the time constituting the phases differed. Stance phase was observed to last for 0.67 sec and 0.80 sec for NG and DG respectively.

Swing phase lasted for 0.40 sec in case of NG and 0.47 sec for DG. It is interesting to note that 65% of the prolonged time of 20 sec for DG is spent in stance phase trying to find the body stability. Fig.2 shows the positional movements of the heel, knee and toe. Clearance of both heel and toe is seen to fall by 2 cm making the foot transit closer to the ground

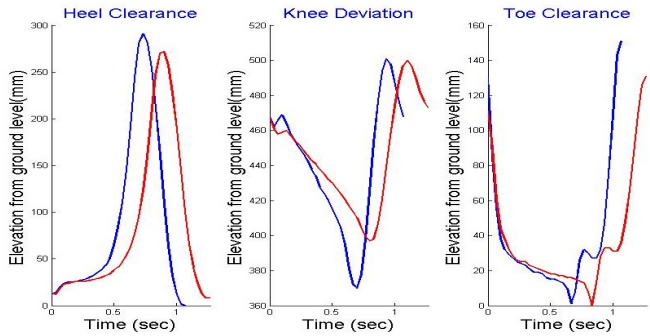

Fig. 2: Positional movement of the joints

surface. A shrinkage effect on the knee's vertical motion is seen along with the curb in its angular motion.

Detailed analysis shows that the distortion in gait produced by distraction has a negative impact of gait. The person becomes more vulnerable to falls. Variability in gait parameters are indicative of risk falls. Capturing subtle variations in it is a key indicator of health risk and safety. Here, we use fuzzy rough concept to design a decision system to factor in the discrepancies in gait arising due to distraction.

III. Fuzzy Rough Instance Selection

A. Set Theory Preliminary

Set theory is the foundation of mathematics. The notion is a core binary relationship between an element and a set. If the element belongs to a set, a membership relation of 1 is established, otherwise 0. Fuzzy set theory and rough set theory are variations of set theory using the classical logic but a non-binary membership relation.

1) Fuzzy Set Theory: Lofti Zadeh introduced fuzziness in set theory [23] dealing with concept of vagueness. In this approach, an element has a degree of belongingness to a set in particular, d ($0 \leq$ d ≤ 1) . The values range from 0 to 1 instead of just being 0 or 1. When X is a set and y is an element, the fuzzy membership function is represented as:

$$\mu_X(y) \in < 0, 1 >$$

The membership of the elements upon union and intersection of two sets is evaluated by its membership to constituent sets and has the following properties:

$$\mu_{X \cup Y}(y) = max(\mu_X(y), \mu_Y(y))$$
$$\mu_{X \cap Y}(y) = min(\mu_X(y), \mu_Y(y))$$

2) Rough Set Theory: Rough sets was introduced by Pawlak, providing the concept of indiscernibility [15]. In this approach, the impreciseness of the data is represented with the help of boundary regions, lower and upper approximations. In an information system (I, A) where I and A is a set of objects and attributes, for each subset Z of A, the indiscernibility relation is defined by using an equivalence relation, R_Z.

The lower approximation of J $\subseteq$ I w.r.t R_Z is given by

$$R_Z \downarrow J = i \in I \mid [i]R_Z \subseteq J$$

and the upper approximation of J $\subseteq$ I w.r.t R_Z is given by

$$R_Z \uparrow J = i \in I \mid [i]R_Z \cap J \neq \emptyset$$

The boundary region of J is: $R_Z \uparrow J - R_Z \downarrow J$

Lower approximation contains objects that has strong membership values and guarantees to meet the concept, while upper approximation has objects with weak membership which have a probability of belonging to the concept.

3) Fuzzy Rough Set Theory: Fuzzy and rough set theory were merged and bought to limelight by Dubois and Prade [4]. This hybridization lead to a fuzzified boundary regions, modeling imperfect knowledge. The concept of generalized fuzzy rough sets are as follows:

If U is an universal set with a fuzzy relation R and F(U) a fuzzy power set of the universal set U, then $(R \uparrow X, R \downarrow X)$ represents a fuzzy rough set on U such that for every $x \in U$

$$(R \downarrow X)(x) = \wedge_{y \in U}((1 - R(x, y)) \vee X(y) \quad (1)$$

$$(R \uparrow X)(x) = \vee_{y \in U}(R(x, y) \wedge X(y)) \quad (2)$$

In a classic example of age where classes are defined by age range[10-20],[20-30],.. a person celebrating his /her twenty-first birthday will not be considered in the [10-20] class, even though a little reduction will grant him /her full sanction to the class. This is taken care by the fuzzy relation R, which allows progressive transition amidst classes rather than crisp, inline with intuitive thinking.

B. Instance Selection

With the amount of data increasing day by day, the time taken to process them to extract relevant information is also increasing along with the cost. Being able to shed out the irrelevant data and retain the information is of central importance in the field of practical applications. This can be achieved by doing data reduction, commonly accomplished by dimensionality reduction or feature selection [17]. Popular dimensionality reduction techniques like principal component analysis [1] combines the features based on correlation, and produces a compact representation of them. Linear dependencies among attributes are captured and attribute space compressed. Feature selection downsizes the data column-wise eliminating unwanted or redundant features.

Another data reduction method is instance selection [7], which is row-wise. This is particularly useful in handling noisy values, superfluous instances in the data. It is an effective way of reducing training samples in supervised learning while still having the essential information. This decreases the time for learning process and also prevents the system from concluding any spurious patterns in the data. Reduction of data not only helps in improved visualization but also brings out a better understandable model. The aim here is to remove noisy, inconsistent instances in the training set. We adopt fuzzy rough set theory [2] to achieve the purpose as it can deal with both vagueness and indiscernibility of the data. Also unlike rough sets, fuzzy rough sets do not need discretization of data.

C. Method

Given an information system (U,A), in the form of decision table, for any B $\subseteq$ A, an equivalence relation R_B is given by

$$R_B(x,y) = \{(x,y) \in U^2 \mid \forall a \in B, a(x) = a(y) \quad (3)$$

The relation R is then transformed to a fuzzy τ-equivalence relation by satisfying the conditions as in equations 4-6,

$$\forall x \in U, R(x,x) = 1 \quad (4)$$

$$\forall x, y \in U, R(x,y) = R(y,x) \quad (5)$$

$$\forall x, y, z \in U, \tau(R(x,y), R(y,z)) \leq R(x,z) \quad (6)$$

The indiscernibility model [8] is next attained for expressing the approximate equality between objects x and y on a quantitative attribute 'a' with range l(a) in the training set by

$$R_a^{\alpha}(x,y) = max(0, 1 - \alpha \frac{|a(x) - a(y)|}{l(a)}) \quad (7)$$

where α parameter determines the granularity of R_a^{α}.

The fuzzy B-lower approximation of the information system is characterized by

$$(R_B \downarrow A)(y) = inf_{x \in U} \tau(R_B(x,y), A(x)) \quad (8)$$

and the union of it for all classes will make the positive region.

The fuzzy B-positive region for the decisive attribute 'd' , y in X is defined as

$$POS_B^{\alpha,X}(y) = (R_B^{\alpha} \downarrow^X R_d^{\alpha} y)(y) \quad (9)$$

Algorithm: Given the input I(X, α, τ) for fuzzy rough instance selection the output expected is Z.
where, X is a training set, n instances;
α is the parameter of granularity;
τ is the threshold for selection;
Z is a reduced set, m instances

Step 1: Y $\leftarrow \emptyset$

Step 2: For each x $\in$ X

$$\text{if} \quad POX_B^{\alpha,X}(x) < \tau$$

$$\text{then} \quad Y \leftarrow Y \cup (x)$$

Step 3: Z $\leftarrow X \setminus Y$

The reduced training set is such that $Z \subset X$, $m \leq n$.

D. Similarity Measure

Similarity measure is used to estimate how similar two objects are. There is no single definition that defines similarity. Generally distance metrics are used for evaluation of similarity. Unlike [8], the approximate equality in this paper makes uses of equation 10 for its indiscernibility model.

$$max(min(\frac{a(y) - (a(x) - \sigma(a))}{a(x) - (a(x) - \sigma(a))}, \frac{(a(x) + \sigma(a)) - a(y)}{(a(x) + \sigma(a)) - a(x)}), 0) \quad (10)$$

The spread measure, σ used here is much more suited to handle the variability in gait. The input for instance selection is in the form of decision table consisting of conditional and decision attributes. Here we have five conditional attributes which are the extracted gait features and one decision attribute which is the type of gait.

IV. Decision System for Gait

In the realm of artificial intelligence where machines are to become an integral part of the real world, binary logic crumbles. Intelligent machines need to decide on the basis of its environment and input, where a high degree of uncertainty exists. We propose a decision system for distracted gait detection. The system decides whether the gait of an individual is normal or distracted. The framework of the decision system based on fuzzy rough dealing with gait is shown in Fig.3.

A. Data

Gait cycles of an individual were averaged using time series model and 326 different gaits were considered. This captured the intra-variability for an individual. A person's gait is cyclic in nature. But while walking, the components of various gait cycles of an individual is not exactly the same. Possibly, if one's gait cycle is same every time he /she steps, one is a robot. The selected gaits were classified as distracted gait (DG) or normal gait (NG). The candidates comfort factor with the usage of smart devices while walking was also taken into consideration. The gaits with low comfort factor where eliminated leaving us with 292 samples.

B. Gait Feature Extraction

The objective is to learn and identity irregular gait from the given feature space. Only standard temporal-spatial features were considered. For each gait, five features created our feature vector space. These include step length, left stride length, right stride length, speed and cadence.

1) Step length: The distance covered in the interval of two consecutive steps. Heel strike is an indicator of step. (in mm)
2) Left stride length: Stance and swing phase of the left limb decides the left stride length in terms of distance traveled. (in mm)
3) Right stride length: Distance covered by the right limb in two consecutive heel strikes. (in mm)
4) Speed: The rate of movement by the person. It is the distance traveled per unit of time. (m/s)
5) Cadence: The total number of steps taken in minute.

From the given raw data of motion capture, the above features were extracted based on step detection using gradient descent method.

C. Processed Data

Table I gives the statistical parameters of the dataset. Both classes NG and DG have their own description for each features separately where as the one in bold is the aggregate statistical description of the feature for the entire dataset. As

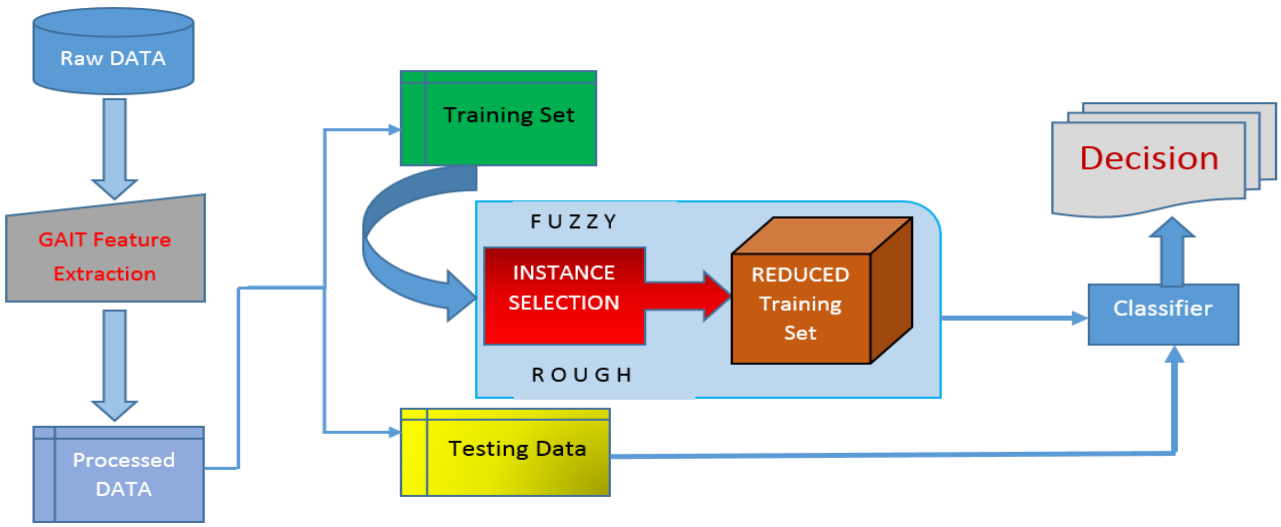

Fig. 3: Framework for Decision System for Gait.

Gait Feature		Dataset Statistical Description						
	Minimum	Maximum	Mean	Std. Dev.	Coeff. Var.	Lower Quartile	Upper Quartile	Quartile Range
(NG)	576.37	808.75	708.57	51.10	7.21	676.50	751.33	74.83
Step Length	**479.16**	**808.75**	**653.96**	**81.79**	**12.50**	**583.00**	**722.91**	**139.91**
(DG)	479.16	772.20	599.36	69.34	11.57	560.87	618.57	57.69
(NG)	1163.66	1695.00	1432.49	104.52	7.29	1367.00	1519.50	152.50
Left Stride	**958.33**	**1695.00**	**1318.65**	**168.83**	**12.80**	**1167.50**	**1473.75**	**306.25**
(DG)	958.33	1535.50	1204.81	142.07	11.79	1117.50	1453.66	136.16
(NG)	1152.75	1617.50	1422.18	104.00	7.31	1351.33	1508.00	156.66
Right Stride	**973.00**	**1617.50**	**1313.94**	**163.50**	**12.44**	**1175.33**	**1451.50**	**276.16**
(DG)	973.00	1557.50	1205.70	138.72	11.50	1121.66	1255.66	134.00
(NG)	0.94	1.79	1.29	0.19	14.74	1.19	1.36	0.16
Speed	**0.49**	**1.79**	**1.12**	**0.26**	**23.41**	**0.95**	**1.29**	**0.33**
(DG)	0.49	1.34	0.95	0.20	21.99	0.80	1.13	0.32
(NG)	94.03	140.62	109.34	11.53	10.54	102.85	111.34	8.48
Cadence	**62.30**	**140.62**	**102.04**	**15.08**	**14.77**	**94.73**	**109.75**	**15.01**
(DG)	62.30	126.00	94.73	14.70	15.51	86.40	103.84	17.44

TABLE I: Statistical features of the gait dataset.

expected, distracted gait has a lower range of value and higher standard deviation than normal gait. The chaos for classification of gait into distracted and normal lies in the overlapping middle ranges as the lower extreme of the data contributes more towards distracted gait while the upper extreme tend to belong to the normal gait.

The statistical parameters for the dataset were calculated for the each class and the entire sample separately using the following:

1) Minimum: $min(x_i)$ gives the smallest value in the given sample.
2) Maximum: $max(x_i)$ picks the greatest value in the sample available.
3) Mean: $\frac{\sum(x_i)}{N}$ provides with the popular measure of central tendency. It is the arithmetic average of the sample values.
4) Std.Deviation: $\sqrt{\frac{\sum(x_i - Mean)^2}{N-1}}$ is the measure of spread in the dataset, given by square rooting its variance.
5) Coeff.Variance: $Std.Deviation/Mean$ is useful to compare the degree of variation from one dataset series to another, better known as relative std. deviation.
6) Lower Quartile: $(\frac{N+1}{4})^{th}$ term of the data when arranged in ascending order. It divides the lower half of the data into two halves.
7) Upper Quartile: $(\frac{3(N+1)}{4})^{th}$ term of the data when arranged in ascending order. The upper half of the data

is divided into two.

8) Quartile Range: $UpperQuartile - LowerQuartile$ provides with the measure of dispersion in the samples.

D. Training and Testing

Human gait is a voluntary process but regulated by central pattern generator neurons [21]. The gait of an individual is not constant all the time. Expert systems can assist clinicians and specialists to cope with the variability of patterns. To avoid performance of the system from being biased, the testing samples are different from the training samples. Approximately 30% of the data samples are randomly selected for testing purposes each time. The training set consists of 204 samples while 88 are there for testing.

Table II describes the initial training set. The initial training set then goes through fuzzy rough based instance selection. In this process, a subset of the instances is chosen for training purposes. Each instance obtains a fuzzy positive region membership based on the method described above. Any instance falling below the threshold, τ is discarded. Storage and time requirements are reduced. Table IV shows the reduced model size. The model size reduction is based and varies with the uniqueness of the data.

Since large variability exists in the gait patterns, it is important to remove noisy samples which exist and overlap in the data. Eliminating them will prevent the system from picking up spurious patterns which lead to misclassification. The reduced training set consisted of 100 samples. Table III illustrates the reduced training set. Lower measures in the mean parameter of spatial features of step and stride were noticed, whereas temporal features, like speed and cadence, show rise in values. The spread, variance and range were seen to increase across all features.

E. Classifiers and Evaluation

A decision table was built with instances construed by their attributes. Using this table, classifiers are employed to build a model and try to predict the decisional attribute of any new instance with conditional attributes fed to the system. Experiments were conducted over the gait dataset with variety of classifiers using instance selection. For instance, Bayesian Network(Bayes Net) which is a probabilistic graphical model, Support Vector Machine (SVM) that formulates separating borders and K-Nearest Neighbour (KNN) where closest neighbour wins. A leader-follower classifier which learns rapidly: Fuzzy Lattice Reasoning (FLR), a decision tree learner J48 and Random Forest (RF) which is an ensemble learner also forms the part of experiment. Table V shows the classification performance of the classifiers in terms of accuracy and ROC.

Looking at the above results, the reader can notice that accuracy of Bayes Net and KNN are not affected by instance selection but there is a slight drop in the ROC in case of KNN. SVM and FLR see a rise in accuracy as well as the ROC. It is interesting to observe that J48 and Random forest witness an increase in overall accuracy but at the same time suffer a drop in the ROC. Results show that the accuracy of classification is either retained or increased by adopting an instance selection method. Over-fitting during training is avoided. The sensitivity is seen to have improved among classifiers, which serves the purpose. It is more important for us to accurately detect an irregular gait than a normal gait because misclassifying a normal gait is not as critical as a distracted gait.

V. Conclusion

This paper presents a decision system for distracted gait identification by using fuzzy rough instance selection. The use of fuzzy rough concept helps dealing with vagueness and incompleteness. It is to consider any gait pattern generation allowing for a better discrimination between irregular and normal gait. It is seen from the results that instance selection helps the system to deal with noisy instances. Computer aided diagnostic systems are of particular interest to medical informatics. Automated methods to detect changes in gait will benefit many medical applications. Future work will focus on examining instance selection and exploring fuzzy rough based feature selection and classification techniques for a more robust and accurate decision system for gait. Our goal is to assess gait in everyday life to detect distracted gait and prevent falls as prevention of falls is much more beneficial than detecting falls. If cases of distracted gait can be automatically identified by an assistive technology implementing the proposed method, then health care costs can be cut and the risk of falling reduced.

Acknowledgment

This work was supported by MELoR, Malaysian Elders Longitudinal Research, under High Impact Research Grant, UM.C/625/1/HIR/MOHE/ASH/02, Malaysia.

References

[1] Bro, Rasmus, and Age K. Smilde. "Principal component analysis." Analytical Methods, 6.9 (2014): 2812-2831.

[2] Cornelis, Chris, Martine De Cock, and Anna Maria Radzikowska. "Fuzzy rough sets: from theory into practice." Handbook of Granular computing, (2008): 533-552.

[3] "Distracted walking: A serious issue for you, not me: Study on distracted walking perceptions, behaviors released." ScienceDaily. ScienceDaily, 02 December 2015. www.sciencedaily.com/releases/2015/12/151202132710.html.

[4] Dubois, Didier, and Henri Prade. "Rough fuzzy sets and fuzzy rough sets*." International Journal of General System, 17.2-3 (1990): 191-209.

[5] Ebersbach, Georg, Milan R. Dimitrijevic, and Werner Poewe. "Influence of concurrent tasks on gait: a dual-task approach." Perceptual and Motor Skills, 81.1 (1995): 107-113.

[6] Hamacher, Dennis, et al. "Brain activity during walking: a systematic review." Neuroscience Biobehavioral Reviews, 57 (2015): 310-327.

[7] Jankowski, Norbert, and Marek Grochowski. "Comparison of instances selection algorithms I. Algorithms survey." Artificial Intelligence and Soft Computing (ICAISC), 2004. 598-603.

[8] Jensen, Richard, and Chris Cornelis. "Fuzzy-rough instance selection."IEEE International Conference on Fuzzy Systems (FUZZ-IEEE), 2010.

[9] Kelly, Valerie E., Alexis J. Eusterbrock, and Anne Shumway-Cook. "Factors influencing dynamic prioritization during dual-task walking in healthy young adults." Gait and Posture, 37.1 (2013): 131-134.

[10] Lee, Hyo-Ki, et al. "Novel algorithm for the hemiplegic gait evaluation using a single 3-axis accelerometer.", Annual International Conference of the IEEE Engineering in Medicine and Biology Society, 2009.

[11] Licence, Sammy, et al. "Gait pattern alterations during walking, texting and walking and texting during cognitively distractive tasks while negotiating common pedestrian obstacles." PLoS One, 10.7 (2015): e0133281.

Gait Feature		Training Set (204 samples)						
	Minimum	Maximum	Mean	Std. Dev.	Coeff. Var.	Lower Quartile	Upper Quartile	Quartile Range
Step Length	479.88	808.75	653.78	80.81	12.36	586.60	724.90	138.30
Left Stride	968.00	1695.00	1319.47	167.57	12.70	1181.66	1473.75	292.08
Right Stride	975.75	1617.50	1313.70	160.97	12.25	1182.25	1449.75	267.50
Speed	0.49	1.79	1.11	0.25	23.20	0.96	1.29	0.33
Cadence	62.30	140.62	101.58	14.82	14.59	94.73	109.09	14.35

TABLE II: Details of training sample before instance selection.

Gait Feature		Training Set after Instance Selection (100 samples)						
	Minimum	Maximum	Mean	Std. Dev.	Coeff. Var.	Lower Quartile	Upper Quartile	Quartile Range
Step Length	479.88	808.75	643.62	97.06	15.08	562.67	743.25	180.57
Left Stride	968.00	1695.00	1298.52	198.34	15.27	1126.12	1496.25	370.12
Right Stride	975.75	1617.50	1297.00	194.79	15.01	1133.62	1507.41	373.79
Speed	0.49	1.79	1.12	0.34	30.41	0.84	1.34	0.50
Cadence	62.30	140.62	103.10	20.42	19.80	88.04	114.41	26.36

TABLE III: Details of training sample after instance selection.

Training Data	Samples	Features	Model Size
Unreduced	204	5	1020
Reduced	100	5	500

TABLE IV: Training model size.

Classifier	Accuracy%		ROC	
	Without IS	FRIS	Without IS	FRIS
Bayes Net	88.63	88.63	0.946	0.953
SVM	87.50	88.65	0.877	0.888
KNN	89.72	89.77	0.910	0.898
FLR	81.81	84.09	0.815	0.839
J48	88.63	90.90	0.952	0.910
RF	90.88	93.18	0.960	0.937

TABLE V: Classifiers performance.

[12] Loudon, Janice Kaye, Marcie Swift, and Stephania Bell. "The clinical orthopedic assessment guide." Human Kinetics, 2008, 395-408.

[13] Mannini, Andrea, Vincenzo Genovese, and Angelo Maria Sabatin. "On-line Decoding of Hidden Markov Models for Gait Event Detection Using Foot-Mounted Gyroscopes." IEEE Journal of Biomedical and Health Informatics, 18.4 (2014): 1122-1130.

[14] Marschollek, Michael, Anja Rehwald, Klaus-Hendrik Wolf, Matthias Gietzelt, Gerhard Nemitz, Hubertus zu Schwabedissen, and Mareike Schulze. "Sensors vs. experts-A performance comparison of sensor-based fall risk assessment vs. conventional assessment in a sample of geriatric patients." BMC Medical Informatics and Decision Making, 11 (2011): 48

[15] Pawlak, Zdzisaw. "Rough sets." International Journal of Computer and Information Sciences, 11.5 (1982): 341-356.

[16] Population ageing and sustainable development, United Nations, Department of Economic and Social Affairs, Population Division, January 2015, accessed. [Online]. Available: www.unpopulation.org

[17] Saeys, Yvan, Iaki Inza, and Pedro Larraaga. "A review of feature selection techniques in bioinformatics." Bioinformatics, 23.19 (2007): 2507-2517.

[18] Strayer, David L., and William A. Johnston. "Driven to distraction: Dual-task studies of simulated driving and conversing on a cellular telephone." Psychological Science, (2001): 462-466.

[19] Umemura, Koji, Koki Tachikawa, Yosuke Kurihara, and Kajiro Watanabe. "Analysis of human walking by 3-D acceleration sensor and its application." SICE Annual Conference, 2008.

[20] Vaughan, Christopher L. "Theories of bipedal walking: an odyssey." Journal of Biomechanics, 36.4 (2003): 513-523.

[21] Winters, Jack M., and Patrick E. Crago, eds. Biomechanics and neural control of posture and movement. Springer Science and Business Media, 2012.

[22] Yogev-Seligmann, Galit, Jeffrey M. Hausdorff, and Nir Giladi. "The role of executive function and attention in gait." Movement Disorders, 23.3 (2008): 329-342.

[23] Zadeh, Lotfi A. "Fuzzy sets." Information and Control, 8.3 (1965): 338-353.