Prediction of Elderly Falls Using the Degree of Cyclostationarity of Walk Pressure Signals

Reem Brome
Univ Lyon, UJM Saint Etienne
LASPI, EA 3059
F-42334, IUT de Roanne, France
reem.abou.marak.dit.brome@univ-st-etienne.fr

Jad Nasreddine
Computer & Information Systems Dep.
Rafik Hariri University
Meshref, Lebanon
nasreddinejn@rhu.edu.lb

Frédéric Bonnardot
Univ Lyon, UJM Saint Etienne
LASPI, EA 3059
F-42334, IUT de Roanne, France
frederic.bonnardot@univ-st-etienne.fr

Mohamad O. Diab
Electrical & Computer Engineering Dep.
Rafik Hariri University
Meshref, Lebanon
diabmo@rhu.edu.lb

Mohamed El Badaoui
Univ Lyon, UJM Saint Etienne
LASPI, EA 3059
F-42334, IUT de Roanne, France
mohamed.elbadaoui@univ-st-etienne.fr

***Abstract*—There is an increasing interest in developing older adult fall-risk prediction models that can be used as a preventive approach to predict future risk of falling in the elderly community. This study's primary objective is to implement and compare supervised machine-learning methods to classify elderly subjects as fallers or non-fallers. Features used for building the models were extracted from the pressure signals of the innersoles of 520 elderly people who reported whether they had experienced previous falls or not. Two different types of feature sets were used as inputs to the classification models and were compared. The first feature set includes ten time-domain features, while the second set includes a single cyclostationary property, which is the degree of cyclostationarity of the average walk pressure signal. Our study showed that the use of the degree of cyclostationarity as a single feature improved the model prediction accuracy by 6.58%, compared to the use of the time-domain features. The results obtained prove that cyclostationary features are essential features for the development of classification models for identifying fallers in the elderly community.**

***Index Terms*—ANOVA, classification models, cyclostationarity, degree of cyclostationarity, elderly people, fallers, machine learning, walk pressure signals**

I. Introduction

According to the World Health Organization's (WHO) facts sheet updated in January 2018, falls are considered the primary cause of accidental injuries leading up to deaths [1]. The WHO defines the case of falling as an event that results in an individual becoming at rest inadvertently on the ground, floor, or other lower levels. In some cases, injuries that are caused by falls could be fatal. Each year an estimated number of 646 thousand people worldwide die from inadvertent falls. Over 80% of fatalities caused by accidental falls belong to low and middle-income countries. Around 37.3 million fall cases require medical help and attention yearly. The most significant number of fatal falls involved older adults aged 65 years and above [1].

Rubenstein studied the risk factors for falls in elderly people [2]. Results in their study showed that some of these risk factors include, but are not limited to, being older than 80 years old, muscle weakness, arthritis, depression, previous falls, the use of several medications, the use of an assistive device, impairments in gait, balance, cognition, and vision. Most elderly falls result from a combination of multiple factors. They also stated that the significance of falls among elderly people is not limited to the fact that the frequency of occurrence of falls increases with old age, but also that the injury rate is highest among the oldest subjects who have a history of multiple previous falls. This leads to the unfortunate increase in the expenses of medical services and rehabilitation, but more importantly, it raises the likelihood of disabilities and fatalities [2].

Reducing the risk of elderly falls is significantly important from social and economical point of views. Therefore, prevention strategies should emphasize education, training, creating safer environments, establishing effective policies to lower susceptibility, and prioritizing elderly fall-related research [2]. In this context, there is increasing interest in the prediction of elderly falls to reduce its risk. Swanenburg, de Bruin, Uebelhart, Mulder [3] studied whether force plate variables can be used to predict multiple fallers though statistical analysis. They found that the amplitude of medial-lateral movements in single-task conditions was a significant independent predictor of elderly fallers, along with having a history of multiple falls [3]. Howcroft, Lemaire, Kofman, and McIlroy [4] found statistical significant differences in the static posturography measures between fallers and non-fallers. In this study, they investigated eyes open and eyes closed standing posturography with elderly adults and were able to identify differences and determine the measure cut-off scores for classifying prospective fallers, single-fallers, multi-fallers, and non-fallers [4]. Howcraft, Lemaire,and Kofman [5] also studied prediction of elderly falls using machine learning where their highest rank classification model achieved 65% accuracy and 59% sensitivity, with pressure-sensing-insole and left-shank-accelerometer as input features [5]. Pressure sensing insoles have been used thoughout the literature to predict or analyze chronic medical conditions and diseases in elderly people such as Parkinson's disease [6], dementia [7], and elderly falls [8].

Properties of cyclostationarity are used in modeling and analysis of gait and ground reaction force (GRF) signals [9] [10] [11]. Sabri et al. [9] proposed an alternative framework for the analysis of GRF signals, based on cyclostationary properties rather than the traditional use of signal processing methods, which assume statistically stationary signal characteristics. The proposed framework was able to model the periodicity of the signal statistics and showed improved results in demonstrating the development of runners' fatigue identification. Zakaria et al. investigated and exploited the Cyclostationary (CS) properties and indicators such as the cyclic autocorrelation function. Their work demonstrated that there is a significant difference in the cyclic autocorrelation of fallers and non-fallers [10].

Another indicator of cyclostationarity is the degree of cyclostationarity (DS) [12] [13]. In this paper we investigated the use of the degree of cyclostationarity as a single input to different classification algorithms to identify elderly people with falling risk. The developed classification models were compared to classification models using classical time-domain features. Three different walking conditions were considered in the classification models: normal walking (MS), walking while fluently naming animals (MF), and walking while counting backward from 50 (MD). The proposed model did not only improved the performance of the system but also reduced its complexity.

This paper is organized as follows. The model description section is subcategorized into the explanation of the dataset used for training the model, the Cyclostationarity properties used in the analysis of walking signals with light shed on the degree of cyclostationarity, using ANOVA for selecting ten best classical features for prediction of fallers and non-fallers, and the five different machine learning models used for classification. In section III, the results of the ANOVA tests and the classification models are presented and discussed. The paper is then concluded in section four, with a summary of findings, contributions, limitations, and future work.

II. Model Description

In this paper five different classification algorithms are used with two different feature sets and in three different walking conditions. Therefore a total of thirty classification models were implemented to classify elderly participants as fallers or non-fallers.

A. Database Description

The database used in this study is from the original series of the study by the LPE (Laboratoire de Physiologie de l'Exercice) [14] and CHU (Centre Hospitalo-Universitaire) of Jean Monnet St-Etienne University [15]. They recorded the innersole pressure signals of participants using The SMTEC electronic Foot switches system shown in Figure 1. A pair of innersoles (with different sizes) were fitted inside the subjects' shoes. Each innersole contains two independent foot switches placed at the heel and the toe and connected to a portable data logger worn at the waist. A pressure of above 40g/cm2 activates the sensors and defines the state of contact. The activation of the heal sensors defines the first contact, while the last contact corresponds to the time when the toe sensor goes off. According to the manufacturer, the data is sampled from foot-switches at 100 Hz, which allows a temporal resolution of 10 ms. The signals collected were processed using a software designed specifically for the task by SMTEC software. The system was designed to record four independent pressure signals: left heel, left toes, right heel, and right toes. Elderly patients were recruited to participate in this experiment and they were instructed to walk wearing these sensors for 20 meters in a straight line. After the test trial, each participant was asked to walk this distance three times. The first time is the baseline where they walked without performing secondary tasks. The second time, they walked the same distance again but while de-counting from 50. The third time, they walked while enumerating aloud as many animal names as they could remember. Some measures were taken while collecting the data to block other factors that could influence participants' walk. These measures included insuring proper lighting, a quiet area, and the use of comfortable flat shoes.

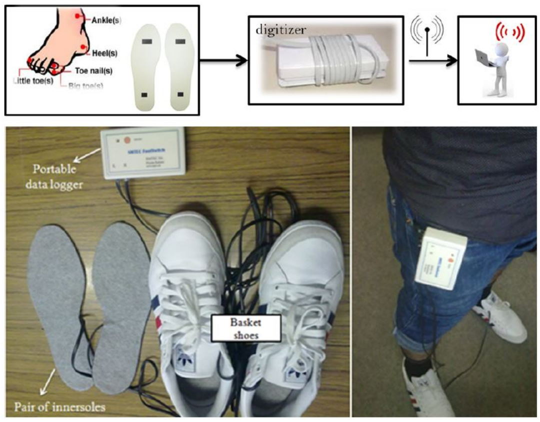

Fig. 1. The SMTEC electronic foot switches system [16].

520 healthy elderly patients were recruited for building this database at the Hospital University of Saint Etienne [15]. Their age was 78±1.08. Out of the 520 subjects, 302 were females, and 217 were males. Only 54 reported that they had previous falls in the past while the rest reported that they had not. As a first stage working with this largely unbalanced data, we included in our study the 54 fallers and randomly chose 54 non-fallers to build classification models that can accurately classify fallers and non-fallers.

B. Cyclostationary Analysis of Pressure Walking Signals

In human locomotion, the human walk can be considered a movement that consists of repeated sequences of cyclic physical actions or strides. Analyzing the cyclostationary characteristics of the walking pressure signals can introduce new features that are indicative of the risk of falling in the elderly [10].

Using cyclostationarity requires a constant number of samples per stride. Therefore, it is imperative to pre-process the signal in order to compensate the speed fluctuation. This is done by estimating this fluctuation as described in the work of Bonnardot, El Badaoui, Randall, Danière, and Guillet [17] and using interpolation in order to stretch the signal and compensate speed fluctuation.

There exist two orders of cyclostationarity as demonstrated in the work of Spooner and Gardner [18]. A signal $S(t)$ is said to be cyclostationary of order 1 with cycle T if the expectation $\mu_{S(t)}$ of $S(t)$, is periodic with period T:

$$\mu_{S(t)}(t) = \mu_{S(t)}(t+T) \tag{1}$$

$\mu_{S(t)}$ represents the repetitive pattern in the signal. The residual signal $r(t)$ can be computed by removing $\mu_{S(t)}$ from the signal:

$$r(t) = S(t) - \mu_{S(t)}(t) \tag{2}$$

A signal is considered cyclostationary of order 2 if the autocorrelation $C_{S(t)}$ of the signal $S(t)$ is periodic with period T:

$$C_{S(t)}(t_2, t_1) = C_{S(t)}(t_1 + T, t_2 + T) \tag{3}$$

where,

$$t = (t2 - t1)/2 \tag{4}$$

and,

$$C_{S(t)}(t_2, t_1) = C_{S(t)}(t_2 - t_1) \tag{5}$$

We define τ as,

$$\tau = t2 - t1 \tag{6}$$

In the case of a cyclostationary signals of order 2 such as the pressure signals involved in this study, the instantaneous autocorrelation function is periodic and therefore can be represented as a Fourier series as shown below [19]:

$$C_{S(t)}[t, \tau] = \sum_{v} CAF_S[v, \tau] e^{(-j2\pi vt)} \tag{7}$$

where, v is the cyclic frequency that belongs to the set of cyclic frequencies such that, v=k/T and $k \in$ Z. The cyclic autocorrelation function CAF is defined as:

$$CAF_S[v, \tau] = \lim_{T \to \infty} \frac{1}{T} \sum_{t=0}^{T-1} C_S[t, \tau] e^{(-j2\pi vt)} \tag{8}$$

In order to remove the influence of cyclostationarity at order 1 in cyclic autocorrelation, it is possible to compute the cyclic autocorrelation $CAF_R[v, \tau]$ of the residual signal $r(t)$, from Equation (2), instead of the autocorrelation $CAF_S[v, \tau]$ of the signal $S(t)$.

With the CAF being a 3-dimensions representation of the cyclostationarity of the pressure walking signal. It is possible to also obtain another 3-dimension representation called the spectral correlation $SCD_R(v, f)$ by taking the Fourier Transform of τ to obtain a frequency f. In this case, all the information are contained in the cyclic frequencies v associated to the characteristics cycles of the signal. At other cyclic frequencies, the spectral correlation should have zero energy. In figure 2, the cyclic frequencies not associated to signal cycles are not zero but are negligible since this is an estimated representation.

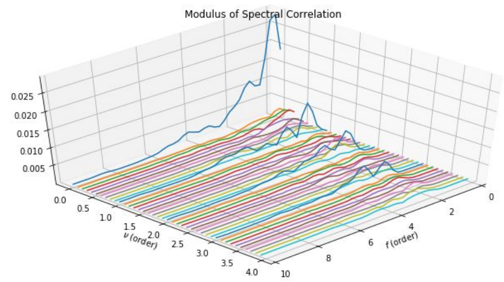

Fig. 2. The Spectral Correlation of the average walk pressure signal during normal walking

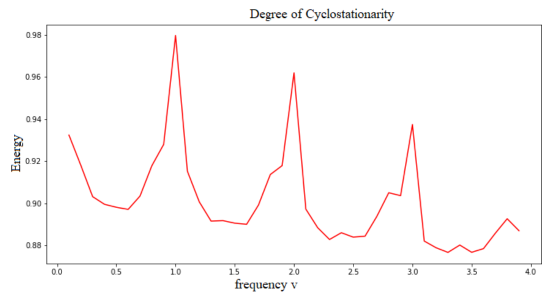

Fig. 3. The degree of cyclostationarity of walk pressure signals during normal walking with frequency v.

This representation is complicated to use directly as input features for classification methods. Hence, the degree of cyclostationarity is used to summarize the cyclostationarity of the signal with less complexity. Zivanovic and Gardner [12] described the Degree of Cyclostationarity (DC) as a proper measure of the degree of non-stationarity for stochastic processes that exhibit cyclostationarity. The DC can be described as the distance to the closest stationary process exhibiting a comparable power spectral density. The cyclic frequency having non-zero energy on the cyclic statistics of order 2 is a parameter that proves the presence of a cyclostationary signal. The degree of cyclostationarity is defined by the following equation:

$$DC_S^v = \frac{\sum_f |SCD_R[v, f]|^2}{\sum_f |SCD_R[0, f]|^2} \tag{9}$$

$$DC_S = \sum_{v} DC_S^v \tag{10}$$

The pressure signals from the 4 sensors (toes and heels from right and left feet) are synchronized and averaged to obtain the degree of cyclostationarity DC_S^v which can be viewed in 2 dimensions integration on frequencies axis as shown on Figure 3. The summation DC_S could serve as a valuable single feature extracted from walk pressure signals for the identification of elderly fallers and is used in the classification models explained in the following sections.

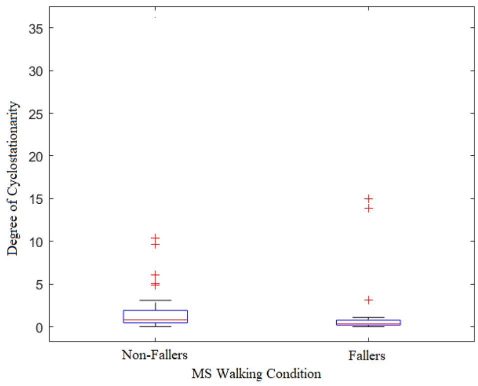

Fig. 4. The average degree of cyclostationarity between fallers and non-fallers in the case of MS walking condition

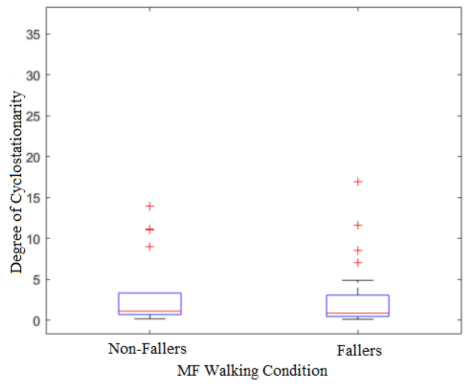

Fig. 5. The average degree of cyclostationarity between fallers and non-fallers in the case of MF walking condition

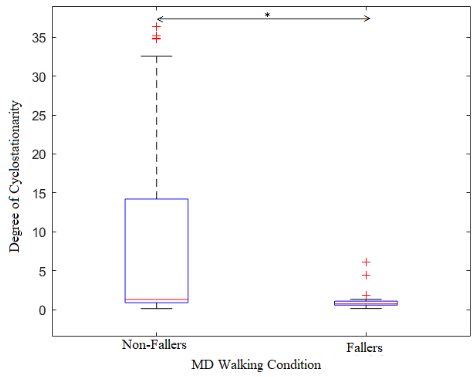

Fig. 6. The average degree of cyclostationarity between fallers and non-fallers in the case of MD walking condition

C. ANOVA Test for Statistically Significantly Features

Two sets of features are compared in this part of the study. The features are extracted from the innersole pressure signals of the 108 subjects divided equally between fallers and non-fallers. The first set includes 10 classical features chosen from well known time-domain features (10 CF), while the second set includes a single feature, which is the degree of cyclostationarity (DC).

The classical features extracted from the pressure signals are: mean, rise time, fall time, pulse width, overshoot, undershoot, duty cycle, slew rate, midcross, autocorrelation, standard deviation, band power, median, root mean square, range, Pwelch, skewness, interquartile range, kurtosis, and 95 percentile of the signal distribution. The statistical significance of these features to separate falling from non-falling elderly were tested using a one-way repeated measures ANOVA [20]. The results showed that 10 features out of those have statistically significant differences between fallers and non-fallers, in at least 1 type of walking condition. These features, considered in the following as classical features are: pulsewidth (right foot), undershoot (right and left feet), duty cycle (left foot), slew rate (right and left feet), range (right and left feet), and skewness (right and left feet).

The ANOVA test [20] was also conducted to determine whether there is a statistically significant difference in the DC between fallers and non-fallers in the three different cases of walking. There were relatively few outliers in the three cases. No statistical significant differences were found between faller and non-fallers in the cases of MS (Figure 4) and MF (Figure 5) walking conditions. However in the case of MD case of de-counting while walking, the average DC was statistically significantly different (Figure 6) between fallers and non-fallers ($p<0.05$).

D. Classification Models

Five classifier models were used: K-Nearest Neighbors [21], Support Vectors Machines [22] with polynomial kernels of degree 3, Artificial Neural Networks [23] with 10 nodes in a single hidden layer, Decision Trees [24], and Logistic Regression [25].

The results of a 100 times 10 folds cross validation was compared to the 10 times 10 folds cross validation and found to have no statistical significant differences using the ANOVA [20] test. Therefore, a 10 times 10 folds cross validation process was chosen to be used in all classification models.

III. Results and Discussion of the Classification Models

Table 1 shows the results of the different supervised classification models with 3 different walking conditions, 2 different feature sets, and 5 different classification methods. The best performance with the ten classical features as inputs was 61.85% accuracy, 53.52% sensitivity, 70.19% specificity, and 64.24% precision using K-nearest neighbors as a classifier. The use of the averaged degree of cyclostationarity as a single feature instead of the ten classical features improved model performance to 68.43% accuracy, 54.26% sensitivity, 82.59% specificity, and 75.83% precision using K-nearest neighbors.

The statistical t-test for pairwise comparison was computed and it was confirmed that there is statistical significant differences between the KNN model of highest accuracy and the other models listed in the table.

TABLE I
RESULTS OF THE CLASSIFICATION MODELS

Walking Condition	Feature Set	Classification Model	Accuracy%	Sensitivity%	Specificity%	Precision%
MS	10 CF	KNN	52.04% ± 2.54%	39.07% ± 13.04%	65% ± 14.14%	53.24% ± 4.90%
	DC		63.06% ± 1.27%	55.56% ± 2.14%	70.56% ± 2.54%	65.40% ± 1.75%
MF	10 CF		48.06% ± 2.20 %	29.07% ± 20.62%	60.56% ± 9.24%	38.61 %±18.23 %
	DC		48.52% ± 5.37%	36.48% ± 15.02%	67.04% ± 22.88%	46.58% ± 8.07%
MD	10 CF		61.85% ± 2.17%	53.52% ± 3.32%	70.19% ± 2.95%	64.24% ± 2.68%
	DC		**68.43**% ± **1.66**%	54.26% ± 0.89%	82.59% ± 3.05%	75.83% ± 3.38%
MS	10 CF	SVM	58.15% ± 1.62%	77.41%± 7.19%	38.89%± 7.15%	55.95% ±1.31 %
	DC		62.78% ± 1.62%	80.37% ± 1.79%	45.19% ± 1.79%	59.45% ± 1.20%
MF	10 CF		50.56% ± 5.51%	52.22%± 5.08%	48.89% ± 7.16%	50.65% ± 5.28%
	DC		56.85% ± 2.70%	59.07% ± 20.22%	54.63% ± 16.22%	56.93% ± 1.90%
MD	10 CF		59.91% ± 0.62%	70.19% ± 4.32%	28.70% ± 2.66%	56.10% ± 0.33%
	DC		**63.33**% ± **1.81**%	90.63% ± 3.24%	56.48% ±6.25%	61.87% ± 2.23%
MS	10 CF	ANN	60.00%± 5.55%	63.15% ± 16.76%	56.85% ± 12.92%	59.37% ± 6.05%
	DC		62.69% ± 6.83%	72.22% ± 26.99%	53.15% ± 24.65%	60.39% ± 5.81%
MF	10 CF		57.31% ± 7.20%	54.07% ± 19.96%	60.56% ± 18.06%	58.36%± 6.72%
	DC		56.48% ± 6.16%	72.96% ± 12.35%	40.00% ± 13.92%	55.09% ± 5.44%
MD	10 CF		59.91% ± 0.62%	60.93% ±26.12%	70.93% ± 11.84%	69.73% ± 12.45%
	DC		**65.93**% ± **8.83**%	91.11% ± 3.24%	28.70% ± 2.66%	56.10% ± 0.33%
MS	10 CF	Decision Trees	54.44% ± 2.86%	55.00% ± 5.02%	53.89% ± 3.54%	54.36% ± 2.67%
	DC		**64.63**% ± **2.95**%	62.41% ± 5.52%	66.85% ± 2.82%	65.26% ± 2.52%
MF	10 CF		51.85% ± 4.39v	50.74% ± 7.67%	52.96% ± 5.03%	51.75% ± 4.37%
	DC		44.44% ± 5.38%	44.81% ± 7.45%	44.07% ± 5.84%	44.35% ± 5.62%
MD	10 CF		56.76% ± 4.56%	56.11% ± 6.18%	57.41% ± 6.05%	56.88% ± 4.45%
	DC		58.33% ± 1.85%	54.81% ±3.83%	61.85% ± 2.50v	58.95%± 1.82%
MS	10 CF	Logistic Regression	56.11% ± 3.09%	62.22% ± 3.29%	50.00% ± 4.09%	55.47% ± 2.85%
	DC		50.28% ± 3.15%	75.19%± 5.32%	25.37% ± 4.46%	50.17% ± 20.8%
MF	10 CF		55.00% ± 4.46%	57.96%± 4.79%	52.04% ± 6.79%	54.85% ± 4.36%
	DC		49.72% ± 2.55%	73.33% ± 5.87%	26.11%± 4.66%	49.79% ± 1.69%
MD	10 CF		59.81% ± 0.48%	62.96% ± 2.31%	30.74% ± 0.62%	56.21% ± 0.34%
	DC		**60.56**% ± **2.06**%	88.89% ± 0.36%	58.15% ± 3.40%	60.11% ± 2.06%

IV. CONCLUSION

Utilizing the degree of cyclostationarity can improve model predictive performance while reducing its complexity. Therefore, we advocate its inclusion for elderly fall-risk prediction. In addition, the MD walking condition (de-counting as a dual task) improved model prediction accuracy in the KNN, SVM, ANN, and Logistic Regression classifiers. KNN achieved the highest accuracy using a single cyclostationary feature during the MD walking condition. A drawback that needs to be noted, is that KNN compared to other classification methods requires a large real time computation as it needs the complete data for every classification. This opens the door to look into further improvement and optimization. As a future perspective, we intend to combine all the features from the 3 walking conditions, other sets including physiological data and additional cyclostationary features as inputs to the classification models and compare their outcomes.We also plan to develop feature selection models such as Relief-F that was used in the literature of similar work and has been found to improve prediction results of fallers and non-fallers.

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