Fuzzy logic-based risk of fall estimation using smartwatch data as a means to form an assistive feedback mechanism in everyday living activities

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This Letter aims to create a fuzzy logic-based assistive prevention tool for falls, based on accessible sensory technology, such as smartwatch, resulting in monitoring of the risk factors of falls caused by orthostatic hypotension (OH); a drop in systolic blood pressure (DSBP) >20 mmHg due to postural changes. Epidemiological studies have shown that OH is a high risk factor for falls and has a strong impact in quality of life (QoL) of the elderly's, especially for some cases such as Parkinsonians. Based on smartwatch data, it is explored here how statistical features of heart rate variability (HRV) can lead to DSBP prediction and estimation of the risk of fall. In this vein, a pilot study was conducted in collaboration with five Greek Parkinson's Foundation patients and ten healthy volunteers. Taking into consideration, the estimated DSBP and additional statistics of the user's medical/behavioural history, a fuzzy logic inference system was developed, to estimate the instantaneous risk of fall. The latter is fed back to the user with a mechanism chosen by him/her (i.e. vibration and/or sound), to prevent a possible fall, and also sent to the attentive carers and/or healthcare professionals for a home-based monitoring beyond the clinic. The proposed approach paves the way for effective exploitation of the contribution of smartwatch data, such as HRV, in the sustain of QoL in everyday living activities.

1. Introduction: The exploitation of internet of things (IoT) as an infrastructure for creating assistive technology solutions is a necessity to healthcare self-management systems. This would lead to improvement of the quality of life (QoL) standards, due to the proactively management of the risks that progressive diseases can cause, such as Parkinson's disease (PD). PD patients face the risk of fall, frailty and depression daily. An unobtrusive approach to reduce the risk of fall in PD patients by using non-invasive wearable technology is crucial in maintaining their QoL. The biometric data acquired by wearable technology can reveal statistical characteristics from user's interaction and mine useful information about the user's physiology. To prevent falls, a prediction model could be developed estimating the risk of falls, based on orthostatic hypotension (OH) episodes in PD, capturing unobtrusively biometric data through a smartwatch. Neurogenic OH is affecting up to 60% of the PD's patients, and the multidimensionality of the disease creates an increased risk in PD patients. On the later stages of the disease, up to 20% of the PD patients face symptomatic OH [1, 2]. In addition to PD, up to 40% of the elderly adults >65 years old experience an indoor fall each year, which decreases the mobility and self-confidence. The cost of fall-related injuries has been reported \$19 billion for a year [3].

In this work, an innovative risk of fall estimation (RFE) system is introduced as a healthcare assistive self-management tool based on a smartwatch. A pilot study was conducted with ten controls and five PD patients applying a previously accepted experimental protocol [4]. Heart rate variability (HRV) and blood pressure (BP) data were captured while the subjects performed postural changes from supine to upright position. Exploiting the heart rate sensor, embedded in all market's smartwatches, RR intervals were acquired and a digital sphygmomanometer was applied for recording the BP values during the experiment. Time-, frequency- nonlinear domains and higher-order spectrum analyses of the HRV signal have already achieved high accuracy in predicting drop in systolic blood pressure (DSBP) in healthy subjects [5]. This work takes this predictive

potentiality a step further and expands the predictive model of the BP drops to the case of PD patients, aiming at a target group with disorders in autonomous nervous system (ANS) and increased risks, providing a fuzzy logic-based RFE to act as assistive feedback mechanism to fall prevention.

2. Background

2.1. OH and PD: The result of postural changes from supine to upright standing in the first minutes is that the filling pressure and the stroke volume are reduced causing a drop in BP. The healthy response of the homeostasis is the adjustment of HRV and the stabilisation of the BP, to avoid dizziness. If the drop in BP is >20 mmHg in systolic or 10 mmHg in diastolic BP, there is an OH syndrome. The most common symptoms of OH are lightheaded, weakness and fainting, which are crucial factors of falls. The 40% of PD patients face OH, correlating the symptomatic homeostasis response to the cardiovascular autonomic regulation [2]. The sympathetic response in baroreceptors input is limited in PD's patients and the α -synuclein accumulation intends the problems in nervous degeneration. These result in causing anomalies in patient while standing, as their ANS reduced reflection cannot regulate the venous pooling due to gravitational forces in blood. The medication complexity and frequency have side effects in OH and, in most cases, it is advised to be combined with non-pharmaceutical treatment. PD patients with OH have failure of both the cardio vagal and sympathoneural limbs of the baroreflex, and also face the loss of sympathetic noradrenergic innervation of the left ventricular myocardium. Actually, decreased renal sympathetic innervation and noradrenergic innervation on the whole body are evidences of PD patients with increased risk of fall due to OH [6].

2.2. Importance of HRV: The HRV signal is the product of ANS response, which defines the amplitude of the DSBP and the regulation of homeostasis caused by the postural changes. In this Letter, the HRV signal, captured while the subjects were in a lying position, is used to determine the key features that reveal

the condition of the ANS and predict the DSBP to both PD patients and healthy subjects. The rationale behind this is the fact that the irregularity seen in the HRV sequences depends on sympathetic condition and external factors. In fact, the ANS status dynamically changes according to the human's physiology condition and the differences seen in the morphology and the amplitude distribution of the HRV signals reveal shifting to a more nonlinear behaviour between the ANS systems of a healthy individual and of a patient. To this end, various methods were used to describe the different physiology in heart rate sequences drawn from the domains of time, frequency and nonlinearity, due to the complexity of ANS system and its adaptive behaviour. Fig. 1 shows the ANS system and the way it is correlated with the BP [7].

3. Data collection and protocol: To create a holistic model for detecting the different physiology cases and response of the ANS, two target groups took part in the pilot study, i.e. PD patients who were facing OH and healthy subjects. By using a market smartwatch (Microsoft Band 2) in the right hand of the subjects, the RR interval data were acquired, while the BP was measured with a digital sphygmomanometer (SANITA, www.sanitas-online.de) in the left arm. The protocol, approved in [4], was in compliance with the Aristotle University of Thessaloniki's and North Greece Parkinson's Disease Foundation's Ethics Committee, and included measurements of heart rate and BP realised in tow posture phases of the subject:

- Phase 1: lying in supine position for 10 min,
- Phase 2: standing in upright position for 5 min.

The two phases were successively repeated three times for each subject. The healthy subjects were not under any medication, alcohol or caffeine and the PD patients participated in the experimental protocol 3 h after their morning medication. The total number of instances was built by five PD patients (mean age $\pm$ std: 66 ± 3.72 years) drawn from the Greek Parkinson's Disease Foundation and ten healthy volunteers (mean age $\pm$ std: 24 ± 1.5 years).

4. Predictive feature analysis: Heart rate signals captured during lying were preprocessed, to remove the artefacts which may interfere, caused by technical or psychological factors. To reveal useful information from the HRV, the RR intervals should be artefact free, using interpolation methods. The cubic spline interpolation method was used for artefact removal with a 5% threshold for a reliable estimation of HRV [8], realised in Kubios and a Matlab-based software package, [9]. Using the Kubios software, HRV was further analysed in three categories, extracting time-, frequency- and nonlinear analysis-based features.

Fig. 1 Baroreflex pathways adapted from [7]

4.1. Time domain analysis: The HRV signals were analysed in the time domain where the following features (sequentially numbered) were extracted: mean value (1), standard deviation (2), square root of the mean squared differences of RR intervals (3), number of successive RR intervals pairs that differ more than 50 ms (4), the value of (4) divided by total number of RR intervals for the specific time slot (5), standardised integral of the HRV histogram (6) and its baseline width (7).

4.2. Frequency-domain analysis: In the frequency domain, the spectral power density (SPD) of HRV was estimated based on the Welch method [10]. A pre-processing process employed removes the very low frequency (LF) (0.003–0.04 Hz) components. The three features that were, hence, estimated in the frequency domain included: absolute power of the LF band (0.04–0.15 Hz) (8); absolute power of high-frequency (HF) band (0.15–0.4 Hz) (9), (both were calculated with autoregressive modelling); and the ratio (LF/HF) as a combined feature (10).

4.3. Nonlinear dynamics analysis: Moreover, the nonlinear dynamics of HRV signals were also analysed. Poincare plot arranges the HRV sequences into pairs of adjacent RR intervals, in two dimensions, with two consequents (RR, RR+1) in the x- and y-axes, respectively [11]. An ellipse is generated to fit the data points, from where the width (11) and the length (12) can be calculated as features. Additionally, entropy metrics were calculated [2], i.e. approximate entropy (ApEn) (13) and sample entropy (14). Furthermore, the correlation dimension (D2) (15) and both short- (DFA1) (16) and long-term (DFA2) (17) fluctuation slope of a detrending fluctuation analysis (DFA) [12] were estimated. The DFA analysis was used to reveal the correlation within the signal. Moreover, additional nonlinear features that can be extracted from the recurrence plot analysis [12] were estimated, i.e. recurrent plot (RP) mean line length (18); RP maximum line length (19); RP recurrence rate (20); RP determinism (21); and RP Shannon entropy (22).

4.4. HOS analysis: Calculating the power spectrum density (PSD) of the HRV signals cannot sufficiently describe the response of ANS, as the PSD stems from the second-order moment of the signal and does not include the information of phase variation of the signal. To increase the granularity of the correlation between ANS nonlinear status and HRV signals, features were extracted from the HOS domain, which sets a poly-spectral representation of high-order moments or cumulants of the HRV signal [13]. HOS of third-order cumulants were employed to calculate the bispectrum of the HRV signal intending to reveal the hidden information of quadratic-phase coupling that cannot otherwise be observed by using regular PSD calculated from the second-order moment of the signal. Heuristic HOS-based features were estimated, i.e. the peak value of Bispectrum (Bispec) (23), the frequencies (F1, F2) (24, 25) of the maximum peak value and the standard deviation of the values which are 10% of the maximum along the frequencies (26, 27). The disorders of the system can be associated with nonlinear features of the HRV in the HOS domain.

These features used to solve the PSD restrictions in acquiring the phase coupling information and describing the correlation of the nonlinear response of ANS with the HRV signals. As it was shown in an authors' previous work, DSBP seems to strongly correlate with the quadratic phase coupling of the HRV signals [5]. Examples of bispectrum representation of HRV signals from both healthy (Fig. 2a) and PD patient (Fig. 2b) are shown in Fig. 2. From the latter, it is clear that the differences in the morphology and the amplitude distribution of the HVR signals due to the higher nonlinearity between the ANS condition of a patient and of a healthy individual are reflected in the bispectrum domain.

Fig. 2 Bispectrum calculation of
a Healthy HRV signal
b PD patient HRV signal

The Matlab HOSA Toolbox (The Mathworks, Natick, USA) was used for the bispectrum analysis.

4.5. Estimation and distribution of DSBP instances: The HRV signals captured from the smartwatch during the experimental procedure were associated with the BP measurements in a dataset consisting of the HRV excerpts of each stage for every subject. Therefore, every instance constituted from a 27 features vector of HRV recordings of 10 min lying and the DSBP after standing. The DSBP was calculated as the maximum difference between the systolic BP value measured during the standing action (Phase 2) and the mean of the BP measurements taken while lying (Phase 1). The nominal error of the sphygmomanometer was ± 3 mmHg and supposing the three repeated measurements, a typical error of ± 4.7 mmHg was estimated as the accepted error margin in three repetitions. Moreover, taking into consideration the distribution of the DSBP values, a resample of subset of data, where the instances with similar DSBP values were randomly deleted from the dataset, was performed, to address the class imbalance problem. The final distribution of the DSBP values used is presented in the histogram of Fig. 3. To reduce the feature vector size, some feature selection algorithms were tested, as described next.

5. Feature selection and regression analysis: For the feature selection, the Correlation-based Feature Subset algorithm [14] was used; it evaluates the subset of attributes by considering the individual predictive ability of each feature along with the degree of redundancy between the highly correlated with the class, while having low internal (within the subset) correlation. Also, the Relief algorithm [14] was used to test the ranking of attributes. The search methods used to find the feature subset was the Best First algorithm [14], where its settings were tested for backward

Fig. 3 Distribution of DSBP instances

(BestFirst1) and forward (BestFirst2) search. Also, the exhaustive search (Exhaustive) was tested, to find the best subset of features. The feature selection was realised via the WEKA Toolbox 3.6.1 [15].

The ranking of the eight best features, numbered in accordance to Section 4, along with their abbreviations, is: (5) HRVtri, (16) DFA1, (3) RSSD, (22) SampEn, (24) F1, (12) SD2, (27) Std2 and (18) Lmean. Further to their selection, a reduced feature vector was explored, to avoid overfitting of the model, employing regression algorithms, such as linear regression, SVM with different Kernels and neural networks [15]. The best algorithm was selected on the basis of the outputted minimum root mean-squared error. Using the eight best features as a starting set, feature selection algorithms clustered the subsets of features that were tested. The results of the subset feature selection (corresponding to the algorithm employed) are summarised in Table 1. The regression algorithm for each derived subset of Table 1 was evaluated from the corrected predicted instances in a 10 cross-fold validation and the corresponding results are presented in Table 2.

As it can be seen from the combination of the results in Tables 1 and 2, the best resulted regression algorithm (Exhaustive) uses the four features of HRVtri, DFA, F1 and D2 and the linear regression approach is the one that succeed the maximum predictive accuracy (**73%** (Bold value indicates the accuracy of the best model predicting blood pressure drops)) in correctly predicting the DSBP values. This is expressed via the following input-output model

$$\text{DSBP} = 4.15\text{HRVtri} - 0.3\text{SD2} + 16.7\text{DFA1} + 0.14\text{F1} - 71.7725. \quad (1)$$

Table 1 Feature selection algorithm and the selected features per subset

Algorithm	Features				
	First	Second	Third	Fourth	Fifth
Bestfirst1	HRVtri	F1	DFA1	Std2	SD2
Bestfirst2	HRVtri	RSSD	Std2	SampEn	SD2
exhaustive	HRVtri	DFA1	F1	SD2	—

Table 2 Algorithms performance (predictive accuracy in %) for the different subsets of Table 1

Subset	SVM, %	Linear regression, %	Neural network, %
Bestfirst1	61	65	51
Bestfirst2	60	57	66
exhaustive	58	73	66

(Bold value indicates the accuracy of the best model predicting blood pressure drops)

Fig. 4 Predicted error (in mmHg) against DSBP

Fig. 5 Proposed RFE system architecture

The prediction error distribution along the values of DSBP is presented in Fig. 4. From the latter, it is clear that the error is evenly distributed <10 mmHg in the most cases, which can give sustainable results in predicting DSBP in classifying the OH cases from the healthy ones. Clearly, the performance of the proposed model (1) can be further refined by employing a larger scale experiment, to collect dense data from the whole range of DSBP and build a more efficient DSBP model.

6. Risk of fall estimation

6.1. Fuzzy logic model: To develop a holistic model that could predict the risk of fall based on reliable inputs and result in a useful feedback mechanism as an outcome, real-time data from smartwatch and additional information about the user's status were integrated in a Mamdani fuzzy controller that created with the Fuzzy Controller Toolbox of Matlab. The inputs of this controller were the predicted DSBP using model (1), the age of the user, the health status and the falls history, as it was advised by medical consultants. Age and health status inputs provide information correlated with the reflections and stability of the user; the information about the previous falls is advantageous for the future falls risk prevention and management, as the falls have a big recurrence rate [16]. Fig. 5 shows the architecture of the proposed RFE system. The latter is developed to be integrated in the smartwatch software and be provided as an assistive feedback to the users with high risk of fall. The architecture of RFE is based on the user's interaction as s/he can easily provide the external knowledge once, at the beginning as initial values, and the system can unobtrusively monitor the HRV data and predict the DSBP.

Each input to the fuzzy logic model is described by a membership function, which sets the valuation thresholds (see Fig. 6). The DSBP is divided into three categories, i.e. low DSBP, medium DSBP and OH symptomatic drops. Age was separated into three categories in a (20–80 years) range and described as young, medium and elderly. The health status membership functions are defined in a 0–5 scale from healthy to patient status, quantifying the severity of symptoms. Finally, due to the recurrence of the syndrome of falls, the model has as an input the fall history, which considers the falls that happened the last 365 days as an input, according to the literature [17]. The RFE output categorises the fall risk in three main categories, i.e. low, medium, high, complying with the relevant research categorisation of the risk of fall based on biometric data [18]. A set of 54 fuzzy rules was constructed as the experts' knowledge representation built under their medical experts' input and supervision. Fig. 7 illustrates the membership functions for the output of the Mamdani system used in the proposed RFE.

6.2. RFE testing results: The proposed RFE model was tested in the dataset, consisting of the predicted values from the DSBP model outcome (based on (1)), with the additional external information that volunteers provided, and the results are shown in Table 3. As

Fig. 6 Membership functions for DSBP, AGE, health status and fall history of the Mamdani system used in the proposed RFE

Fig. 7 Membership function for the risk estimation output of the Mamdani system used in the proposed RFE

it can be seen from the latter, the estimated risk is higher in cases of PD patients in contrast to healthy volunteers, which is an expected outcome.

7. Discussion: This work exploits the use of data from a smartwatch, introducing the concept of ambient assistive living combined with the use of the emerging IoT technology, as an assistive tool for people in high risk of falls. The proposed RFE model, based on sensorial data and external knowledge that the user can provide as inputs, estimates the user's risk of fall in a quantified way. The outcome information can be used to prevent falls of the users, interpreted with an alarm notification. The increased risk of fall is a result of the frailty that pathological disorders cause, so the variance over time in the estimated risk

Table 3 Results of the Mamdani controller

−10DSBP, mmHg	Age, years	Health status	Falls history (normalised to the last 365 days)	Estimated risk, %
2.7113	65	4	0.03	77.06
2.5751	65	4	0.03	76.14
2.4887	65	4	0.03	75.95
2.6453	67	3	0.03	73.31
1.9981	67	4	0.02	77.07
2.5369	70	4	0.02	77.26
1.8712	70	4	0.02	76.85
2.1977	70	4	0.02	77.21
2.1977	22	3	0.01	52.88
1.8513	67	4	0.02	76.80
1.6254	59	1	0.01	31.7
1.4678	67	4	0.02	72.91
0.4124	59	2	0	29.27
1.2555	22	2	0	29.71
1.5955	22	2	0	30.39
1.7729	22	2	0	31.10
0.7726	23	2	0.01	33.70
1.4197	25	2	0	26.81
1.7799	24	1	0.01	31.46
1.5265	27	1	0.01	31.06
1.324	25	1	0	20.07
1.0288	23	2	0.01	37.33
0.7502	24	1	0	25.50
0.7479	23	1	0	26.37
1.3622	25	1	0	19.81
1.267	24	1	0	20.68
1.4988	27	1	0	22.85
0.7881	25	1	0	25.24
1.2159	23	0	0	22.38
1.2821	24	0	0	20.57
1.8475	23	0	0	22.48
0.1712	25	0	0	25.18
1.1801	24	0	0	21.42
0.4597	23	0	0	26.35

can be provided to the relevant doctor as diagnostic information. The integration of DSBP in the Mamdani system personalises the solution and leads to falls prevention in a daily bases and steps beyond the state-of-the-art in falls management, which integrate data within clinical facilities [19]. Additionally, this Letter quantifies the risk of fall using user's inputs, which personalise the system as is proposed for a medical decision system [20]. In comparison with other methodologies which use heart rate data to predict falls, e.g. [21] this Letter is independent of ECG or wiring, which makes the current methodology applicable to a wider community due to the integration to an everyday device. Also, in [21], the prediction model achieves 80% in prediction of falls; however, the subjects face similar hypertensive dysfunctions, limiting the generalisability of the model. A relevant study [22] uses gait quality as a predictor succeeds in predicting at 66–72% of the falls in a 320 people sample. A future integration of accelerometer signals in the RFE system could boost the prediction of fall results.

The results of this approach to project the pathology of OH syndrome in PD in HRV data in the four domains differ from similar methods [4, 5] and encourage the exploration of additional medical cases and enlargement in the clinical scale. In [23], the treatment evolution of various diseases has been limited over the past years. The exploitation of IoT devices as medical decision support systems, which provide continuous recordings of signals, correlated with biomarkers of the patients, can lead to early detection of diseases and achieve better supervised-medication treatment towards a healthy and active ageing. However, the proposed RFE model has a moderate need of data collection due to the external knowledge that is integrated. Especially, the medical advice makes the creation of a mature biomedical decision-making system feasible. This way, the feedback mechanism to patient can assist to his/her condition management. Additional inputs on the system, such as the vision status, the medication type or similar nested models using acceleration signals to identify the different gait patterns, which are also strong indicators of fallers in PD [24], could be explored to inclusively regulate the estimation system to handle decisions in different pathologies.

8. Conclusion: The work presented here introduced the concept of home-based falls prevention and management using vital signals for instantaneous risk estimation, employing predictive modelling and fuzzy logic-based decision making. The promising results presented here pave the way for its further expansion towards further studies using its feedback mechanism to prevent high-risk situation and the recordings of users' stability detection in gait patterns, using accelerometer data, so to explore a dataset of long-term monitoring.

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