Unified framework for triaxial accelerometer-based fall event detection and classification using cumulants and hierarchical decision tree classifier

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In this Letter, the authors present a unified framework for fall event detection and classification using the cumulants extracted from the acceleration (ACC) signals acquired using a single waist-mounted triaxial accelerometer. The main objective of this Letter is to find suitable representative cumulants and classifiers in effectively detecting and classifying different types of fall and non-fall events. It was discovered that the first level of the proposed hierarchical decision tree algorithm implements fall detection using fifth-order cumulants and support vector machine (SVM) classifier. In the second level, the fall event classification algorithm uses the fifth-order cumulants and SVM. Finally, human activity classification is performed using the second-order cumulants and SVM. The detection and classification results are compared with those of the decision tree, naive Bayes, multilayer perceptron and SVM classifiers with different types of time-domain features including the second-, third-, fourth- and fifth-order cumulants and the signal magnitude vector and signal magnitude area. The experimental results demonstrate that the second- and fifth-order cumulant features and SVM classifier can achieve optimal detection and classification rates of above 95%, as well as the lowest false alarm rate of 1.03%.

1. Introduction: Automatic detection of fall events is one of the important and challenging research areas in many ubiquitous context-aware applications including fall alarm and fall injury prevention, ambulatory patient monitoring, physical rehabilitation and monitoring the health and well-being of the elderly and patients with cognitive disorders [1–7]. Many fall detection (FD) systems have been developed based on the use of body movement, environmental and physiological signals acquired from a single sensor and or multiple sensors (including accelerometers [2–12], gyroscopes [3], barometric pressure sensor [11, 12], microphone sensors and floor vibration sensors [13], floor electric field sensors [14], physiological sensors [5, 15], and video-based cameras and Microsoft Kinect sensors [16–20]). There are two major types of fall monitoring systems: (i) *wearable sensing-based method* [2–12]: falls are detected using the acquired signals from body-worn sensors attached to different positions on subject's body; and (ii) *non-wearable sensing-based method* [16–20]: falls are detected using the acquired signals from sensors distributed in a predefined space environment. In the non-wearable computer vision-based methods, the FD is performed based on the visual features extracted from short video clips recorded using the calibrated or uncalibrated single camera or multiple cameras placed in a predefined space. By using the traditional video cameras and Microsoft Kinect sensors [16–20], many computer vision-based FD methods were proposed based on the human body silhouette extraction, the motion and body silhouette features such as ellipse, shape and structure, position, lighting, flow features and the machine learning techniques.

Both methodologies have their own pros and cons and have potential practical applications. The computer vision-based methods have the following advantages: (i) they are more comfortable [4]; and (ii) multiple subjects can be monitored simultaneously. However, the method also has some drawbacks: (i) it demands camera view calibration and privacy issues [13, 21]; (ii) it is difficult to achieve higher accuracy with the method due to clutter, lighting under different settings and the presence of multiple moving objects; (iii) it demands extensive resources and complex processing; (iv) it requires background model learning process for body foreground extraction; (v) it is not cost effective as it requires at least one calibrated camera in each room [5, 6, 15]; and (vi) scalability is poor in outdoor monitoring environments. The advantages of wearable FDs are that (i) sensed data have no influence on environmental conditions [6]; (ii) they are compact and portable [4]; (iii) processing data does not demand more resources and computing platform; (iv) sensor data are subject-specific; (v) they have low power consumption and are of low cost and (vi) scalability can be done for wide area monitoring. In the next subsection, we briefly summarise the components of wearable sensor-based fall detectors.

1.1. Existing FD methods: The wearable FD methods generally include preprocessing, feature extraction and classification. Most of the methods were developed based on time-domain features including signal magnitude vector (SMV) [4–6], signal magnitude area (SMA) [5, 6, 9, 22], tilt angle [5, 9, 22], averaged negative entropy [15], sum of the variance of accelerations, autocorrelation coefficient of tilt angle, root mean square [23], frequency domain features (spectral peak, spectral energy and spectral entropy) [4, 23], autoregressive model features [22] and wavelet-domain features [4]. As for the classification techniques, many classifiers such as simple heuristic thresholding rules [2, 3], naive Bayes (NB), multilayer perceptron (MLP), support vector machine (SVM) and finite state machine [4], cascade-AdaBoost-SVM classifier [6], hidden Markov model (HMM) [7], nearest neighbours [8], fuzzy logic [24] and combining classifiers have been investigated for improving the accuracy. Many wearable FD systems use multiple kinematic sensors, sound and floor vibration sensors and electrophysiological sensors.

In [2], Yuan *et al.* presented power-efficient interrupt-driven algorithms for FD and classification of activities of daily livings (ADLs) using wrist-worn wearable device integrated with accelerometers. In [3], vertical velocity-feature-based pre-impact FD method is proposed using both the accelerometer and gyroscope signals from a wearable inertial sensor attached on the anterior side of the waist. In [4], pocket-based fall accident detector is proposed using the angles acquired by the electronic compass and waveform sequence of the triaxial accelerometer on the smart phone around the chest of the user. The FD is performed using features such as SMV and angles, high-frequency energy, Haar wavelet analysis and cascade classifier. In [5], an enhanced FD system is proposed based on body-worn smart sensing module including triaxial accelerometer, heartbeat pulse pressure, temperature and humidity sensors and operating through consumer home networks. The SMA and truck angle features are used for detecting body movements and fall events, respectively. The method achieved an accuracy of 97.5%, sensitivity and specificity being 96.8 and 98.1%, respectively, on a group of 30 healthy subjects. In [6], the triaxial accelerometer-based FD method is proposed based on the SMV and SMA features and the cascade-AdaBoost-SVM classifier that combines AdaBoost classifier and SVM. The performance of the method is evaluated for the accelerometers on the chest, waist, left ankle and right ankle. The experimental results show that the triaxial accelerometers worn on the chest and waist have the optimal performance. In [7], Tong *et al.* presented a HMM-based human FD and prediction method using a triaxial accelerometer placed at the upper trunk, which is below the neck and above the waist. In [8], a data mining method is presented for FD by using acceleration sensor and *k*-nearest neighbour algorithm under wireless sensor network environment. The method had an accuracy rate of 89.4% and the true positive rate of 100%, and the precision is almost 85% on the test case. In [9], the normalised SMA and title angle features are used to determine user activity, rest and postural orientation, respectively. In [11], Tolkiehn *et al.* presented a direction-sensitive fall detection using a triaxial accelerometer and a barometric pressure sensor. The fall detection was performed using features such as moving-window standard deviation, standard deviation of the vector magnitude, ratio of the polar angle, difference of the polar angles and the thresholding rules. The method achieved the directional fall identification rate of 94.12%.

Recently, numerous methods were developed for distinguishing fall and non-fall activities using a single triaxial accelerometer sensor. In addition to FD, it is very important to determine the direction of a fall. This has significant potential in effectively identifying the most serious dangers of fall injuries due to particular joints and fractures. It can also enable immediate rehabilitation treatment depending on the type of serious fall injuries including head and neck injuries, shoulder and forearm fractures, spine and foot fractures, and pelvic and hip fractures [8]. Therefore, in this Letter, the primary aim of the proposed framework is to detect a fall and then classify the detected falls into four classes: fall front (FF), fall back (FB), fall right (FR) and fall left (FL) using higher-order cumulants description, which can provide more discriminative characterisations of the different types of ACC signals composed of Gaussian and non-Gaussian process plus constant.

1.2. Contribution of the Letter: We present a FD and classification framework using the cumulant features extracted from the ACC signals acquired using a single waist-mounted triaxial accelerometer. The main contribution of this work is to identify a set of robust and discriminative cumulant features and classifiers for developing effective and efficient FD, fall event and ADL classification algorithms. To improve overall processing speed, the hierarchical decision tree (HDT) structure is presented for performing FD, fall direction determination and ADL classification tasks in a sequential manner. In this Letter, we investigate the effectiveness of different detection and classification methods that are constructed using cumulants of order 2–5 and the SMA and SMV features, and classifiers including the decision tree (DT), NB, MLP and SVM. Performance evaluation results show that the SVM-based method with fifth-order cumulants can provide promising results in distinguishing fall and non-fall activities and classifying fall events into FF, FB, FR and FL classes. Further, the results show that the second-order cumulants with a SVM classifier can achieve better classification of ADLs.

The remaining structure of the Letter is as follows: Section 2 describes an overview on the architecture of the proposed fall event monitoring system. Section 2.1 presents a noise reduction scheme to filter out abnormal spikes in the acquired acceleration (ACC) signals. Section 2.2 addresses the extraction of proposed cumulant features and the commonly used features for performance comparisons. The fall event detection and classification system will be given in Section 2.4. Section 3 presents the experimental results of the detection and classification methods that are developed using the cumulant features and different classifiers. Finally, conclusions are drawn in Section 4.

2. Cumulants-based detection and classification methods: Fig. 1 depicts an overall architecture of the proposed wearable single triaxial accelerometer-based fall monitoring system. As can be seen in Fig. 1, the proposed system is mainly composed of six functional blocks: (i) *preprocessor*; (ii) *fall activity detector*; (iii) *fall event recogniser*; (iv) *human activity recogniser*; (v) *fall injury impact analyser* which integrates both the fall direction information such as FF, FB, FR, and FL, magnitude and duration of fall activity and the past activity information such as standing, sitting, walking and running; and (vi) *fall pattern behavioural predictor* which generates a history of repetitive falling patterns of a person for enabling effective diagnosis of person-specific fall injury. The proposed framework implements FD, fall direction determination and activity classification in a sequential manner by considering the computational and power consumption burden of the system.

2.1. Experimental setup: A waist-mounted Android phone with a triaxial accelerometer sensor is used for real-time implementation of the proposed fall monitoring system including the following features: fall event detection and classification using cumulants, fall alarm, SMS notification to personal contacts of caregivers with fall geolocation and voice notification. The ACC signal database of different fall events and ADLs is created using our waist-mounted belt prototype. The ACC signals of a single waist-mounted triaxial accelerometer are sampled at the rate of 40 Hz. The ACC signals along the *x*-axis, *y*-axis and *z*-axis are denoted as $a_x[n]$ (left/right), $a_y[n]$ (up/down) and $a_z[n]$ (front/back), respectively, at the sampling index n.

2.2. Preprocessing: The major preprocessing performed on the acquired ACC signals includes two steps: noise reduction and signal blocking. The real-time ACC signals of a waist-worn triaxial accelerometer contain abnormal noise spikes that need to be suppressed before performing the fall event detection and classification task [1]. The noise reduction unit includes a three-point median filter to filter out the abnormal spike outliers. The filtered ACC signal is divided into smaller segments (windows) of fixed length before extracting the features. The size of window is fixed between 0.25 and 1.4 s in the fall event detection problem [9]. In this Letter, sliding window size of 0.25 s and window shift of one sample is considered for detection, localisation and classification of fall activity in the acquired ACC signals.

2.3. Higher-order cumulants for ACC signals: The time-domain higher-order cumulants are extensively used for characterising the random signals and can serve as new statistical features for detecting and quantifying the non-linear characteristic signals [25–27]. In practice, the ACC signals obtained for daily activities under both resting and ambulatory recording conditions may be composed of Gaussian and non-Gaussian process plus constant. Many studies show that the higher-order cumulants can serve as an effective time-domain analysis tool for characterising the non-stationary and non-Gaussian signals [26, 27]. In this Letter, we investigate the application of higher-order cumulants to achieve reliable FD, fall direction determination and ADL recognition.

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Let us consider $x(n)$ is a real-valued kth-order stationary random process, and $\omega = [\omega_1, \omega_2, \omega_3, \ldots, \omega_k]^{\mathrm{T}}$ and $\boldsymbol{x} = [x(n), x(n+\tau_1), x(n+\tau_2), \ldots, x(n+\tau_{k-1})]^{\mathrm{T}}$, where $\tau_1, \tau_2, \tau_3, \ldots, \tau_{k-1}$ are time shifts. Then, the kth-order moment of $x(n)$, m_{kx} is defined as the coefficient in the Taylor expansion of the moment generating function (MGF) [26]

$$\Phi(\omega) = E[\exp(\mathrm{j}\omega^{\mathrm{T}}\boldsymbol{x})] \tag{1}$$

where $E[.]$ is the expected value operator. In practice, the kth-order moment can be computed by taking an expectation over random process multiplied by $(k-1)$ lagged version of itself [25–27]

$$\begin{aligned}
m_{1x} &= E\,[x(n)]\\
m_{2x}(\tau_1) &= E\,[x(n)\;x(n+\tau_1)]\\
m_{3x}(\tau_1, \tau_2) &= E\,[x(n)\;x(n+\tau_1)\;x(n+\tau_2)]\\
m_{4x}(\tau_1, \tau_2, \tau_3) &= E\,[x(n)\;x(n+\tau_1)\;x(n+\tau_2)\;x(n+\tau_3)]\\
m_{5x}(\tau_1, \tau_2, \tau_3, \tau_4) &= E\,[x(n).\prod_{i=1}^{4}\;x(n+\tau_i)]\\
&\ldots\ldots
\end{aligned} \tag{2}$$

Similarly, the kth-order cumulants of $x[n]$, denoted by $c_{kx}(\tau_1, \tau_2, \ldots, \tau_{k-1})$ can be computed from the cumulant generating function (CGF), which is defined as

$$x(\omega) = \ln \Phi(\omega) = \ln E\,[\exp(\mathrm{j}\omega^{\mathrm{T}}\boldsymbol{x})] \tag{3}$$

From the above-mentioned Taylor expansion of MGF and CGF, it is obvious that cumulants can be expressed in terms of moments and vice versa by combining (1) and (3). The kth-order cumulant is defined as the joint kth-order cumulant of the random variables $x(n), x(n+\tau_1), x(n+\tau_2), \ldots, x(n+\tau_{k-1})$. For a given random real-valued discrete-time signal $x(n)$, the second-, third- and fourth-order cumulants can be computed as [26]

$$\begin{aligned}
c_{1x} &= m_{1x}\\
c_{2x}(\tau_1) &= m_{2x}(\tau_1) - m_{1x}^2\\
c_{3x}(\tau_1, \tau_2) &= m_{3x}(\tau_1, \tau_2)\\
&\quad -m_{1x}[m_{2x}(\tau_1) + m_{2x}(\tau_2) + m_{2x}(\tau_2 - \tau_1)] + 2m_{1x}^3\\
c_{3x}(\tau_1, \tau_2, \tau_3) &= m_{3x}(\tau_1, \tau_2, \tau_3) - m_{2x}(\tau_1)m_{2x}(\tau_3 - \tau_2)\\
&\quad -m_{2x}(\tau_2)m_{2x}(\tau_3 - \tau_1) - m_{2x}(\tau_3)m_{2x}(\tau_2 - \tau_1)\\
&\quad -m_{1x}[m_{3x}(\tau_2 - \tau_1, \tau_3 - \tau_1) + m_{3x}(\tau_2, \tau_3)\\
&\quad +m_{3x}(\tau_2, \tau_4) + m_{3x}(\tau_1, \tau_2)] + m_{1x}^2[m_{2x}(\tau_1)\\
&\quad +m_{2x}(\tau_2) + m_{2x}(\tau_3) + m_{2x}(\tau_3 - \tau_1)\\
&\quad +m_{2x}(\tau_3 - \tau_2) + m_{2x}(\tau_2 - \tau_1)] - 6m_{1x}^4
\end{aligned}$$

The above expressions establish the correlation between the original signal and its associated time-shifted versions. The kth-order cumulant is the kth degree of similarity among the aforementioned signals. With zero-mean assumption, the second- and third-order cumulants are the same as the second- and third-order moments, respectively [26]. Higher-order cumulants are used in this paper for two reasons: they are (i) insensitive to additive Gaussian noise interference and (ii) well suitable to analyse non-stationary and non-Gaussian signals. In this Letter, the cumulants up to five will be computed from each of the ACC signals. The cumulants are used as new representative features individually for recognition of different fall events and human activities. For illustrating the effectiveness of the higher-order cumulants, the histograms of the cumulants and the commonly used SMA and SMV features are shown in Fig. 2 for ACC signals such as $a_x[n]$, $a_y[n]$ and $a_z[n]$ along the x-axis, y-axis, and z-axis, respectively. The feature distributions show that the third-, fourth- and fifth-order cumulants extracted from the ACC signal of the z-axis can achieve better FD rates when compared with the SMA and SMV features. Since the fall monitoring system must be capable of detecting fall events in all the directions, the distributions of the cumulant features of ACC signals from the x-axis (FL and FR) and z-axis (FF and FB) are analysed for the detection of fall events. From the plots of feature distributions, it is observed that the fifth-order cumulant features can effectively distinguish the fall and non-fall activities as compared with the other features.

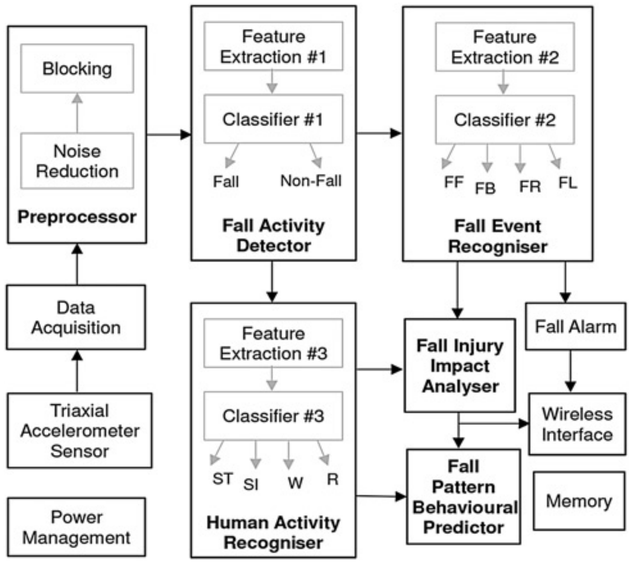

Figure 1 *Architecture of the proposed triaxial accelerometer-based fall monitoring system including major functional modules: fall detector; fall event recogniser; human activity recogniser and fall injury impact predictor*

2.4. HDT classifier: In this Letter, we present a HDT structure that implements the detection and classification tasks in a sequential manner by considering the complexity of the aforementioned primary functional tasks. In our framework, the HDT structure first distinguishes fall and non-fall activities that can be easily distinguished, instead of using conventional classification of ADLs including standing, sitting, walking, running, lying, falling and climbing classes as first step processing of the fall monitoring system. In the second level, the detected falls are classified into four classes: FF, FB, FR and FL using higher-order cumulants extracted from three ACC signals. In the third level, the acceleration windows from the instances of the fall are used for determining activities of daily living as followed in the existing methods. The HDT framework is empirically beneficial to improve the FD accuracy and to reduce processing power, instead of considering multiclass problem as the first step processing. Furthermore, since the fall events of interest differ depending on the activities of daily living, the recognition accuracy of the ADL may be improved based on the direction of the fall and contextual information. The levels in the hierarchical structure are carefully designed to place the easier classification task at the top level. The proposed structure helps us to find significant relevance of activities for effectively predicting the impacts of fall injuries. At each level of HDT structure, the feature extraction module extracts a selected higher-order cumulants and the decision module uses the specific features to perform detection and classification tasks using a predefined classifier.

3. Results and discussion: In this section, we evaluate the performance of the proposed FD, fall event classification (FEC) and ADL classification methods that are constructed using cumulants of order 2–5 and the SMA and SMV features, and classifiers including DT, NB, MLP and SVM.

3.1. Data collection: The datasets for our experiment are collected in an unsupervised study using designed prototype of a

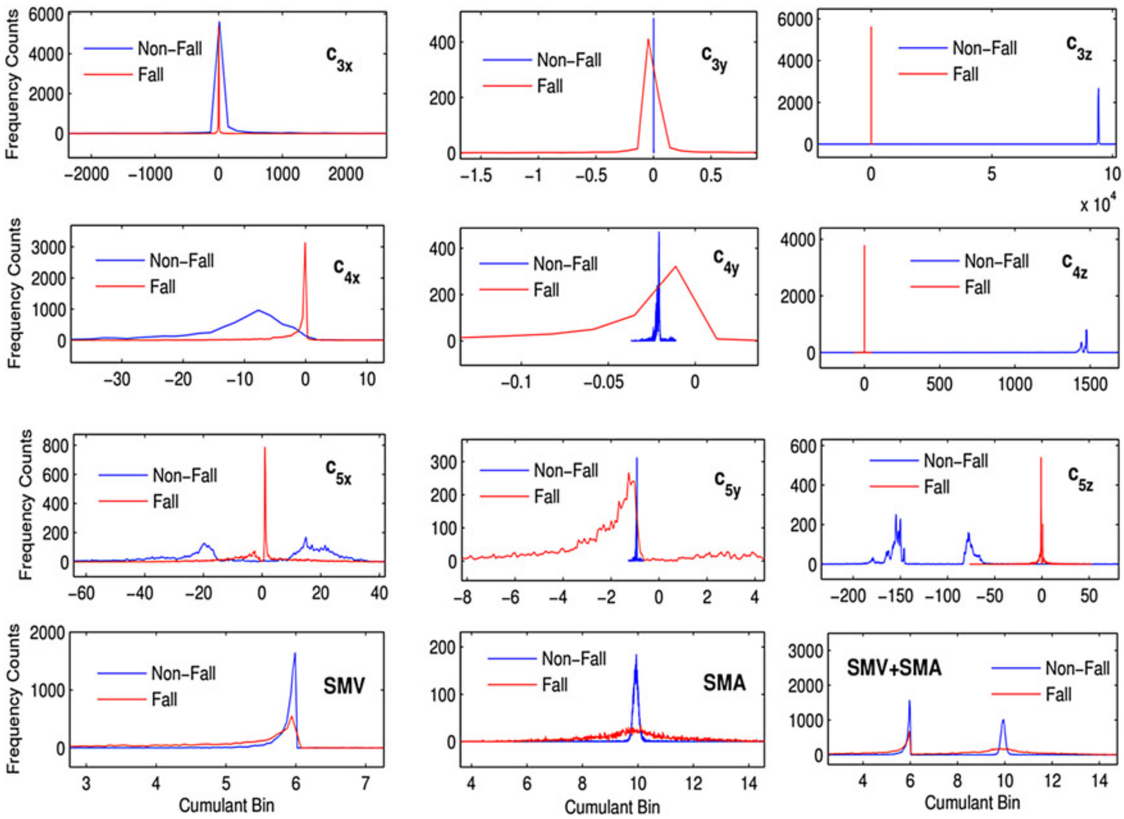

Figure 2 *Histograms of the third-, fourth- and fifth-order cumulants and the commonly used SMA and SMV features that are computed for the triaxial ACC signals of fall and non-fall activities. It can be observed that the fifth-order cumulant features can distinguish the fall and non-fall activities as compared with other features*

waist-worn belt model with a triaxial accelerometer. Our study included six healthy subjects, that is, three females and three males with different hip sizes, that is, small, medium and large, and heights varying from 148 to 162 cm. For each subject, the datasets were collected for specific activities such as sitting, standing, walking, bending and running with consecutive falls in different orientations. The fall events were FF, FB, FL and FR. A sample sequence of the activities performed for our experimental study was: sitting → standing, standing → walking, walking → running, running → walking, standing → sitting, sitting →FF, sitting → FB, sitting → FR, sitting → FL, standing →FF, standing → FB, standing → FR, standing → FR, walking →FF, walking → FB, walking → FR, running →FF, running → FR, sitting → bending, standing → bending. For each activity case, a total of ten datasets for each subject collected to validate the performance of detection and classification methods. The subjects were provided with approximate time duration for each activity. In our experimental study, 70% of the ACC segments in the database were randomly selected and used as a training sample set for training the classifiers, and the remaining 30% were used as a testing set to measure the performance of FD and classification methods.

3.2. Performance evaluation metrics: To investigate the performance of the proposed FD and classification method, we computed three benchmark parameters [4, 6]: (i) accuracy rate (AR) which is defined as the percentage of all correctly detected fall and non-fall segments divided by the number of total segments; (ii) detection rate (DR) which is defined as the percentage of the number of correctly detected fall segments divided by the number of falls; and (iii) false alarm rate (FAR) which is defined as the percentage of the number of non-fall segments detected as a fall divided by the number of fall segments. The AR, DR and FAR are computed as follows

$$\mathrm{AR} = \frac{\mathrm{TP} + \mathrm{TN}}{N_{\mathrm{F}} + N_{\mathrm{NF}}} \times 100\% \qquad (4)$$

$$\mathrm{DR} = \frac{\mathrm{TP}}{N_{\mathrm{F}}} \times 100\% \qquad (5)$$

$$\mathrm{FAR} = \frac{\mathrm{FP}}{N_{\mathrm{NF}}} \times 100\% \qquad (6)$$

where TP, TN and FP denote the true positive, the true negative and the false positive, while N_{F} and N_{NF} denote the number of falls and non-falls, respectively. A larger AR, DR and a smaller FAR would be considered for assessing the effectiveness of the fall event detection system.

3.3. Performance of cumulant-based fall detector: In the first experiment, we investigate the effectiveness of each of the cumulants (order 2–5) in distinguishing the fall and non-fall activities. Table 1 summarises the experimental results of the FD algorithms that are constructed with commonly used classifiers such as NB, MLP, decision tree (DT) and SVMs. At this stage, the performance of each combination of cumulant and classifier is evaluated using the AR, DR and FAR metrics. The detection results show that the NB-based and MLP-based algorithms achieve the AR of 93.14%, DR of 87.70% and FAR of 5.02%, and the AR of 96.91%, DR of 91.40% and FAR of 1.24%, respectively, for the second-order cumulants. The DT-based and SVM-based algorithms achieve the AR of 95.98%, DR of 89.98% and FAR of 2.01%, and the AR of 97.32%, DR of 92.43% and FAR of 1.03% for the third-order cumulant and fifth-order cumulant features, respectively. The evaluation results demonstrate that the proposed cumulant features significantly improve the overall accuracy as compared with the SMA and

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Table 1 Comparison of FD and non-FD results

Signal feature	Metric, %	Classifier			
		NB	SVM	MLP	DT
second-order	AR	93.14	93.82	96.91	95.29
cumulant	DR	87.70	95.59	91.40	90.44
(c_2)	FAR	5.02	6.77	1.24	3.08
third-order	AR	92.00	94.92	92.22	95.98
cumulant	DR	86.66	83.25	87.57	89.98
(c_3)	FAR	6.20	1.18	6.21	2.01
fourth-order	AR	92.15	96.36	92.22	95.60
cumulant	DR	85.95	90.02	87.57	87.70
(c_4)	FAR	5.76	1.15	6.21	1.74
fifth-order	AR	91.56	97.32	92.70	95.34
cumulant	DR	81.92	92.43	90.73	88.40
(c_5)	FAR	5.19	1.03	6.63	2.33
SMA + SMV	AR	91.38	94.54	95.11	94.21
	DR	83.42	90.36	85.37	86.58
	FAR	5.95	4.05	1.62	3.22

SMV features. Further, the results show that the best detection performance of a FD method can be achieved by selecting a suitable cumulant feature and a classifier. Our experimental study shows that the second-order cumulants with MLP classifier and fifth-order cumulant with SVM classifier can achieve promising FD results when compared with the other FD methods.

3.4. Performance of cumulant-based fall event classification: In practice, falls can be grouped based on the major ADL scenarios of fall occurrences: fall from sleeping; fall from sitting; fall from walking; fall from running, fall from standing; and fall from climbing. Falls are of three basic types based on the height and body movements: same floor level falls, elevated falls and vehicle ambulatory falls. Certain ADLs may increase the risk factors of falls and the severity of injury resulting from falls. Therefore, in addition to FD, it is very important to determine the direction of a fall, which could further indicate the weakness in particular joints and fractures [8]. In our framework, the second level of the HDT structure performs a classification of detected falls into semantically meaningful events: FF, FB, FL and FR.

Table 3 Comparison of HAR results

Classifier type	Activity type	Classification accuracy, %				
		Cumulant features				SMA + SMV
		c_2	c_3	c_4	c_5	
NB	running	95.73	99.53	99.53	95.02	95.02
	sitting	85.69	83.23	84.70	81.48	81.77
	standing	98.55	92.52	92.82	97.99	98.09
	walking	47.27	19.49	33.63	64.37	60.51
SVM	running	100.00	89.10	92.18	89.10	97.87
	sitting	90.54	88.29	86.44	88.68	86.46
	standing	98.88	95.32	97.89	96.67	99.57
	walking	92.93	74.66	89.32	89.52	90.80
MLP	running	83.89	79.15	79.62	83.89	72.99
	sitting	83.47	82.48	82.14	83.37	81.48
	standing	99.18	98.71	98.62	87.45	98.32
	walking	92.03	85.85	85.98	75.95	89.90
DT	running	79.38	80.81	79.38	80.57	79.15
	sitting	83.56	84.51	83.56	84.79	83.56
	standing	98.91	98.78	98.91	98.78	98.88
	walking	83.41	87.52	83.41	84.12	83.34

In the second experiment, we evaluate the performance of different event classification methods that are constructed using the cumulant features (second-, third-, fourth- and fifth-order cumulants) and the SMA and SMV features and the classifiers (including MLP, DT, NB and SVM). Table 2 summarises event classification performance for four classes such as FF, FB, FR and FL. On the basis of our evaluation results, it is observed that the cumulant features can provide very promising results for the classification methods with MLP, DT, NB and SVM when compared with commonly used SMA and SMV features. Furthermore, the fifth-order cumulants with SVM classifier-based method outperformed all the other classifiers and features tested for classification of fall events.

3.5. Performance of cumulant-based activity recognition: Human-activity recognition has significant potential in effectively identifying the most serious dangers of fall injuries due to particular

Table 2 Performance of FEC methods (FF, FB, FR and FL)

Classifier type	Fall events	Total frames	Classification accuracy, %				
			Cumulant features				SMV + SMA
			c_2	c_3	c_4	c_5	
NB	front	1549	91.20	97.43	95.76	91.90	86.70
	left	2284	94.68	88.96	91.64	91.60	90.24
	right	2215	90.33	58.83	66.14	84.09	89.07
	back	1548	98.38	12.58	35.18	73.29	85.79
SVM	front	1549	69.22	94.79	95.24	97.04	86.77
	left	2284	96.66	93.44	95.25	95.25	95.14
	right	2215	81.50	90.66	92.69	95.47	92.78
	back	1548	87.67	92.40	96.76	96.51	89.34
MLP	front	1549	85.93	78.08	80.46	85.56	84.76
	left	2284	84.25	92.92	91.29	91.42	92.86
	right	2215	78.63	88.81	88.67	90.71	92.69
	back	1548	94.52	99.50	99.13	99.32	84.43
DT	front	1549	85.35	85.35	85.35	88.62	83.80
	left	2284	93.58	93.58	93.58	94.02	92.47
	right	2215	87.14	87.14	87.14	90.33	89.75
	back	1548	91.41	91.41	91.41	92.65	94.19

Table 4 Coding delay for extracting specific cumulant and performing FD, FEC and HAR for each of the classifiers (NB, MLP, DT and SVM)

Classifier	Coding delay for computing cumulants [c_2, c_3, c_4, c_5]			Testing coding delay			Overall accuracy of methods		
	FD method cumulant (time)	FEC method cumulant (time)	HAR method cumulant (time)	FD, ms	FEC, ms	HAR, ms	FD, %	FEC CA, %	HAR CA, %
NB	c_2(3.53 ms)	c_2(3.53 ms)	c_5(18.3 ms)	0.0240	0.0342	0.0295	AR = 94.14, FAR = 5.02	93.64	84.71
DT	c_3(8.9 ms)	c_5(18.3 ms)	c_3(8.9 ms)	0.0042	0.0132	0.0098	AR = 95.98, FAR = 2.01	91.40	87.90
MLP	c_2(3.53 ms)	c_5(18.3 ms)	c_2(3.53 ms)	0.0031	0.0118	0.0056	AR = 96.91, FAR = 1.24	91.75	89.64
SVM	c_5(18.3 ms)	c_5(18.3 ms)	c_2(3.53 ms)	2.764	4.333	6.832	AR = 97.32, FAR = 1.03	96.06	95.58

joints and fractures, and also enabling immediate rehabilitation treatment based on the type of serious fall injuries including head and neck injuries, shoulder and forearm fractures, spine and foot fractures and pelvic and hip fractures. In this Letter, we present an automated activity recognition method for recognising daily physical activities such as sitting, standing, walking and running using the cumulants extracted from the ACC signals. In the third experiment, we investigate different sets of cumulants and classifiers to find a proper combination that can achieve promising classification results. Table 3 summarises the classification accuracy (CA) of the developed methods. The experimental results show that the NB-based method achieves higher average CA of 84.71% for the fifth-order cumulants extracted from the ACC signals. The MLP- and SVM-based methods yield higher average CA of 89.64 and 95.58%, respectively, for the second-order cumulants. The DT-based method achieves higher average CA of 87.90% for the third-order cumulants. From the results, it is noted that the cumulant-based activity recognition methods outperform the SMA- and SMV-based methods. On the basis of our experimental results, the SVM-based method with second-order cumulants can achieve promising classification results when compared to the results of other activity classification methods reported in Table 3.

3.6. Computational burdens of the proposed methods: In this subsection, we investigate the computational speed of the proposed detection and classification methods developed using a different combination of cumulant features and classifiers that gives promising results as summarised in Tables 1–3. The coding delay required for each method is summarised in Table 4. As can be seen in Table 4, the execution time required for implementing detection and classification based on the fifth-order cumulants and SVM classifier is high when compared with the other methods. However, the SVM-based methods had optimal detection and classification rates as well as the lowest FAR. The overall computation time required for executing all the three levels of HDT-based system is 54.05 ms, which is much smaller than the duration of three-axis ACC signals used in our experimental study. However, in the future, we will further study the computational speed by implementing the proposed detection and classification algorithms on real-time processors. On the basis of our results, we believe that the proposed framework has great potential in context-aware fall injury impact prediction system.

4. Conclusion: In this Letter, we present a unified framework for waist-mounted triaxial accelerometer-based fall monitoring system including the FD, fall direction determination and human activity recognition (HAR) for effectively predicting the impact of fall injury. We investigate the effectiveness of higher-order cumulants combining with classifiers for better characterisations of different types of ACC signals. By considering the processing power and speed, the HDT structure implements FD, fall event and ADL classification tasks in a sequential manner. The FD and FEC methods are proposed using the fifth-order cumulants and support vector machine (SVM). The proposed FD method achieves the AR, DR and FAR of 97.32, 92.43 and 1.03%, respectively. The FEC method achieves an average CA of 96.06%. The HAR is implemented using the second-order cumulants and SVM. For daily physical activities, the proposed HAR method yields an average CA of 95.58%. The experimental results demonstrate the superiority of the proposed methods using the cumulants and SVM classifier.

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