

Applying PSO to improve the pedestrian fall detection rate using wearable sensor data

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Abstract— Pedestrian fall detection attracts a lot of research due to its importance in building a warning system to avoid negative consequences. There are many techniques for fall detection that have used different devices such as cameras, environmental sensors, wearable sensors, etc. However, the popularity of wearable devices with many embedded sensors has motivated research on detecting abnormal activity such as falling based on sensor data. High accuracy of fall detection in daily life activities is always a practical challenge. This paper investigates different classifiers using a combined feature set that computes from Time, Frequency, and Hjorth domains using the wearable device's accelerometer data only. This study also employs Particle Swarm Optimisation (PSO) to find the parameters of the Random Forest classification, which aims to improve the accuracy of the fall detection system. The experimental results on the UP-Fall dataset have shown a better performance than the study of L. Martínez-Villaseñor et al. Combining the RF classifier with PSO also improves the stability and performance of the model.

Keywords— Fall detection system; classification model; feature extraction, Particle Swarm Optimization; accelerometer

I. INTRODUCTION

Smartphones have become popular over the world with several integrated sensors. Therefore, they become helpful devices for human activity recognition (HAR) to detect users' activities [1]. With the increasing number of the elderly, therefore necessary to develop applications or devices that can monitor and detect unusual actions in daily life. However, abnormal behaviors such as falls need to be exactly detected because the consequences of falls are often more severe, especially for the elderly.

Many factors pose a risk of falls which can be classified: internal factors related to behaviors and the state of human health; external factors related to the environment [2], [3]. Identifying multiple links between these factors will better determine the level of risk for a fall. The unknown environmental factor will create a big challenge when evaluating the level of risk that causes a fall. In this study, we investigate the fall detection model which only uses data captured from an accelerometer on wearable devices. It is really

challenging when the data size of falls is much smaller than that of daily activities which causes the imbalanced distribution of activity classes resulting in the downgraded performance of activities recognition and especially fall detection. Therefore, this paper focuses on determining the best classifier in abnormal activities recognition like falls. Furthermore, an optimization method which is the PSO algorithm will be used to optimize the parameters of the classifier to significantly improve the accuracy of the fall detection model.

The rest of the paper has been organizing as follows: Section II introduction related studies a brief description of some modern methods proposed by other researchers to solve the HAR problem. In Section III, we present the proposed fall detection model. Section IV introduces the test dataset, describes the test process and the test results. Section V provides conclusions and puts forward future researches.

II. RELATED WORKS

In this section, we review relevant fall detection approaches using a wearable device, inertial measurement unit (IMU), or smartphone.

Adnan Nadeem et al. [4] built a dataset using wearable electrocardiographic and inertial measurement sensors for activity recognition, fall detection, and a basic heart abnormality detection system. Yan Wang et al. [5] surveyed wearable sensor modality-centered human activity recognition in health care. H. F. Nweke et al. [6] have shown the difficulties and challenges of using deep learning algorithms to recognize human activity using mobile and wearable sensor networks. Netra Ganesh Chigateria et al. [7] used an accelerometer to measure activity of old people. Emma Stack et al. [8] have a study that identifying balance impairments in people with Parkinson's disease using video and wearable sensors. Pierleoni et al. [9] proposed a fall detection system based on an accelerometer placed on the belt. For classification, they used an algorithm that combines training thresholds with a Support Vector Machine. Martínez-Villaseñor et al. [10] present a UP-Fall Fall Detection Dataset. Activities detection performance when combining data of three types of sensors IMU, EEG, and

CAM achieves the best results. The MLP classifier achieved the best results on the Accuracy scale (95.0%). However, on the precision, sensitivity, and F1-score measures, the results are 77.7%, 69.9%, and 72.8%, respectively, which are much lower than the Accuracy measure. The results of the identification of fall activities were also low. That proves that their proposed feature set and model are not suitable for multiclass classification based on an unbalanced dataset. Le et al. [11] propose a new feature set to reduce the number of input attributes based on the APGWO model. They used three types of data included in the UP-Fall dataset to train the model. Various classifiers like Logistic Regression (LR), K-Nearest Neighbor, Support Vector Machine (SVM), Decision Tree (DT), Naïve Bayes (NB), Random Forest (RF), Multilayer Perceptron (MLP) and the proposed model (APGWO) were used to evaluate the effectiveness of the proposed feature set. The best performance in Accuracy and F1 scores are 99% and 96% respectively. Although Le et al. [11] proposed an identification model based on binary classification, the F1 score is not impressive. On the other hand, this study uses a combination of many different types of sensor data, so it is not suitable for practical implementation. This paper proposes "Applying PSO to improve the pedestrian fall detection rate using wearable sensor data" to partially this sub-shortcoming.

III. THE FALL DETECTION SYSTEM

A. Activities detection system

The daily activities including abnormal behaviors such as falls are commonly recognized in a framework, namely Human Activity Recognition (HAR), described in Figure 1.

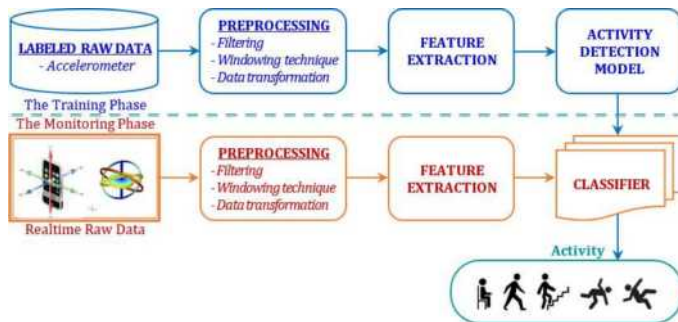


Figure 1. Human Activity Recognition System

It was divided into two phases (training and monitoring phases), which are depicted as following:

- The Training phase using the collected data with labeled to construct optimizing model. Data preprocessing techniques are used to build the feature sets with the combination of different domains including time-domain, frequency-domain and Hjorth-domain. Then, these feature sets are used to train the fall detection model. A number of classification algorithms were surveyed to select the best one for this data.
- The Monitoring phase: the data of daily activities are collected, preprocessed and then it was predicted by the optimizing model which was train in the first phase for the suitable activities.

B. Proposed method

1) **Particle Swarm Optimization (PSO)** is a swarm intelligence method inspired by the social behavior of bird flocking or fish schooling and developed for the global optimization algorithm. The algorithm was announced in 1995 at the IEEE conference by J. Kennedy and R. Eberhart. It has become one of the most popular techniques applied in optimization problems, due to its ease and capability to find near-optimal solutions. Since the PSO algorithm came out, it has attracted a lot of research interests.

The positions and velocities of the individuals are updated according to the iterative formula of the basic particle swarm optimization algorithm (bPSO) [12], [13] as follows:

$$v_i^{t+1} = \omega * v_i^t + c_1 * r_1 * (P_{best} - x_i^t) + c_2 * r_2 * (G_{best} - x_i^t) \quad (1)$$

$$x_i^{t+1} = x_i^t + v_i^{t+1} \quad (2)$$

Subject to:

- x_i^t : The position of individual i in the t generation
- v_i^t : The velocity of individual i in the t generation
- x_i^{t+1} : The position of individual i in the $t+1$ generation
- v_i^{t+1} : The velocity of individual i in the $t+1$ generation
- P_{best} : The best position individual i achieved
- G_{best} : The best location in the complex
- ω : inertia coefficient
- c_1, c_2 : Acceleration coefficients, the values between 1.5 and 2.5
- r_1, r_2 : Random numbers, the values between 0 and 1

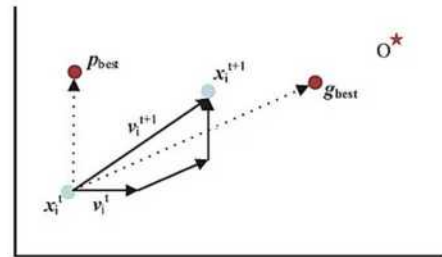


Figure 2. The process of updating the location of the PSO algorithm

The steps to implement the algorithm for parameter optimization are described in pseudocode as follows:

Algorithm 1: Particle Swarm Optimization

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1. P = Particle_Initialization()
2. For i:=1 to tmax do
3.   For each particle p in P do
4.     If p > Pbest
5.       Then Pbest ← p
6.     EndIf
7.   EndFor
8. Gbest = best Pbest in P
9.   For each particle p in P do
10.    v = ω*v + c1*r1*(Pbest-x) + c2*r2*(Gbest-x)
11.    x = x + v
12.   EndFor
13. EndFor
14. Return Gbest

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2) The proposed objective function (F function): It used to evaluate the performance of classifier based on several assessment matrices like Accuracy, Precision, Recall, F-measure, and AUC. Among those, the F-measure is the best one for the imbalancing dataset. Therefore, we take advance of this assessment matrix to build the objective function of PSO which help to improve the performance of Random Forest classifier. The objective function is constructed as follows:

$$F_{\text{Fall}} = \frac{1}{n} \sum_{i=1}^n w_i F_i \quad (3)$$

Subject to:

- n : the number of fall activities in the training set
- i : the i^{th} fall activity
- w_i : the percentage of the i^{th} fall activity over the total number of training samples
- F_i : the F-Measure value of i^{th} fall activity

3) Random Forest Classifier: Random Forest (RF) [14] is an ensemble learning method for classification and regression. It has been developing by Leo Breiman. Breiman is also the co-author of the book Classification and Regression Trees [15]. RF is an improvement of the bootstrap (bagging) synthesis method. RF uses two randomization steps, first is sample randomization using the bootstrap method with reimbursement. The second is to take a random number of attributes from the original. The sub-datasets generated from these two random times are highly diverse and have little relation to each other, which helps to reduce the error of variance. The CART trees built from this subset of data sets form the forest. When aggregating the results, RF uses the voting method for the classification problem and takes the average value for the regression problem. Combining these CART models to give the final result, RF is called the ensemble learning method.

In RF, each tree selects only a small set of attributes during construction (2nd random step). This mechanism makes RF perform with data sets with many attributes. The user can set the default number of attributes to build trees in the forest.

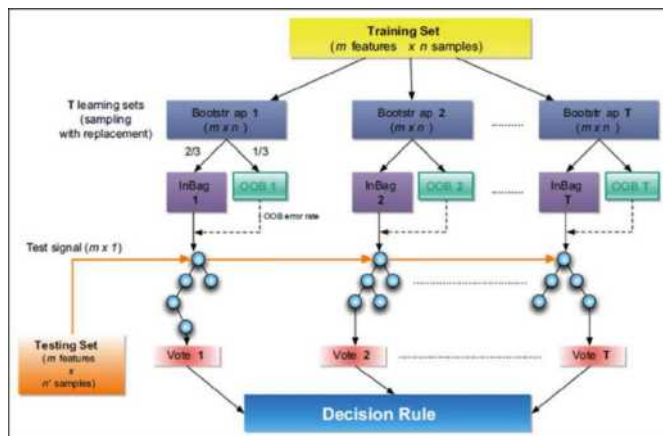


Figure 3. The scheme of random forest algorithm

RF uses the bootstrap method of refundable random sampling. So the sub-datasets have about two-thirds of the samples that do not overlap. These samples have been used to

build the tree, and they are called in-bag. About a 1/3 samples are called out-of-bags. Since it does not participate in tree construction, RF uses these out-of-bag samples to test and compute the important properties of CART trees in the forest. The Random Forest algorithm is shown in Figure 3.

The parameters of the classifier affect the predictability. The degree of influence of the parameters is different. Therefore, it is necessary to select key parameters of the algorithm for optimization. The optimal parameters will be vitally important. Changing these parameters will make the accuracy of the model increase or decrease significantly. We investigated and proposed to use RF classifier parameters as input parameters for the PSO algorithm as follows:

- P (Bag size percent): Size of each bag, as a percentage of the training set size.
- I (num Iterations): Number of iterations (i.e., the number of trees in the random forest).
- Num-slot (numExecutionSlots): The number of execution slots (threads) to use for constructing the ensemble.
- K (numFeatures): Number of attributes to randomly investigate.

IV. EXPERIMENTAL EVALUATION

A. Dataset

UP-Fall Detection (UP-Fall) is a large dataset mainly for fall detection, that includes 11 activities and 3 trials per activity. Subjects performed six simple human daily activities as well as five different types of human falls. These data were collected over 17 healthy young adults without impairment using a multimodal approach, i.e., wearable sensors, ambient sensors, and vision devices. This dataset is publicly available at <http://sites.google.com/up.edu.mx/har-up/>.

This dataset is collected and described by Martínez-Villaseñor et al. [16]. It was collected over four weeks, from June 18th to July 13th, 2018 on the third floor of the Faculty of Engineering, Universidad Panamericana, Mexico City, Mexico. All the devices and equipment for measurements were connected locally to a set of computers. These computers centralized all the information and saved the data on hard drives.

TABLE 1. ACTIVITIES PERFORMED BY SUBJECTS

Activity	Label	Duration (s)	Description
Falls	A01	10	Forward using hands
	A02	10	Forward using knees
	A03	10	Backward
	A04	10	Sideward
	A05	10	Attempting to sit in an empty chair
Daily activities	A06	60	Walking
	A07	60	Standing
	A08	60	Sitting
	A09	10	Picking up an object
	A10	30	Jumping
	A11	60	Laying

The activities performed are related to six simple human daily activities (walking, standing, picking up an object, sitting, jumping and laying) and five human falls (falling forward using

hands, falling forward using knees, falling backwards, falling sitting in an empty chair and falling sideward). Falls occurs performing a great variety of circumstances and manners. All daily activities were performed during 60s, except jumping that was performed during 30s and picking up an object which it is an action done once within a 10s period. A single fall was performed in each of the three ten seconds period trials. For all these activities, a mattress was located in the falling area to prevent injuries. Each activity was performed three times (trials) by each young healthy subject without any impairment. Table 1 summarizes the activities and the duration each trial takes in the dataset.

B. Results and Discussion

1) The effect of the sliding window size and overlapping ratio

The purpose of this experiment is to find the best sliding window size and overlap ratio. First, we investigate the effect of the different window sizes of samples with overlapping ratios from 0% to 90%. In our previous studies, each window size extracted 44 combined features from the raw data for the best performance. So in this investigation, we use a combined vector of 44 features for each sliding window size. Six window sizes ranging from 2^5 samples to 2^{10} samples have been used for the experiment.

Five basic classifiers - i.e., Random Forest (RF), Artificial Neural Network (ANN), Decision Tree (J48), k-nearest neighbor (k-NN), and Support Vector Machine (SVM) have been used to evaluate the influence of feature sets on different classifiers as well as to select the best classifier for the fall detection system. The default parameters in the classifiers' have been set as shown in Table 2. The 10-fold cross-validation and the F-score metric have been used to evaluate the performance of classifiers.

TABLE 2. THE PARAMETER SET OF THE CLASSIFICATION ALGORITHMS.

No.	Algorithms	Parameters
1	RF	Size of each bag $P = 100$; Number of iterations $I = 100$; Number of execution slots = 1; Number of attributes to randomly investigate $K = 0$;
2	J48	Set confidence threshold for pruning $C = 0.25$; Set minimum number of instances per leaf $M = 2$
3	k-NN	Number of nearest neighbours (k) used in classification $K = 1$; Maximum number of training instances maintained. Training instances are dropped FIFO $W = \text{no window}$; The nearest neighbour search algorithm to use <code>weka.core.neighboursearch.LinearNNSearch</code> .
4	ANN	Learning rate for the backpropagation algorithm $L = 0.3$; Momentum rate for the backpropagation algorithm $M = 0.2$; Number of epochs to train through $N = 500$; Percentage size of validation set to use to terminate training $V = 0$; The value used to seed the random number generator $S = 0$; The number of consecutive increases of error allowed for validation testing before training terminates $E = 20$.
5	SVM	The complexity constant $C = 1$; The tolerance parameter $L = 0.001$; The epsilon for round-off error. $P = 1.0e-12$; Whether to 0=normalize/1=standardize/2=neither $N = 0 = \text{normalize}$; The number of folds for the internal cross-validation $V = -1$, use training data.

Figure 4 shows the performance is improved when the window size increases from 32 to 64 samples. Then there is a decline in the performance at longer window sizes in all classifiers. On the other hand, the best performance attains with the optimal window size of 64 samples.



Figure 4. Effect of sliding window size on the detection performance of the model.

In simultaneous multi-activities recognition, it is really challenging and important to select an optimum window size. For fast-changing activities like falls, the smaller window size is preferred to obtain high accuracy of fall detection. At longer window size, the fast-changing activity gets more noise from other daily activities which can degrade the performance of fall detection models. For daily activities like walking or jumping, however, the periodic characteristics of these activities can be more captured at a longer window size that helps classifiers improve activity recognition. While these characteristics can be lost at shorter window sizes. Therefore, the optimum window size is short enough to avoid noise interference but long enough to sufficiently capture the characteristics of activities.

The next step is to evaluate the effect of the overlapping ratio. The sliding window size has been fixed at 64 samples (equivalent to 1.28 seconds for the UP-Fall dataset). The nine overlap rates (from 10% to 90%) have been set up, results as shown in Figure 5.



Figure 5. Effect of overlapping ratio on the detection performance of the model.

An increase in the overlap rate improves the performance of ADLs recognition and fall detection. A higher overlap rate requires new data to be read in a shorter subsequent window, allowing for efficient detection of rapid activities such as falls.

As the overlap ratio increases, the performance of the model also increases.

In general, the performance of the model is directly proportional to the overlap. Sliding window size at 64 data samples and 90% overlap rate has the best and stable detection. In this case, the RF classifier gives the highest result of 99.5% in the F-measure.

2) The experimental results: As mentioned above, in this experiment, we focus on the F-measure weights of fall actions (A01, A02, A03, A04 and A05) to build a parameter optimization algorithm for RF classifiers. The obtained results are showing in Figure 6.

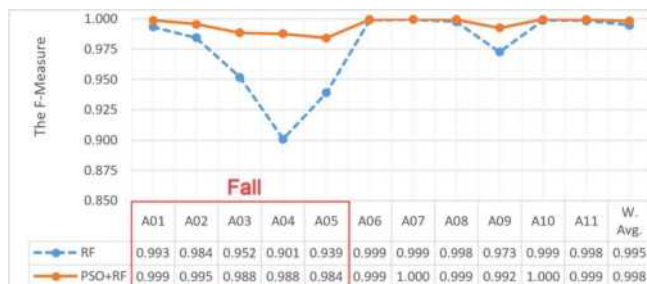


Figure 6. Compare the classification results of the standalone RF model, and a model combines the RF classifier with the PSO algorithm in each activity.

Figure 6 shows a clear improvement of the performance in all activities, especially fall activities. The F-measure score in all activities, especially fall activities, is better than the original RF model. Using the PSO algorithm combined with the RF classifier, the average F-measure score of fall actions increased from 95.39% to 99.09%.

Comparison with the Recent Works: For objective comparison results, we have been setting the sliding window size at 128 and the overlapping ratio at 50% as L. Martínez-Villaseñor et al. [16]. The experimental results show that the detection rate of our proposed model is similar to [16] in terms of Accuracy and Specificity. However, the Precision, Sensibility, and F-measure score outperformed [16], as shown in Figure 7.



Figure 7. Detection performance of L. Martínez-Villaseñor [16] and ours.

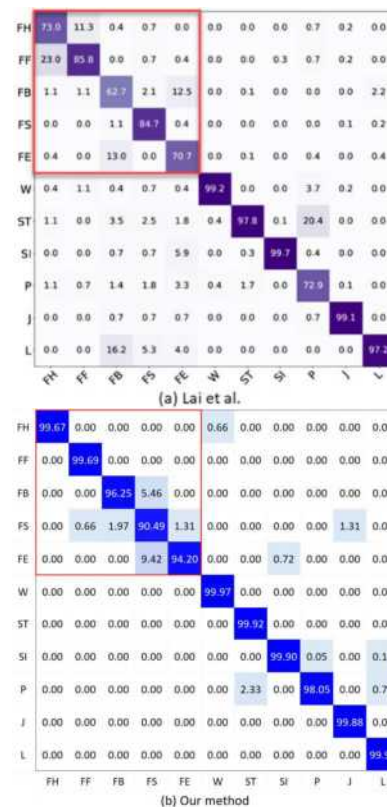


Figure 8. Detection performance of Lai et al. [17] (a) and ours method (b).

The confusion matrix in Figure 8 is the activities recognition result of Lai et al. (8. a) and our method (8. b). The elements on the diagonal are the percentage of correct predictions and off the diagonal are the wrong predictions.

In the study of Lai et al. [17], the recognition performance of falling and non-falling activities have a big difference. The ability to detect falls and activities that confuse (P - Picking up an object) is not good and only reaches 62.2% to 85.8%. Meanwhile, our method also achieves at least 90.49%, including confusing activity (P - Picking up objects).

V. CONCLUSIONS

In this paper, we proposed a novel method for improving classifiers using Particle Swarm Optimization to deal with wearable sensor data. The wearable sensor data was preprocessing and transform into Time, Frequency and Hjorth domains and then, the PSO optimization algorithm has been applied to find the optimal set of parameters for the RF algorithm to improve its detection rate.

Experimental results show that the detection rates have been improved from 99.48% to 99.82% in the F-measure score. The average detection efficiency at fall activities increased up to 3.71%. In addition, with the proposed feature set, our measures of precision, sensibility, and F-measure are superior to [16]. From the obtained results, it well detects the fall activities of pedestrians. Therefore, in the future, we will expand our research towards building a feature set from many sensors to improve and enhance the stability of the fall detection system.

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