A Sparse Representation Classification for Noise Robust Wrist-based Fall Detection

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Keywords: Additive White Gaussian Noise, Machine Learning, Supervised Dictionary Learning, Wearable Fall detection.

Abstract: Elderly falls are becoming a more crucial and major health problem relatively with the significant growth of the involved population over the years. Wrist-based fall detection solution gained much interest for its comfortable and indoor-outdoor use, yet, a very moving and unstable location to the Inertial measurement unit. Indeed, acquired data might be exposed to random noises challenging the classifier's reliability to spot falls among other daily activities. In this paper, we address the limits faced by Machine Learning models regarding noisy and overlapped data by proposing a study of the Supervised Dictionary Learning (SDL) technique for on-wrist fall detection. Following the same prior work experimental protocol, the five most popular SDL models were evaluated and compared in performance with two benchmark Machine learning models. The evaluation setup follows two main experiments; processing clean data and casting different additive white Gaussian noise (AWGN). A distinguishable achievement was obtained by the SDL algorithms, of which the Sparse Representation-based Classifier (SRC) algorithm surpass other models especially using noisy data. The latter maintained almost 98% for 0db AWGN versus 96.4% for KNN.

1 INTRODUCTION

The rate of the elderly population has seen an imposing growth over the last decades and is projected to be still increasing throughout the upcoming years to outpass children under-five population. This notable phenomenon has been aroused by both proportions: a steady increase in life expectancy and the decline in fertility rate (World Health Organization and US National Institute of Aging,2011). Indeed, this dramatic increase of such a fragile population will eventually affect the global world's health and well being as the dependency rate will respectively boost. One of the most crucial health risks faced by the older population is falling. It has been classified as a disease in the eleventh version of the International Classification of Diseases (World Health Organization, 2019). Therefore, statistics from (World Health Organization, 2008) show that 30% of people older than age 65 and 50% of people older than age 85 will face a fall risk at least once per year. Accordingly, one-third of those who fall, seek for medical care, believing it may lead to losing their independence.

Wearable fall detection systems have attracted much research interest with the emergence of smart wearable devices and sensors over the recent years, stimulated by their anywhere-anytime accessibility and comfortable use. Two main wearable fall detection approaches have been proposed in the related literature, namely, threshold-based and machine learning-based, as the latter has received more interest lately (Xu et al., 2018), (Ramachandran and Karuppiah, 2020). To enhance system's reliability, an optimal combination of feature extractors and classifiers has been extensively researched in most related works as (Vallabh et al., 2016), (Casilari-Pérez and García-Lagos, 2019), (Zhang et al., 2019), (de Quadros et al., 2018). However, classification performance can degrade substantially, since hand-crafted features may be very specific to a given acquisition device, its on-body placement and the trained dataset (Casilari-

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Othmen, F., Lazzaretti, A., Baklouti, M., Jmal, M. and Abid, M.
A Sparse Representation Classification for Noise Robust Wrist-based Fall Detection.
DOI: 10.5220/0010238804090416
In *Proceedings of the 14th International Joint Conference on Biomedical Engineering Systems and Technologies (BIOSTEC 2021) - Volume 5: HEALTHINF*, pages 409-416
ISBN: 978-989-758-490-9

Pérez et al., 2017), (Aziz et al., 2016).

Dictionary learning approaches (DLA) have gained a lot of interest in image processing including sparse representation based classification algorithm for face recognition (Xu et al., 2017), as it has shown robustness especially for a narrow number of channels and samples. Recently, DLA has emerged to cover classification and pattern recognition tasks in many fields in order to reduce the need to select the best feature and classifier combination for the application. Thus, some related works have been proposed based on Supervised Dictionary Learning Technique (SDL) for biomedical signal processing field, mainly for Electroencephalogram (EEG) (Mo et al., 2017), (Sheykhivand et al., 2020) and Electrocardiogram (ECG), (Ceylan, 2018), (Andrysiak, 2018) for anomaly detection.

To the extent of our knowledge, such a dictionary-based approach is still uncharted in the wearable-based fall detection systems. We have first started by proposing the SDL as main contribution for on-wrist based fall detection as an autonomous feature extractor and classification combiner from acquired raw data in a previous work (Othmen et al., 2020). This paper aims to conduct an advanced exploration of the SDL technique to demonstrate its efficiency and robustness in fall detection systems and to compare its performances with previous machine learning-based study (de Quadros et al., 2018). Therefore, the implemented machine learning model may face challenges caused by the unstable on-wrist location that affects the inertial measurement unit (IMU), as the acquired data may face random distortion resulting in noisy and overlapped data. Assuming that IMU measurement noise can be accurately modeled using the white noise model (Barrett et al., 2012), we will be adapting the same experimental protocol of the previous study along side with Additive White Gaussian noise (AWGN) to assess the robustness, reliability of various SDL, and sparse representation algorithms, compared to ML methods.

The paper is organized as follows: Section II provides an overview of the proposed method and briefly describes the SDL techniques, where the most used algorithms are also presented. Section III illustrates the obtained results and compares them with prior work. Conclusion and future related works are provided in Section IV.

2 METHOD AND BACKGROUND

Considering that wrist-worn devices are the most comfortable body location for the patient (Ozdemir, 2016), they are yet very unstable for the IMU. Since arms are usually very moving parts of the body, many hand movements, i.e., clapping, rising and releasing hands, may present similar motion patterns compared with fall movements. These movement features similarities may present a bottleneck in the MLM, especially when it comes to noisy acquired data. One of the most faced challenges for MLM is the overfitting problem that is mainly caused by learning noisy and overlapped data. Although we can manage to filter some external influence, low cost MEMS IMU has random internal noise sources associated with it that manipulates the classification algorithm structure (Barrett et al., 2012), (Kj et al., 2016).

To overcome this issue while bearing in mind the system reliability, we propose SDL technique as it has previously proven its effectiveness to manage raw and noisy data processing and maintaining a considerable efficiency (Othmen et al., 2020). To compare prediction performances, we adapt the same implemented experimental protocols employed in (de Quadros et al., 2018) using clean and different Signal-to-Noise Ratios (SNR). Therefore, different SDL algorithms will be evaluated and compared through their prediction performances with Machine Learning classifiers.

The pipeline of the designed architecture is illustrated in **Fig 1** and it is detailed in the following subsections.

2.1 Data Collection and Preprocessing

The data set has been gathered all through the (de Quadros et al., 2018) study. In fact, the signal acquisition was done by the employment of three main tri-axial IMU sensors, namely, accelerometer, gyroscope, and magnetometer which are embedded within the GY-80 IMU model device. To amass and register data signals from the latter sensors, an Arduino Uno was integrated with the IMU device into a wrist-worn band paced at the non-dominant hand. The raw sensors data were obtained in a 100 Hz sampling rate and therefor the accelerometer, gyroscope, and magnetometer sensors were configured as 4g, 500 degrees/sec and 0.88 Ga respectively.

In order to create a more generalized and accurate dataset, twenty-two volunteers with different ages, heights, and weights were engaged during this experimentation. Each one performs two main event categories, i.e, fall incidents and activities of daily living (ADL). The registered falls enclose forward to fall, backward fall, right-side fall, left-side fall, fall after rotating the waist clockwise, and fall after rotating the waist counterclockwise. The ADL's performed activi-

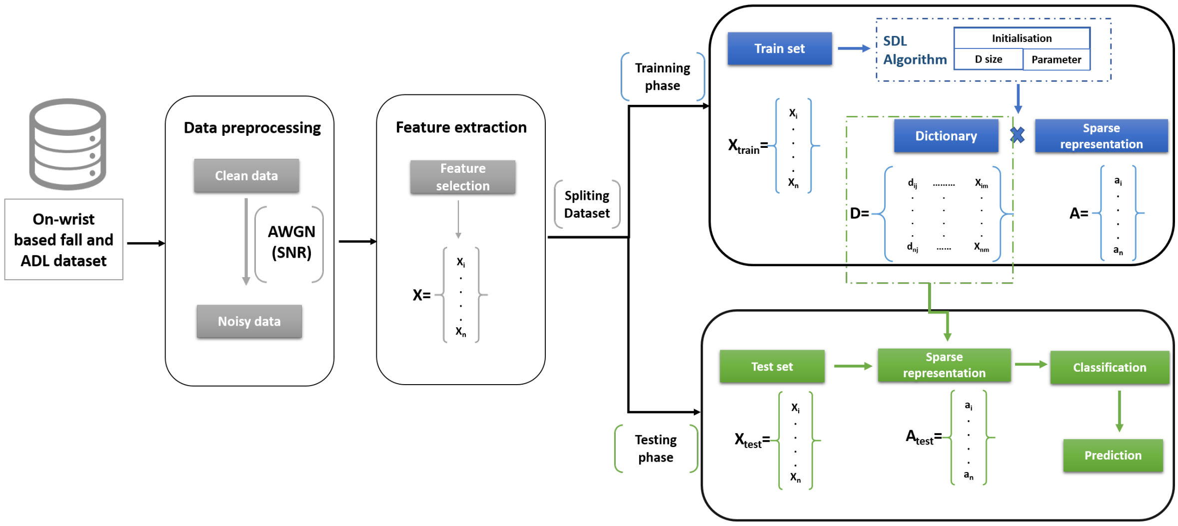


Figure 1: Pipeline of the proposed achitecture.

ties cover walking, clapping hands, moving an object, tying shoes, and sitting on a chair. The average duration of the recorded activities is 9.2 seconds, assuming that every one starts with a resting arm (resting state) followed by a few steps before the activity's performance.

For the sake of removing any external influence that affects the accelerometer (Vallabh et al., 2016), the accelerometer data was preprocessed with a moving average filter with a window size of 40 and a subtraction of a fixed value equal to 1G to eliminate the gravity-related information.

2.2 Feature Extraction

This work implements SDL classification approaches in a wrist-based fall detection system while benefiting from its capacity to generate more discriminative features using sparse representation. For this purpose, we maintained the same feature engineering protocol adopted in the previous work (de Quadros et al., 2018), since the selected features will play an imperative role in system efficiency and its comparison with other proposed approaches.

The feature extraction depends on two main signal categories, i.e., movement-based and orientation-based. Concerning the movement, the most used popular extracted movement pattern is the Total acceleration (TA) (Vallabh and Malekian, 2017), (Pannurat et al., 2014), described by the following equation (1):

$$TA = \sqrt{x(t)^2 + y(t)^2 + z(t)^2}, \quad (1)$$

where x(t), y(t), z(t) represents respectively the registered x, y and z axis of the accelerometer. For a clearer movement decomposition, five other signals have been obtained, which are described as: (a) VA is The Vertical Acceleration considering only the vertical component of TA; (b) TV is the Total Velocity obtained through time window integration of TA; (c) Vertical Velocity VV is the time window integration of VA; (d) TD is the Total Displacement considering the time window integration of TV; (e) Vertical Displacement VD obtained from the time window integration of VV.

The orientation-based decomposition is acquired through an orientation filter. In fact, the Madgwick's orientation decomposition method defined in (Madgwick, 2010) has been employed. Indeed, it uses data provided from IMU sensors to describe the estimated nature of orientations in three-dimensions through a quaternion representation. These angle representation of the quaternion are called Euler angles and defined by the Yaw, Pich, and Roll angles.

Taking into account the feature extraction, the selected features were the maximum and mean of each window interval of the obtained vertical component, VA, VV, and VD respectively. On the other hand, only the mean values of the sine and cosine corresponding to the Euler angels (Yaw, Pich, and Roll) were considered. Afterward, the twelve selected features were normalized in the range of [-1, 1].

2.3 Supervised Dictionary Learning Technique

In general, the main idea of dictionary learning is to find a sparse representation of a signal or an image using a dictionary from a predefined training set. DLA is fitted to many problem domain as it has proven state-of-the-art achievements mainly in computer vision, both in supervised and unsupervised tasks, i.e., in information retrieval, image reconstruction, and pattern recognition (Gangeh et al., 2015). Taking into account the classification task, several Supervised dictionary-based learning methods are recently presented in the literature to enhance it's efficiency. As discussed in (Xu et al., 2017), SDL methods can be divided into shared, class-specific, commonality and particularity, auxiliary, and domain adaptive dictionary learning.

As being a branch of Machine Learning, the classification based on SDL involves two main phases, namely the training and the testing phases. In the training phase, the goal of the SDL algorithm is to map the low dimensional training data $\mathbf{X}$ to a high and sparse dimensional representation denoted $\mathbf{A}$ over an optimised and learned dictionary $\mathbf{D}$, to make more discriminative pattern and easier to be distinguished. The objective here is to define $\mathbf{D}$ and the sparse representation $\mathbf{X}$ while respecting extra constraints $f_A(.)$ and $f_D(.)$ through an optimization problem generally defined by the following equation (2):

$$\min_{\mathbf{D},\mathbf{A}} \{ \sum_{i=1}^{N} (\frac{1}{2} ||\mathbf{x}_i - \mathbf{D}\mathbf{a}_i||_2^2 + \lambda_1 ||\mathbf{a}_i||_q) \\ + \lambda_2 f_A(\mathbf{A}) + \lambda_3 f_D(\mathbf{D}) \}, \tag{2}$$

Based on (Suo et al., 2014), the function $f_A(.)$ could be a logistic function, a linear classifier, a label consistency term, a low-rank constraint or Fisher discrimination criterion. As for $f_D(.)$ is to force the incoherence of the dictionary for different classes. Hence, it is possible to jointly learn the dictionary and classification model, which attempt to optimize the learned dictionary for classification tasks (Jiang et al., 2011). The testing phase follows two fundamental processes:

First, the used algorithm generates the sparse coefficient $\mathbf{a}_{test}$ of the test sample $\mathbf{x}_{test}$ directly through the learned Dictionary $\mathbf{D}$ satisfying the previous equation (2).

Second, the label of each test sample is assigned while maintaining the class with the minimum reconstruction error rate according to:

$$Label(\mathbf{x}_{test}) = \min_i r_i(\mathbf{x}_{test}), \tag{3}$$

where, $r_i = ||\mathbf{x}_{test} - \mathbf{D}\sigma_i(\mathbf{a}_{test})||_2^2$ designs the error rate equation, σ_i is the selective function of the coefficient vector associated to the class i. and used as a feature descriptor of the data. Thus, the test samples are represented as a linear combination of just the training samples corresponding to the same class.

Assuming that supervised dictionary learning methods and sparse representation differ in the way they exploit class labels, we focused on the most popular and utilized ones in the experimentation. For this purpose, five different SDL algorithms for classification were evaluated and compared in term of performance, namely, sparse representation-based classifier (SRC) (Wright et al., 2009), Label consistent K-SVD (LC-KSVD) (Jiang et al., 2013), Dictionary Learning with Structured Incoherence (DLSI) (Ramirez et al., 2010), Fisher Discrimination Dictionary Learning (FDDL) (Yang et al., 2011), and two versions of Low-Rank Shared Dictionary (LRSDL and D2L2R2) (Vu and Monga, 2016), (Vu and Monga, 2016).

3 EXPERIMENTAL VALIDATION

In this section, we present a set of results to illustrate the performance of our proposed approach based on the most popular SDL for classification and those of the Machine Learning algorithms experienced in (de Quadros et al., 2018). Hence, we consider three benchmark Machine Learning Models in fall detection (Aziz et al., 2016) which are: Support Vector Machine (SVM), K-Nearest Neighbour (KNN) and Linear Discriminant Analysis (DLA). Additionally, five SDL-based techniques which were briefly introduced in section II, namely SRC, FDDL, DLSI, and both versions of LRSDL, are presented. The evaluation is implemented based on an open-source Matlab Dictionary Learning Toolbox "DICTOL" available on Github[1], as used in (Vu and Monga, 2016) and (Vu and Monga, 2016).

In this section, we will initiate our experimental validation with a preliminary study in which we will extract the best fitted amount of data needed to train the SDL algorithms and the best configuration. Afterwards, we will follow two main experiments. In the first experiment (A), we evaluate SDL and ML algorithms based on clean data. As for the second experiment (B), we will assess both techniques robustness for different generated AWGN.

3.1 Evaluation Metrics

This study is evaluated based on two common metrics, namely, Accuracy (AC) and Sensitivity (SE). In this sense, AC represents the overall true detection and SE represents the ability to detect authentic falls among all detected falls.

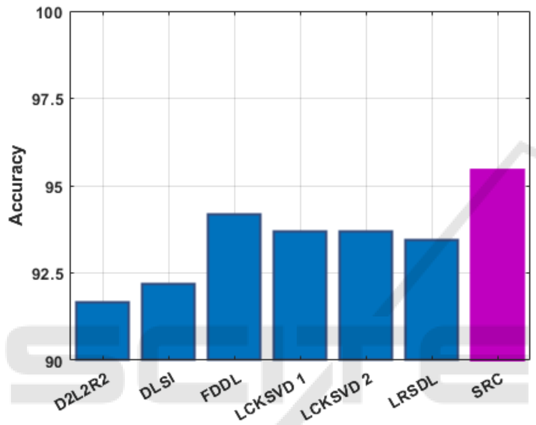
[1] https://github.com/tiepvupsu/DICTOL

3.2 Preliminary Experiment and Configuration

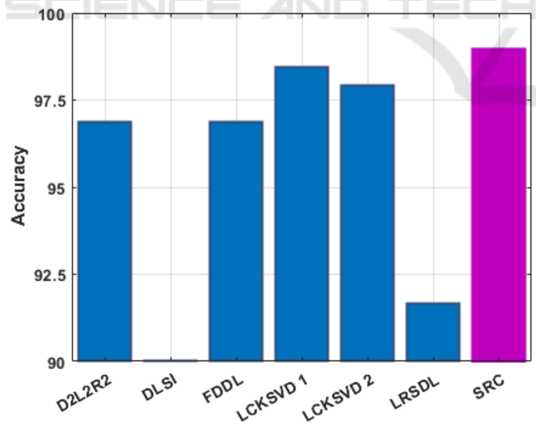
For a preliminary SDL analysis, we consider two random data splitting scenarios in order to extract the best fitted amount of data needed to train the SDL algorithms as follows:

1. 50% for training and 50% for testing;
2. 75% for training and 25% for testing.

For each experiment scenario, we have fixed the number of the atoms in Dictionary equal to the number of samples in the training data, i.e., 300 and 594, respectively.



(a) Scenario 1



(b) Scenario 2

Figure 2: Performance of Dictionary learning algorithms based on fixed Dictionary size.(a) Scenario 1: 50% of the data for training; (b) Scenario 2: 75% of the data for training.

Figure 2 demonstrates the performance of every SDL algorithm tested on both mentioned scenarios based on a Dictionary size equal to the number of training samples. Results show that increasing the training data has an impact on increasing the fall detection performance for most SDL algorithms. In both tests, the SRC outperforms other algorithms with an accuracy of 96.2% and 99% for scenario 1 and scenario 2 respectively. However, the DLSI algorithm showed a decrease from 92.2% to 90% in performance as the training set increased from 50% to 75% of the data.

From our exploratory experiment, the SDL algorithms' hyper-parameters are founded on the best-achieved performances for our dataset using random training features. Thus, collected data set is subdivided such as scenario 2, namely 75% of the data is for the training phase and 25% for the test phase. Accordingly, every used SDL algorithm is configured as follows: SRC: λ =0.01; LC-KSVD:α=0.01, β=0.1; DLSI: λ_2=0.1, η=0.001; FDDL: λ_1 = λ_2=0.001; LRSDL and D2L2R2: λ_1=0.001, λ_2=0.01, η=0.02.

3.3 Experiment (A): Clean Data Evaluation

In order to observe the performance behavior of the each of the assessed SDL models in consonance with the variance of the dictionary size, we have compared different SDL algorithms based on the number of dictionary atoms per class that ranges between 50 and 300. The result is shown in Fig. 3. Accordingly, the best overall result was accomplished by the D2L2R2 algorithm that is the extended version of LRSDL which showed, in contrast, the lowest overall performances. In this sense, the best algorithm achieved an accuracy rate of 99% for a dictionary size of 200 atoms per class, very close to 98.96% of SRC and DLSI algorithms based on a Dictionary size equals to 300 and 150 respectively.

Intending to prove the efficiency of our proposed method, we additionally compared the best performance of each classification SDL algorithm with the result reported in previous work (de Quadros et al., 2018) based on the machine learning approach. As summarized in Table 1, the accuracy rate obtained by SRC and D2L2R2, for D equals respectively 300 and 200 atoms/class, are very analogous with the one obtained by KNN algorithms in the previous work.

3.4 Experiment (B): Noisy Data Evaluation

In this experiment, we have managed to randomly adjust different SNR decibel values, i.e., 0dB, 0.5dB, 5dB, 10dB, 20dB, and 100dB to generate multiple Additive white Gaussian noise. Fig.4 illustrates an example of VA signal and the extracted features mentioned in section II for fall and ADL events. As one

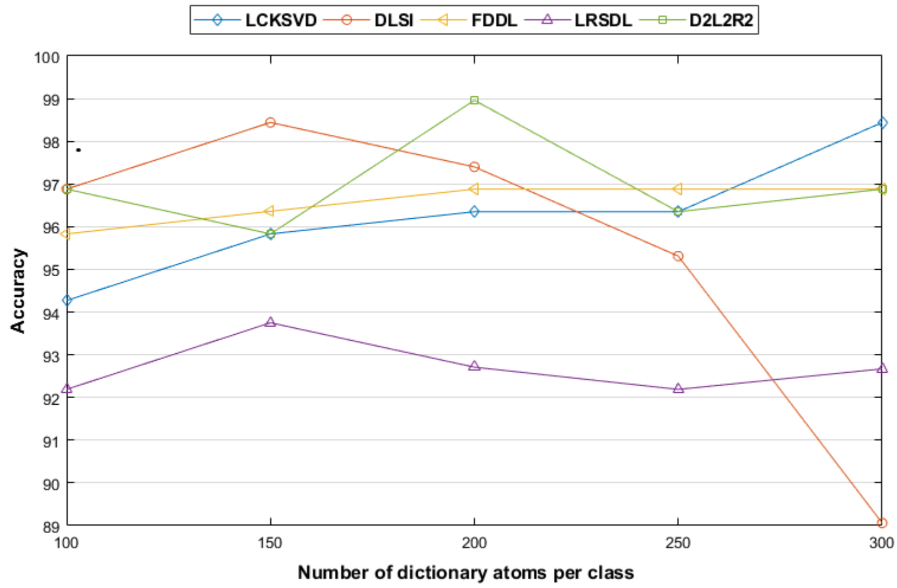


Figure 3: Comparison between classification-based SDL algorithms in accordance with Dictionary size.

Table 1: Comparison of DL-based approach and previous ML-based approach.

Approach	Algorithm	Best performance	
		Accuracy	D size
SDL	**SRC**	**98.9**	300
	LC-KSVD	98.5	300
	DLSI	**98.9**	150
	FDDL	96.9	200
	LRSDL	93.8	150
	D2L2R2	**99.0**	200
MLM	**KNN**	**99.0**	
	SVM	97.4	
	DLA	96.4	

Table 2: Robustness of Supervised Dictionary learning models to Additive White Gaussian Noise.

	SRC		DLSI		D2L2R2	
SNR	AC	SE	AC	SE	AC	SE
0dB	**97.9**	100	96.9	100	95.3	100
0.5dB	**97.9**	97.9	96.4	96.9	95.3	95.8
5dB	**98.4**	99.0	**98.4**	99.0	97.9	97.9
10dB	**98.4**	100	**98.9**	100	97.9	100
20dB	**98.9**	100	**98.9**	98.9	98.4	97.9
100dB	98.4	100	98.9	98.9	**99.0**	100

Table 3: Robustness of Machine learning learning models to Additive White Gaussian Noise.

	KNN		SVM	
SNR	AC	SE	AC	SE
0dB	**92.7**	100	91.7	84.4
0.5dB	**92.7**	96.9	90.6	82.3
5dB	**94.3**	97.9	2.19	84.8
10dB	**94.3**	97.9	92.71	85.4
20dB	**95.5**	99.0	92.71	90.1
100dB	**96.4**	99.0	91.7	98.9

can observe, features 6 to 12, i.e the selected features corresponding to Euler Angles, are the most affected by the insertion of noise.

Taking into account result obtained in experiment (A), we have fixed the best obtained D size correspondingly to the most efficient models: SRC, DLSI, and D2L2R2 for SDL; KNN and SVM for ML. Table 2 and 3 exhibit the efficiency behavior of SDL and ML models respectively to different AWGN signals. Based on table 3, SDL algorithm showed a remarkable stability throughout the decreasing on the SNR value. Despite the fact that D2L2R2 reached the best performance in regard of clean data, SRC showed the best overall performances for almost all the tested SNR. Giving the example of AWGN equals to 0dB, SRC has reached approximately 98% of accuracy and an appreciable capacity to detect true falls of 100% compared to the notable performance decrease of DLSI and D2L2R2. Regarding Table 3, both algorithms showed a massive decrease in performances reaching 92.7% and 91.7% for 0dB SNR. Even though, KNN algorithm has maintained a good Specificity for falls compared to SVM. In general, SRC outperformed other SDL and ML models by maintaining its robustness regarding overlapped data, thus, confirms the main objective of Dictionary learning based approach.

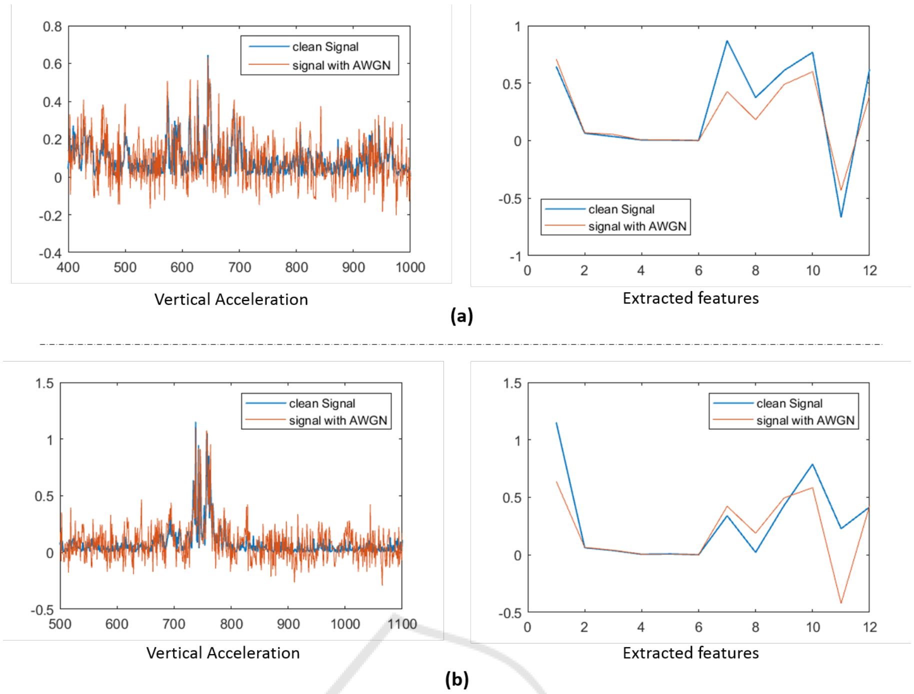


Figure 4: Illustration of Vertical acceleration (VA) signal and the 12 respective extracted features of clean and 0dB AWGN data (a) Fall event, (b) ADL event.

4 CONCLUSION

In this work, we introduced a novel classification method, Supervised Dictionary Learning, for a Robust wrist-based fall detection system. Being a very moving part of the body, fall detection systems placed on wrist are highly susceptible to acquire noisy yet overlapped data that can affect their efficiency and reliability. For this propose, our contribution mainly lies in exploring and applying the effectiveness of Dictionary Learning-based classifiers into a wearable fall detection system located on wrist. The study explores Supervised dictionary learning models for classification and compares their performances to those reported in previous work while preserving the same standard protocol, i.e., data collection and preprocessing. Indeed, two main experimental evaluations were conducted. The first explores six of the most common SDL-based classifiers namely, SRC, LC-KSVD, DLSI, FDDL, LRSDL, and D2L2R2 with different scenario for clean data-set. In the second, we generated Additive white Gaussian noise using multiple Signal-to-noise ratios in order to bring out the effectiveness of the proposed method. The conducted results showed that the SDL algorithm presents a very robust model regarding original and noisy data. Indeed, SRC has proved its efficiency reaching almost 99% of accuracy, similar to the achieved one by the machine learning classifier KNN, still maintained the best achievement for noisy data reaching an accuracy of almost 98% with 100% of sensitivity.

A thorough experimentation will be conducted in future work, to take further advantage of the DLA benefits. As being a popular representation based paradigm, we plan next to test the performance of the SDL on jointly learn a frame-like representation of raw data vectors (over-complete dictionary and sparse representation) and classification parameters in order to enhance system's reliability.

In our future related work, we expect additional improvement of results even further by incorporating the feature extraction phase and the learning phase using the DLA technique in order to automatically learn relevant feature of the acquired raw signals.

ACKNOWLEDGEMENTS

This research and innovation work is supported by MOBIDOC grants from the EU and National Agency for the Promotion of Scientific Research under the AMORI project and in collaboration with Telnet Innovation Labs.

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