Iterative Learning for Human Activity Recognition from Wearable Sensor Data

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Introduction

- Wearable sensor technologies are gaining interest due to the use of significatively miniaturized electronic components, with low power consumption, which makes them ideal for applications in human activity recognition in multiple practical applications
  - health rehabilitation, respiratory and muscular activity assessment, sports and safety applications [1].
- In practical situations, collected data are affected by several factors related to sensor data alignment, data losses and noise, among other experimental constrains, all deteriorating their quality [2].
- The non-ergodicity of the acquisition process, especially when processing signals from acceleration sensors, will result in a poor learning performance [3], especially in applications involving multi-class classification [4].
- The problems become even more complex if the multi-class classification process is applied on high dimensionality data vectors.
- Feature extraction becomes a critical component for finding the multi-variable correlations that allow the classifier to improve the model precision reflected by a low misclassification rate.

Iterative Learning Method for Classifying Human Locomotion

- We present a new method for classifying human locomotion activities (e.g. walk, stand, lie and sit) by implementing a data-driven architecture based on an iterative learning framework.
- The proposed solution optimizes the model performance by choosing the best training dataset for non-linear multi-class classification that makes use of an SVM classifier, while also reducing the computational load.

Iterative Learning Method for Classifying Human Locomotion

- Dataset
  - The work in this paper is based on data acquired by body–worn sensors, and extracted from the Opportunity dataset [6].
    - twelve 3D-acceleration customized sensors [7] and seven inertial measurement units (Xsens MT9).
  - The dataset has a total of 58 dimensions including the time stamp.
  - Records are labeled according to four primitive classes: walk, lie, sit and stand.
  - The signal acquisition protocol is performed under a pre-established scenario with six experimental sessions, performed independently by four users.
  - The extracted dataset contains a total of 869,387 samples, which are distributed as follows:
    - 234,661 samples for user 1; 225,183 samples for user 2; 216,869 samples for user 3, and 192,674 samples for user 4.
  - The goal of is to extract from these data the best training samples that enable the classification of the locomotion activity of the users independently

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- Data Pre-Processing:
  - Exclusion of values affected by data losses and random noise, issues that are very common in wireless acceleration sensors.
    - In the dataset roughly 30% of the data contains such values.
    - we fused all readings produced by each sensor, for each user and each experiment, to work exclusively from a data-driven perspective.
  - Wavelet filtering to eliminate noise
    - The noise present in the acceleration sensor measurements has commonly a flat spectrum. This means that the noise is present in all frequency components.
    - Decomposition of the noisy signal into wavelets [10] will eliminate small coefficients, commonly associated with the noise, by zeroing them, while concentrating the signal in a few large-magnitude wavelet coefficients

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- **Feature Extraction and Selection**
  - This process focuses on the extraction of kinematics features, such as roll, pitch, yaw (RPY)
  - Our first feature set is based on the single magnitude vector $\left|a_{j,k}\right|$.
  - A second feature set is related to roll, pitch and yaw (RPY), calculated as follows:

$$roll_{j,k} = atan\left(\frac{acc_x}{\sqrt{acc_y + acc_z}}\right), pitch_{j,k} = atan\left(\frac{acc_y}{\sqrt{acc_x + acc_z}}\right), yaw_{j,k} = atan\left(\frac{acc_z}{\sqrt{acc_x + acc_y}}\right)$$

  - A matrix with all axial components produced by all sensors under observation is built:

$$acc_{x,y,z,k} = \{[acc_{x,k}], [acc_{y,k}], [acc_{z,k}]\}$$

  - To deal with the absence of some values, we used principal component analysis (PCA) and singular value decomposition (SVD). The new target function $f_{j,k}()$ is represented as follows:

$$f_{j,k} = f\left(pca\ (RPY), pca(SMV), pca(acc_{x,y,z,k}), svd(RPY), svd(SMV), svd(acc_{x,y,z,k})\ \right)$$

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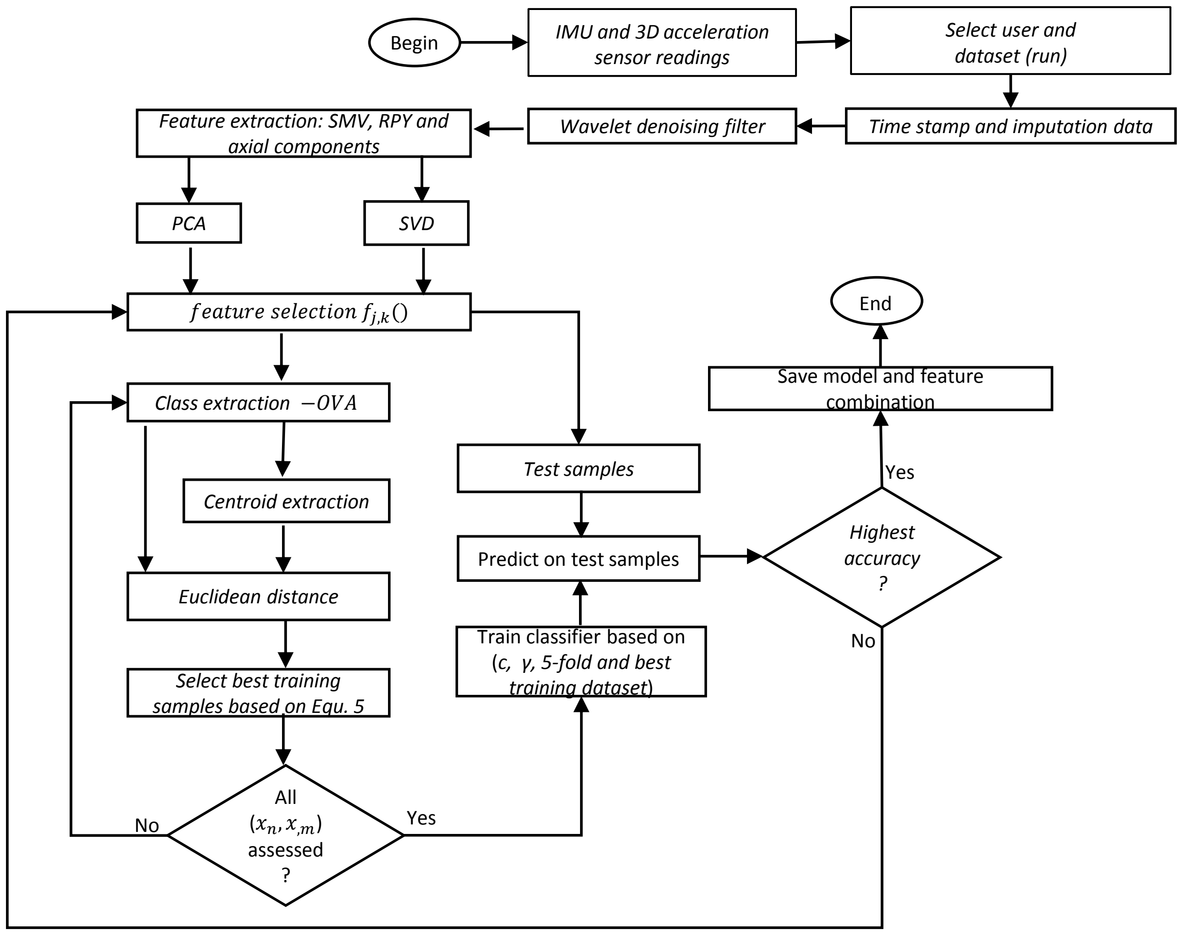
- Learning Architecture



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- Training Data Selection
  - Select a user.
  - Select a user experiment.
  - Extract two features (f_j, f_k) from the experiment.
  - Extract all classes from (f_j, f_k).
  - Select a pair of classes $(x_n, x_{,m})$ (i.e. a one-versus-all methodology is used) and extract their corresponding centroids.
  - Extract the Euclidean distance between each class member (x_n) and the centroid of the class (x_m). Store the results in a vector of distances $R_{n,m}(j)$:

$$R_{n,m}(j) = \left|\left(x_{n,m}(j)\right) - Centroid_{n,m}\right|$$

where *n* and *m* are the classes of (f_j, f_k), j is a class member and $Centroid_{n,m}$ is the opposite centroid with respect to the discriminating hyperplane of the class member under evaluation.

  - If the resulting Euclidean distance vector $R_{n,m}(j)$ satisfies condition (5), then the class member is a candidate for the training dataset.

$$R_{n,m}(j) \geq \overline{R_{n,m}} + \sigma(R_{n,m})$$

where $\overline{R_{n,m}}$ and $\sigma(R_{n,m})$ are the mean and standard deviation of the Euclidean distance vector $R_{n,m}(j)$. The candidate is stored in a vector of candidates BoC($x_{n,m}(j)$) (Fig. 1c).

  - Repeat steps 3 to 7 until all classes in (f_j, f_k) have been evaluated.

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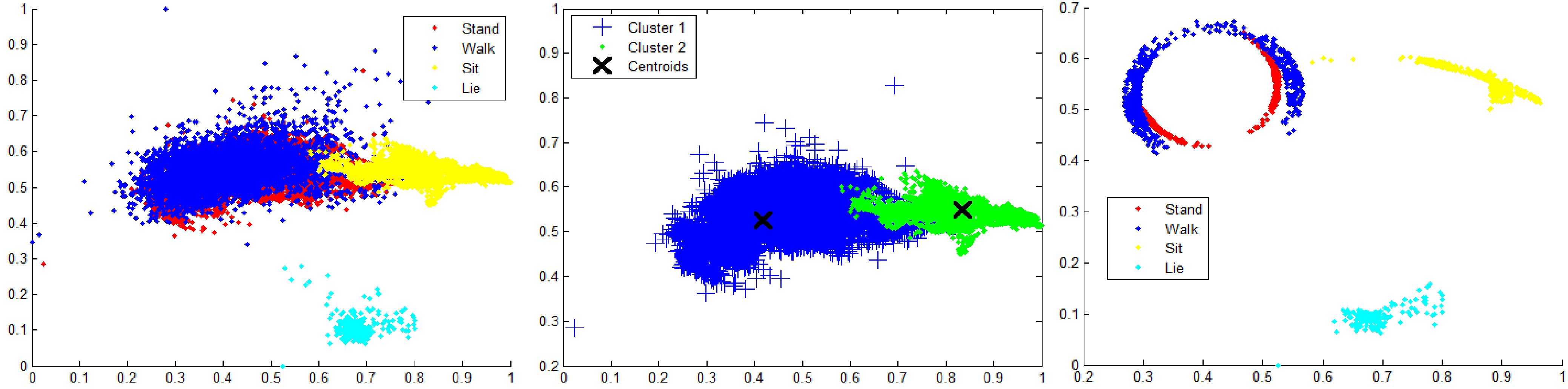
- Training Data Selection



(a) (b) (c)

(a) PCA is applied to $acc_{x,y,z,k}$ (data distribution corresponds to the first and second principal components);
(b) Classes are extracted in pairs $(x_n, x_{,m})$, centroids are extracted and Euclidean distances are calculated;
(c) Training candidates are produced by the selection algorithm.

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- Model Selection
  - Once the best training dataset BoC($x_{n,m}(j)$) has been identified, we proceed with the selection of the best classification model using a multi-class SVM classifier with an RBF kernel.
  - The problem of model selection is reduced to finding the best combination of parameters cost, *c* and *γ* extracted in a 5-fold cross validation process, in which the values of *c* and *γ* are chosen according to a grid of values, i.e. $(2^{-5}, .., 2^{7})$.
  - The best model produced by the combination of *c* and *γ* achieves the lowest misclassification rate.
  - This model is then used to predict the labels on the testing dataset.

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- Experimental Results
  - Two measures are to validate the results

$$\text{Acc} = \frac{Labels\ correctly\ predicted}{(size\ of\ user's\ dataset)} \times 100\%;\ \ Ts = \frac{size(R_{n,m})}{(size\ of\ user's\ dataset)} \times 100\%$$

  - Classification performance obtained from IMU sensors

User	**Experiments**					
	Experiment 1 (Acc% / TS %)	Experiment 2 (Acc% / TS %)	Experiment 3 (Acc% / TS %)	Experiment 1 (Acc% / 80%)	Experiment 2 (Acc% / 80%)	Experiment 3 (Acc% / 80%)
User 1	80 / 4.47	75.36 / 1.19	**81 / 3.31**	**83.92**	74.76	80.55
User 2	**71.56 / 4.97**	47.43 / 11.96	65.23 / 10.18	77.53	77.17	**78.31**
User 3	70,64 / 5.70	57 / 7.70	**73.28 / 0.16**	71.46	69.43	**75.19**
User 4	66.19 / 2.8	61.27 / 2.70	**78 /1.86**	77.2	74.46	**79.88**

Iterative Learning Method for Classifying Human Locomotion

- Experimental Results
  - Classification performance obtained from 3D acceleration sensors

User	**Experiments**					
	Experiment 1 (Acc% / TS %)	Experiment 2 (Acc% / TS %)	Experiment 3 (Acc% / TS %)	Experiment 1 (Acc% / 80%)	Experiment 2 (Acc% / 80%)	Experiment 3 (Acc% / 80%)
User 1	82.82 / 3.03	79.23 / 11.38	**83.71 / 9.11**	**83.12**	79.12	80.56
User 2	52.42 / 2.96	50.86/12	**57.84 / 1.89**	69.9	75	**73.56**
User 3	69 / 13.16	67.86 / 0.60	**76.62 / 3.37**	72.09	65.21	**77.51**
User 4	66 / 1.63	64 / 10.4	**77.53 / 3.45**	71.59	76.15	**87.55**

Iterative Learning Method for Classifying Human Locomotion

- Experimental Results
  - Classification performance obtained from IMU and 3D acceleration sensors

User	Experiments					
	Experiment 1 (Acc% / TS %)	Experiment 2 (Acc% / TS %)	Experiment 3 (Acc% / TS %)	Experiment 1 (Acc% / 80%)	Experiment 2 (Acc% / 80%)	Experiment 3 (Acc% / 80%)
User 1	80.62 / 7.15	77.21 / 8.3	**84.77 / 8.17**	**81.11**	75.92	80.85
User 2	65.85 / 8.78	45.16 / 12.49	**66.25/ 0.90**	71.54	**76.68**	74.56
User 3	58.49 /13.93	67.62 / 1.42	**70.35 / 2.97**	72.30	65.18	**77.08**
User 4	66.48 / 0.70	66.64 / 11.41	**71.54 / 4.14**	73.43	75.80	**87.38**

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- Experimental Results
  - Accuracy comparison

User	(Acc/TS)	(Acc/80%)
User 1	80.52/6.23	79.99
User 2	58.03/7.43	74.49
User 3	67.87/5.40	71.71
User 4	68.62/10.29	77.98
Average	**68.76/7.33**	**76.04**

Iterative Learning Method for Classifying Human Locomotion

- **Conclusion**
  - A novel iterative learning process is proposed to reduce the number of samples and subsequently of the processing time for the classification of measurements from wearable sensors.
  - The challenges related to the large percentage of missing data and the noise affecting the measurements were successfully dealt with by the use of data fusion and of a robust filtering stage based on wavelets.
  - The inclusion of a mechanism for the selection of the training dataset allows to work with only a fraction of the total dataset for the SVM multi-class training process.
  - The minimization of the number of samples is an important contribution that allows to deal efficiently with large data sets as those explored in this paper.

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