Feature Selection Evaluation for Light Human Motion Identification in Frailty Monitoring System

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Abstract: In order to plan and deliver health care in a world with increasing number of older people, human motion monitoring is a must in their surveillance, since the related information is crucial for understanding their physical status. In this article, we focus on the physiological function and motor performance thus we present a light human motion identification scheme together with preliminary evaluation results, which will be further exploited within the FrailSafe Project. For this purpose, a large number of time and frequency domain features extracted from the sensor signals (accelerometer and gyroscope) and concatenated to a single feature vector are evaluated in a subject dependent cross-validation setting using SVMs. The mean classification accuracy reaches 96%. In a further step, feature ranking and selection is preformed prior to subject independent classification using the ReliefF ranking algorithm. The classification model using feature subsets of different size is evaluated in order to reveal the best dimensionality of the feature vector. The achieved accuracy is 97% which is a slight improvement compared to previous approaches evaluated on the same dataset. However, such an improvement can be considered significant given the fact that it is achieved with lighter processing using a smaller number of features.

1 INTRODUCTION

The ageing population around the world is increasing and it is estimated that two billion people will be aged over 65 years by 2050. This will affect the planning and delivery of health and social care as well as the clinical condition of frailty. Frailty is a medical syndrome which is characterized by diminished strength, endurance, and reduced physiologic function that increases an individual's vulnerability for developing increased dependency and/or death (Morley et al., 2013). Frailty is characterized by multiple pathologies such as weight loss, weakness, low activity, slow motor performance, balance and gait abnormalities, as well as cognitive ones (Chen et al., 2014). Frailty increases risks of incident falls, worsening of mobility, disability, hospitalization or institutionalization, and mortality (Abellan et al. , 2008; Mitnitski et al., 2002; Morley et al., 2006), which in turn increase the burden to cares and costs to the society.

It is assumed that early intervention with frail persons will improve quality of life and reduce health services costs. Thus it is essential to develop real life tools for the assessment of physiologic reserve and the need to test interventions that alter the natural course of frailty since frailty is a dynamic and not an irreversible process. Several efforts have been done in this direction through research and development activities. In (Seacw Project) an Ecosystem for training, informing and providing tools, processes, methodologies for ICT and active, healthy aging was developed mainly targeting to caregivers, older people and general population. In (Eldergames Project) an interactive tabletop platform able to integrate potentialities derived from both technology and leisure activities was designed. Another purpose of (Eldergames Project) was the monitoring of the older people status, with information about his/her progression /regression in

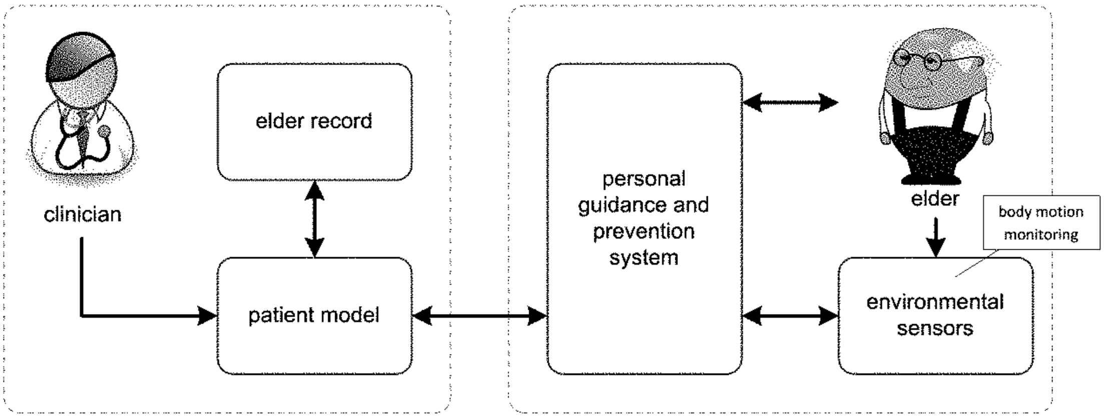

Figure 1: The FrailSafe conceptual diagram for motion monitoring

cognitive health. In (Kinoptim Project) a home-care solution that will address older people living in the community in a preventive manner and rely on ICT and virtual reality gaming through the exploitation of haptic technologies, vision control and context awareness methods was developed and integrated, while promising to redefine fall prevention by motivating people to be more active, in a friendly way and with tele-supervision if necessary. In (Mporas et al., 2015) a more holistic, personalized, medically efficient and economical monitoring system for people with epilepsy was provided. In (Doremi Project) multidisciplinary research areas in serious games, social networking, Wireless Sensor Network, activity recognition and contextualization, behavioral pattern analysis were combined in pilot setups involving both older users and care providers. In (Alfred Project) a mobile, personalized assistant for older people was developed, using cutting edge technologies such as advanced speech interaction, which helps them stay independent, coordinate with carers and foster their social contacts. In (Home Sweet Home Project) new, economically sustainable home assistance service which extends older people independent living was introduced, measuring the impact of monitoring, cognitive training and e-Inclusion services on the quality of life of older people, on the cost of social and healthcare delivered to them, and on a number of social indicators. In (Mobiserv Project) the objective was to develop and test a proactive personal robotic, integrated with innovative sensors, localization and communication technologies, and smart textiles to support independent living for older adults, in their home or in various degrees of institutionalization, with a focus on health, nutrition, well-being, and safety. In (Fate Project) innovative ICT-based solution for the detection of falls in ageing people were studied, covering prevention and detection of falls in all circumstances.

Human motion monitoring is a must in surveillance of older people, since the related information is crucial for understanding the physical status and the behavior of the older people. This is typically achieved using image/video and accelerometer based data (Foroughi et al., 2008; Xiang et al., 2015;Yang et al., 2010). In this article we focus on the physiological function and motor performance thus we present a light human motion identification scheme together with preliminary evaluation results, which will be further exploited within the FrailSafe (Frailsafe Project) architecture.
The main contributions of this paper are summarized in the following:

- the classification accuracy in the examined dataset is slightly improved (about one unit) compared to previous approaches.
- a lighter human motion identification module using less features but achieving equal accuracy in comparison to the one previously proposed for the dataset under consideration is achieved by feature selection

The reminder of this article is organized as follows. In Section 2 we present the FrailSafe concept. In Section 3 we describe the human motion identification scheme. In Sections 4 and 5 we present the experimental setup and the evaluation results respectively. Finally, in Section 6 we conclude this work.

2 THE FRAILSAFE CONCEPT

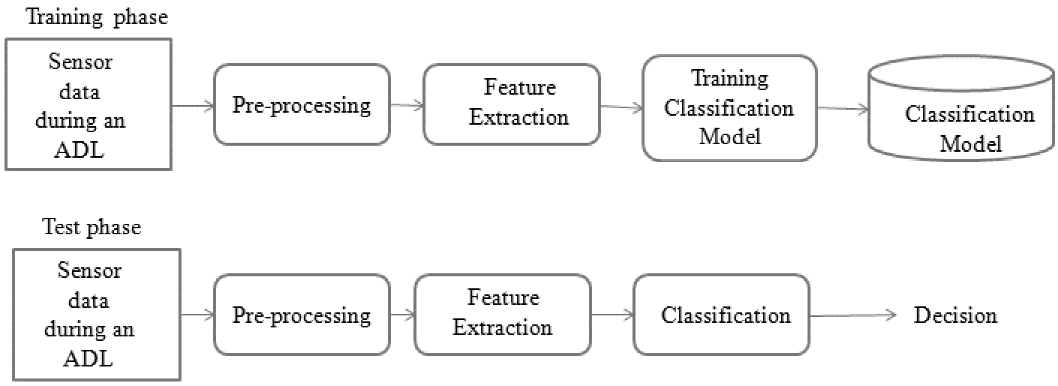

Figure 2: Human Motion Identification Module Architecture

FrailSafe aims to better understand frailty and its relation to co-morbidities, to develop quantitative and qualitative measures to define frailty and to use these measures to predict short and long-term outcome. In order to achieve these goals real life tools for the assessment of physiological reserve and of external challenges will be developed. These tools will provide an adaptive model (sensitive to changes) in order that pharmaceutical and non-pharmaceutical interventions, which will be designed to delay, arrest or even reverse the transition to frailty. Moreover, FrailSafe targets at creating "prevent-frailty" evidence based recommendations for older people regarding activities of daily living, lifestyle and nutrition, as well as strengthening the motor cognitive, and other"anti-frailty" activities through the delivery of personalized treatment programs, monitoring alerts, guidance and education. The FrailSafe conceptual infrastructure for motion monitoring is illustrated in Figure 1.

Through patient-specific interventions, FrailSafe aims to define a frailty measure. This measure is initially constructed from prior knowledge on the field, and then globally updated based on analysis of long-term observations of all older peoples' states. This update is then applied to the individual patient models, modifying them accordingly, to fit different needs per patient. The monitoring of the older people's motion activity is performed through the environmental sensors module, which includes accelerometer sensors for the monitoring of the human motions. Details about the light motion identification implementation are provided in the next section.

3 ARCHITECTURE FOR LIGHT HUMAN MOTION IDENTIFICATION

The presented architecture for light human motion identification is part of an end-to-end system for sensing and predicting treatment of frailty and associated co-morbidities using advanced personalized models and advanced interventions, the FRAILSAFE framework.

The proposed classification methodology can be used as a core module in order to discriminate the detected motions to six basic activities: walking, walking-upstairs, walking-downstairs, sitting, standing and laying. The block diagram of the overall workflow for learning the activity classifiers is illustrated in Figure 2.

The multi-parametric sensor (accelerometer and gyroscope) data are pre-processed as in (Anguita et al., 2012; Reyes-Ortiz et al., 2013) by applying noise filters and then sampled in fixed-width sliding windows $W_i, 1 \leq i \leq I$ (frames) of 2.56 sec and 50% overlap. The sensor acceleration signal, which has gravitational and body motion components, was separated using a Butterworth low-pass filter into body acceleration and gravity. The gravitational force is assumed to have only low frequency components, therefore a filter with 0.3 Hz cut-off frequency was used. From each frame, a vector of features $V_i \in R^k$, $k = |F_T| + |F_F|$ was obtained by calculating variables from the time $F_T^i \in R^{|F_T|}$ and frequency domain $F_F^i \in R^{|F_F|}$.

The extracted time domain and frequency domain features are concatenated to a single feature vector as a representative signature for each frame.

Details on the type of extracted features are provided in Section 4.

All frames are used as input to FRAILSAFE's human motion identification module which classifies basic activities of daily living (ADLs) in order to obtain some preliminary evaluation results for the proposed architecture. In this module, a model for multiclass classification between six basic ADLs (walking, walking-upstairs, walking-downstairs, sitting, standing and laying), which has been previously built in a training phase, is used in order to label the frames. Each frame is classified independently.

During the training phase of the classification architecture, frames with known class labels (labeled manually) are used to train the multiclass classification model. During the test phase the unknown multi-parametric sensor signals are pre-processed and parameterized with similar setup as in the training phase. Each extracted feature vector is provided as input to the trained classifier.

4 EXPERIMENTAL SETUP

4.1 Data

The previously described classification methodology was evaluated on multi-parametric data from the UCI HAR Dataset (Anguita et al., 2013). The dataset consists of accelerometer and gyroscope recordings from 30 volunteers within an age bracket of 19-48 years when performing six activities (walking, walking-upstairs, walking-downstairs sitting, standing, laying). For the experiments each person worn a smartphone (Samsung Galaxy S II) on the waist. Using its embedded accelerometer and gyroscope, 3-axial linear acceleration and 3-axial angular velocity at a constant rate of 50Hz were captured. The data were labelled manually using the corresponding video recordings which were captured during the experiments. Since the evaluation here was held using a subject dependent cross-validation setting, data were initially merged in a single dataset and then split in 30 datasets, one for each subject.

4.2 Feature Extraction and Classification Algorithm

Initially, the sensor signals (accelerometer and gyroscope) were pre-processed as proposed in (Anguita et al., 2012, Reyes-Ortiz et al., 2013) in order to proceed with feature extraction. The features selected for this analysis are those proposed in (Anguita et al., 2012, Reyes-Ortiz et al., 2013) which come from the accelerometer and gyroscope 3-axial raw signals denoted as tAcc-XYZ and tGyro-XYZ with prefix 't' used to denote time. The sampling frequency of these time domain signals was 50 Hz. In order to remove noise Anguita et al. performed low pass filtering using a median filter and a 3rd order low pass Butterworth filter with a corner frequency of 20 Hz. Then, in order to separate the acceleration signal into body and gravity acceleration signals denoted as tBodyAcc-XYZ and tGravityAcc-XYZ, they used another low pass Butterworth filter with a corner frequency of 0.3 Hz.

Subsequently, Jerk signals denoted as tBodyAccJerk-XYZ and tBodyGyroJerk-XYZ were obtained by the time derivation of the body linear acceleration and angular velocity. Also, they used the Euclidean norm to calculate the magnitude of these three-dimensional signals yielding the following signals: tBodyAccMag, tGravityAccMag, tBodyAccJerkMag, tBodyGyroMag and tBodyGyroJerkMag.

Finally a Fast Fourier Transform (FFT) was applied to signals tBodyAcc-XYZ, tBodyAccJerk-XYZ, tBodyGyro-XYZ, tBodyAccJerkMag, tBodyGyroMag, tBodyGyroJerkMag producing fBodyAcc-XYZ, fBodyAccJerk-XYZ, fBodyGyro-XYZ, fBodyAccJerkMag, fBodyGyroMag, fBodyGyroJerkMag. Here, the prefix 'f' were used to indicate frequency domain signals.

These signals were used to estimate variables of the feature vector for each pattern: '-XYZ' is used to denote 3-axial signals in the X, Y and Z directions. The aforementioned signals which were produced by processing accordingly the initial sensor recordings are tabulated in Table 1.

The set of features that were extracted from these signals are those proposed by Anguita et al. (Anguita et al., 2012) including the mean value, the standard deviation, the median absolute deviation, the largest value in array, the smallest value in array, the signal magnitude area, the energy measure as the sum of the squares divided by the number of values, the interquartile range, the signal entropy, the autoregression coefficients with Burg order equal to 4, the correlation coefficient between two signals, the index of the frequency component with largest magnitude, the weighted average of the frequency components to obtain a mean frequency, the skewness of the frequency domain signal, the kurtosis of the frequency domain signal, the energy

Table 1: Pre-processed Signals

Signals
tBodyAcc-XYZ
tGravityAcc-XYZ
tBodyAccJerk-XYZ
tBodyGyro-XYZ
tBodyGyroJerk-XYZ
tBodyAccMag
tGravityAccMag
tBodyAccJerkMag
tBodyGyroMag
tBodyGyroJerkMag
fBodyAcc-XYZ
fBodyAccJerk-XYZ
fBodyGyro-XYZ
fBodyAccMag
fBodyAccJerkMag
fBodyGyroMag
fBodyGyroJerkMag

Table 2: Additional Signals

Additional Siganls
gravityMean
tBodyAccMean
tBodyAccJerkMean
tBodyGyroMean
tBodyGyroJerkMean

of a frequency interval within the 64 bins of the FFT of each window and the angle between two vectors.

Additional vectors were obtained by averaging the signals in a signal window sample. These are used on the angle variable (Table 2).

In conclusion, for each record a 561- feature vector with the aforementioned time and frequency domain variables was provided.

The computed feature vectors were used to train a classification model. In order to evaluate the ability of the above features to discriminate between ADLs we examined the SMO (Keerthi et al., 2001; Platt et al., 1998) with RBF kernel classification algorithm, which was implemented by the WEKA machine learning toolkit (Hall et al. 2009). SMO algorithm is an implementation of Support Vector Machines provided by the WEKA toolkit. Here we selected SMO for the classification since SVMs are used mostly in relevant literature.

During the test phase, the sensor signals were pre-processed and parameterized as during training. The SMO classification model was used to label each of the activities. Evaluation was performed in a subject dependent cross-validation setting.

In a further step we examined the discriminative ability of the extracted features for the human motion identification. The ReliefF algorithm (Kononeko, 1994) (which is an extension of an earlier algorithm called Relief (Kira and Rendell, 1992)) was used for estimating the importance of each feature in multiclass classification. In the ReliefF algorithm the weight of any given feature decreases if the squared Euclidean distance of that feature to nearby instances of the same class is more than the distance to nearby instances of the other class. ReliefF is considered one of the most successful feature ranking algorithms due to its simplicity and effectiveness (Dietterich, 1997; Sun and Li, 2006; Sun and Wu, 2008) (only linear time in the number of given features and training samples is required), noise tolerance and robustness in detecting relevant features effectively, even when these features are highly dependent on other features (Dietterich, 1997; Kononeko,1997). Furthermore, ReliefF avoids any exhaustive or heuristic search compared with conventional wrapper methods and usually performs better compared to filter methods due to the performance feedback of a nonlinear

Table 3: Subject Dependent Human Motion Identification Accuracy

Subject	Accuracy
1	100%
2	93,71%
3	97,36%
4	93,69%
5	86,09%
6	92,92%
7	93,83%
8	98,93%
9	85,76%
10	95,92%
11	98,42%
12	97,50%
13	95,41%
14	95,67%
15	96,65%
16	94,81%
17	90,76%
18	96,70%
17	98,33%
20	96,33%
21	98,53%
22	99,38%
23	96,77%
24	98,95%
25	94,87%
26	96,94%
27	99,73%
28	93,72%
29	100,00%
30	97,65%

Table 4: Mean across subjects confusion matrix. Rows represent the actual class and columns the predicted class.

	Standing	Sitting	Laying	Walking	Downstairs	Upstairs
Standing	1795	110	0	0	0	1
Sitting	289	1485	2	0	0	1
Laying	0	0	1944	0	0	0
Walking	0	0	0	1718	2	2
Downstairs	0	0	0	5	1397	4
Upstairs	0	0	0	0	0	1544

Table 5: ReliefF Feature Ranking

Ranking	Feauture
1	tGravityAcc_energy_X
2	fBodyAccJerk_entropy_X
3	fBodyAcc_entropy_X
4	fBodyAccJerk_entropy_Y
5	tBodyAccJerkMag_entropy
6	angle(X_gravityMean)
7	tGravityAcc_min_X
8	tGravityAcc_mean_X
9	tBodyAccJerk_entropy_X
10	tGravityAcc_max_X
11	fBodyBodyAccJerkMag_entropy
12	tBodyAcc_max_X
13	tBodyAccJerk_entropy_Y
14	fBodyAccMag_entropy
15	fBodyAcc_entropy_Y
16	fBodyAccJerk_entropy_Z
17	tBodyAccJerk_entropy_Z
18	tBodyGyroJerkMag_entropy
17	tGravityAcc_energy_Y
20	tBodyAccMag_entropy
21	tGravityAccMag_entropy
22	tGravityAcc_mean_Y
23	tBodyGyroJerk_entropy_Z
24	tGravityAcc_max_Y
25	fBodyAcc_entropy_Z
26	tGravityAcc_entropy_Z
27	tGravityAcc_min_Y
28	fBodyGyro_entropy_X
29	fBodyGyro_entropy_X
30	tBodyGyroJerk_entropy_X
31	fBodyAcc_mad_X
32	fBodyAcc_std_X
33	tBodyAcc_std_Y
34	fBodyAcc_mad_Y
35	tBodyAcc_std_X
36	fBodyBodyGyroJerkMag_entropy
37	tBodyAcc_mad_Y
38	fBodyGyro_entropy_Y
39	tBodyGyroMag_entropy
40	fBodyAcc_std_Y

classifier when searching for useful features (Sun and Wu, 2008).

In this study, ranking is performed on the whole dataset including all frames from all subjects. We examined the performance of the method, in terms of accuracy for different number of N-best features (N =10, 20, 30, ... 560), with respect to the ReliefF feature ranking algorithm.

. 5 EXPERIMENTAL RESULTS

The classification methodology presented in Section 3 was evaluated using the classification algorithm and the cross-validation scheme described in Section 4. The classification performance was evaluated in terms of accuracy

$$Accuracy = \frac{TP+TN}{TP+FP+TN+FN} \quad (1)$$

where TP denotes the true positives, TN the true negatives, FP the false positives and FN the false negatives. The results of the method using all features are shown on Table 3.

As can be seen in Table 3, the overall highest accuracy of the proposed methodology for human motion identification is 100% for subjects 1 and 29 and the lowest accuracy 85.76% was obtained for the 9th subject. However, the mean accuracy is relatively high 95,84%. The mean across all subjects confusion matrix is shown in Table 4. As can be seen all ADLs except sitting and standing are nearly perfectly discriminated from the others with only a few false dismissals or false alarms (2 to 5). The misclassification of some sitting and standing instances are probably owed to the similarity of these ADLs.

In a further step, we applied feature ranking on the whole dataset (consisting of all available subjects) using the ReliefF algorithm as described in Section 4. The performance of the classification, in terms of accuracy, for different number of N-best features (N =10, 20, 30, ..., 560) for the SMO algorithm is shown in Figure 3.

As can be seen in Figure 3 the highest classification accuracy is achieved when a large subset of discriminative features are used. Specifically, the highest accuracy is achieved for a

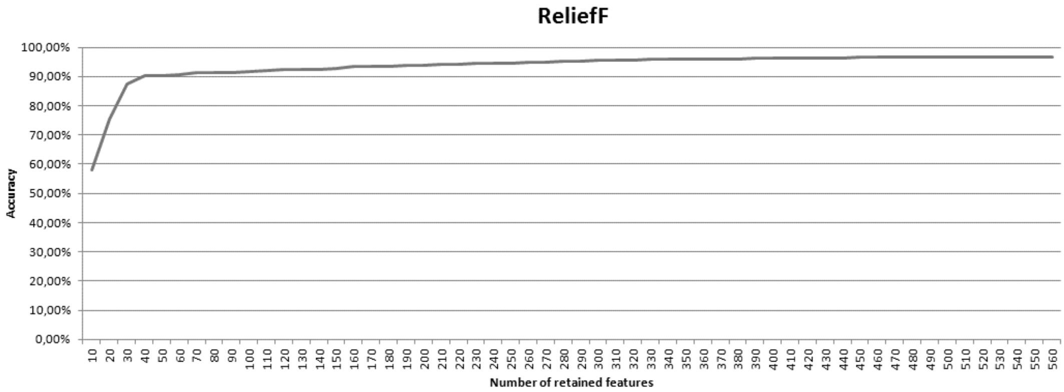

Figure 3: Classification Accuracy for different subsets of N-best features (N=10,20,..., 550)

subset of 550 best features with a percentage of 97% which is equal to the accuracy achieved when all features are used. It seems that the size and the variability of the dataset is relatively large requiring a feature vector of high dimensionality to accurately discriminate between the six classes. However, with only 40 features a high accuracy equal to 90% can be achieved.

Table 5 shows the 40 best features according to the ReliefF ranking algorithm. Although it is best to use a high dimensional feature vector to achieve higher classification accuracy, feature selection is still important in cases where a light human motion identification module is needed such as in FRAILSAFE.

Although direct comparison with other studies performed on the same dataset is not feasible due to different problem identification (subject dependent classification studied here versus subject independent classification studied in previous works) and different validation protocols followed as well (cross validation used here instead of 70% and 30% train and test sets respectively in the literature), the proposed method for the subject independent classification slightly improves the classification accuracy from 94% and 96% achieved in (Reiss et al., 2013) and (Romera-Paredes et al., 2013, Kastner et al., 2013) respectively to 97%. This improvement is significant since it is being achieved with less features providing the means for lighter approaches for human motion identification.

6 CONCLUSIONS

In this paper, we investigated the problem of human motion identification from multi-parametric sensor data acquired from accelerometers and gyroscopes using a large number of time-domain and frequency domain features in order to be used as part of an end-to-end system for sensing and predicting treatment of frailty and associated co-morbidities using advanced personalized models and advanced interventions. The proposed methodology was evaluated in multi-parametric data from 30 subjects. The evaluation of the multiclass SMO classification algorithm showed that a mean accuracy of 96% was achieved. Feature ranking investigation and evaluation of the classification models using subsets of features were performed and revealed the most significant features for the classification task. The use of the most discriminative features (N = 550) achieved accuracy equal to the accuracy achieved when all features are used.

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REFERENCES

Abellan van Kan, G., et al., 2008. The I.A.N.A Task Force on frailty assessment of older people in clinical practice. *J Nutr Health Aging, 12(1): p. 29-37.*

Alfred Project: http://cordis.europa.eu/project/rcn/110629_en.html

Anguita, D., Ghio, A., Oneto, L., Parra, X., Reyes-Ortiz, J.L., 2013. A Public Domain Dataset for Human

Activity Recognition Using Smartphones. *ESANN 2013, 21th European Symposium on Artificial Neural Networks, Computational Intelligence and Machine Learning.*

Anguita, D., Ghio, A., Oneto, L., Parra, X., Reyes-Ortiz, J.L., 2013. Human Activity Recognition on Smartphones using a Multiclass Hardware-Friendly Support Vector Machine. *IWAAL 2012 International Workshop of Ambient Assisted Living*.

Chen, X., Mao, G., Leng, S.X., 2014. Frailty syndrome: an overview. *Clin Interv Aging, 9: p. 433-41*.

Dietterich, T. G., 1997. Machine learning research: Four current directions. *Artificial Intelligence Magazines, vol. 18, pp. 97–136.*

Doremi Project: http://cordis.europa.eu/project/rcn/110829_en.html

Eldergames Project: http://cordis.europa.eu/project/rcn/80186_en.html

Fate Project: http://cordis.europa.eu/project/rcn/191694_en.html

Foroughi H., Aski B.S., Pourreza H., 2008. Intelligent video surveillance for monitoring fall detection of elderly in home environments, *11th International Conference on Computer and Information Technology. ICCIT 2008.*

Hall, M., Frank, E., Holmes, G., Pfahringer, B., Reutemann P., Witten, I. H., 2009. The WEKA Data Mining Software: *An Update. SIGKDD Explorations, vol. 11.*

Home Sweet Home Project: http://cordis.europa.eu/project/rcn/191712_en.html

Kastner, M., Strickert, M., Villmann, T., 2013. A sparse kernelized matrix learning vector quantization model for human activity recognition. *European Symposium on Artificial Neural Networks, Computational Intelligence and Machine Learning (ESANN).*

Keerthi, S.S., Shevade, S.K., Bhattacharyya, C., Murthy, K.R.K., 2001. Improvements to Platt's SMO algorithm for SVM classifier design. *Neural Computation, vol. 13, pp. 637-649.*

Kinoptim Project: http://cordis.europa.eu/project/rcn/106678_en.html

Kira, K., Rendell, L. A., 1992. A practical approach to feature selection. *Proc. 9th Int. Conf. Mach. Learn., pp. 249 – 256.*

Kononenko, I., 1994. Estimating attributes: Analysis and extension of RELIEF. *Proc. Euro. Conf. Mach. Learn., vol. 784, pp. 171– 182.*

Kononenko, I., Simec, E., Robnik-Sikonja, M., 1997. Overcoming the Myopic of Inductive Learning Algorithms with RELIEF-F. *Applied Intelligence*

Mitnitski, A.B., et al., 2002. Frailty, fitness and late-life mortality in relation to chronological and biological age. *BMC Geriatr, 2: p. 1.*

Mobiserv Project: http://cordis.europa.eu/project/rcn/93537_en.html

Morley, J.E., et al., 2006. Frailty. *Med Clin North Am, . 90(5): p. 837-47.*

Morley, J.E., et al., 2013. Frailty consensus: a call to action. *J Am Med Dir Assoc, 14(6): p. 392-7.*

Mporas, I., Tsirka, V., Zacharaki, E.I., Koutroumanidis, M., Richardson, M., Megalooikonomou, V., 2015. Seizure detection using EEG and ECG signals for computer-based monitoring, analysis and management of epileptic patients. *Expert Systems with Applications, Volume 42, Issue 6, 15, Pages 3227–3233.*

Platt, J., 1998. Fast Training of Support Vector Machines using Sequential Minimal Optimization. *Advances in Kernel Methods - Support Vector Learning.*

Reiss, A., Hendeby, G., Stricker, D., 2013. A competitive approach for human activity recognition on smartphones. European Symposium on Artificial Neural Networks, *Computational Intelligence and Machine Learning (ESANN).*

Reyes-Ortiz, J.L., Ghio, A., Parra, X., Anguita, D., Cabestany, J., Catala, A., 2013. Human Activity and Motion Disorder Recognition: Towards Smarter Interactive Cognitive Environments. *ESANN 2013 21th European Symposium on Artificial Neural Networks, Computational Intelligence and Machine Learning.*

Romera-Paredes, B., Aung, H., Bianchi-Berthouze, N., 2013. A one-vs-one classifier ensemble with majority voting for activity recognition. European Symposium on Artificial Neural Networks, Computational Intelligence and Machine Learning (ESANN).

Seacw Project: http://cordis.europa.eu/project/rcn/191786_en.html

Sun, Y., Li, J. 2006. Iterative RELIEF for feature weighting. *Proc. 21st Int. Conf. Mach. Learn., pp. 913–920.*

Sun, Y., Wu, D., 2008. A RELIEF based feature extraction algorithm. *In Proceedings of SIAM International Conference on Data Mining.*

Xiang, Y., Tang, Y., Ma, B., Yan, H., Jiang, J., Tian, X., 2015. Remote Safety Monitoring for Elderly Persons Based on Omni-Vision Analysis, *PLoS One, 10(5).*