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An Optimized Classification Method for Human Behavioral Patterns Recognition

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***Abstract*—The paper proposes an innovative supervised learning method for human behavioral recognition in which the behavioral patterns are classified according to the classes importance. A detector classifier is trained to recognize the human behavioral patterns belonging to the most important class. The optimization is performed by fixing the classifier operating point to provide the appropriate performance trade-off between a target and non-target behavioral class. The applications include public and personal safety, for instance elderly people home tele-assistance and other systems in which the early detection of abnormal behaviors is required.**

Keywords— target class; optimization; behavioral pattern

I. INTRODUCTION

The human behavior recognition is a big challenge for personal and public safety applications. The automatic detection of abnormal behaviors requires high-performance classification systems to recognize patterns related to gestures, actions, postures and several daily activities.

A human behavioral recognition system contains those devices and algorithms that recognize the abnormal features of human behavior [1]. The goal is public and personal safety/security risks minimization. A reliable application is the home tele-assistance of elderly people [2].

The existing solutions use supervised learning and context-based classification with Hidden Markov Models. The HMMs are suitable for applications with relationships among the classes, such as human behavior recognition or voice recognition [3]. The supervised learning is applied for behavioral pattern recognition systems with several constraints. Despite of them, there is a significant potential to design optimized classifiers for human behavioral recognition in personal and public safety applications. Our contribution is a classification method in which the behavioral patterns are processed according to their class importance, with only focus on one target class.

The remainder of the paper is structured as follows: Section II-related works; Section III-the classification method and performance achievements; Section IV- conclusions.

II. RELATED WORKS

Most of the actual human behavior recognition systems use acceleration data to provide informative features for the behavioral patterns classification.

An accurate algorithm for human behavioral patterns recognition is defined in [4]. The patterns are related by Activities of Daily Living (ADL) of elderly people at their homes. The classifier is based on Gaussian Mixture Models and Mahalanobis distance.

Another human behavior recognition system with smartphone sensors is presented in [5], in which data classification is based on Least Square-Support Vector Machine.

Another optimized SVM-based classification method is evaluated in [6]. The classifier was adjusted for multi-class extension and complexity reduction.

A non-linear SVM decision tree was applied for human actions recognition in [7]. The vision-based human action recognition is approached with a SVM classifier combined with a decision tree into one multi-class algorithm.

A statistical model with Multiple Hidden Markov Model Regression was proposed in [8] for an automatic analysis of activities. The achievements are compared with other algorithms that were applied for activities classification.

An approach with Hidden Semi-Markov was presented in [9]. The authors addressed a large class of exponential family distributions to model state durations. They considered a home monitoring scenario for which the system was learned to recognize a set of complex ADL-related behaviors.

A behavioral recognition system with a Conditional Random Field model is defined in [10]. The system is based on a hierarchical semantic model exploiting the dynamic and hidden features of behavior and applying a high-level semantic tree.

The multimodal approach for human behavioral patterns recognition was applied for smart home environment [11]. The HMM statistical models were used, with the automatic offline analysis of human behavior recordings and the online detection of learned human behavior patterns.

There is an increasing interest to design high-performance human behavioral recognition systems for several applications. These developments are based on various modeling and classification techniques for behavioral patterns. The actual methods are subject to further improvements when dealing with applications requiring optimal performance vs. complexity trade-offs. This is a reliable reason to consider a target vs. non-target classification method for human behavioral pattern recognition.

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III. THE CLASSIFICATION METHOD

The proposed classification method for behavioral patterns derives from our previous works in biometrics [12], [13]. Actually the behavioral patterns are generated from human traits or actions. While the biometric recognition is applied for users authentication, the human behavioral recognition addresses applications for public and/or personal safety in smart environments. The method definition framework includes: the system architecture for its development, the behavioral features and patterns definition and, finally, the classifier design, evaluation and optimization.

A. The System Architecture

The behavior recognition system architecture is depicted in Fig. 1. This is used for the classification method development. The main components are the following:

- the *data acquisition subsystem* with tri-axial accelerometers sensors providing primary data samples;
- the *behavioral feature extraction subsystem* with: data pre-processing (to remove the outliers); feature representation (to achieve a compact representation of the feature space datapoints); feature, optionally in our design; behavioral patterns generation.
- the *classification subsystem* which is the target vs. non-target classifier. This module is designed for applications in which there is a well-defined target behavioral class that is the most important for the recognition process.

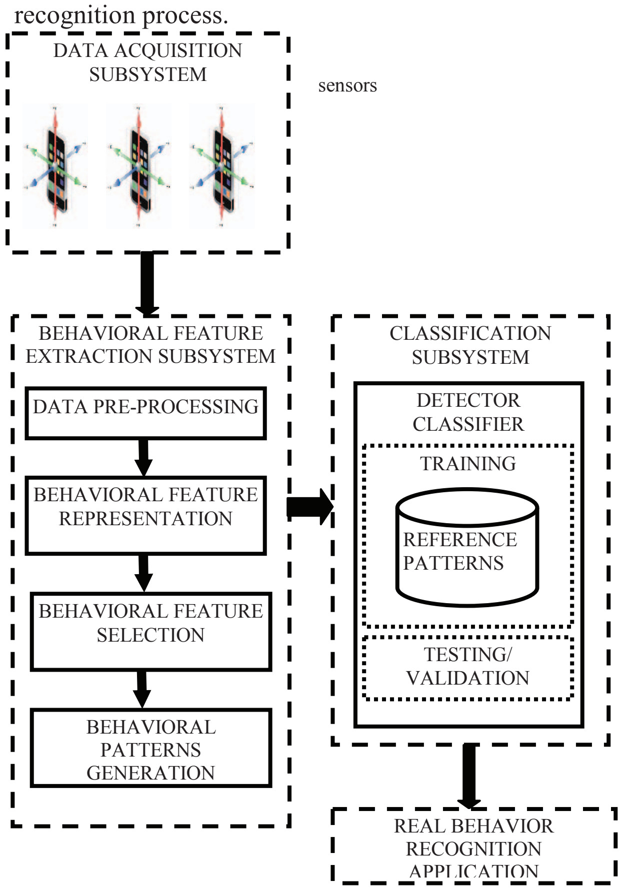

Fig.1. The behavioral recognition system architecture

B. Behavioral Features and Patterns

The behavioral pattern of an individual is derived from a set of sensors data that are acquired during a certain time and describe some attributes of his/her gestures, actions or postures. The data are labeled such as to provide a meaningful association with some typical human actions or activities. Actually the behavioral classes are related to the Activities of Daily Living (ADL) of the individuals within their homes. Here we only considered mobility-related behavioral features provided by acceleration data.

A behavioral pattern is represented as a vector containing several variables that describe some mobility features of the subjects.

For the behavioral patterns acquisition and processing we basically applied the methodology given in [4] for data acceleration, using a tri-axial accelerometer and asking the individuals to perform a given set of movements during a fixed period. For this process we retained only the gravity and body acceleration components (g_x, g_y, g_z and b_x, b_y, b_z, respectively). The difference is that in our representation we defined an overall feature vector containing all these acceleration components as behavioral features. This operation generated a behavioral pattern with 6 components. This feature space dimensionality seems to be very small for the goal of an accurate behavioral recognition. However, it is actually a starting point for our research in which we will be interested to find out the optimal behavioral features number able to efficiently manage the **peaking** case (the performance improvement limitation for a certain feature space size vs. training examples number ratio). Further experiments and evaluations should be conducted with various datasets and several feature space dimensionalities, also varying the training examples number.

Also we sampled the gravity and body acceleration features with up to 200 samples per component and for the same training example.

For the further behavioral patterns processing we used some automatic tools developed in Netherlands (Delft University), actually the Matlab-based tools for pattern recognition systems design and evaluation: PR Tool version 5 and Per Class, respectively.

C. The Detector Classifier for Behavioral Patterns Recognition

The behavioral classes are defined according to typical mobility-related daily home activities:

- Class C1: *getting up* from the bed;
- Class C2: *lying down* on the bed;
- Class C3: *standing up* from a chair;
- Class C4: *sitting down* on a chair

These actions belong to a general framework for human activities recognition named Activities of Daily Living (ADL). Then we proceeded to the following steps:

- the target vs. non-target (detector) classifier design;
- the classifier performance evaluation and optimization

1. *Detector Classifier Design and Training*

The classification model is depicted in Fig. 2. It is a target vs.

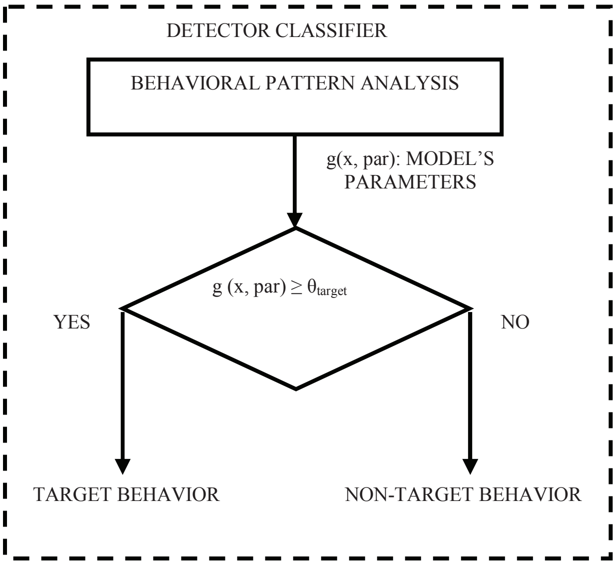

Fig. 2. The human behavior patterns classification with target and non-target outputs

non-target classification approach in which C2 is the most important behavioral class for our example. The samples belonging to all the other classes are grouped together into a single non-target class. A classifier which is trained for only one target class is named **detector**. Within the detector design process a decision threshold is fixed for the target class (the behavioral class C2 in this case).

The 2 functional components of the classification module are the following:

- The *Behavioral Pattern Analysis*, that performs the detector classifier training according to the target vs. non-target model. The target is the behavioral class C2. The non-target contains all the other behavioral classes: C1, C3, C4;
- The Decisional Function, which provides threshold-based outputs concerning the target vs. non-target behavioral recognition for the real application.

We applied a simple classification model, namely LDC (Linear Discriminant Classifier). This is because the resulted feature space is low-dimensional (6 features) and according to [3] a low-dimensional feature space could be easily covered with less training examples; this allows to apply classification models with lower complexity but maintaining a reliable performance.

The LDC model is applied for the behavioral target vs. non-target classification, according to the discriminant function *g(x)* [14]:

$$g(x) = \left(\mu_t - \mu_{non-t}\right)^T \cdot \Sigma_0^{-1} \cdot x + const \qquad (1)$$

where:
x is the feature vector that represents the behavioral pattern;
μ_t and μ_{non-t} are the mean vectors for the target and non-target classes, respectively;
Σ_0 is the weighted covariance matrix. The standard LDC model is optimal for Gaussian distributions with equal class covariance matrices. In our case the resulting matrices (Σ_t, Σ_{non-t}) are different, so we applied the weighted version given by (2) [14]

$$\Sigma_0 = P_t \cdot \Sigma_t + P_{non-t} \cdot \Sigma_{non-t} \qquad (2)$$

The weights P_t and P_{non-t} are the class prior probabilities that are estimated from the training dataset. The class covariance matrices are computed with the following equations for target and non-target class:

$$\Sigma_t = E\left[\left(x_t - E[x_t]\right) \cdot \left(x_t - E[x_t]\right)^T\right] \qquad (3)$$

$$\Sigma_{non-t} = E\left[\left(x_{non-t} - E[x_{non-t}]\right) \cdot \left(x_{non-t} - E[x_{non-t}]\right)^T\right] \qquad (4)$$

x_t and x_{non-t} are the feature vectors belonging to target and non-target class, respectively. *E[x]* is the expected value of a random variable *x*. Finally, in (1) the amount *const* is given by

$$const = -\frac{1}{2} \cdot \mu_t^T \cdot \Sigma_0^{-1} \cdot \mu_t + \frac{1}{2} \cdot \mu_{non-t}^T \cdot \Sigma_0^{-1} \cdot \mu_{non-t} + \log\left(\frac{P_t}{P_{non-t}}\right) \qquad (5)$$

The training dataset contains 50 samples per behavioral class. This is a small value of the training set size but reasoned by the fact that we applied a lower-complexity classifier. However, further experiments will be performed while considering several behavioral classes and extended feature sets, in order to find out the **peaking** point for a certain training set size vs. feature space dimensionality ratio.

We applied a leave-one out cross-validation procedure in order to ensure a reliable generalization performance of the designed classifier, despite of the small sizes of the training dataset and feature space.

2. *Performance Evaluation and Optimization*

The human behavioral recognition system is evaluated using generated samples for only 5 individuals, because the classification process is focused on human behavior recognition; each individual could exhibit several behavioral patterns according to his/her conditions. The objective is to identify a behavioral pattern. Further research will be conducted on extended data from several individuals, with more behavioral classes and various behavioral features.

Fig. 3 depicts the FPR (False Positive Rate) vs. FNR (False Negative Rate) curves for the following cases:

a) C2: the target class, C1: the non-target class;
b) C2: the target class, C1+ C3: the non-target class;
c) C2: the target class, C3+ C4: the non-target class;
d) C2: the target class, C1+ C3 + C4: the non-target class

These show the influence of classes unbalancing on a human behavioral recognition system performance with

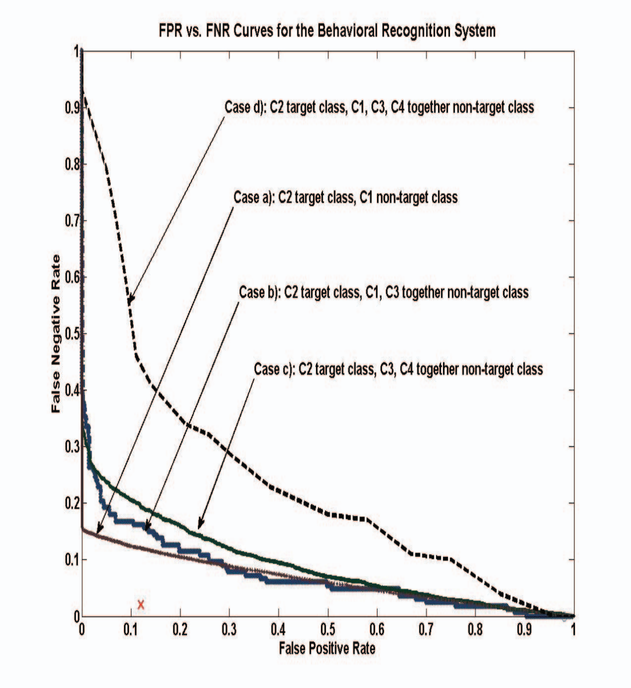

Fig. 3. The performance of target vs. non-target classification for human behavioral pattern recognition

target vs. non-target classification. We used 50 samples per each of the original behavioral classes to select the optimal classifier for a low-dimensional feature space. The target class size is fixed, but the non-target class size increases for cases b), c) and d). One can see the performance reduction with the classes unbalancing degree. However the class unbalancing does not always have the same negative impact. This effect depends on the real available data with their specific patterns. Also we operated on a reduced feature space and this is another difference between our approach and the actual developments in human behavioral recognition systems design.

Despite of this reduction, it is possible to fix the classifier's threshold-based operating point allowing to adjust the performance according to the applications requirements. The **optimization** means to find the best operating point for the designed system in order to meet the required performance with an appropriate computational cost. This could be done for each of the 4 use cases, depending on the behavioral recognition applications purposes.

IV. CONCLUSION

In this paper we approached the human behavioral pattern recognition task with a supervised learning method. The behavioral patterns are processed with a target vs. non-target classification method in which first we defined the most important behavioral class to be recognized. The reason is that in real applications not all the behavioral classes have the same relevancy degree and a certain optimization should be done in order to provide the desired performance level. The main challenge for human behavior/activities modelling and classification is that the corresponding patterns relate to dynamic human traits and not to the static ones like in typical biometric systems (e.g. with fingerprint or iris).

This approach is suitable for real-time public but especially personal safety applications. One example is the remote tele-assistance of elderly people at their homes; the application goal is to early detect the most significant deviations in their daily behavioral patterns in order to prevent the individuals conditions degradation.

REFERENCES

[1] S.Soviany, S.Puşcoci: "A Hierarchical Decision System for Human Behavioral Recognition", ECAI 2015- International Conference -7th Edition, Electronics, Computer and Artificial Intelligence, Bucharest, România, June 25-27, 2015.

[2] S.Soviany, S.Puşcoci: "Multimodal Analysis for Behavioural Recognition in Tele-assistance Applications", ICT4AgeingWell 2015 – International Conference on Information and Communication Technologies for Ageing Well and e-Health, Lisbon, Portugal, May 20-22, 2015.

[3] S.Theodoridis, K.Koutroumbas: "Pattern Recognition", 4th edition, Academic Press, Elsevier, 2009.

[4] B.Bruno, F.Mastrogiovanni, A.Sgorbissa, T.Vernazza, R.Zaccaria: "Analysis of Human Behavior Recognition Algorithms based on Acceleration Data", 2013 IEEE International Conference on Robotics and Automation (ICRA), Karlsruhe, Germany, May 6-10, 2013.

[5] L.Pei, R.Guinness, R.Chen, J.Liu, H.Kuusniemi, Y.Chen, L.Chen, J.Kaistinen: "Human Behavior Cognition Using Smartphone Sensors", Sensors 2013, 13, 1402-1424.

[6] D. Anguita, A. Ghio, L. Oneto, X.Parra and J.L.Reyes-Ortiz: "Human Activity Recognition on Smartphones using a Multiclass Hardware-Friendly Support Vector Machine", 6th International Conference on Ubiquitous Computing and Ambient Intelligence &4th International Workshop on Ambient Assisted Living-UCAmI&IWAAL 2012, December 3-5, 2012, Vitoria-Gasteiz, Spain.

[7] H.Zhao, Z.Liu: "Human Action Recognition Based on Non-linear SVM Decision Tree", Journal of Computational Information Systems 7:7 (2011) 2461-2468.

[8] D.Trabelsi, S.Mohammed, F.Chamroukhi, L.Oukhellou, Y.Amirat: "Supervised and unsupervised classification approaches for human activity recognition using body-mounted sensors", ESANN 2012 Proceedings, European Symposium on Artificial Neural Networks, Computational Intelligence and Machine Learning, Bruges, Belgium, April 25-27, 2012.

[9] T.V.Duong, D.Q.Phung, H.H.Bui, S.Venkatesh:"Human Behavior Recognition with Generic Exponential Familiy Duration Modeling in the Hidden Semi-Markov Model", the 18th International Conference on Pattern Recognition (ICPR'06), Hong Kong, August 20-24, 2006.

[10] F.Bu:"Human Behavior Recognition based on Conditional Random Field and Bag-Of-Visual Words Semantic Model", International Journal of Signal Processing and Pattern Recognition, Vol. 8, No. 1 (2015), pp. 23-32.

[11] O.Brdiczka, M.Langet, J.Maisonnasse, J.L.Crowley:"Detecting Human Behavior Models from Multimodal Observation in a Smart Home", IEEE TRANSACTIONS ON AUTOMATION SCIENCE AND ENGINEERING, 2008.

[12] S.Soviany, C.Soviany, S.Puşcoci: "An Optimized Iris Recognition System for Multi-level Security Applications", 2014 International Conference on Security and Management (SAM'14), World Academy of Science, Las Vegas, SUA, July 21-24, 2014.

[13] S. Soviany, S. Puşcoci: "An Optimized Multimodal Biometric System with Hierarchical Classifiers and Reduced Features", IEEE International Symposium on Medical Measurements and Applications MeMeA, Lisbon, Portugal, June 11-12, 2014.

[14] ***:"PerClass Training Course: Machine Learning for R&D Specialists", Delft, Netherlands.