Università Politecnica delle Marche
Scuola di Dottorato di Ricerca in Scienze dell'Ingegneria
Curriculum in Ingegneria Elettronica, Elettrotecnica e delle Telecomunicazioni

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# Ambient Intelligence: Computational Audio Processing For Human Fall Detection

Ph.D. Dissertation of:
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XVII edition - new series

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*alla mia famiglia*

# Abstract

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# Chapter 1

# Introduction

Outline, obiettivi, controbuti

The decreasing birth rate [1] and the contemporary increase of the life expectancy at birth [2] in the majority of industrialized countries have been generating new challenges in the assistance of the elderly. The scientific community, companies and governments are trying to face them by investing in the development of efficient healthcare systems and solutions. The direction taken goes towards the development of smart home capable of taking care of the inhabitants by supporting and monitoring them in their daily actions [3, 4]. Since falls are one of the main cause of death for the elderly [5], several efforts have been devoted to the development of algorithms for automatically detecting these events.

## 1.1 Fall Detection Systems

The continuous and unprecedented growth rate of the elderly world population is one of the primary aspects of concern for society and governments. Nowadays about 8.5% of people in the world are more than 65 years old [6, 2]. Although the average life of the world population is getting longer, elderly people may not necessarily live a healthier life. It is enough to say that 37.5 million falls require medical interventions and more than 600 thousand are cause of death every year worldwide. In particular, the population segment most affected by this problem is composed of elderly over 65 years that, with the growing mobility of the population, are more frequently left alone in their homes without aid in the case of need. Moreover, since falls are the leading cause of death and hospitalizations for older adults, this phenomenon leads to a substantial increase in the cost of healthcare [7, 5]. It is not surprising, thus, that the research community is encouraged, even by governments, to find reliable and performing solutions to minimize the damage caused by the human falls problem. This is also confirmed by the presence in the literature of several reviews dedicated to this specific topic [5, 8, 9, 10, 11, 12]. In fact, in the past few years, a variety of systems have been presented. One way to divide the methodologies for approaching the falls detection problem is based on the placement of the sensing devices [5]. The main categories are wearable, vision and environmental, with each category presenting their own advantages and disadvantages. Wearable systems do not suffer from ambient condition, but people may forget to wear them and they are not operational during the charging time, thus, some people may consider them annoying. Furthermore, a device must be installed on each person to be monitored. An environmental sensor may be used to avoid this kind of problems, but with other limitations. Vision systems, although they are actually environmental sensors, deserve a dedicated category because of many systems proposed in the literature based on this type of sensors [5]. This category includes several types of sensors like, e.g., cameras for which the major limitations are field-of-view constraints, lighting condition, positioning of multiple cameras and lack of privacy. The ambient category includes several types of sensors. For example, radar doppler based systems used in [13] raise fewer privacy concerns, but they suffer from reflection and blind spots. In particular, for a data-driven system, another aspect that should not be underestimated is the need for a re-training when changing the environment to be monitored or even just some of its components such as the arrangement of furniture as happens in [14]. All this implies that there is no optimal choice, which is instead, a compromise that depends on the type of environment that is monitored as well as on personal sensitivity of the subjects under monitoring. Going into more detail, another significant distinction between falls detection systems can be made based on the type and amount of data used for the algorithm development [8]. In fact, the problem can be approached either as supervised or unsupervised based on the availability of data in the hands of the researchers as well as their goals. Most state-of-the-art works tackle the problem under fully supervised conditions assuming they have enough data for falls. Almost all of these falls are simulated with professional mannequins [15, 16] or by people with adequate protections [17, 18] that however may not correctly emulate an actual fall. Although this approach leads to more accurate results, there is no guarantee that it will generalize well in real situations. Other researchers opt for approaches based on outlier/anomaly detection [19, 20, 21] because of the plentiful availability of data that can represent normal activity. However, it is challenging to define what “normal activities” are for such approaches, and the risk is to raise several false alarms. Perhaps the situation that most closely approximates reality is a hybrid between the previous ones, in which a large amount of data representing the normality are easily available, with just a few samples of real human fall (*RHF*) and eventually some related synthetic or simulated data. In these situations, supervised approaches that suffer from strong data imbalance have to apply subsampling [22] or weighting [8] techniques to mitigate this effect. Thus, the need to find an effective way to exploit the few available falls data is evident.

## 1.2 State-Of-The-Art

Review dei sistemi per la fall detection basati sui vari tipi di sensori accelerometers, vision, ambient. Per gli ambient paricolare enfasi sugli approcci basati su aduio.

### 1.2.1 Problem Statement

# Chapter 2

# Background

In recent years, the IoT revolution has led to the creation of enormous amounts of data. The use of intelligent devices that can interface with cloud computing systems or perform complex calculations directly on board, in homes and cities, has allowed the affirmation of data-driven algorithms compared to other methodologies used so far. In fact, these approaches try to emulate the functioning of the human mind, enabling computers to perform tasks that are unthinkable until now. In this chapter are resumed the data-driven and machine learning algorithms used for developing the proposed methodologies for fall classification systems.

## 2.1 Support Vector Machines

Support Vector Machines (SVM) [23] are one of the most popular classification algorithms and are well known for their strong theoretical foundations, generalization performance and ability to handle high dimensional data. This section presents an overview of support vector machine, starting with linear SVMs, followed by their extension to the nonlinear case and finally the One-Class SVM for novelty detection.

**Linear Support Vector Machines** In the binary classification setting, let $((x_1, y_1) \dots (x_n, y_n))$ be the training dataset where $x_i \in \Re^n$ are the $n$-dimensional feature vectors representing the instances (i.e. observations) and $y_i \in \{-1, +1\}$ be the labels of the instances. Support vector learning is the problem of finding a separating hyperplane that separates the positive examples (labeled +1) from the negative examples (labeled -1) with the largest margin:

$$f(\vec{w}) = \mathrm{sign}(\vec{w}^T \cdot \vec{x} + b), \tag{2.1}$$

where a value of $-1$ indicates one class, and a value of $+1$ the other class. In the simpler linearly separable problem, the margin of the hyperplane is defined as the shortest distance between the positive and negative instances that are

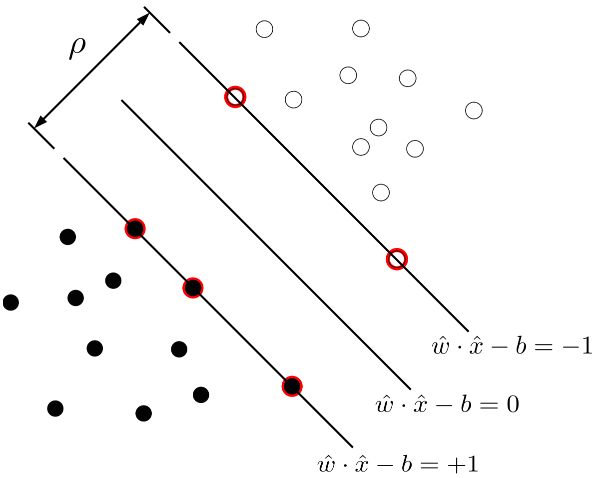


Figure 2.1: A hyperplane separating two classes with the maximum margin. The red highlighted points are the support vectors.

closest to the hyperplane. The intuition behind searching for the hyperplane with a large margin is that a hyperplane with the largest margin should be more resistant to noise than a hyperplane with a smaller margin.

Formally, suppose that all the data satisfy the constraints

$$\vec{w} \cdot \vec{x}_i + b \geq +1 \text{ for } y_i = +1, \tag{2.2}$$

$$\vec{w} \cdot \vec{x}_i + b \leq +1 \text{ for } y_i = -1, \tag{2.3}$$

where $\vec{w}$ is the normal to the hyperplane, $\frac{|b|}{\|\vec{w}\|}$ is the perpendicular distance from the hyperplane to the origin, and $\|\vec{w}\|$ is the Euclidean norm of $\vec{w}$. These two constraints can be expressed in compact form as:

$$y_i(\vec{w} \cdot \vec{x}_i + b) \geq 1. \tag{2.4}$$

The *canonical hyperplane* is the hyperplane that separates the data and has maximal margin. The margin $\rho$ can be computed as the distance between the two canonical hyperplanes:

$$\rho = \frac{1-b}{\|\vec{w}\|} - \frac{-1-b}{\|\vec{w}\|} = \frac{2}{\|\vec{w}\|} \tag{2.5}$$

Thus, we need to solve an optimisation problem, finding the hyperplane that maximises the margin and ensures the classes are separable

$$\min_{\vec{w}_i, b} \frac{1}{2}\|\vec{w}\|^2 \text{ subject to } y_i(\vec{w} \cdot \vec{x}_i + b) \geq 1. \tag{2.6}$$

The problem can be expressed in the Lagrangian formulation:

$$\mathcal{L}(\vec{w}, b, \lambda) = \frac{1}{2}\|\vec{w}\|^2 + \sum_{i=1}^{m} \lambda_i (1 - y_i(\vec{w} \cdot \vec{x}_i + b)) \tag{2.7}$$

with Lagrange multipliers $\lambda_i \geq 0$ for each constraint in 2.6. The objective is then to minimize 2.7 with respect to $\vec{w}$ and $b$ and simultaneously require that the derivatives of $\mathcal{L}(\vec{w}, b, \lambda)$ with respect to all the $\lambda$ vanish. The advantage is twofold: the training vectors only appear as a scalar product among the vectors, and the constraints are easier to manage.

With the formulation presented above, the SVM fails in some situation. In fact, there is no solution if samples can not be separated by a hyperplane. Moreover, although data are linearly separable the SVM may overfit to some outlier compromising system performance. For dealing with this type of problem, has been developed the soft margin SVM [23] which allows data points to lie within the margins. Introducing *slack variables* $\xi_i$ into the constraints and penalize them in objective, the new problem becomes

$$\min_{\vec{w}_i, b, \vec{\xi}} \frac{1}{2}\|\vec{w}\|^2 + C\sum_{i=1}^{m} \xi_i \tag{2.8}$$

subject to $y_i(\vec{w} \cdot \vec{x}_i + b) \geq 1 - \xi_i$ and $\xi_i \geq 0$ for $i = 1 \cdots m$.

The cost coefficient C $> 0$ is a hyper-parameter that specifies the misclassification penalty and is tuned by the user based on the classification task and dataset characteristics.

**Non-Linear Support Vector Machines** A way to solve the problem when data are not linearly separable, is to map the data on to a higher dimensional space and then to use a linear classifier in the higher dimensional space. This methods is referred to as "the kernel trick " that exploit the fact that the training data appears as a dot product between vectors in the Lagrangian formulation to from non-linear decision boundaries. Suppose to use a transformation $\Phi : \vec{x} \rightarrow \phi(\vec{x})$ to map every data sample into higher dimensional space, the dot product becomes $\phi(\vec{x}_i)^T \phi(\vec{x}_j)$. By the use of a kernel function

$$K(\vec{x}_i, \vec{x}_j) = \langle \phi(\vec{x}_i), \phi(\vec{x}_j) \rangle, \tag{2.9}$$

it is possible to compute the separating hyperplane without explicitly carrying out the mapping into feature space. The classifier become:

$$f(\vec{x}) = \text{sign}(\sum_i \lambda_i y_i K(\vec{x}_i, \vec{x}_j) + b) \tag{2.10}$$

The most popular kernel functions are:

- Linear Kernel:
$$K(\vec{x}_i, \vec{x}_j) = \langle \vec{x}_i, \vec{x}_j \rangle \tag{2.11}$$

- Polynomial Kernel:
$$K(\vec{x}_i, \vec{x}_j) = (\langle \vec{x}_i, \vec{x}_j \rangle)^d \tag{2.12}$$

- Sigmoid Kernel:
$$K(\vec{x}_i, \vec{x}_j) = tanh(\gamma \langle \vec{x}_i, \vec{x}_j \rangle - \theta) \tag{2.13}$$

- RBF Kernel:
$$K(\vec{x}_i, \vec{x}_j) = \exp(-\frac{\|\vec{x}_i - \vec{x}_j\|}{2\sigma^2}) \tag{2.14}$$

Up to now the SVM algorithm for binary classification has been described. This algorithm can be extended to the multi-class case using the "one vs all" technique [24].

### 2.1.1 One-Class Support Vector Machines

One-Class SVM (OCSVM) proposed by Schölkopf et al. [25] is a natural extension of the support vector algorithm to the case of unlabeled data that makes them useful for novelty detection problems. In the OCSVM, a new parameter $\nu$ that controls the trade-off between maximizing the distance of the hyperplane from the origin and the number of data points contained by the hyperplane has been introduced. To separate the data from the origin, the following quadratic program has to be solved:

$$\min_{\vec{w}_i, \vec{\xi}, \rho} \frac{1}{2}\|\vec{w}\|^2 + \frac{1}{\nu l}\sum_{i=1}^{m} \xi_i - \rho \tag{2.15}$$

$$\text{subject to } (\vec{w} \cdot \phi(\vec{x}_i)) \geq \rho - \xi_i \text{ and } \xi_i \geq 0 \text{ for } i = 1 \cdots m.$$

Now the optimization problem of the OCSVM can be solved as the dual quadratic problem

$$\min_{\lambda} \frac{1}{2}\sum_{ij} K(\vec{x_i}, \vec{x_j}) \tag{2.16}$$

$$\text{subject to } 0 \leq \lambda_i \leq \frac{1}{\nu l} \text{ and } \sum_i \lambda_i = 1,$$

where $\lambda_i$ is a Lagrange multiplier and $l$ is the number of points in the training dataset.

## 2.2 Gaussian Mixture Model

https://pdfs.semanticscholar.org/734b/07b53c23f74a3b004d7fe341ae4fce462fc6.pdf
A Gaussian Mixture Model (GMM) is a parametric probability density function represented as a weighted sum of Gaussian component densities. Generally, GMMs are used as a parametric model of the probability distribution of some features. To estimate the parameter of GMM the algorithm Expectation-Maximization (EM) algorithm or Maximum A Posteriori (MAP) are used starting from a well-trained prior model usually named Universal Background Model (UBM). A Gaussian mixture model is a weighted sum of M component Gaussian densities as given by the equation

$$p(\vec{x, \lambda}) = \sum_{i=1}^{M} w_i g(\vec{x}|\vec{\mu}_i, \vec{\Sigma}_i) \tag{2.17}$$

where $\vec{x}$ is a D-dimensional features vector, $g(\vec{x}|\vec{\mu}_i), \vec{\Sigma}_i)$ are the components of the mixture and $w_i$ are the weight of each component. Each component of the mixture is a D-variate Gaussian density function expressed as

$$a \tag{2.18}$$

## 2.3 K-Nearest Neighbor

## 2.4 Deep Neural Network

### 2.4.1 Convolutional Neural Network

### 2.4.2 Autoencoder

# Chapter 3

# Dataset

poichè non erano presnti dataset adui suabili, ce ne siamo fatti uno noi. Poi per ogni metodo verranno esplicitati i dati usati.

## 3.1 A3ALL-v1.0

### 3.1.1 Signals Analysis

parte del ESWN

## 3.2 A3ALL-v2.0

# Chapter 4

# Supervised Approach

qua vengono presentati sia il metodo multilabel classifier GMM-UBM SVM (ESWN) che il binary GMM-UBM SVM (WIRN2016)

# Chapter 5

# Unsupervised Approach

Autoencoder wirn 2017 + Qua veine presentato il metodo solo OCSVM

# Chapter 6

# Semi-Unsupervised Approach

modifica user-aided(CIN) siamese semplice siamese autoencdoer

# Chapter 7

# Other contributions

# List of Publications


[1] R. Bonfigli, A. Felicetti, E. Principi, M. Fagiani, S. Squartini, and F. Piazza, "Denoising autoencoders for non-intrusive load monitoring: Improvements and comparative evaluation," *Energy and Buildings*, to appear.

[2] R. Bonfigli, E. Principi, M. Fagiani, M. Severini, S. Squartini, and F. Piazza, "Non-intrusive load monitoring by using active and reactive power in additive factorial hidden markov models," *Applied Energy*, vol. 208, no. Supplement C, pp. 1590 – 1607, 2017.

[3] patent, "Metodo per il monitoraggio non intrusivo del consumo di apparecchiature elettriche collegate ad una linea di alimentazione comune," Domanda numero: 102017000004554, patent pending.

[4] R. Bonfigli, E. Principi, S. Squartini, M. Fagiani, M. Severini, and F. Piazza, "User-aided Footprint Extraction for Appliance Modelling in Non-Intrusive Load Monitoring," in *Proc. of the IEEE Symposium Series on Computational Intelligence*, Athens, Greece, Dec. 6-9 2016, pp. 1–8.

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