Activity Recognition by Classification Method for Weight Variation Measurement with an Insole Device for Monitoring Frail People

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Abstract. Healthcare has become a major field of scientific research and is beginning to merge with new technologies to become connected. Measurement of motor activity provides physicians with indicators in order to improve patient follow up. One important health parameter is weight variation. Measuring these variations is not obvious when a person is walking. This paper highlights the difficulty of providing reliable weight variation values with good accuracy. To reach this objective, the paper presents ways to classify the activity of walking, in order to propose a method to measure weight variation at the right time and in a good position. Many methods were studied and compared, using Matlab. We propose a classification tree that uses the standard deviation of acceleration magnitude to define normal walking. The algorithm was embedded in an insole equipped with two force-sensing resistors and tested in laboratory.

Keywords: Smart insole · Frail people monitoring · Classification methods
Embedded system · Actimetry · Weight variation measurement
Walking

1 Introduction

Home monitoring of the elderly is a well-identified goal of current health policy that aims to favor home support and prevent loss of autonomy. This policy is essential as life expectancy increases. It also is a strategy that should provide more comfort to those concerned by allowing them to stay at home, while helping to improve global health spending management. Thanks to technological tools, tele-monitoring permits ad hoc follow up in order to detect deteriorating health and facilitate timely assistance. Given the non-intrusive and user-friendly characteristics of recent technologies, it is possible to ensure optimized acceptability in a use case context. Dependency prevention and home support of frail people is a huge challenge. Frailty is an emerging concept that encompasses a high risk of death, and, more generally, of dependency. Correlations between frailty and some health parameters are today clearly established: walking speed, loss of weight, spontaneous activity…Thus, walk monitoring and evaluation are key points potentially predictive of unhealthy evolution among the elderly. Fried and al.

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criteria [1] currently are largely used in clinical studies to characterize frailty patients. These studies rely essentially on analysis of the physical component of frailty. In fact, Fried and al. criteria that make it possible to identify frailty syndrome are: diminution of walking speed, physical activity decrease or exhaustion and diminution of weekly calorific expenditure (which can be linked to reduced weekly walking distance), reduction of grasping force and involuntary weight loss. This paper is focused on the last criterion by proposing a way to measure weight variation thanks to a connected insole. The insole seems to be a good means to measure walk parameters [2] and weight [3]. A comparative study already has been realized concerning insole-embedded technologies used to measure weight [4]. The question, now, is to determine the moment when the measurement should be done. To do so, we evaluated several existing methods. We focused on supervised approaches, and we evaluated performances of generative and discriminative methods thanks to Matlab software. We discussed obtained results based on data collected during test scenarios in laboratory. The paper is organized as follows: Sect. 2 describes the objective of weight measurement. Section 3 gives classification techniques and an analysis method for spotting signals. Section 4 presents the equipment used for tests. Section 5 shows modelling results. Section 6 introduces the first results of weight measurement. Section 7 ends the paper with a conclusion.

2 Weight Measurement

Weight measurement during walking and its evolution is original. Most instrumented insoles in research projects use force (or pressure) sensors distributed on the insole area to analyze weight distribution under the sole of the foot. Optimally, a single sensor would measure resultant vertical forces over the entire insole area and would be sensitive to high loads. Non-linearity, hysteresis and sensibility criteria could be taken into account with software, thanks to sensor calibration. The most important point concerning weight monitoring is to achieve replicable measurements over time. Vertical forces on the under-foot area depend on walking cadence, stride length and weight of the user. The load measurement does not rely exclusively on these parameters, however. The activity of the user also has an influence. For the same cadence, the weight load is different, depending on whether the patient is walking, running or climbing stairs, for example. Thus, we want here to evaluate the user's mean weight variation (and not absolute weight which can be obtained thanks to the integral of the load curve divided by time) over a certain period of time (a week, for example); the aim is to be able to detect meaningful weight loss (3 kg), which would indicate the risk of diminished physical abilities and, therefore, loss of autonomy for the elderly person. In order to reduce energy consumption, we decided to measure weight variation with a sufficiently reliable algorithm and low computational resources (which it is not possible if we consider absolute weight), several times per day during a few strides, in order to obtain daily averages and to observe significant evolution during a week. To obtain the most replicable measurement, we decided to measure weight variation only during well-known and frequent circumstances – during a "normal" speed walk on a flat surface ("normal" meaning usual for each individual), for example. It is thus necessary to recognize this activity in order to measure weight only when a variation is detected. The principle of the "weight variation" function runs through three steps:

- First: determination of how that particular person walks by measuring his average walking speed with a calibration system developed specifically for measuring speed on a distance of 4 m [5];
- Second: online determination of walking activity. When sufficiently sustained activity is detected, we determine if it is a walking activity close to that identified during the learning phase.
- Third: weight variation calculation. If the activity matches, we retrieve the maximal pressure value during each walking cycle on flat surface. By calculating the average several times each day, we obtain a daily average which allows us to observe and monitor the evolution of weight variation.

3 Classification Techniques for Learning Signals

3.1 Classification Models

Concerning embedded weight variation measurement, we propose a walking activity classification, since this measure, in order to be reliable, must be realized under classic walking conditions. This means walking on a flat surface at "normal" speed (normal meaning the personal usual speed of the monitored patient, not the usual speed of all monitored patients). Indeed, the process will be different if weight is measured during stair climbing, running or walking. It is thus necessary to develop a classification algorithm of activity to discriminate walking from others activities.

Several supervised classification methods exist in the literature [6]: generative methods, discriminative methods [7]. Authors in [8] demonstrate that the discriminative approach usually surpasses the generative approach to classification tasks. Parameters to take into account ideally are simple implementation and reliability (In this type of study, 95% reliability is targeted [9]). The replicable ability also is a crucial point, since measurement will be carried out several times during the day in order to obtain accurate values. Finally, we want to limit energy consumption of the system, so we need to make sure not to choose a method that requires too much computation resource. Use of the supervised method is justified by the fact that activity models are carried out, initially, on a first database before being used in the embedded system. We want to develop an appropriate method on a computer and then to adapt it to real data on the embedded microprocessor.

Supervised methods have a predictive role. Indeed, from a first learning dataset, we will be able to evaluate the distribution of a class of activity without direct measure, by taking into account values linked to the activity. The aim will thus be to minimize the prediction error. Discriminative approach models directly use a classification rule, with $P(Y \mid X)$, Y being the output and X the input. Generative approach models use the joint distribution $P(X, Y)$ and deduce the classification rule afterwards. Generative models differ from discriminative models in that they are complete probabilistic, while the discriminative approach only determines models from conditional probabilities.

Considering that classification and regression do not necessitate joint distribution, discriminative models seem to perform better. Furthermore, generative models typically are more flexible than discriminative ones to express dependencies during complex learning. Most discriminative methods are supervised and may not be extended easily to unsupervised learning (Fig. 1).

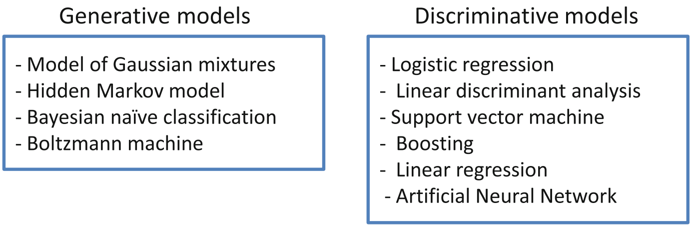


Fig. 1. Classification models.

3.2 Analysis Method and Signal Characteristics

In literature, the standard approach consists of selecting a fixed set of indicators [10] and a sliding window with fixed length for gathering data of studied activities [7]. A combination of temporal and frequency parameters seems to be more precise. In literature, numerous indicators extracted from signals for activity classification are used. It is important to have a significant number of signals in order to improve precision. In any case, we need to extract uncorrelated indicators in order to avoid uselessly increasing the system's complexity. In the field of activity recognition, different sensors can be used, with an accelerometer usually the principal choice [11]. Acceleration data often are associated with a pressure sensor to measure weight with an insole [12, 13]. Some articles also mention the use of a barometer to measure elevation or of a gyroscope to measure rotation angle [14].

Center of Pressure (COP): In the literature, it is proposed to watch pressure distribution, in addition to pressure amplitude. In [15], authors look at the evolution of COP (central point of pressure) and speed in order to recognize activities. We do not use enough pressure sensors to take advantage of this system.

Study of front and back foot forces: The system presented in [16] uses pressure sensor mesh on an insole divided into two parts (front and back). The parameters used to recognize activities (sitting, standing, walking) are: subject's weight, estimated force both on left and right insole…

Classification with rejection: In [17, 18], authors propose to recognize activities and postures thanks to a system similar to our smart insole (insole composed of 5 pressure sensors and a 3-axis accelerometer). Data from sensors are sampled at 100 Hz and then brought back to 25 Hz by averaging (as in our case).

Indicators computed on each 2-s sequence of signal are:

- Step pace/step duration
- Mean of signal for one step
- Variance of signal for one step
- Maximum and minimum of signal amplitude for one step
- MAD (Mean Absolute Deviation) for one step
- Energy for one step (for acceleration, mean of the norm for each step)
- Entropy for one step.

Two other parameters are used to form an indicator: relation between maximum acceleration and maximum pressure. Activity recognition is then realized thanks to a learning phase.

4 Instrumentation System

4.1 Equipment

Our system is composed of a development card designed at LAAS-CNRS, an insole equipped with 2 FSR Teksan A401 sensors and a computer with Matlab software (Fig. 2). The development card has been designed in order to lay out the electronics of the smart insole. Microprocessor used is a nRF51822: this System on Chip is composed of a low-consumption radio emitter-receiver at 2.4 GHz. The 3-axis accelerometer chosen is the ADXL362 ultra low consumption. The two pressure sensors are respectively placed in the region of the metatarsal bones and the heel.

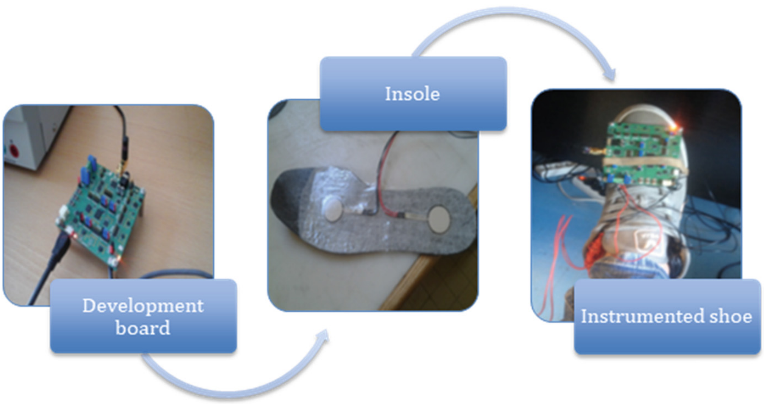


Fig. 2. Instrumentation.

4.2 Measurement Protocol

Data are obtained from raw data collected by sensors in the insole (Fig. 2) during a complete route. The insole sends 100 radio frames per second. A program in C++ allows the saving and the timestamping of received data by a beacon in an Excel datasheet. Retrieved parameters are:

- Acceleration a_x according to X-axis (horizontal and perpendicular to walk direction) in g;
- Acceleration a_y according to Y-axis (horizontal and in walk direction) in g;
- Acceleration a_z according to Z-axis (vertical) in g;
- Acceleration magnitude V_s in g;
- Output tension V_0 of the integrated circuit linked to FSR sensors in V.

The protocol consisted in three different activities in diverse situations (Fig. 3):

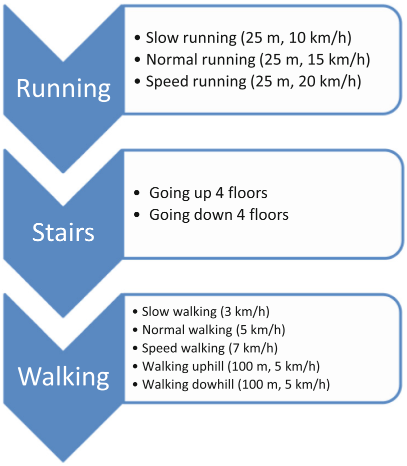


Fig. 3. Walking scenario for data collection.

We searched to determine if it was possible to distinguish these three different activities using data delivered by sensors.

5 Modelization with MATLAB

5.1 Comparison of Classification Methods

For each classification method, we implemented the complete previously described measure protocol twice to build two datasets: learning dataset and test dataset. In our modelling, we divided each dataset in three parts (walking, running and stairs), themselves cut into three sub-parts: duration of walking cycle, amplitude of cycle, cycle areas for pressure and acceleration signal. The learning dataset is thus composed of 60 to 90 walking cycles based on data coming from pressure and acceleration sensors. Among them, 30 to 60 cycles represent walking at different speeds, 15 correspond to running activities at three different speeds and the last 15 cycles are for stairs (up and down). The test dataset is composed of 15 cycles, 5 for each of the three

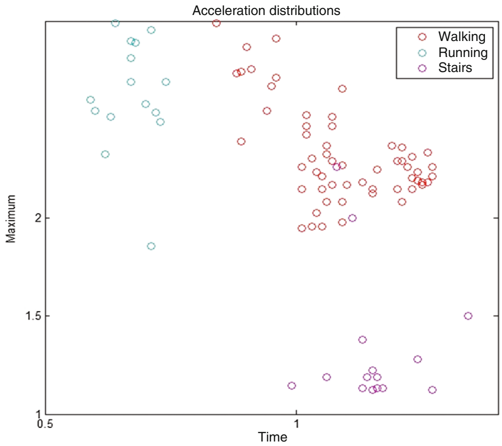


Fig. 4. Distribution of accelerations in learning phase

activities. Each cycle is randomly chosen in the original dataset: no duplication and each cycle belong to only one dataset (learning or test). Thus, we have a learning vector X, a vector Y representing classes and a test vector Z (Fig. 4).

$$X_i = \lceil\ Acc_i\,Time \quad Acc_i\,Max \quad Acc_i\ Area \quad Press_i\,Time \quad Press_i\,Max \quad Press_i\,Area \rceil$$

Each color corresponds to a particular activity, respectively: walking, running and walking up and down stairs.

Main classification methods have been tested with Matlab using several consecutive tries in order to obtain maximum precision for results. Table 1 compares the error rate of each tested method: pressure data only, acceleration data only and pressure and acceleration combined.

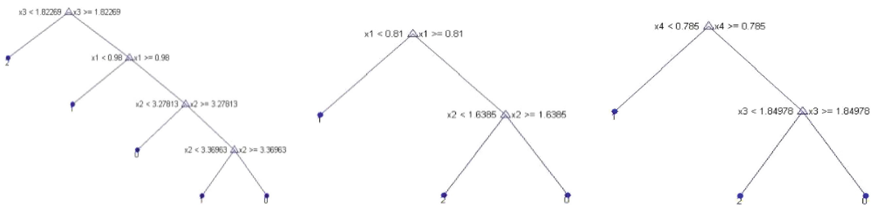
Table 1. Comparison of error rates for each method in Matlab.

Methods	Acceleration+Pressure	Acceleration	Pressure Data
LDA lin	5.53%	23.00%	3.19%
LDA quad	8.59%	23.55%	3.77%
LDA custom	9.31%	23.00%	3.19%
Naive Bayes	**5.21%**	**21.04%**	**3.67%**
SVM lin	16.05%	47.64%	8.48%
SVM quad	75.43%	50.53%	69.56%
SVM rbf	7.84%	23.49%	3.36%
Weighted Distances	**5.25%**	**15.99%**	**3.64%**
Reg Tree	7.72%	29.40%	4.83%
Class Tree	**5.32%**	**17.43%**	**2.92%**
k-NN	8.84%	21.89%	3.72%

We can see that Naïve Bayes, Weighted Distances and Class Tree are the most efficient, with a precision rate of at least 95% using either combination of pressure and acceleration or only pressure data. Of them all, Class Tree requires less computational resource while allowing good precision. Thus, we selected this method to develop our algorithm.

After some trials, duration of walking cycles, their maximum value and area have offered good results and have been chosen to design our classification algorithm based on Class Tree.

In the Class Tree approach, leaf represents values of the targeted variable and branching corresponds to the input variable combinations that lead to these values. Matlab software can return a regression or a classification tree (Fig. 5) based on predictors and Y response. Then, the algorithm predicts classes in which Z data belong.



Acceleration Pressure Acceleration+Pressure

Fig. 5. Class Tree classification with acceleration and pressure data

5.2 Walking Parameters Measurement

As we saw the redundancy of standard deviations and means with Class Tree, we computed these two indicators for the different walking stages. We proposed a classification tree that uses standard deviation of acceleration amplitude to define way of walking and speed.

Indicators used for strides and cadence are acceleration amplitude (also called Sum Vector V_s^2), its mean and variance.

- Computation of square of sum vector, square of acceleration amplitude:

$$V_s^2 = a_i^2 = a_{xi}^2 + a_{yi}^2 + a_{zi}^2. \tag{1}$$

- Mean computation over a sliding window with w = 25 of the square acceleration amplitude a_q:

$$Moy2 = \overline{a_j^2} = \frac{1}{2w+1} \sum_{q=i-w}^{i+w} a_q^2. \tag{2}$$

- Computation of variance of square acceleration amplitude over a sliding window:

$$Var2 = \sigma^2_{a_i^2} = \frac{1}{2w+1}\sum\nolimits_{j=i-w}^{i+w}\left(a_j^2 - \overline{a_j^2}\right)^2. \tag{3}$$

$$and\ Var2 = \frac{1}{2w+1}\sum\nolimits_{j=i-w}^{i+w}\left(V_s^2 - Moy2\right)^2. \tag{4}$$

Variances obtained after modification are presented in Table 2.

Table 2. Variance of square acceleration amplitude depending on the walking stages: up and down stairs, flat surface at three different speeds, in g^2.

Class	Slow (flat)	Normal (flat)	Speed (flat)	Going up	Going down
Running	159	647	1043		
Walking	0.5	3.8	34.4	34.3	110
Stairs				22.4	18.1

Execution of this method is simple since we just have to compute Var2 over a sliding window and request pressure data acquisition related to weight variation, when Var2 is within an optimal space (Fig. 6).

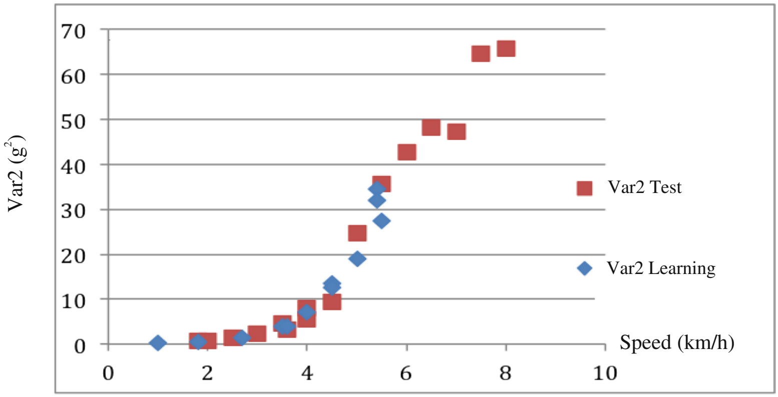


Fig. 6. Variance of square acceleration amplitude as a function of gait speeds, in learning and test phases

Using these characteristics, we have built a database in order to identify each walking stage. We can observe, in Table 2, differences between variances of acceleration amplitude, depending on step stages and then on walking speeds. Each variance is related to a particular speed.

We tested this approach on a treadmill, by varying walking speed. Figure 7 illustrates walking sequentially at 4, 6, 2 and 8 km/h and a return at normal condition (4 km/h). We can notice a huge variation of Var2 depending on speed.

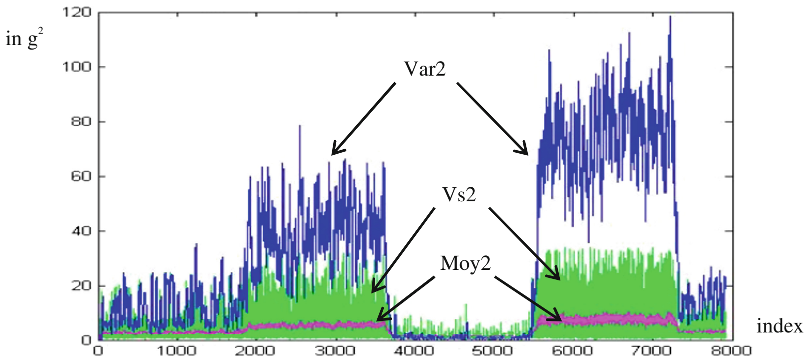


Fig. 7. Evolution of Var2 (Blue), Moy2 (Pink) and Vs2 (Green) depending on walking speed (index 0 to 2000 : 4 km/h, 2000 to 4000 : 6 km/h, 4000 to 5500 : 2 km/h, 5500 to 7500 : 8 km/h, 7500 to 8000 : 4 km/h) in g^2

6 Weight Variation Measurement

Continuous data collection of pressure during stable walking periods on a flat surface showed that we obtained peaks at each step, slightly shifted between the two FSR sensors (front and back of foot). We thus decided to compute an average of the maxima of the two sensors (resultant vertical force) over a sliding window of 25 data. At the end of the day, we computed an average of these averages which allowed us to obtain a daily average.

As a first step, we carried out walking scenarios on a treadmill at 4 km/h speed with different loads in a backpack. In Fig. 8, we can notice the difference in pressure when a new load is added at each stop. In detail, we have phase 1 with no extra load, phase 2 with +2.6%, phase 3 with +4.5%, phase 4 with +5.4% and phase 5 with +7.2% of subject's weight.

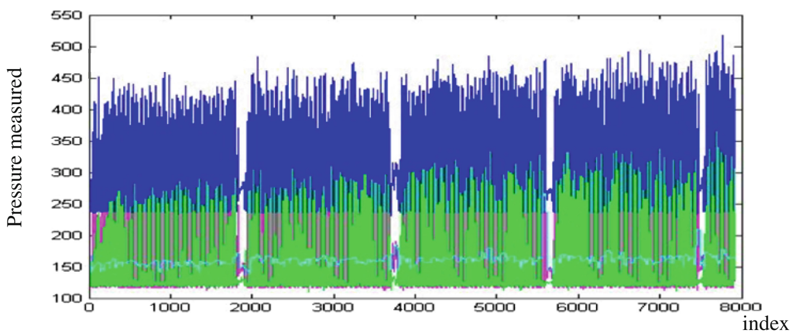


Fig. 8. Pressure variations depending on load

Table 3 summarizes pressure variations, in percentage terms, depending on the load.

Table 3. Evolution of average pressures and their maxima according to applied weights

Index	Additional weight (%)	Maxima average (%)	Average of average (%)
1:1890	0	–	–
1890:3750	+2.6	+2.7	+3.9
3750:5640	+4.5	+4.4	+5.5
5640:7470	+5.4	+4.8	+5.8
7470:7870	+7.2	+7.3	+7.0

We can see that increases, in percentage terms, of maxima averages are close to those for additional loads under real conditions. Indeed, results are better in this case because maximum pressure value is obtained when the foot is flat and contact between foot and the two pressure sensors is highest. This is why we decided to use maxima average pressure to calculate daily average weight variation.

7 Conclusion and Perspectives

We studied, with Matlab, performances (in terms of error rate) on sensor datasets (with acceleration and pressure) of the main classification methods. We proposed a classification tree, using standard deviation of acceleration amplitude, to define the type of walk and a speed. Our proposed approach combines precision, easy implementation, low cost computation and low energy consumption. Results obtained in laboratory are promising. When an elderly person receives an insole, he or she will be asked to walk at normal and fast speed in order to calibrate the insole. Thanks to the Var2 indicator, during this calibration step, we will be able to determine a space with two variances and a 10% (more or less) margin, for example. This space will make it possible to recognize his personal normal walking activity on a flat surface, and, thereafter, to measure weight variation. The interest of automatic measurement at home is that it can be repeated, thereby enabling longitudinal medium and long term monitoring, ensuring systematic measurement in ecological and similar conditions and making it possible to detect meaningful variations in a timely manner. Personalized monitoring of frail people at home should allow care to be adapted earlier, depending on the evolution of frailty indicators, preventing dependency and allowing the elderly to stay at home as long as possible. Developed algorithms may propose walking activity and weight variation monitoring by identifying the appropriate time to implement significant measures. Relative weight variation is targeted. Algorithms' reliability must, henceforth, be tested in real conditions.

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