A Visual Computing Approach for Estimating the Motility Index in the Frail Elder

Chiara Martini[1], Nicoletta Noceti[1], Manuela Chessa[1], Annalisa Barla[1], Alberto Cella[2], Gian Andrea Rollandi[2], Alberto Pilotto[2], Alessandro Verri[1] and Francesca Odone[1]

[1]*Department of Informatics, Bioengineering, Robotics and System Engineering, Università degli Studi di Genova, Genova, Italy*

[2]*E.O. Ospedali Galliera, Genova, Italy*

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Abstract: The accurate estimation of frailty is an important objective to assess the overall well-being and to predict the risk of mortality of elderly. Such evaluation is commonly based on subjective quantities both from self-reported outcomes and occasional physicians evaluations, leading to possibly biased results. An objective and continuous frailty screening tool may be more appropriate for routine assessment. In this paper, we present a data driven method to evaluate one of the main aspect contributing to the frailty estimation, i.e. the motility of the subject. To this aim, we define a *motility index*, estimated following a visual computing approach analysing streams of RGB-D data. We provide an extensive experimental assessment performed on two sets of data acquired in a sensorised facility located within a local hospital. The results are in good agreement with the assessment manually performed by the physicians, nicely showing the potential of our approach.

1 INTRODUCTION

According to the World Bank, Italy has the second-highest share of population aged over 65 worldwide, i.e., 22% in 2014, and statistics related to G20 countries are becoming increasingly similar. Our region, is among the highest in this ranking worldwide. Aging causes, in general, the reduction of the individual's potential, leading to a state of vulnerability and instability of the clinical condition. To highlight this condition, recent medical literature has proposed the notion of *frail* elderly, an individual with an elevated risk of complications that may result in loss of functional autonomy or death (Fried et al., 2004). The accurate estimation of the frailty of an elderly is therefore an important objective to assess the overall well-being and to predict the risk of mortality (Pilotto et al., 2008) (Angleman et al., 2015). Moreover, an hospital stay, especially if prolonged, can lead an elderly person to develop new disabilities (Volpato et al., 2007) and dramatically worsen the risk of mortality (Volpato et al., 2016). Therefore, it is of particular clinical interest to correctly quantify the frailty of the patient just before being discharged. One of the most commonly accepted operational definition of frailty is the classification proposed by Fried et al. (Fried et al., 2001). In this study the authors define frailty as a clinical syndrome in which three or more of the following criteria are present: unintentional weight loss, exhaustion, decrease grip strength, slow gait speed, low physical activity. The criteria of weight loss, exhaustion, and grip strength are usually self-reported measures and may be prone to bias. An objective frailty screening tool may be more appropriate for routine assessment.

Another universally shared strategy for the estimation of patients frailty index and related risk of mortality is the Multidimensional Prognostic Index (MPI) score (Pilotto et al., 2008), that is based on the evaluation of the clinical, cognitive, functional, nutritional, and social domains, as defined in the International Classification of Functioning, Disability, and Health[1]. The evaluation is mostly carried out through questionnaires and self-reported outcomes.

Recently, with the advent of the assistive technologies, various approaches for the automatic estimation of frailty have been proposed (Cao et al., 2009),(Zouba et al., 2010),(Liu and Liu,

[1]http://apps.who.int/classifications/icfbrowser/

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2010),(Bathrinarayanan et al., 2013).

In this paper, we present a data driven method to evaluate the *motility index*, one of the main aspect contributing to the frailty estimation, with visual features.

We aim to perform a continuous motility assessment of frail persons and to produce reports informing medical staff in case of medical assistance is required. We target elderly and people with mild cognitive impairments, partially autonomous, but in need of a light assistance, possibly in a post-hospitalisation stage. This study is a part of a larger project whose aim is to design and implement a model of protected discharge, in which the patient, after being discharged from the hospital, is hosted for few days (about one week) in an apartment. This is novel with respect to the state of the art, since current literature is based on long observation of the patient (6-12 month)(Scanaill et al., 2006), our new challenge is instead to infer the frailty of the patient in a short time. The facility is located within the Galliera Hospital a local hospital in Genova (Italy) and equipped as a comfortable apartment, where the patient can be monitored by a system of sensors, while physicians and nurses have the opportunity of monitoring the patient remotely. We report an extensive analysis on two sets of data, acquired within the facility. The obtained estimates are in line with the geriatricians assessment, even if the two evaluations have been carried out in a different way and consider different aspects of the overall health status. The structure of the paper can be summarised as follows. Firstly, we describe the facility and our research objectives (Sec. 2). Then we present data analysis and the obtained results (Sec. 3). The paper is closed with conclusion and future works (Sec. 4).

2 CONCEPT

In this section we first describe the apartment, then we summarise the sensors installed in the facility and the corresponding measurements. The experimental set up is rich of sensors, we will briefly illustrate all the devices but, for the purpose of the study, we will use only a subset of them.
The aim of our project is the continuous monitoring of the patient's motility. In particular, we focus on the automatic estimation of the *motility index* (see Sec. 3.3) based on walking time and physical activity that, according to (Fried et al., 2001), are strongly related to the patients frailty.

As shown in Figure 1 and Figure 2, the apartment consists of two bedrooms, one with a bed and a sofa-bed (for an accompanying person) and one with

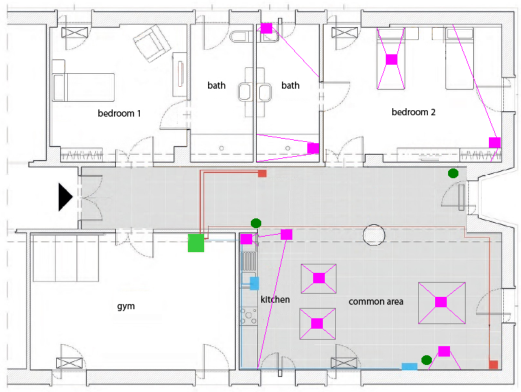

Figure 1: Apartment plan. Blue rectangles represent the RGB-D sensors, the small red squares correspond to the cameras. Green circles represent the localisation tags, while purple rectangles indicate the Passive Infra-red (PIR) sensors and their field of view (through purple lines). They are all wired to the workstation (green square), placed in the gym.

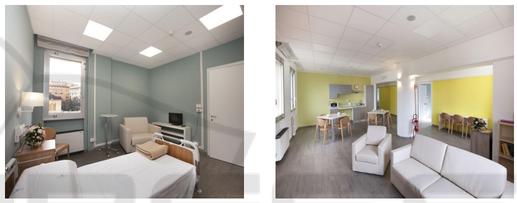

Figure 2: Left panel shows one of the two bedrooms, right panel shows the common room.

two beds (patient and caregiver), a gym, and a common room with kitchenette and living room. To make the atmosphere homely, an architectural study was conducted to choose appropriate colors, arrangements and furniture, leading to an environment similar to a regular apartment rather than a hospital room.

The common room, where most of the daily activities take place, hosts the majority of the sensors, including cameras and RGB-D sensors, localisation anchors, presence sensors, occupancy sensors for the chairs (pressure sensors), usage sensors on some cabinet door of the kitchenette (luminosity sensors). Health monitoring devices are located on a console table in the same area. Bedrooms and bathrooms, for obvious privacy concerns, are only equipped with presence sensors, which detect whether there is any movement in the room.

Lastly, presence sensors have also been placed for monitoring specific meaningful disjointed locations, such as: the kitchen table, the desk, the bed and the shower. Similarly, an additional luminosity sensors has been installed to monitor the status of the TV set.

The redundancy of sensors and measures to monitor similar activities is a design choice that guarantee the robustness of the results.

2.1 Distributed Sensors and Health Devices

For the sake of completeness we first describe all the non-vision sensors installed in the apartment.

The localisation system, Eliko KIO RTLS[2], is a Real Time Locating System (RTLS) based on the Ultra WideBand (UWB) technology, which allows for a positioning precision of about 30cm. The system is based on the "tag and anchor" paradigm, which assumes the tag to be always attached to the person and the anchors to be in fixed, a-priori known locations in the environment (green dots in Figure 1). The system allows for a continuous and unambiguous tracking of the monitored person.

The presence sensors, Aeotek MultiSensor 6[3], are devices integrating six channels,incuding the Passive Infra-Red (PIR) and the light sensors. They have been placed in different locations (in purple in Figure 1) and calibrated in such a way to monitor disjointed locations.

Chair occupancy sensors, SparkFun Force Sensitive Resistor, detect whether there is a load or not on the chair by monitoring the pressure level measured below its legs.

For gesture recognition purpose, we endow the patient with a LG G Watch R5 equipped with a triaxial accelerometer.

Health Monitoring sensors allow to acquire a minimal set of vital parameters including: weight, blood pressure, heart rate, Oxygen saturation SpO2 level, glucose. To this aim, we identified a set of wearable and non-invasive devices, selected to guarantee the patient complete freedom of movement (no cables, data are transmitted via wireless communication). All devices are provided by iHealth Labs[4].

2.2 Vision Sensors

Figure 3 shows the arrangement of visual sensors in the living room of the apartment, highlighting their fields of view and overlaps. The RGB-D sensors are Asus Xtion Pro, acquiring a depth stream with VGA resolution (640×480 pixels, at 30 fps). They cover a field of view of about 58 deg horizontal, 45 deg vertical and 70 deg diagonal, with a range of operation between 0.8m and 3.5m. The first RGB-D sensor ($RGBD_1$) is located over the kitchen's sink. Its Field Of View (FOV) is highlighted in blue in Figure3, right, and it covers all the kitchen and table area, i.e.

[2]http://www.eliko.ee/products/kio-rtls/

[3]http://aeotec.com/z-wave-sensor

[4]https://ihealthlabs.com/

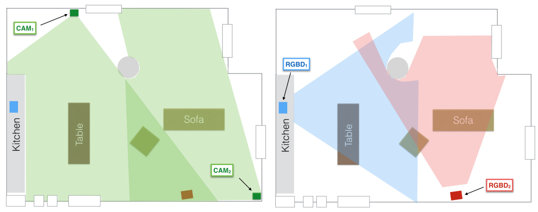

Figure 3: A sketch of the visual sensors fields of view and their overlap. Left panel shows the field of view of the two cameras, while right panel shows the field of view of the two RGB-D sensors.

where patients are supposed to have breakfast, lunch and dinner. The second one ($RGBD_2$) is located near the TV in front of the sofa, its field of view is highlighted in red in Figure 3 right, and it covers the living room, i.e. the sofa, the armchair, the library, and the area of the vital monitoring devices. The cameras, henceforth referred to as CAM_1 and CAM_2, are high resolution mini-dome IP cameras acquiring 1920×1080 pixels frames at 25 fps. They are located in the two opposite corners of the room, indicated in green in Figure 3 left. The mutual position of RGB-D sensors and cameras is intended to provide a partial overlap of the fields of view while covering complementary areas.

3 VISUAL DATA ANALYSIS AND RESULTS

Figure 4 shows the pipeline of our monitoring system, from the acquisition and processing stages, to the computation of the motility quantities, and to the estimation of the *motility index*. Finally, all evaluated motility quantities and associated statistics are made available to physicians on a daily report. In the remainder of this section we introduce the dataset, the motion analysis pipeline and discuss the results.

3.1 Dataset

The dataset we consider in our experimental analysis is composed of two batches of data acquired with the help of 10 volunteers.

The first batch is used for validating the system, the other to assess its performance. All subjects had not constraints in the apartment, and spontaneously performed common daily-life activities.

The first batch includes 5 young volunteers (3 male and 2 female, mean age 27 ± 4) who spent at least 3 days in the facility, alone or in pairs, for a total of about 123 hours of data. The collected data include

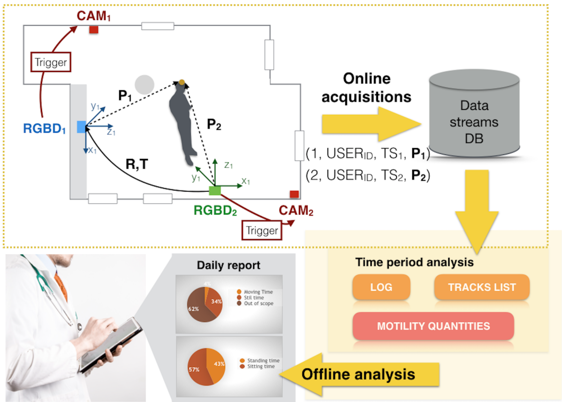

Figure 4: A visual sketch of the pipeline of our system. Video acquisition is triggered by the RGB-D depth sensors which detect the presence of individuals in the common room. Acquired data are stored online in a Data Base that makes data available for offline analysis.

simpler and more complex scenarios (single or multiple persons in the apartment), and they represent a suitable test-bed for the evaluation of our algorithms. Our current analysis considers three activities types: *walking, sitting, standing*. To provide a quantitative evaluation of the proposed methods, we selected 5 sequences from the data set in which a single subject is observed, and we carefully annotated them by exploiting the available video sequences. A coarser annotation is provided also for the rest of the data, allowing us to present a broader quantitative analysis.

The experimental results comparing the geriatric assessment and the automatic analysis are presented on data acquired from 5 healthy elder subjects (3 male and 2 female, mean age 72.4±5.2) who spent at least two hours each inside the facility alone. During their stay clinical test were performed by physicians and data were collected and manually analysed. This ground truth that incorporates both the geriatric assessment and the manual annotation of the data is summarised in Table 1.

3.2 Localisation

The first task we need to address, prior higher level analysis, is localisation. The goal of localisation is to determine, at each time instant, the position of a person in the apartment. For this task we used the information coming from the RGB-D *depth* sensors providing (X,Y,Z) coordinates of the body joints.

Figure 5 provides an overall visual impression of the localisation obtained by RGB-D sensors installed in the common room, considering measures obtained on a temporal span of 30 minutes. The figure clearly shows the complexity of the trajectories collected in

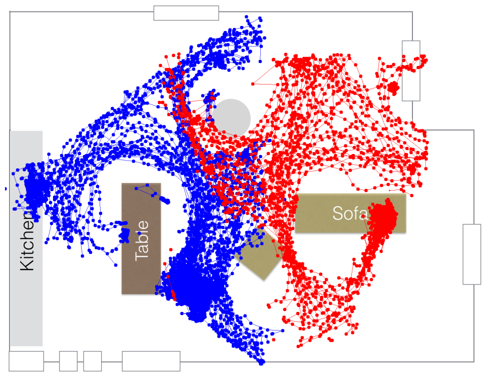

Figure 5: A visual impression of the trajectories collected in the environment. A volunteer was asked to perform normal daily activities for 30 minutes (points are color-coded according to the acquisition sensor).

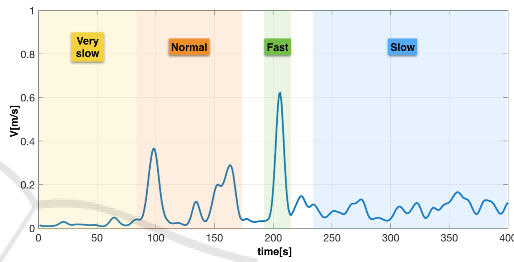

Figure 6: Estimation of the velocity of a person moving at different speeds.

the environment by the RGB-D sensors. The maps are computed automatically and incorporate information from the two different sensors, one of which is considered as a reference frame (blue dots), while the other is related to the reference frame through a rigid roto-translation transformation which is learnt from data (red dots). As expected (see also Figure 3 right), there are a few blind spots. This issue will be easily overcome by integrating data from the cameras.
Notice how from a simple analysis of these data it is immediate to identify regions of the common room where the volunteers spend most of the time, e.g. sitting at the bottom-right corner of the table, at the rightmost part of the sofa, or standing at the kitchen.

3.3 Motility Analysis

In this section we aim at automatically analyse patient's motility and postural transfers.

We first consider a low-level motion feature, i.e., an estimate of instantaneous velocity which we derive directly from localisation measurements. In Figure 6 we provide an example of a velocity estimation in which a subject has been asked to walk at different speeds. As it can be noticed, the different dynamics are nicely estimated.

At a higher level, we compute the following *mo-*

Table 1: Geriatric evaluation of 5 elder subjects in good health: summary of the geriatricians assessment, in terms of MPI (Multidimensional Prognostic Index), gait speed measured during test by physicians in a 4 meters walk. The last three columns report a manual annotation carried out by the authors on the percentage of time spent standing still, sitting or walking.

ID	Gender	Age	*MPI*	Measured Gait Speed [m/s]	% STILL	% SIT	% MOVING
#v1	M	68	0.063	1.299	20	54	26
#v2	M	71	0.063	1.026	15	71	14
#v3	M	66	0.125	1.556	26	50	24
#v4	F	79	0.125	0.875	19	62	19
#v5	F	78	0.188	1.084	4	89	7

Table 2: A summary of the quantitative analysis on the motility quantities we performed on 5 annotated sequences. When appropriate, we report the ground truth value between brackets. The final column reports the estimates of the *motility index*.

Seq.	Age	Time [min]	$T_{sit}[s]$	$TS[s]$	$TM[s]$	TR_{2st}	TR_{2sit}	W	S	MI
#u1	23	90	496 (478)	74 (79)	283 (296)	10 (8)	8 (8)	6 (5)	13 (14)	0.65
#u2	22	150	5239 (5260)	752 (755)	1189 (1165)	20 (23)	21 (23)	37 (38)	57 (48)	0.83
#u3	24	120	202 (224)	164 (174)	213 (181)	5 (5)	5 (5)	11 (13)	10 (12)	0.60
#u4	36	30	128 (126)	84 (79)	377 (384)	9 (10)	8 (10)	9 (9)	18 (14)	0.34
#u5	40	30	92 (99)	81 (77)	167 (196)	3 (3)	3 (3)	7 (7)	7 (7)	0.46

tility quantities, identified with the help of geriatricians:

- Number of postural changes, i.e. from sitting to standing (TR_{2st}) and vice-versa (TR_{2sit}): this is done by looking at the variation in heights of the detected skeletons (through RGB-Ds) in the scene;
- The total time spent moving (TM), standing still (TS), and sitting (T_{sit}): this is done by checking the variation in the distribution of the velocity modulus;
- Number of instances of walk (W) – i.e. how many times, in a given observation period, people start walking – and stop (S) events;
- Longest walk distance;
- Longest walk time.

Such quantities are empirically estimated according to (Chessa et al., 2017) analysing the instantaneous measures or series of temporally adjacent observations. More specifically we follow an approach based on thresholding the y coordinate of the skeleton representation and the velocity (see Figure 6). Then, some of them are used to compute the *motility index* which we see as a first quantitative continuous contribution to the *frailty index*.

We formalise the estimation of the *motility index* MI on the time period $\mathcal{T}$ as follows

$$\begin{aligned} MI(\mathcal{T}) &= (1-\alpha)\left(\frac{T_{sit}+TS}{TT}\right)+ \\ &+ \alpha\left[C\left(1-\frac{TR_{2sit}+TR_{2st}+W+S}{TT}\right)\right] \end{aligned}$$

where the first term quantifies the percentage of inactivity time, while the second determines the relative amount of postural and dynamic transitions with respect to the entire time period (TT). The parameter α is a value to be chosen to weight the importance of the two terms of the equation, while C is a factor to make the second term numerically comparable with the first ones. The *motility index* takes values between 0 and 1, approaching 1 when the motility of the subject is not satisfactory.

A coarse quantitative analysis carried out on all the sequences of the young volunteers (for which we have a partial annotation available) shows an accuracy in estimating the overall moving time of $\sim$95%. Users are correctly associated with a sitting state with an accuracy of $\sim$99%, and the percentage of correctly detected sit-to-stand transitions is $\sim$ 79%. Table 2 reports a more detailed experimental analysis performed on the 5 fully annotated sequences of young volunteers. All the above mentioned measurements have been assessed, and the estimate of the overall MI is reported. The latter can not be associated with an objective ground truth, but we can comment on the appropriateness of the estimate with respect to a diary of activities maintained by the volunteers. For instance, in sequence #2 the volunteer spent most of the time sitting (about the 83% of the total time of observation) and this corresponds to a high value of MI. Conversely, the dynamism of subject for sequence #4 is richer (the volunteer spent about the 64% of the total time walking around the apartment), thus the *motility index* is much lower.

Table 3 reports an analysis on the set of data acquired with elderly healthy patients. We first observe

Table 3: Automatic evaluation of 5 elder subjects in good health: the observation time, the estimated percentage of time spent standing still, sitting, or walking, the estimated average speed, and the overall estimated *motility index* (MI).

ID	Time [min]	% STILL	% SIT	% MOVING	Avg. Velocity	MI
#v1	150	22	52	26	0.39±0.21	0.52
#v2	90	12	70	18	0.27±0.19	0.62
#v3	90	24	51	25	0.31±0.21	0.70
#v4	30	19	61	20	0.19±0.12	0.82
#v5	120	9	86	5	0.26±0.18	0.91

how our estimate, in percentage, of the amount of time spent by patients in standing, sitting, moving state is very coherent with the manual annotation performed in Table 1. We can also notice that our estimated average speed, albeit difficult to compare with the speed estimated by geriatricians in a single walk, produces the same relative ordering among volunteers. Lastly, the *motility index* produces a result which is very much in line with the reported MPI: in particular, the healthier volunteer is #*v*1, the weaker is #*v*5. From this analysis it appears that the *MI* could effectively complement and enrich the *MPI* estimation.

Finally, Figures 7 and 8 report for each volunteer the details on some of the estimated motility quantities carried out on the elderly volunteer data. Figure 7 shows the average number of state transitions (TR_{2sit}, from stand to sit and TR_{2st} from sit to stand) and the number of walk instances in the observed time span. Figure 8 reports for each subject the longest walk distance and the longest walk time: here in particular we notice how #*v*1 walks faster and spans longer distances than other subjects, confirming the conclusions obtained from the *motility index*.

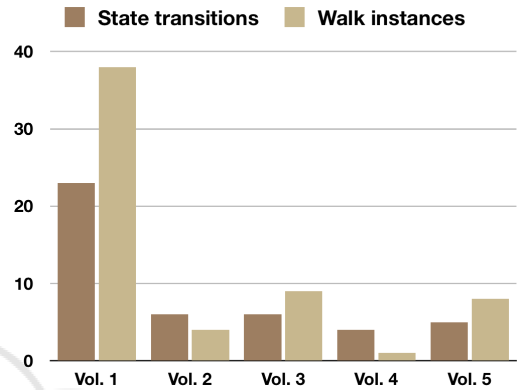

Figure 7: Number of state transitions evaluated as the average of TR_{2sit} and TR_{2st} and walk instances W for each volunteer (#*v*1 to #*v*5).

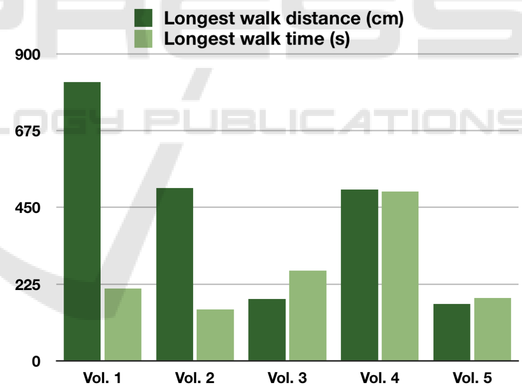

Figure 8: Longest walk distance and walk time for each volunteer (#*v*1 to #*v*5).

4 CONCLUSION AND FUTURE WORKS

In this paper we presented a visual computing approach to estimate frailty in elderly based on the evaluation of the *motility index*. The experimental setup is a protected discharge facility which has been planned, implemented, and validated within the Galliera Hospital. After being discharged from the hospital, the patients are hosted in the apartment for a few days. Here, a system, based on vision sensors, continuously assesses patients' *motility index* while physicians and nurses have the opportunity of monitoring them remotely.

The system was validated on 5 volunteers and tested on 5 healthy elder subjects. The results are very encouraging, as they show correlation between the automatic motility evaluation and the corresponding clinical analysis performed by the physicians. Hence, the *motility index* may be used as a valid integration to the *frailty index*, with the advantage of a continuous, automatic and objective assessment.

In the next future we aim at adding further dimensions to the assessment of frailty, by integrating data coming from all different devices installed in the facility. The investigation of other physical and cognitive domains will allow the evaluation of frailty in the widely used context of the multidimensional assessment according to the International Classification of Functioning, Disability and Health.

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REFERENCES

Angleman, S. B., Santoni, G., Pilotto, A., Fratiglioni, L., Welmer, A.-K., Investigators, M. P., et al. (2015). Multidimensional prognostic index in association with future mortality and number of hospital days in a population-based sample of older adults: results of the EU funded MPI_AGE project. *PloS one*, 10(7):e0133789.

Bathrinarayanan, V., Fosty, B., Konig, A., Romdhane, R., Thonnat, M., Bremond, F., et al. (2013). Evaluation of a monitoring system for event recognition of older people. In *Advanced Video and Signal Based Surveillance (AVSS), 2013 10th IEEE International Conference on*, pages 165–170.

Cao, Y., Tao, L., and Xu, G. (2009). An event-driven context model in elderly health monitoring. In *Ubiquitous, Autonomic and Trusted Computing, 2009. UIC-ATC'09. Symposia and Workshops on*, pages 120–124. IEEE.

Chessa, M., Noceti, N., Martini, C., Solari, F., and Odone, F. (2017). Design of assistive tools for the market. In Leo, M. and Farinella, G., editors, *Assistive Computer Vision (SUBMITTED)*. Elsevier.

Fried, L. P., Ferrucci, L., Darer, J., Williamson, J. D., and Anderson, G. (2004). Untangling the concepts of disability, frailty, and comorbidity: implications for improved targeting and care. *The Journals of Gerontology Series A: Biological Sciences and Medical Sciences*, 59(3):M255–M263.

Fried, L. P., Tangen, C. M., Walston, J., Newman, A. B., Hirsch, C., Gottdiener, J., Seeman, T., Tracy, R., Kop, W. J., Burke, G., et al. (2001). Frailty in older adults: evidence for a phenotype. *The Journals of Gerontology Series A: Biological Sciences and Medical Sciences*, 56(3):M146–M157.

Liu, R. and Liu, M. (2010). Recognizing human activities based on multi-sensors fusion. In *Bioinformatics and Biomedical Engineering (iCBBE), 2010 4th International Conference on*, pages 1–4. IEEE.

Pilotto, A., Ferrucci, L., Franceschi, M., D'Ambrosio, L. P., Scarcelli, C., Cascavilla, L., Paris, F., Placentino, G., Seripa, D., Dallapiccola, B., et al. (2008). Development and validation of a multidimensional prognostic index for one-year mortality from comprehensive geriatric assessment in hospitalized older patients. *Rejuvenation research*, 11(1):151–161.

Scanaill, C. N., Carew, S., Barralon, P., Noury, N., Lyons, D., and Lyons, G. M. (2006). A review of approaches to mobility telemonitoring of the elderly in their living environment. *Annals of biomedical engineering*, 34(4):547–563.

Volpato, S., Daragjati, J., Simonato, M., Fontana, A., Ferrucci, L., and Pilotto, A. (2016). Change in the multidimensional prognostic index score during hospitalization in older patients. *Rejuvenation research*, 19(3):244–251.

Volpato, S., Onder, G., Cavalieri, M., Guerra, G., Sioulis, F., Maraldi, C., Zuliani, G., Fellin, R., of Pharmacoepidemiology in the Elderly Study (GIFA, I. G., et al. (2007). Characteristics of nondisabled older patients developing new disability associated with medical illnesses and hospitalization. *Journal of general internal medicine*, 22(5):668–674.

Zouba, N., Bremond, F., and Thonnat, M. (2010). An activity monitoring system for real elderly at home: Validation study. In *Advanced Video and Signal Based Surveillance (AVSS), 2010 Seventh IEEE International Conference on*, pages 278–285. IEEE.