At the bedside, what you know and what you don’t know: a 3D dataset for ageing studies.

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We need help in care because the percentage of the global population over 60 is projected to double in 2050. Several specific problems related to aging will need specific attention, falls are one of those. Sensing in devices for fall recognition is vulnerable to external conditions. An extended dataset is key to the development of fall detection systems to run robustness and non-regression tests in real life conditions. 18 “time of flight” “sensors were used to collect a dataset of depth map images at the bedside in two different geriatric hospital wards of the Brussels region. From this large amount of data, we have analysed and labelled manually 15% of the content and extracted most relevant parts for evaluation. Patients are inactive most part of the day (61% laid and 15% sit). The analysed dataset contains 9 falls, 6 of them unknown by the nurse. The movement-tracking algorithm shows a sensitivity of 72% and specificity of 97%. Not to be aware of each fall is an important loss of clinical information. There is a gap in fall prevention. Building a comprehensive dataset for further machine learning development and using an automated fall detection system may allow a better quality of care.

Keywords: Fall detection systems, Time-of-flight, Fall dataset, machine learning

I. Introduction

Healthy ageing is key to the sustainable development of the world. The percentage of the global population over 60 is projected to double in 2050. Frailty increases with age and each fall leads to dependence. Lack of attention in the first hour of the accident increases the risk of death and chronic affections. Then, there is a growing interest for fall detection systems. The right balance between Gerontotechnologies and care for the elderly are difficult to strike. Especially when it comes to fall prevention, because they require a multidisciplinary approach. Technologies are both vulnerable to external conditions in terms of sensing and to social and psychological issues of the elderly in terms of usability.

Isa© is a tool that analyses the behaviour of elderly patients by tracking their movements in their bedroom (focusing on falls) which is based on gesture recognition and a 3D intelligent sensor embedding a movement-tracking algorithm. The advantages for the patient are therefore its non-intrusiveness, its complete autonomy and its respect for privacy.

A hospital bedroom can be a challenge for the sensor based on computer vision. Datasets of falls are needed to evaluate fall detection systems. There are two approaches: simulated falls by actors or real-life falls. Efficiency of fall detection systems severely decrease under real-life conditions. Therefore, we collated a database of depth images with real elderly people falls to develop and test the Isa sensor.

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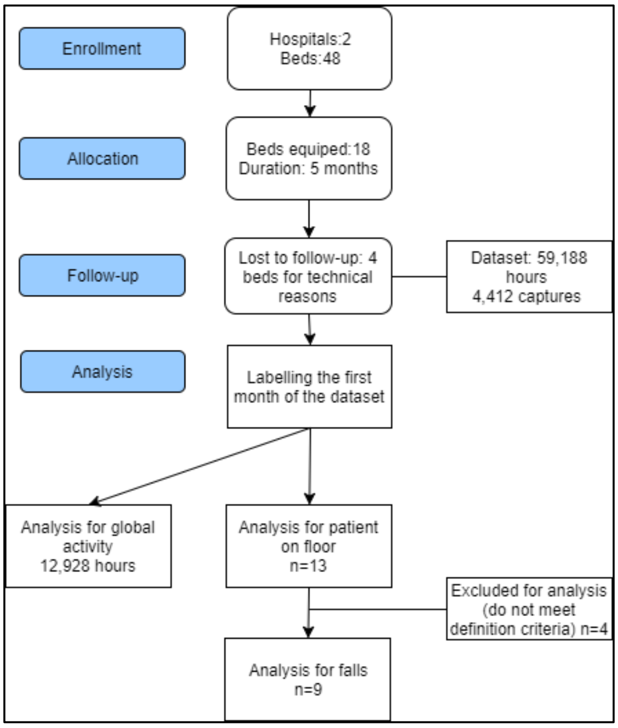
II. Material and method

A small part of a 3D dataset was labelled (~15%), as described in the chart flow. This preliminary work was intended to roughly evaluate the algorithm as a simple fall detector and this exploratory approach is helping to design a more extensive tool for data labelling. It will guide us to a better comprehension of falling and train the sensor to a better recognition of each object in the scene and allow behavioural pattern recognition.

A. Experimental set-up

We used the O3D303 Time-of-Flight sensor manufactured by ifm electronics with an embedded fall detection algorithm. An automated process allows semantic segmentation of the scene, features extraction and patient tracking. The system, which grabs the frames 24/7, sends an alarm when a combination of conditions is fulfilled. All 3D data were encrypted and stored in a datacenter that allows both the labelling of the dataset and the evaluation of the algorithm. Fourteen Isa© devices were placed in 2 distinct sites. They grabbed 213,079,700 frames in 4,412 captures for 59,188 hours stored. 12,928 hours were annotated. Sensors are pointing down and around the bed. All admitted patients were included in this observational study.



B. *Dataset analysis*

The dataset had to be very descriptive and unbiased, so we labelled it in a succession of different unambiguous states and transitions. To have an overview of the activity of the elderly, we merged the actual classification of the dataset into four parts: lying down, sitting, walking or not in the field of view.

Each time the label “on floor” or “falling” occurs, we extract frames of the database to process the algorithm on them. (see figure 1).

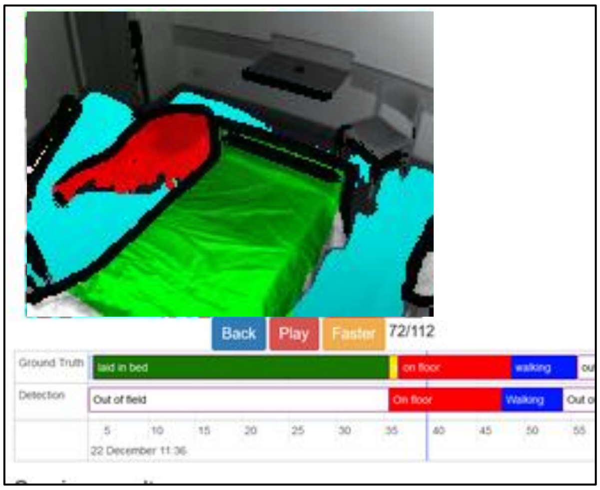


Figure. 1 Compare automatic process with a ground truth

We propose a binary labelling to discriminate fall events from any other movement of the elderly. We segment the detection results as fall or non-fall events and compare them to a ground truth. Then, we can calculate the specificity and sensitivity of the fall detection system. The parts of the videos before and after a fall in the ground truth are considered as activities of daily living (ADL).

The sensitivity of the system is {true positive/ (true positive + false negative)} and the specificity is {true negative/ (true negative + false positive)}.

Due to ethical considerations, no personal data or medical data were collected, depth map images stored preserve privacy. Each participant was informed and gave their consent.

The authors are both founder of the company MintT, which commercialize Isa©.

III. RESULTS

A. *Global activity*

The total time spent in bed at rest is 6,971 hours. The cumulative time spent seating on the edge of the bed, seating on the bed or seating on the chair is 1,720 hours. Other activities totalize 4,237 hours (1,255 hours of walk and 1,491 activities out of the field of the captor). The activity or the non-activity of all the patients in the dataset can be measured as seen in fig 2.

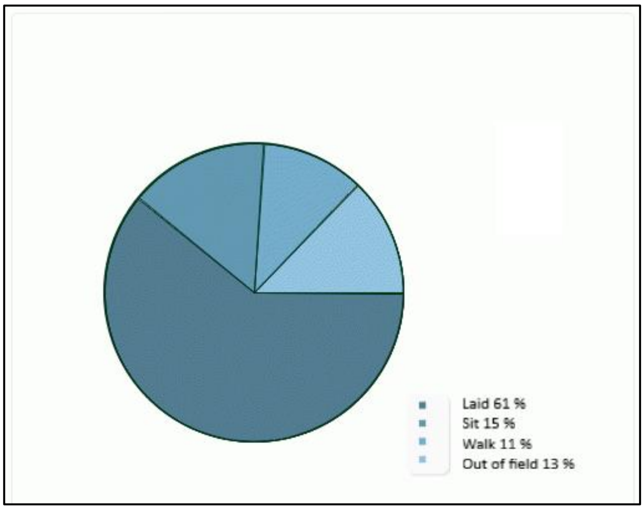


Figure. 2 Daily activity in bed side

B. *Fall description*

Falls are defined as “inadvertently coming to rest on the ground, floor or other lower level, excluding intentional change in position to rest in furniture, wall or other objects” by the International Classification of Diseases (ICD-9). During the reporting period, 13 videos of falls were labelled “on floor”, but only 9 videos from patients were considered as falls according to the definition. In 3 videos, a patient was praying and in one video another patient was lying voluntarily on the floor. Only 3 falls were known by the nurse and 6 were not (see table 1 and figure 2).

TABLE 1. KNOWN AND UNKNOWN EVENTS

"On floor"	description	Time spent on floor	Known by the nurse
1	Laying down	01:25'15''	No
2	Praying	00:05'58''	No
3	Praying	00:08'12''	No
4	Fall	00:08'08''	Yes
5	Praying	00:02'56''	No
6	Reverse fall	00:02'31''	No
7	slip from bed	00:00'51''	No
8	slip from bed	00:00'44''	No
9	slip from bed	01:15'13''	Yes
10	slip from bed	00:00'19''	No
11	slip from bed	00:02'27''	Yes
12	slip from bed	00:01'16''	No
13	slip from bed	00:00'45''	No

Fig.2: Known and unknown events (falls and fall-like ADLs)

C. Detection results

The detection results show true positives and false negatives (see table 2).

The result of the automatic process shows a sensitivity of 72% and specificity of 97%.

TABLE 2. DETECTION RESULTS

Fall	"On floor" detection score (true positive)	Non-fall detection score (true negative)	False alert (false positive)	"On floor" not detected (False negative)
1	1	2	1	0
2	4	5	0	0
3	7	9	0	1
4	0	2	0	1
5	1	4	0	2
6	1	1	0	0
7	1	2	0	0
8	1	2	0	0
9	0	2	0	1
10	1	2	0	0
11	0	2	0	1
12	0	2	1	1
13	1	2	0	0

IV. Discussion

Getting an overview of the patient's behaviour in their bedroom might be important to know for a predictive approach of issues in the elderly. Lowering the physical activity and increasing the time spent in bed leads to increasing the risk of falling. The more precise the labelling of the dataset, the more the system can be trained to recognize behaviours. It appears rapidly that the way to describe the dataset is good enough for movement description but not for behaviours. Qualitative studies are needed to set the architecture of the database and make it sharper. Deep learning is a new method of machine learning which can improve behavioural pattern recognition in specific settings such as drug intakes or medical issues that can interact with behaviours. In this purpose, we must collect a wide medical data about issues and treatments that can interact with the ability to move and the behaviours of the patient.

The results show that we don't know the real prevalence of falls in hospitals. Two thirds of the falls are unknown. This loss of clinical information is a gap in fall prevention. We must consider a fall as critical data in the risk assessment of the patient because one fall leads to many others. In this dataset, most of the falls are caused by the patient slipping from the bed. In further qualitative research, we will explore how a better knowledge in terms of behaviours and falls can lead to a better care.

The semantic segmentation of the scene (recognition of individual objects in the scene) is a process which needs the algorithm to teach from itself. The better this segmentation, the better the results. A specificity of 72% and a sensitivity of 97% is a starting point, but this dataset is too small: to get final results we must capture and analyse more falls. These preliminary results invite us to label falls from the whole dataset. If an analytic approach allows good enough results for specifics falls, a machine-learning-based algorithm such as deep learning will diversify the kinds of detectable falls (falls in occlusion, falls on bed, etc.).

V. Conclusion

Nurses know only what they can see. Therefore, daily living in hospital has some secrets for them. We can learn from these results that many falls are unknown (two thirds in this dataset). It leads to a lack of clinical knowledge about the patient, and risks might not be detected by the nursing team.

Today, the system can detect falls with a specificity of 72% and a sensitivity of 97%. The labelling of the whole dataset is ongoing. Big data allows a deep learning approach in algorithm development. It may improve the quality and the diversity of the detections.

Even if designing a dataset for activities of daily living is not a goal of this work, it is a good starting point to build a classification of ADLs in bedrooms. Qualitative studies are needed to design a comprehensive dataset and define which kind of clinical data will trigger a better quality of care.

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