Towards predicting frailty symptoms through a smart walking stick

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***Abstract*—A warning sign of frailty is imbalance. Psychomotor therapists run tests to evaluate the balance deterioration but not often enough to track the rapidly changing condition of the elderly. The proposed system collects fine-grained data from a smart cane and processes them with Machine Learning (ML) techniques. The originality of our proposition lies in its personalization by the elderly biomarkers in ML algorithms. Our experiments indicate that we can observe the orientation of locomotion through the cane as well as recognize characteristics of specific participants ambulation in the uncontrolled scenario.**

***Index Terms*—Smart Cane, Tinetti, Personalized Elderly Tracking, Frailty Prediction, Lambda Architecture**

I. Introduction

As living conditions have gotten better in most developed countries, a specific group of citizens has started growing in numbers: the elderly. While this situation allows for information exchange and experience sharing among generations, it also introduces new challenges, especially from a health care point of view. Aside from diseases related to neurodegeneration and heart conditions, senior citizens are prone to accidents. One such event is the fall of an elderly person. Even though it may only happen once, a fall may have tremendous repercussions on the lifestyle: in case of broken bones, the pain and a long recovery period may instill fear in the person's mind. Because of this fear, they might stop participating in social activities, thus drastically reducing their human interactions. This isolation brings about other health issues and makes them hard to detect.

Entering "fall detection" in the search engine of the IEEExplore website yielded 4,842 results. Among these publications, 3 standards, 4,174 conference papers and 642 journal papers are listed. More than 89% of this research has been published over the last 20 years. This situation shows how important fall detection has been. Various technological approaches have been tested: video-based fall detection [1], inertial sensors based detection [2] and so on... Some solutions have relied on body-mounted sensors and others have chosen to have the environment tracking the patient. While the obtained performance varies depending on multiple factors, two observations can be made:

- Fall detection comes too late: while we are thankful for systems that allow for a timely response in case of fall, it's already too late. At this point, the focus should be on appropriate reeducation tools that would ensure a speedy recovery while helping the patient to regain his/her confidence;
- The whole world is not (yet) a smart environment: the Blagnac Smart Home (Maison Intelligente de Blagnac, MIB) [3] is an apartment that is equipped with various technologies, from home automation devices to voice recognition and fall detection, through wired and wireless networks. Since projects such as Eco-SESA [4], CANet [5] and SENUM (*Seniors et Numérique*) aim at making these types of apartments available to the public, we expect more and more elderly people to benefit from the services offered by an MIB-like environment. Unfortunately, as soon as the elderly steps out of the apartment-complex, he/she will be catapulted back in time to an urban jungle. Outside of their homes, they may be wearing a smart pendant or a smart watch running the fall detection software but, as indicated before, it's already too late.

Based on these observation, the research community has also produced solutions aimed at fall prediction. By estimating the risk, appropriate reeducation or monitoring can be provided. Fall prediction makes sense in studies focusing on screening and early diagnosis of frailty. The frailty phenotype can be characterized by several symptoms like slow walking speed, weak grip strength, exhaustion, low physical activity level, and unintentional weight loss [6]. In this paper we focus mainly on the slow mobility and imbalance problems.

In this paper, we introduce our proposal for avoiding this situation altogether through a proactive approach: instead of focusing on fall detection, we will investigate the root causes and propose a decision support tool to health care staff members. In addition to providing fine-grained monitoring data about the patient, the objective is to reach personalized healthcare: the prediction model's parameters will be tailored to a specific patient and evolve in conjunction with the patient's health condition.

The remainder of the paper is organized as follows: first, we will review existing approaches to the problem. Then we will describe the architecture of our solution and its components. We then present the preliminary results which show the suitability of a cane-based approach to data collection in our context before concluding this document.

II. Related Work

Health care facilities have been using different types of tests such as Tinetti, Timed Up-and-Go (TUG) or Freid'test. Those test serve as means to assess the risk of fall or frailty for the elderly population. The Tinetti and TUG tests are both composed of 6 phases:

- Sitting situation: the observer reports whether the patient sits properly or is at risk of falling/slipping from the chair,
- Sitting to standing transition: the observer reports whether the patient is able to stand up by himself and characterizes the balance during the five first seconds of standing up,
- Balance while standing: while asking the patient to close his eyes or applying a light push on the sternum, the caregiver evaluates the ability to retain balance,
- Rotation: the patient is asked to make a complete 360° turn and the observer reports the continuity of the pace and the stability during rotation,
- Walking: the patient walks at least 3 meters on a straight line then quickly comes back. During this phase, the patient uses his usual tool, either a cane or a walker. This phase leads to the collection of signals such as :
  - stride length,
  - stride width,
  - symmetry,
  - pace continuity,
  - path deviation,
  - trunk stability.
- Standing to sitting transition: the observer reports on the patients ability to sit in a secure fashion instead of simply falling on the chair.

Each item is associated with options which in turn correspond to points. A low score is associated with a high probability of fall.

While the Tinetti test is simple and repeatable, it involves a dedicated caregiver, a psycho-motor therapist, and usually happens once a year and following an event that may affect mobility (accident, being bed-ridden for a lengthy period...). The obtained data is thus a snapshot of the situation. Since society is moving toward proactive and predictive health, fine-grained capture of this balance information is required. In the scientific community, many have addressed the problem using various tools. For example, in [8], the skeleton representation of the patient is generated by a Kinect network in the context of home monitoring and fall detection. Similarly, in [9], the authors use a multi-Kinect system to evaluate the stride length and width of the patient. The Kinect is a Microsoft camera that is able to provide an RGB image as well as a depth image at a pixel level. This depth information has been used in [10]: the study uses the Kinect's ability to identify body joints and decomposes the body according to the transverse, sagittal and coronal planes. Each body part's motion is characterized during the video by assigning a codeword to it. As the video progresses, some codewords will have the highest count and will be used to classify the activity undertaken by the patient.

Camera-based approaches are often considered in opposition to solutions based on body-mounted sensors. While these can track user movement with great precision, these systems are often cumbersome and limit user freedom. For example, in [23], data is collected from force sensors and IMUs placed in the shoes and at the waist. The work presented in [16] also relies on waist-mounted accelerometers to evaluate patient's ability to retain balance or postural sway. The proposed prediction model uses stride characteristics as well as postural sway evolution to identify patients with a high risk of fall. The work of [13] studies the postural stability of one leg stance on the frontal plane and checks the strategy chosen by volunteers : either ankle strategy or hip strategy. The posture is captured by a Waseda bio-instrumentation system (200Hz) [28] and the IMU measurements are composed of 3-axis accelerometer values, 3-axis gyroscope values and 3-axis magnetometer values. Authors pointed out the importance of the roll and pitch measurements according to the ellipse long axis angle theta projected to the frontal plane.

Another approach to the issue is data collection through devices used by the patient. In order for this approach to provide fine-grained data, the chosen object must be essential for the target population. As observed in [11], the walking stick or cane is indispensable for the elderly. It can therefore be used as a means to communicate with other smart systems: in [11], the cane is used to draw characters and the motion is captured through a pair of accelerometers mounted at the top and bottom of the cane. Said motion is then interpreted to identify user input. In [12], the addition of a differentiation layer to the protocol stack allows the transmission of different types of data flows by the cane: depending on how critical the flow is, the appropriate MAC scheme is used. Other studies around canes and fall detection are [14] and [17]: both solutions use the cane as the support for a fall-detection and alert system. In [14], the fall-detection uses a gyroscope to estimate the angular velocity of the cane. Should this value be greater than a given threshold, the system determines that the cane has gone too far from its stable position and indicates that the user is falling/has fallen. In [17], data from an accelerometer and a magnetometer are combined in order to recognize the fall.

Walking sticks are also involved in gait analysis: in [18], force sensitive resistors (FSRs) and an Inertial Measurement Unit (IMU) are used together with the Timed Up and Go test to detect gait freezing in Parkinson patient ambulation: freezing of gait is defined by a brief absence of forward progression during locomotion despite the intention to walk. In the experiment, inertial sensors were placed on the cane but also on the lower back and ankle of the patient. In the study presented in [7], similar sensors are used to detect parameters such as the amount of weight borne on the cane and cane speed: this objective data will assist a therapist in the diagnosis phase.

In conjunction with these data collection tools, several studies in the literature use Machine Learning (ML) techniques to produce models for the prediction issues : fall, stability or frailty. ML techniques derive these prediction models by observing data representing past behaviors of the system. We compare in table I some of these studies according to different criteria. Our first observation concerns the used features. Those features are globally simple to compute since the experimentation context is controlled (i.e Tinetti or TUG test) even if the population size can be very important (≥ 100 people). From our point of view, the work of [20] stands out as it reproduces realistic evaluations by introducing noise (for example external discussions) to the fall sound. Moreover, authors propose to extract features directly from the sound signal. The models built from these features can be easily deployed later in the environment of elderly people. Our second observation relates to the machine learning techniques, most approaches propose binary classification models or regression models. Finally, these models are generated using a snapshot of the behavior of a coherent group of people (age range, health condition...). They are not personalized and become irrelevant as the patient's health condition deteriorate since their parameters are fixed.

Nonetheless, elderly people could have different styles of gait when they use the stick to walk. The Tinetti test involves some marks to involve the distortion of the signal but this factor is not yet automated and addressed in the prediction approaches as far as we know.

In this paper, we propose a new approach aiming to build predictive and personalized models by ML techniques from IMU data collected by "uncontrolled" and "controlled" protocols. By "uncontrolled" protocols, we mean that experimentation is independent from Tinetti or TUG tests ("controlled" protocols), it is taken for a set population for the same period of time and for the same occurrences of fall or imbalance (i.e 2 falls in two days or 1 imbalance for 5 minutes...). The period of data collection may take several days, weeks or months. The final aim of our work is to provide the practitioners with robust models trained with the most realistic data.

III. Proposed solution

A. Physical infrastructure

1) Components: The system comprises three main components: the cane, the gateway and the processing unit. The current cane is a prototype based on the work of [17]: the homemade sensor board is fitted into a plastic tube while ensuring specific orientation. This board is built around a Teensy 3.2 [25], a LoRa transceiver (HopeRF RFM95), a 3-axis accelerometer and a 3-axis magnetometer (LSM303DLHC). The data is sent over a LoRa link to a ChisteraPi board [26] acting as our gateway to more traditional networks. The ChisteraPi also supports communication using an RFM22 [27]: this will allow future interaction between the cane and other devices using this technology.

We chose to use the LoRa link because of its greater range compared to typical Wireless Sensor Network (WSN) technologies such as IEEE 802.15.4: in the target environment (nursing homes), some of the residents may freely go out of the facility for their daily activities: with the LoRa technology, a communication range of a few kilometres means that the cane will still be able to report measurements to a gateway located on the roof of the facility. In comparison, an IEEE 802.15.4-based WSN would require the deployment of nodes in the public space in order to support a multihop solution, trading complexity for coverage.

The data is delivered to a processing server. These data are uploaded to the Anaconda platform [29] and processed by an R kernel in jupyter notebooks.

2) Network: The Teensy periodically polls the embedded sensors, creates a message following the format of figure 1. The various fields are computed based on the formulae in [17]. No timestamps are carried by the frame: in this small-scale prototype, the timestamps can be derived from the frame sequence numbers. The frame is sent over the LoRa link configured with a Spreading Factor (SF) of 7. This shortens the duration of the experiment as a higher number of frames can be sent in a given time, compared to a SF of 10. As a matter of fact, selecting a higher SF value spreads the original signal more and thus the messages occupy the wireless medium longer in those configurations. This SF configuration also allows the definition of multiple orthogonal channels which can be used for concurrent reception.

Cane ID	Acceleration vector	Magnetometer vector	Gravity vector	Roll	Pitch	Yaw	Distance	Step count	Fall

Fig. 1. Message frame format.

The gateway accumulates the messages and saves them to a CSV file which is transferred through an Ethernet network to the server at the end of the experiment. In the current experiments, data is accumulated during 2 minutes on the gateway.

B. Data processing architecture

In order to predict frailty symptoms, we propose the following system as depicted in Figure 2. The processing system is based on a Lambda architecture characterized by a batch and real-time processing phases.

- The batch processing phase encompasses two steps :
  - The first step is based on an unsupervised processing which aims to automatically label the frailty observed status (for instance : balance, fall, inactivity and so on). This step is an auto-configuration of the system to the studied person. Our system should help

TABLE I

MACHINE LEARNING FOR FALL, BALANCE AND FRAILTY PREDICTION

	Observed measures and test	**Device**	**Population**	**Features**	**ML methods**	**Brief description**
[19]	Angular velocity, accelerometer, iTUG	Dynaport elastic belt	57 healty adults	72 variables from iTUG	PLS-DA combining regression and PCA	detect the 5 steps of the TUG test, study the relation between iTUG variables and two-groups of ages (18-45) and (46-75)
[20]	Sound	-	Imprecise (40 falls by feet)	10 temporal and spectral features	C4.5, 1-NN, Logistic regression, NB , PART, Random Forest, SVM	Use sound to predict falls events
[21]	Chest'acceleration	MTw Development Kit Xsens	3 people	Magnitude of the chest'acceleration	Multivariate Gaussian mixture models (GMM), clustering	Balance assessment with and without vision
[22]	Shank , iTUG, Freid'frailty test	Shank-mounted inertial sensors	399 older people	44 features: temporal and spatial gait , 3-axis angular velocity, turn parameters	ANOVA regression	Frailty (yes/no) prediction based on IMU measures of iTUG
[24]	3-axis accelerometer	Mobile phones attached on a belt	15 people	Time-series features	SVM, SMLR, NB, KNN, Decision trees	Predict four different types of falls
[23]	IMU foot pressure	Connected sole proposed solution	5 young people	8 signals for foot pressure , 8 signals for angular velocity	C4.5 decision trees (J48)	Define thresholds from decision trees to characterize daily activities and recognize falls

to personalize prevention. Before labeling activities, we transform raw signals into more interesting features namely by using mining sequences techniques and exploring short or long-term temporality. We have observed that these techniques are less frequently used in the literature in spite of their useful contribution in such context.

– The second step is based on a supervised processing which follows the well known steps in machine learning : feature selection and model building. Once the features are computed for all signals, we should extract the most informative ones for increased the model accuracy. While different ML techniques can be exploited, we will focus on deep learning implementations (in particular a comparative study between Keras and Tensorflow).

- The real-time processing phase is based on storm topology [30]: it consists in a network composed of spouts and bolts: a spout, in our case, is the raw data coming from the cane. The bolts are programs running the transformation of raw data into the computed features and then apply the built model to predict one of the labelled frailty symptoms.

As said before, our system target is to personalize the tracking of elderly people. A system based on a one-shot model is most likely useless in the case of elderly people frailty evolution. That's why we adopt an incremental machine learning approach. In this case, the model is continuously being tuned according to the interpreted raw signal ingested in the batch step. The storm components will be refreshed in case great differences occurs in the built model.

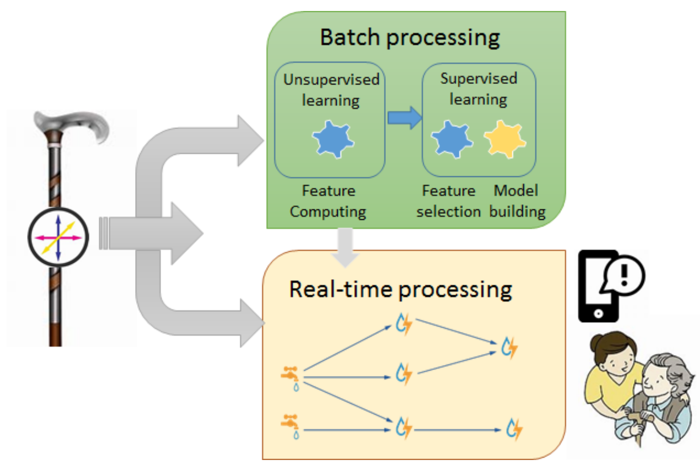

Fig. 2. Stick Data processing architecture

IV. RESULTS

A. Experimentation protocol

Using the setup of figure 3, we conducted an indoor measurement campaign.

The data was collected following this protocol: for each participant, six scenarios were executed. Each scenario lasts 2 minutes and a message is sent over the LoRa link every 100ms. In every scenario, the participant stands up from the chair and walks along the 4meter path with the aid of the cane. The characteristics of each scenario are given below:

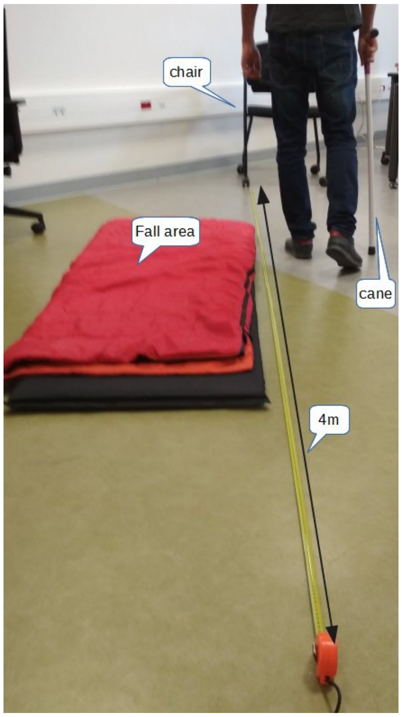

Fig. 3. Experimentation setup

- *Scenario 1*: the user walks naturally with the cane,
- *Scenario 2*: the user imitates the walking process of an elderly person. We observed one of the participant's grandmother and identified the following structure in her walk:
  1) Move the cane forward
  2) Catch up to the cane in four small steps
  3) Move the cane forward again
- *Scenario 3*: the subject walks naturally and falls while holding on to the cane. The fall occurs around 1'58",
- *Scenario 4*: the subject walks naturally and falls while letting go of the cane. The fall occurs around 1'58",
- *Scenario 5*: the participant walks naturally and includes three imbalance occurrences. Imbalance occurs for example when a user trips but does not fall: the body's center of gravity will usually move outside the support polygon and the person will accelerate in order to catch up. The events were scheduled at 1'00", 1'30" and 1'58",
- *Scenario 6*: the participant walks naturally and includes 2 imbalance occurrences and a fall. The imbalance events occur at 1:00 and 1:30 while the fall happens around 1:58.

These scenarios are considered controlled as the path and event timing were imposed to the participants. We also performed uncontrolled scenarios: the same participants were involved for the same scenario specification but the trajectory and the event timing were independently chosen by each person.

Three participants were recruited, aged between 23 and 36. The next section presents the obtained data.

B. Results and analysis

Identifying elements related to gait from the cane has usually been done while the user simultaneousy bore sensors on his/her body. In our case, we restrict our capture to the cane. Therefore, the main objective of this preliminary study is to investigate the repeatability of signal features. The sensors were mounted on the cane in a way that positions the z-axis in the forward direction: the y-axis thus points upwards and the x-axis is orthogonal to the walking direction.

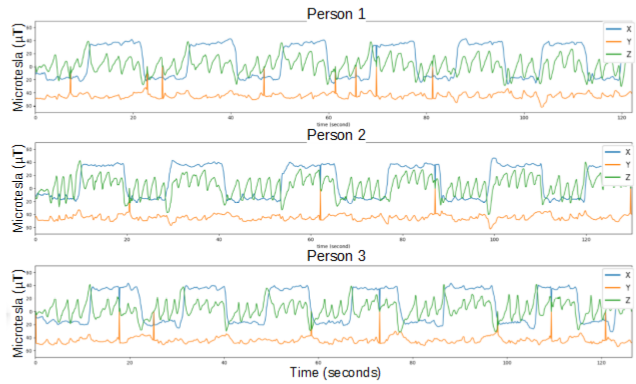

Fig. 4. Scenario 1, magnetometer, controlled execution

Figure 4 corresponds to the output of the magnetometer, which is the decomposition on the sensor reference system of the Earth magnetic field. In this controlled scenario, the fact that all users went back and forth along a predefined path is reflected on the x-axis: the sharp transitions represent changes in orientation at the end of the 4m path. Most participants tried to stick to the line but visual observation showed that, as they reached the end of the path, turning with the cane caused them to take a few steps away from the line and then come back to it. This can also be gathered from the signal as there is a peak right after the transition and this peak is followed by a quasi-horizontal line. With that knowledge, is becomes possible to interpret the data collected in the uncontrolled experiment (figure 5).

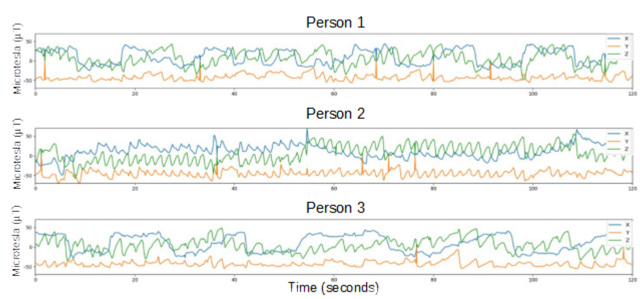

Fig. 5. Scenario 1, magnetometer, uncontrolled execution

In this experiment, each user follows a self-decided path for 2 minutes. Person 1 and person 2 mostly walked in circles in the office while person 3 walked in straight lines and changed direction when encountering an obstacle. The continuous changes in direction (circular path) imply that the local reference system is continuously moving. Therefore, the projection of the magnetic field vector on the three axes is also always changing. In the case of person 3, the direction changes are not as sharp as in the controlled situation but the flat sections in the graph indicate the periods when the person was walking in a quasi-straight line.

This observation suggests that each person has a natural ambulation style: some people walk in straight lines most of the time, others swerve all the time. The long term evolution of this characteristic might indicate a degradation in balance which could lead to falls.

So far, the imbalance event remains difficult to identify. We used the definition provided by a psycho-motor therapist and expected one or multiple peaks on the acceleration. Some participants' data showed this behavior but others did not therefore we considered it less reliable. Another signal of interest is the hand grip strength. In the next version of the walking stick, suitable sensors will be included in order to access this information.

Finally, from the controlled data from scenario 4, we observed that, as long as the user is walking normally, the pitch does not vary much. From this information, we can confirm the timing of the fall from the uncontrolled event (figure 6). For example, person 1 chose to fall 55 seconds after the beginning of the experiment.

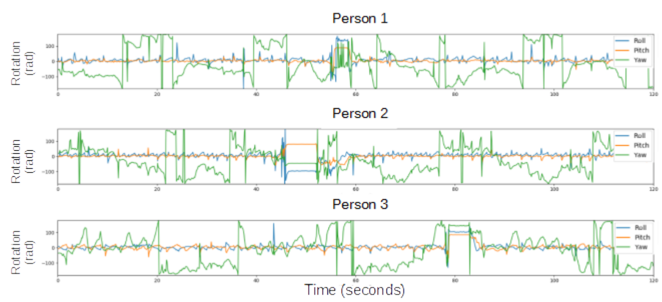

Fig. 6. Scenario 4, Roll-Pitch-Yaw, uncontrolled execution

V. Conclusion and Future work

The study presented in this paper takes place in the context of the analysis of frailty in the elderly. As falls have dire consequences for this age group, we focused on a warning sign which is the imbalance. We used a smart walking stick to gather information. Although the events corresponding to specific imbalance (user tripped but did not fall) were not clearly detected, the data indicated the ability of a person to walk in a straight line, which is one of the parameters of the Tinetti test. Our next course of action is to investigate the relationship between hand grip strength evolution and imbalance. In the same time, we plan on designing an algorithm which can detect medium to long term evolution of the user's ambulation from consecutive straight lines to continuously deviating trajectories. From a network perspective, we will also need to design a LoRa configuration adaptation scheme to take into account energy consumption and multi-user access to the service.

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