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Review

Early diagnosis of frailty: Technological and non-intrusive devices for clinical detection

Francisco Anabitarte-García[a,*], Luis Reyes-González[a], Luis Rodríguez-Cobo[b], Carlos Fernández-Viadero[c], Silvia Somonte-Segares[d], Sara Díez-del-Valle[e], Eneritz Mandaluniz[e], Roberto García-García[e], José M. López-Higuera[a,b,d]

[a] Photonics Engineering Group, University of Cantabria, Edificio I+D+i, Los Castros s/n, 39005 Santander, Spain
[b] CIBER-BBN, Instituto de Salud Carlos III, 28029 Madrid, Spain
[c] Servicio de Psiquiatría, Hospital Universitario Marqués de Valdecilla, Santander, Spain
[d] Instituto de Investigación Sanitaria Valdecilla (IDIVAL), 39005 Cantabria, Spain
[e] Ambar Telecomunicaciones S.L., 39011 Santander, Spain

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ABSTRACT

This work analyses different concepts for frailty diagnosis based on affordable standard technology such as smartphones or wearable devices. The goal is to provide ideas that go beyond classical diagnostic tools such as magnetic resonance imaging or tomography, thus changing the paradigm; enabling the detection of frailty without expensive facilities, in an ecological way for both patients and medical staff and even with continuous monitoring. Fried's five-point phenotype model of frailty along with a model based on trials and several classical physical tests were used for device classification. This work provides a starting point for future researchers who will have to try to bridge the gap separating elderly people from technology and medical tests in order to provide feasible, accurate and affordable tools for frailty monitoring for a wide range of users.

1. Introduction

There are many different view-points and symptoms when analyzing impairment associated with aging. These symptoms can include: poor functional capacity, poor cognitive function, poor balance, muscle loss, reduced cardiac function, obesity, anaemia or arthritis (Petersen et al., 1997; Putnam, 2002). It is difficult to detect and measure all of these to provide a protocol for impairment and disability quantification and treatment due to the large number of parameters involved in frailty (Hamerman, 1999).

Frailty is multi-system impairment associated with increased vulnerability to stressors. It describes individuals who are at increased risk of adverse health outcomes (Cooper et al., 2012) and it can be related with the symptoms mentioned above. Woodhouse defined frail people as "those greater than 65 years of age who are dependent on other people to perform their basic needs" (Woodhouse et al., 1988), while Gillick described frail older persons as "old debilitated individuals who cannot survive without help from others" (Gillick, 1989). Rockwood defined frailty as "the risk of losing the ability to live in the community" (Rockwood and Woodhouse, 1985). Despite these descriptions, it is very difficult to describe frailty syndrome completely in only a few words.

An interesting standard for frailty status measurement is the Groningen frailty indicator (GFI) (Peters et al., 2012; Schuurmans et al., 2004). The GFI is a 15-item screening instrument to determine the level of frailty. It measures the loss in functional status analyzing 4 domains: physical (mobility functions, multiple health problems, physical fatigue, vision, hearing), cognitive (cognitive dysfunction), social (emotional isolation), and psychological (depressed mood and feelings of anxiety). Eight items have two response categories (yes/no), six items have three response categories (yes/sometimes/no), and one item has a Likert response category (1–10). All items were dichotomized to calculate GFI sum scores. A higher GFI sum score indicates a greater level of frailty, with a maximum score of 15 (Schuurmans et al., 2004; Bielderman et al., 2013). The professional version of the GFI was modified from a patient-orientated questionnaire (with items such as "Has the patient recently felt downhearted or sad?") to an individual-oriented questionnaire (with items such as "Have you recently felt downhearted or sad?") and, as a consequence, the formulations of all items have been

* Corresponding author.
E-mail address: anabitartef@unican.es (F. Anabitarte-García).

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Acronyms

ADL	activities of daily living
APP	application
BIA	bioelectrical impedance analysis
BMR	basal metabolic rate
COM	centre of mass
COP	centre of pressure
CPA	coronal plane angle
30-s CST	30 s chair stand test
CT	computerized tomography
DXA	dual energy X-ray absorptiometry
EWGSOP	European 55 Working Group on Sarcopenia in Older People
FBG	fibre Bragg gratings
GFI	Groningen frailty indicator
GPS	global positioning system
HMM	hidden Markov models
ICT	information and communication technologies
IMU	inertial measurement unit
ISCCWG	International Sarcopenia Consensus Conference Working Group
MRI	magnetic resonance imaging
STS5	sit to stand 5
Si-St	sit-to-stand
St-Si	stand-to-sit
TUG	timed up and go test

changed.

Fried et al. (2001) describe frailty as a medical syndrome whereas Rockwood and Mitnitski (2007) consider it as an accumulation of deficits in different body systems. Both authors have defined an indicator to quantify frailty; Fried employs "Fried physical frailty phenotype", classifying Individuals with categories as non-frail (0 Fried criteria present), pre-frail or intermediate (1–2 criteria) or frail ($\leq$3 criteria) based on different impairment indicators while Rockwood employs the Rockwood Index that can be adapted in a similar way to quantify the number of deficits. Frailty phenotype is described in Fig. 1 (Fried et al., 2001).

To try to simplify these different definitions, Fried et al. described frailty in older adults as a phenotype that could be identified through five criteria: unintentional weight loss, self-reported exhaustion, weakness, slow walking speed, and low physical activity (Fried et al., 2001). Bearing in mind this large number of symptoms, a healthy skeleton and muscular system is very important for healthy ageing, providing freedom and autonomy of movement. The medical community was centred in the control of bones, but muscles are now a focal point in musculoskeletal diseases together with skeleton condition analysis (Cooper et al., 2012).

The musculoskeletal system is vital for movement, but different works show that it is also important for other body processes (Deutz et al., 2019). Skeletal muscles are essential for metabolism equilibrium. These muscles are the biggest protein warehouse in the human body and can provide amino acids if the body needs to equilibrate the protein synthesis rate in other vital tissues. Moreover, reduction in muscle mass can impair the metabolism of patients with type 2 diabetes due to glucose consumption in these tissues. This glucose consumption is the greatest in the body and muscle mass reduction can decrease basal metabolic rate (BMR) (Tzankoff and Norris, 1978). This age-associated loss of skeletal muscle mass, function, and quality is termed sarcopenia (Cooper et al., 2012; Evans, 1995; Cruz-Jentoft et al., 2010).

It is difficult to quantify the progress of sarcopenia, but frailty and its associated impairments are widely extended in the elderly population and its incidence increases with age. Despite this fact, several works have quantified prevalence of Sarcopenia in elderly people. Sarcopenia prevalence can be around 10% between 60 and 70 years old but this ratio increases to 30% for over 80 years old (Morley, 2008). Therefore, different systems and sensors based on a wide range of technologies have been adopted to try to obtain information from the body and process it for a sarcopenia and frailty quantification.

Frailty measurement has been described above and several authors have reported methods and algorithms for sarcopenia quantification too. Baumgartner et al. defined sarcopenia as a reduction in muscle mass (Baumgartner et al., 1998); the European Working Group on Sarcopenia in Older People (EWGSOP) define it as a syndrome defined by a progressive and generalized loss of skeletal muscle mass and strength with a risk of adverse outcomes (Cruz-Jentoft et al., 2010). The International Sarcopenia Consensus Conference Working Group (ISCCWG) as loss of skeletal mass and function associated with ageing (Fielding et al., 2011).

Osteopenia has a similar definition to sarcopenia but applied to bones. Osteopenia defines bone density that is not normal but also not as low as osteoporosis. Osteopenia is determined by bone densitometry as a T score of -1 to -2.5 by definition from the World Health Organization

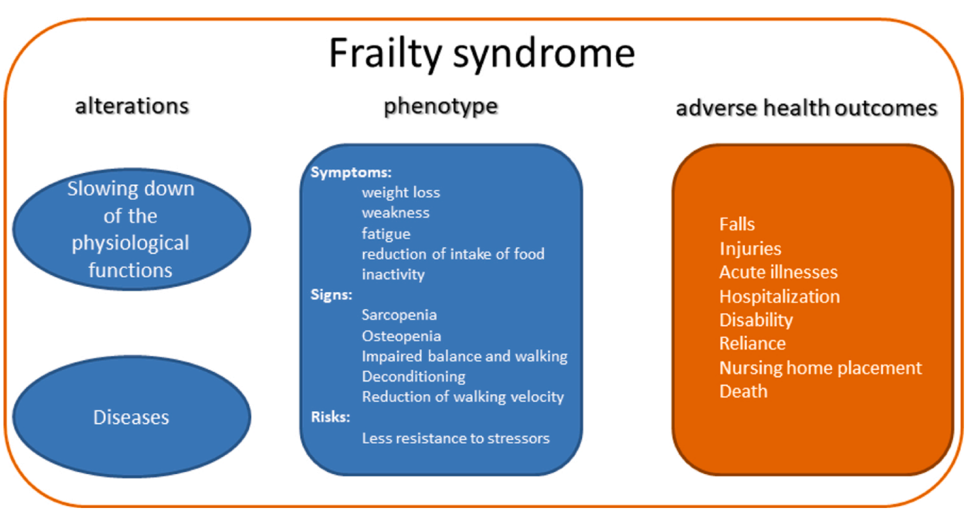

Fig. 1. Frailty syndrome.

(Karaguzel and Holick, 2010). Inactivity, calcium and vitamin D Deficiency or genetic conditions are risk factors for osteopenia. Its early detection can help in osteoporosis and frailty treatment.

Frailty, sarcopenia and osteopenia are linked, but they are not the same. An advanced sarcopenia or osteopenia degree indicates a poor functional capacity, but this impairment can be related to different problems, not only to reduction in skeletal muscle or bones mass. Nevertheless, both symptoms are good pointers of frailty and early detection and measurement is a perfect starting point for frailty prevention and treatment without ignoring the other symptoms and signs described in Fig. 1. Actually, all of them are related to each other because weight loss or impaired walking can indicate sarcopenia or osteopenia and both of them are associated with fatigue or deconditioning.

Sarcopenia and osteopenia are basically the most important signs of frailty, and one of them or both can induce the other symptoms, but their detection and quantification is difficult without complex medical equipment.

For instance, muscular degeneration related to sarcopenia can be detected with dual energy X-ray absorptiometry (DXA) (Andreoli et al., 2009), anthropometry and bioelectrical impedance analysis (BIA) (Fuller et al., 1999). These are among the most commonly used, accessible and relatively low cost methods. Magnetic resonance imaging (MRI) (Hesselink et al., 1990), computerized tomography (CT) (Mitsiopoulos et al., 1998) and creatinine excretion (Oterdoom et al., 2009) are the most specific methods. None of these is the best test in routine clinical practice for reasons of cost, availability, or ease of use.

It is interesting to analyse other devices that can measure additional symptoms that can help to quantify sarcopenia and osteopenia for quantifying frailty accurately. These methods could provide information without complex equipment and in different environments such as ambulatory or home ones.

This work will describe different non-invasive sensors, technologies and devices to help researchers and medical staff to find the best option for frailty symptoms, signs or even adverse health outcomes prediction and detection adapted to their patients' features. These sensors can accomplish different functional tests that provide information about a patient's physical status and thus about frailty status.

This kind of tools is ecological for users (understanding ecology as the level of discomfort or rejection that the whole system can induce in users) as it provides a large amount of user information in a comfortable environment at any time during the day even in the patient's own home, and not only in hospital environment with information obtained during a short medical consultation. These systems could prove useful for medical staff because the detection of some symptoms could be the first stage in frailty diagnosis. Finally, these systems are relatively low cost and enable implementation in different environments.

There are several reviews with the same purpose, even very recent ones (Mugueta-Aguinaga and Garcia-Zapirain, 2017; Gallucci et al., 2020). We can find several options for diagnosis, care, prevention and treatment in Mugueta-Aguinaga and Garcia-Zapirain (2017), but this work is from 2017. On the other hand, the review in Gallucci et al. (2020) is from 2020 and provides a systematic review of information and communication technologies (ICT) for managing frailty. However, the most interesting sensors are not detailed and the analysed works include only a formal assessment of frailty.

This work combines both kinds of reviews to find and analyse the recent developments of tools, providing information about new ideas, analyzing the progress of early ones and opening the concept of management of frailty with not only tools for frailty monitoring, but also with devices useful for its control and phenotype monitoring, with a similar concept to Dasenbrock et al. (2016). This review extends the search period up to 2020 (the papers searched in Dasenbrock et al. (2016) are up to 2016) to analyze the evolution of several tools included in Dasenbrock et al. (2016). In addition, the works analyzed in Dasenbrock et al. (2016) are mainly based on accelerometers and this work will introduce other devices that provide information about the frailty status.

2. Methods

The number of works per year has been detailed in Fig. 2 in order to demonstrate the increasing amount of research in this area.

The number of publications up to 2013 was rather marginal, but the interest in the application of sensors in frailty monitoring rose from that year and the number of works during the last two years was ten times higher than in 2010. This demonstrates that this research field is in full upswing.

We decided to conduct a search from January 2010 to the present (December 2020) with the following criteria:

- Three databases, Web of Science, Scopus and Pubmed.
- Keywords: “weight loss” and “wearable”, “frailty” filtered with “sensor”, “early detection” and “non intrusive”. This search covered the whole frailty phenotype with the kind of devices proposed in this work.
- Databases enabled searches in paper title, abstract, keywords, etc. The search was open to all parameters to avoid information loss.
- Paper selection was based on a critical reading, filtering works with the parameters “No frailty”, “No sensor”, “No aging” and “no frailty phenotype monitoring”.

The strategy adopted in this review is detailed in Fig. 3.

Two reviewers have independently revised all titles and abstracts of all papers with the search strategy followed. Abstracts of the articles selected were read to determine whether they fulfil the inclusion criteria. Conflicts were settled by agreement and/or coordinated review by both reviewers. To ensure suitability of papers and to extract the most interesting tools for frailty management, the final list of the selected studies was reviewed again

After this selection, 39 works were selected and analysed. This final choice was made after several steps. The first one was the word selection for searching. Only concepts related with frailty were included at the beginning, but this selection did not return works related to all Fried's criteria, such as weight loss. For this reason, the words “weight loss” were included in order to cover all criteria. This enabled us to broaden the search beyond frailty with ideas not directly related to frailty but useful for its monitoring, covering five criteria.

After screening, the next step was the selection of works. First, works were chosen following the filter criteria described above, and around 100 works were selected. Then, detailed reading of these works enabled more precise filtering discarding works related to sensors without a novel concept and others more focused on algorithms or frailty model definitions, which were considered beyond the scope of this work. Some of these ideas appear in a few works, but the reviewers positively evaluated their potential due to phenotype detection ability, ecology for users and even price of solution.

Fig. 4shows the type of sensor employed in each selected paper. This information is interesting in order to understand the chapters detailed below.

More than 50% of works employ inertial measurement units (IMUs)

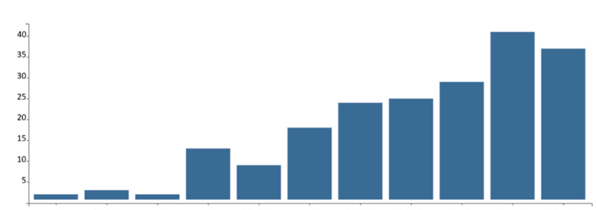

Fig. 2. Number of publications on “frailty sensor” over the last 10 years (source, Web of Science).

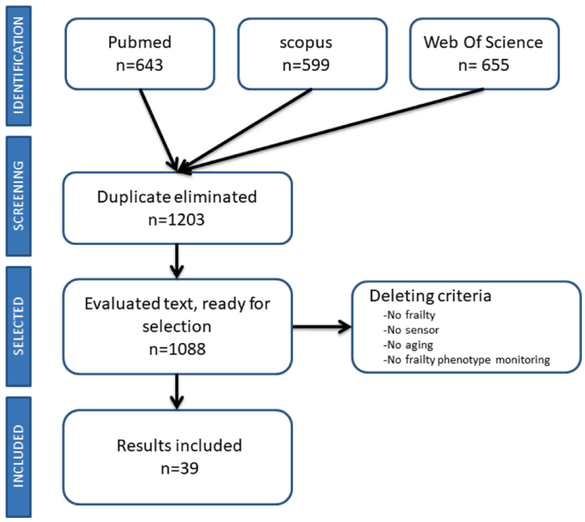

Fig. 3. Flow diagram. Strategy adopted in this review.

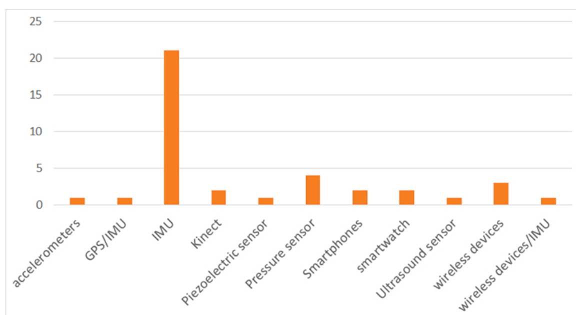

Fig. 4. Selected works by technology.

for frailty monitoring and another couple is based on a combination of Global positioning system (GPS) or wireless devices and IMUs. One work is based on biaxial accelerometers, closely related to IMUs but with fewer features (An IMU is an electronic device that measures and reports a body's specific force, angular rate, and sometimes the orientation of the body, using a combination of accelerometers, gyroscopes, and sometimes magnetometers). Only 18 works are based on different technologies (biaxial accelerometers, pressure sensors, etc.), and the large number of papers that employ IMU's was key for chapter division. It is true that the systems based on smartphones use the embedded IMUs, but they are separated because a smartphone has other interesting features in the same device. The authors decided to create different chapters that are not based on different kinds of sensors or on the Fried criterion covered because several solutions based on different sensors can cover the same criterion at the same time.

Each group of devices provides interesting and attractive technology including several ideas that have comparable capacities for frailty monitoring and all groups cover all kinds of sensors found in the selected papers. Each pool of systems has ongoing research with publications in recent years. This "research in progress" shows that all lines are interesting for the research community.

In summary, this work has been divided in the following sections

- Necklaces for food intake monitoring; sensors for nutritional habits
- Smart shoes; for weight monitoring and gait analysis
- Kinect; non-contact analysis
- Sit-to-stand and stand-to-sit systems; adapting classical tests
- Quiet standing sensors; information from balance analysis
- eFurniture and everyday home devices, a multifaceted system
- Smartphones and smart devices, all-in-one solutions
- Ambient videogames, monitoring and entertainment

3. Necklaces for food intake monitoring: sensors for nutritional habits

One of Fried's five criteria is unintentional weight loss. The best way to monitor weight is on a scale and several options explained below cover this point. However, this is a context free measurement; it could be interesting to know why patients lose weight. Sensors for monitoring of nutritional behaviour could be interesting to complement information from scales.

A wearable device based on a necklace is an example of this concept. This system is based on a piezoelectric sensor and an accelerometer, which detects vibrations in the lower trachea during ingestion (Kalantarian et al., 2015). A voltage signal derived from changes during vibrations provides the data and a Bluetooth unit on the necklace sends the data to a mobile Application (APP) (Fig. 5).

The application includes algorithms for identifying swallowing, performing basic classification between solid and liquid foods, and providing recommendations to the user with respect to the timing, volume, and composition of their meals (Kalantarian et al., 2014, 2015; Hussain et al., 2018).

This Necklace is initially intended for obesity control, but the idea is useful for indirect weight loss detection in elderly people. It allows 24/7 monitoring of food intake, but the sensor has problems detecting swallowing when users walk or move their head (Kalantarian et al., 2015). For that reason, post-processing techniques such as signal feature selection and data classification were implemented to improve system accuracy.

Other kinds of devices can accomplish the same purpose as the necklace, for instance a wearable wrist device with accelerometers and gyroscopes (Sharma et al., 2016). These take advantage of a participant's large wrist movement before and after a meal, detecting and analysing these movements to infer food intake periods during the whole day.

This kind of wireless devices, in addition to 24/7 monitoring, is comfortable for users, but elderly people, especially with cognitive impairment, may reject wearable devices. Nevertheless, the device is interesting for frailty monitoring. In addition, Medical staff can probably use this information to detect other problems in the elderly such as dysphagia and neurological impairment, as well as behavioural changes that may be related to mental syndromes.

4. Smart shoes: for weight monitoring and gait analysis

The greatest problem of the necklace containing an electronic system is that it is not a "usual" wearable article for elderly people, unlike clothing or shoes. It is normal that elderly people forget to put on this kind of equipment if it is not essential, so it is more interesting to add sensors incorporated in "usual" wearable articles.

For instance, there are recent works on gait analysis during daily

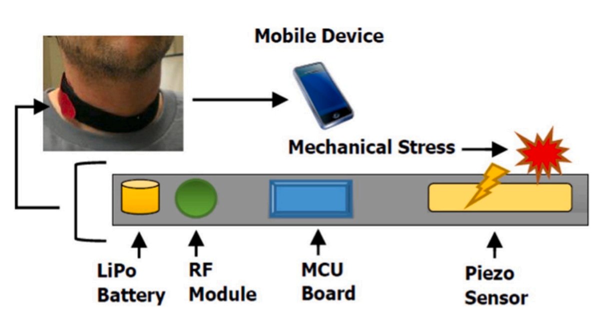

Fig. 5. Necklace system schema (© Monitoring eating habits using a piezoelectric sensor-based necklace).

walking based on IMUs (Pradeep Kumar et al., 2020). These systems are based on a sensor placed on the chest, which could be rejected or forgotten by users.

Sensor-fitted insoles can be added inside footwear to monitor patients as users always have to wear shoes. The key of these insoles is comfort. If users do not notice anything inside shoes, they will always use them and the device will obtain a large amount of data in an ecological and comfortable way for patients.

These insoles can measure the user's weight and activity or more complex sensors can be added for continuous frailty monitoring targeting weight, impaired balance or gait (Campo et al., 2021; Charlon et al., 2018; Avvenuti et al., 2017). The first step was to develop the smart insole, but this idea has evolved into a complex ICT solution that obtains metrics from the insole, sends information to the cloud, processes it and presents it in a comprehensive format for medical staff.

There are different kinds of sensors for smart insoles and these technologies are explained in Campo et al. (2021). Basically, they are pressure sensors. These pressure sensors include resistive, piezoelectric and capacitive sensors, textile sensors based on smart fabric sensitive to pressure or atmospheric sensors that can measure weight or balance using air pressure analysis. Accelerometers can be included in insoles too in order to enhance movement information (Fig. 6).

The main challenge this device faces is to add sensors, batteries and a communication unit to a thin object such as an insole in order to obtain a balance between system measuring capability and comfort, because insoles must not disturb users during walking. Moreover, battery autonomy is very important because it is not feasible to change insoles frequently.

This equipment has a complex communication system that provides continuous remote information to medical staff and alerts if it detects a weight reduction. Furthermore, continuous foot pressure monitoring provides information about average gait, speed or stride detection and cadence.

This large amount of information is directly related to frailty symptoms. The information is obtained in perfect conditions because users do not need to go to medical consultation and it is ecological information obtained within the user's daily environment. Monitoring weight and gait, musculoskeletal degeneration, which is directly related with frailty status, can be measured.

5. Kinect: non-contact analysis

The Kinect sensor, designed and developed by Microsoft, is a device based on 3D depth cameras. It contains a depth sensor, a standard colour camera, and a microphone array that provides full-body 3D motion capture, facial recognition, and voice recognition capabilities (Zhang, 2012). It was originally designed for body tracking in videogames, but a large number of research groups take advantage of its capability for a wide range of purposes outside videogames control, such as computer science, electronic engineering, and robotics. Moreover, several applications have been developed for medical purposes as a tool for gaming for children with autism (Boutsika, 2014) or as a control-free device for medical image exploration (Gallo et al., 2011).

Fig. 6. Insole prototype (© Design and evaluation of a smart insole: application for continuous monitoring of frail people at home).

Among these medical utilities, Kinect is an interesting device for frailty diagnosis and monitoring. Kinect body tracking enables the detection and continuous tracking of body joints and extremities (Kar, 2010), and the depth measurement enables complex gait analysis (Gabel et al., 2012).

Sarcopenia affects walking velocity and equilibrium, and gait analysis is a perfect way for its diagnosis and hence for frailty analysis (Caliskanelli et al., 2018; Gianaria et al., 2016). Moreover, gait analysis gives information about Fried's frailty criteria.

One of the most used and best known test for frailty measurement based on gait analysis is the Timed Up and Go test (TUG) (Podsiadlo and Richardson, 1991). TUG measures, in seconds, the time taken by an individual to stand up from a standard armchair (approximate seat height of 46 cm), walk a distance of 3 m, turn, walk back to the chair, and sit down again. Medical staff follow the TUG process, and the time taken by each patient can be related to his/her balance and gait speed. There are works which use IMUs for TUG test monitoring for frailty status classification (Greene et al., 2014).

Kinect can provide more information during TUG, placing it in front of a chair at a distance of about 4 m at a height of 1 m. Depth measurement and skeletal tracking enables the detection of two kinds of parameters. Firstly, spatial–temporal measurements, such as speed, swing time (i.e. the part of the stride time in which the foot is in air), double support time (i.e. the time for which both feet are on the ground), variability of stride velocity, mean duration or variability of a single walking sequence. Secondly, postural balance features, related to the skeleton posture during motion (Gianaria et al., 2016).

Kinect is a feasible device to use for frailty detection and monitoring at home (Caliskanelli et al., 2018), performing tests and acquiring information even during activities of daily living (ADL). This works by obtaining information during long periods in the home environment in a comfortable place for the patient and not only during a TUG test. It generates indicators for frailty analysis. The information is based on the detection of joints and skeleton (26 joint positions in an x, y and z coordinate system) of users during ADL, which are used to generate a Subject activity profile, considering Speed, Fall Detection, Furniture Crawling (The term "furniture crawling" is used when users need to hold on to furniture, walls, etc. during walking in order to maintain a vertical posture), Gait Speed and Posture Activity as components. This information is employed by medical staff for measuring user frailty and even for home event monitoring, including falls or routines (Fig. 7).

The target of Takeshima et al. (2019) is to assess the utility of the Kinect sensor in providing an objective evaluation of human movement using a measured ADL (chair stand). This work determines Coronal

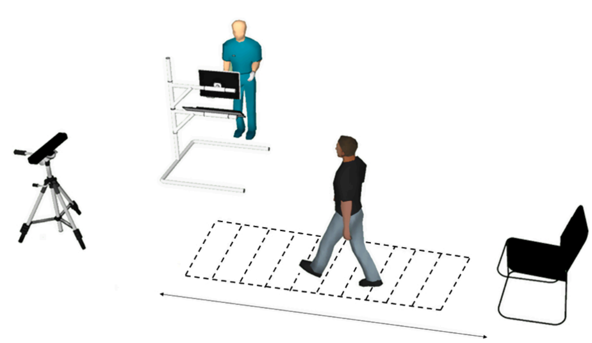

Fig. 7. Kinect gait analysis diagram.

plane angle (CPA) by a line transecting the shoulder-centre and waist relative to the vertical axis and uses it to assess quality of the chair stand movement pattern.

There are even methods to identify users based on the depth images of gait sequences acquired with kinect while the system provides information about user gait (Dubois and Bresciani, 2015). Identification of the person is based on height and gait in sequences in which the user walks and a full body image is acquired by the Kinect sensor. The gait pattern of the user is modeled using a hidden Markov model (HMM) (Rabiner and Juang, 1986) built from features of the trajectory of the centre of mass. A different HMM is built for each user so enabling identification.

The advantages of Kinect are its price, since it is a cheap device, which is useful even in the home environment, and its capacity for contactless gait analysis of large amounts of information. This is very important, because it is ecological for users and at the same time objective parameters are provided for medical personnel to improve diagnosis based only in their own medical background and classical diagnostic tools.

6. Sit-to-stand and stand-to-sit systems: adapting classical tests

One of the hardest everyday functional activities is to rise from a chair, called sit-to-stand (Si-St) postural transition (Schenkman et al., 1996). The performance during this movement is an indicator of everyday functional independence and mobility. Therefore, the Si-St transition is a good test to provide information about the function, strength and balance of the patient's lower extremities and hence about sarcopenia, osteopenia or frailty (Kaya et al., 1998) and even fall risk (Campbell et al., 1989) or proprioception (Hesse et al., 1998).

It may also be useful for assessing general physical performance. In fact Si-St-Si sequences measure it is a basic item of the Short Physical Performance Battery, one of the most commonly used batteries for analysis of musculoskeletal function, gait and balance in the elderly (Guralnik et al., 1994).This kind of test is related to TUG, but focused only on the movement of rising from a chair. It is interesting to analyse the other transition, the stand-to-sit (St-Si) in order to complete the information (Fig. 8).

Several kinematic and kinetic parameters are defined to measure patient performance during Si-St and St-Si tests. These parameters include the movement's time duration, angular Kinematics (provides information about the rotation of a movement), linear kinematics (involves the study and description of the shape, form, pattern, and sequencing of linear movements over time) or frequency domain parameters such as movement energy (Millor et al., 2014).

Different kinds of sensors can obtain this set of parameters, but motion sensors are suitable when placed in different places on the body. Several measurements are based on gyroscopes or accelerometers (Boonstra et al., 2006; Bidargaddi et al., 2007; Najafi et al., 2021). The combination of both sensors provides even more accurate results (Van Lummel et al., 2013) and linear and angular information at the same time.

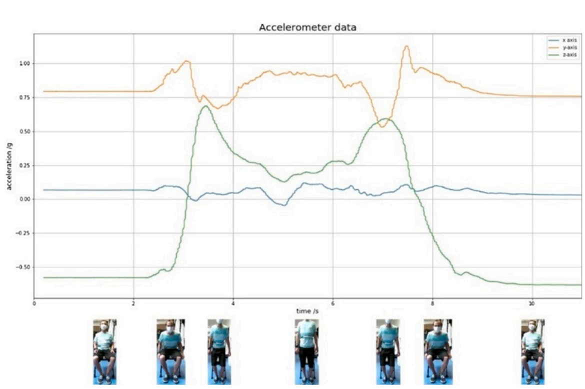

Fig. 8. Si-St phases.

These inertial sensors, which are a combination of several gyroscopes and accelerometers, with suitable data processing are useful for Si-St and St-Si tests used to analyze a patient's movements using their raw data(Ganea et al., 2011). The most common processing techniques include wavelets (Bidargaddi et al., 2007; Najafi et al., 1999) or techniques based on peak detection (Salarian et al., 2010).

One problem of these tests is the lack of a compromise between the analysis of both transitions. The possibilities involve using a battery for everyday life movements, including Si-St and/or St-Si (Salarian et al., 2007), and clinically accepted tests, such as the sit to stand 5 (STS5) test (Doheny et al., 2011), the 30 seconds chair stand test (30-s CST) (Millor et al., 2013) or even the TUG test. Sensors can provide a large number of data-sets, but a standard frailty model based on technological metrics is necessary to assess the correct and accurate data from these devices.

The second problem is placement of sensors. The L3–L5 position is assumed to be the best for measuring the motion of the body, as it is the centre of mass of the human body (Giansanti and Maccioni, 2006). Changes in position can distort results and this is an important consideration for test measurement.

This kind of test with this type of sensor needs contact and wearable devices have problems with patient comfort and rejection. This is a good system for ambulatory testing, but it could be difficult to adapt the device to home monitoring. For this reason, recent works replace an isolated Si-St test for Si-St or St-Si monitoring during ADL (Panhwarr et al., 2020), performed with an inertial sensor. Best practice is not to perform a test if we can obtain information during everyday tasks, as the system will be more ecological.

It is possible to use other kinds of sensors such as Ultrasound-Based Devices fixed on chair backs for monitoring 30-s CST (Cobo et al., 2020). It is beneficial to avoid wearable devices and patient rejection of these devices. This sensor has an Arduino UNO board, a MaxBotix LV-MAXSONAR-EZ ultrasound sensor, a Bluetooth 2.0 + EDR module (HC-06) and an APP on an Android device to control it. The algorithms developed detect sit-to-stand transitions by detecting local maxima and minima in the digital distance signal, taking advantage of the fact that the distance during test is expected to vary in a predictable way, resulting in a semi-periodic signal.

7. Quiet standing sensors: information from balance analysis

The last two paradigms described above, are based on patient movement to generate information about the frailty phenotype, mainly sarcopenia, osteopenia and gait impairments. There is another viewpoint based on the quiet standing tests.

Postural change measurement during quiet standing has often been used to estimate balance and fall risk in the elderly frail population (Campbell et al., 1989; Izquierdo et al., 1999). Quiet standing evaluation typically includes tests with the eyes open and closed performed on a force platform and is usually based on the ability of the patient to maintain the position of the body within defined spatial boundaries without moving the support base (Prieto et al., 1993; Greene et al., 2014).

Shifts of centre of pressure (COP) and body centre of mass (COM) are standard parameters in postural steadiness characterization and they are considered to play an important role in standing balance (Lee et al., 2007; Winter, 1995). On the one hand, large excursion areas and average distances from the mean COP/COM location in double and single static leg posture during a time-domain test are indicative of postural changes (Izquierdo et al., 1999). On the other hand, higher frequencies of postural sway have been related to aging and balance-related impairment (Winter, 1995; Kamen et al., 1998). Some works even use wavelet processing for kinematic signal processing (Martínez-Ramírez et al., 2011) to improve the accuracy.

The force platform for this test is expensive and only dedicated laboratories can perform traditional testing. This article explains other options based on cheap devices suitable for ambulatory environments.

Inertial/magnetic tracking technology is another method to evaluate postural deviation. This system offers an affordable low-cost alternative to more sophisticated instrumented approaches (Martínez-Ramírez et al., 2011; Noamani et al., 2020). This kind of sensor is appropriate for this test because it provides drift-free 3D orientation as well as kinematic data: 3D acceleration and 3D rate of turn, helpful for COP and COM position detection.

There are tools based on optical fibre (Giallorenzi et al., 1982) and fibre Bragg gratings (FBG) (Hill and Meltz, 1997) that can measure postural balance (Chethana et al., 2015) and are suitable for this kind of test. FBG is a periodic perturbation of the refractive index along the optical fibre length that is induced by exposure of the core to an intense optical interference pattern (Hill and Meltz, 1997). Changes in this pattern induced by variations in temperature, pressure or both on fibre will change the reflected and transmitted light in the fibre, and this reflected or transmitted pattern can be correlated with the perturbation.

A moving platform where the patient can be still with several FBGs positioned in different places can measure postural balance and stability based on the pressure applied on each FBG, and this information can complement data from accelerometers (Chethana et al., 2015).

Both inertial/magnetic tracking technology and FBG with accelerometers are based on wearable devices, with the associated problems with these devices explained above. Moreover, this kind of test, as with the St-Si or TUG test, need medical staff supervision and this system is not the most appropriate for home environments. Furthermore, the price of a FBG interrogation unit is relatively high for a home test (Fig. 9).

8. eFurniture and everyday home devices, a multifaceted system

Although ambulatory tests are useful for frailty measurement, it is better to avoid, as far as possible, the inconvenience induced in patients during these tests with tools that provide information during everyday activities, enabling more accurate data acquisition (Lin et al., 2008; Hebert et al., 2006). There are systems which can perform different tests monitoring Fried's criteria (single leg standing, timed up and go, gait speed, self-selected walking speed, Functional reach tests and Grip strength/power tests) (Chen et al., 2020) but they are not optimal for home environments.

The last three systems described above, are different sensors for typical tests for frailty measurement based on detection of different phenotypes, but they need medical supervision because they are designed for ambulatory or laboratory use. However, we have explained options for home frailty monitoring, and eFurniture is another concept for this purpose (Chang et al., 2013). The idea is to add different kinds of sensors to home furnishings to perform everyday tests that provide information about frailty status.

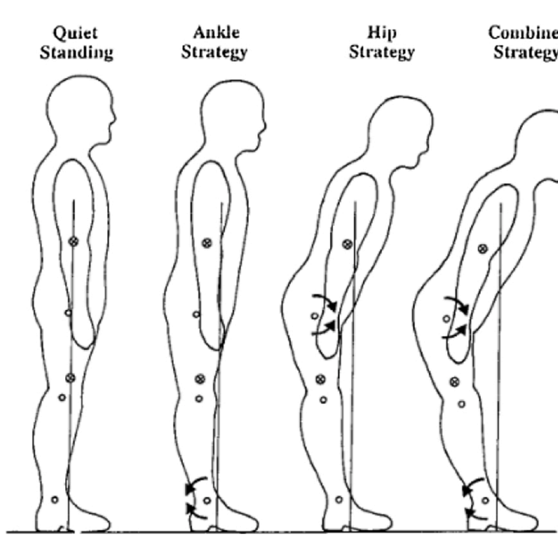

Fig. 9. Main positions for quiet standing sensors (© Human balance and posture control during standing and walking).

There are different items of intelligent furniture with several sensors that can accomplish tests to measure and analyse frailty. For instance, a light-emitting diode (LED) screen and a wireless sensor module inside a lamp for measuring reaction time and speed of the movements or a chair with pressure sensors for measuring weakness and weight (Chang et al., 2013). Another tool is based on several pads hidden under the carpet for gait and balance control (Chang et al., 2013) (Fig. 10).

The tools described above are based on standard furniture improved with sensors, but it is also possible to add new furniture or devices to analyse different phenotypes. Maximal grip strength is measured with a smart anti-stress ball and this maximal strength can be related to sarcopenia (Lunardini et al., 2019; Chkeir et al., 2013).

There are even complex systems which can provide information about Fried's criteria for frailty (unintentional weight loss, self-reported exhaustion, weakness, slow walking speed, and low physical activity (Fried et al., 2001)). This system, called ARPEGE (Jaber et al., 2013), is composed of a set of sensors for monitoring these criteria. A connected bathroom scale obtains the weight loss and balance. Weakness is monitored with a grip-ball game (Chkeir et al., 2013) to motivate users to perform the test. Doppler sensors linked to hardware for signal processing and communications hidden in an object usually encountered at home (e.g. a vase) can be used for walking speed monitoring. A tablet is employed for the assessment of the two remaining criteria with several questionnaires (Jaber et al., 2013). The capability of ARPEGE for frailty monitoring has been tested recently (Chkeir et al., 2019)

This kind of devices can handle Fried's criteria and can help to predict frailty, obtaining information in a home environment, in an ecological way for the patient and under continuous monitoring. However, some of them contain active sensors and users have to do an unusual activity to generate data, and this could prove problematic due to user rejection of exercises outside their ADL.

9. Smartphones and smart devices, all-in-one solutions

Evolution of mobile phones has been exponential during recent years. In less than 20 years, mobile phones have become not only a telephone but also several sensors for different purposes. Accelerometers, gyroscopes, compass and cameras are now common in mobile phones, and their processing power and software development have changed the mobile phone concept from telephone to smartphone. As a result of this explosion, several devices have emerged, such as smartwatches or wristbands, which are partners of smartphones. Smartphones can be rejected by elderly people due to the technology gap, but smartwatches or wristbands are more comfortable and enable the monitoring of ADL. These devices can be worn for the whole day, providing useful information for frailty detection during everyday tasks.

Smartphones are relatively cheap and easily available devices. Furthermore, the large number of sensors and feasibility of software management make smartphones suitable for frailty monitoring through software, which employs sensors to perform tests for patients. Moreover, a smartphone is a communication tool itself, so without aid of other devices it can acquire, process and send information easily. For this reason, mobile phones are interesting tools for medical purposes (Ozdalga et al., 2012) and monitoring of ADL.

Mobile phones can replace other kinds of wearable technology, for instance, frailty monitoring systems with a main data recorder fixed on a belt with several IMUs adhered to different parts of the body (anterior sternum, anterior side of each thigh and the plantar surface under each foot) (Higueras-Fresnillo et al., 2020). There are also works based on smartwatches with accelerometers to analyze walking activity (Mulasso et al., 2019), which needs a Base Station installed in the user's home.

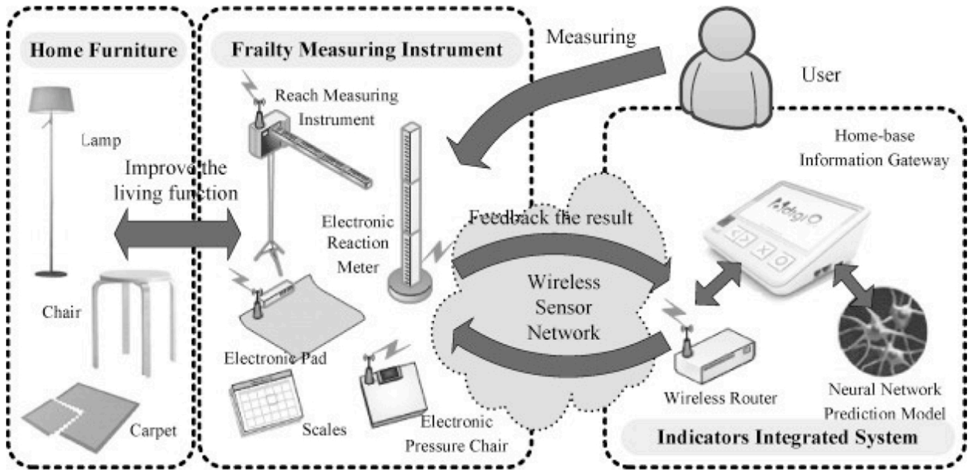

Fig. 10. Schema of a monitored home with eFurniture (© eFurniture for home-based frailty detection using artificial neural networks and wireless sensors).

Mobile phones are more comfortable and are useful for different purposes (communications, positioning, ambient videogames, etc.)

Functional assessment is probably the most important method of frailty detection, and the Tinetti test (Tinetti, 1986) is a useful tool for this purpose, based on gait and balance control. Fontecha et al identified the main indicators from movement analysis of accelerometers attached to a patient's smartphone (Fontecha et al., 2013a) and this work was developed to create a mobile APP that improves device usability (Fontecha et al., 2013b). This APP uses the information provided by mobile phone sensors, processes it and develops a new method based on this data that objectively assesses frailty in elderly population during everyday activities (Fig. 11).

TUG (Podsiadlo and Richardson, 1991) or Si-St (Millor et al., 2014) tests are interesting tools for frailty detection, and the ideas described above are based, for instance, on the Kinect system (Gianaria et al., 2016). These devices can be replaced by mobile phones that have integrated accelerometers (Galán-Mercant and Cuesta-Vargas, 2014; Galan-Mercant and Cuesta-Vargas, 2015).

Although, smartphones with their sensors can be used in isolation, their connectivity can be useful for external device connection. Devices, such as a modified ball to assess maximum grip strength or a scale for weight loss monitoring, can complement the information provided by the accelerometer of the smartphone about gait, and the smartphone can manage and send the information (Hewson et al., 2013).

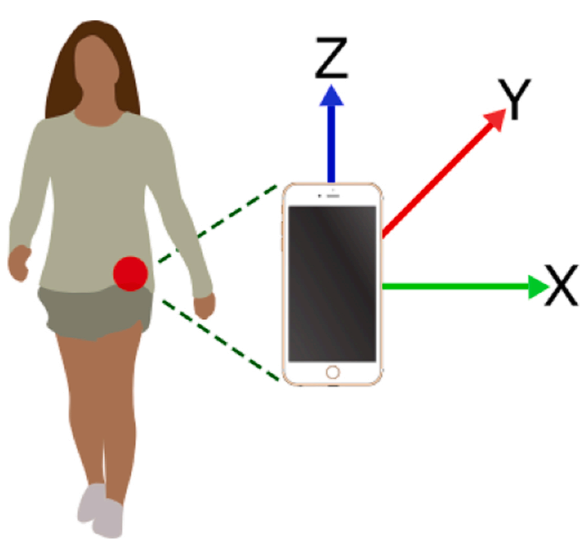

Fig. 11. Smartphone optimal position for gait analysis.

Smartphone infrastructures for frailty detection have evolved with the advent of devices that are less invasive and easier to use for elderly people, such as smartwatches (Garcia-Moreno et al., 2020). Garcia-Moreno et al proposed e-Health System micro-services based on the embedded sensors of a smartwatch (Accelerometer, Gyroscope and Heart Rate sensor) and an accurate frailty assessment model. Smartwatches collect sensory data in a non-intrusive and transparent manner while the patient is on ADL (all the activities during shopping such as Sitting/Standing or walking). Performance of ADL provides a comprehensive vision of elderly people's disorders at physical, cognitive and/or social levels. The score for the frailty model is based on the Fried test and it predicts frailty status from the sensors detailed above.

This idea is extended with the smart city infrastructure for monitoring physical activity and behaviours of users during ADL throughout the city (Abril-Jiménez et al., 2019). The system uses smartphone-embedded sensors (GPS, IMU, Bluetooth, and Wi-Fi), the communication network of the public bus's service of Madrid (Spain), with information from the bus line, stop ID, time per trip, etc. Madrid's open data service includes real-time information about traffic and urban link information, pollution, planned events, etc. and weather. It provides information from smartphone sensors (steps, speed, distance, etc.) and from city devices (distance travelled by bus, bus stops, etc.) and enables the analysis of level of socialization, loneliness and cognitive status of users.

Mobile phones are a perfect fit for frailty monitoring and enable continuous monitoring in different environments, but they have the same problem as other wearable devices; elderly people may have problems handling smartphones, and even with "passive" APPs that do not require user interaction to extract data, it is common that elderly people refuse to use the device or forget it. This problem is mainly solved with wearable devices such as smartwatches and this set of devices is probably one of the most promising tools for frailty monitoring due to its ecology and cost.

10. Ambient videogames, monitoring and entertainment

There are more than 2.5 billion video gamers in the world (WEPC Game Statistics, 2020). Around 15% are over 50 years (375 million) (Statista, 2020). Video games can improve mental and physical condition of elderly people. For instance, the benefits in terms of perceptual skills (reaction time and cognitive performance) of elderly people using classic videogames such as "Pacman" and "Donkey Kong" were studied (Clark et al., 1987). Furthermore, video games not only improve users' skills but also can improve social interaction with other age groups (Khoo et al., 2008) (Fig. 12).

Computers and consoles have a large number of different

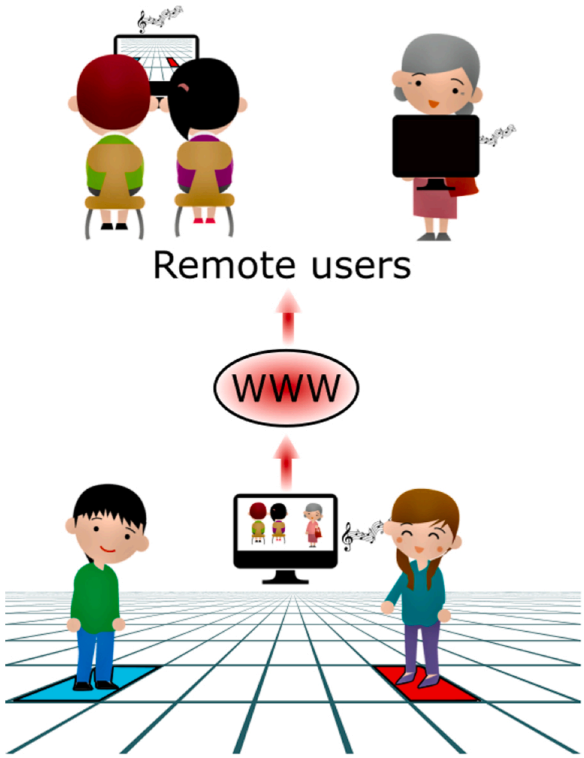

Fig. 12. Example of social interaction in videogames.

videogames, but there is a special kind of console that is very interesting for elderly people; Nintendo Wii opened up video gaming to a wide range of users due to its simplified controller with a unique and intuitive control scheme. This new control paradigm introduced the concept of "ambient games", which enables an embodied, physically active way of enjoying games (Juul, 2010).

In the same way, Kinect was a revolution and expanded ambient games. Watt proposed the term "video game embodied interfaces" as "… an interface which draws on players' spatial and physical skills, and leads players to express themselves through physical actions which have an intuitive and meaningful relation to the game they are playing" (Watts et al., 2008).

These kinds of ambient games can enable the measurement of muscle strength over a long period and can help to detect frailty in a home environment, all in an enjoyable and ecological way for users.

Several ambient games have been developed to provide an interface to measure different phenotypes related to frailty (Zavala-Ibarra and Favela, 2012).One kind is based on pool, in which the users have to control their strength to move the pool cue properly. In another one, the user has to control a bird's path by applying pressure on the controller. This project developed an interactive device based on a hand dynamometer and accelerometers.

Another work has a set of sensors to measure several frailty indicators (Chang et al., 2011).This system has two devices, the first one is an electronic grip strength meter that measures strength and reaction time during a user's hand pressure actions, and the second one is an Electronic Pressure Pad that measures weakness, slowness, balance, and weight, by sensing the pressure exerted by the subject during the sit-to stand test. Measurements are obtained during a video-game, and for instance, one challenge is to catch the apple before it hits Newton, among six different activities in a light-hearted and relaxing atmosphere.

More recent ideas (Lunardini et al., 2018) are based on a instrumented anti-stress ball, designed and built specifically for the project using an 8-cm diameter soft plastic sphere comprising a SensorTile (© STMicroelectronics, Switzerland). The game was designed to implement the clinical protocols to record handgrip strength and endurance with four game activities where a user has to launch a rocket with maximal strength or control hand pressure to move a rocket vertically to collect stars.

The design of these videogames is based on user interest, and if the user plays often, the changes in data about muscle strength during a long period can give ecological and progressive information. The target of this kind of games is to "catch" the user's attention; if the game attracts users, it will be played and, hence, the game will be useful. Recent reviews, such as (Xu et al., 2020), demonstrate that using videogame-based systems can help to improve health-related quality of life and mental health or even to detect frailty.

11. Discussion

This work describes several sensors or concepts that can perform different classical tests and evaluate frailty status using some criteria of the frailty phenotype and other elderly conditions such as sarcopenia. Moreover, these sensors can be more or less adaptable to different environments (hospital, ambulatory, home, etc.), with different levels of ecology, understanding ecology as the level of discomfort or rejection that the whole system can induce in users.

Table 1 summarizes these parameters for each system explained above and provides the reader with a quick comparison among all concepts. Fried's criteria was used for comparison of systems as it is one of the most widely accepted tools for frailty status classification and several tests can be related with these criteria (TUG, Si-St, etc.)

There are no standard tests based on sensors for frailty detection. In fact, all of these different works are based on the goal of obtaining unbiased information from classical tests (TUG, Si-St). This sensorization of classical tests has the disadvantage of the difficulty of achieving consensus about the best way to assess frailty because classical tests for frailty degree are largely subjective. This problem could be solved by the development of a frailty degree standards based on technology with objective parameters.

This absence means that the information provided by the sensors is not standardized. Each device or set of devices provides the data that the research team endorses, based on their experience and adapted to the phenotype criteria that the system can cover. This dataset is processed and described using the criteria of medical staff, and there are divergent ways to cover the same symptom induced by this lack of a standard.

Despite these problems, we analysed several options that can cover the five frailty criteria defined by Fried et al. (2001). Some sensors, such as smart shoes or devices for monitoring nutritional habits cover only one or few frailty principles, but alternatives such as eFurniture or smartphones (or smartwatches) cover all of them. Actually, eFurniture (Jaber et al. (2013) is the most complete option) refers to a set of sensors for ADL monitoring within a user's home and smartphones are perfect for ADL monitoring outside the residence.

It is difficult to evaluate all criteria with only one sensor. However, a set of them can be assessed using the properties of each one and a control unit that can analyse the data and extract information to measure frailty status. Smartphones are therefore interesting because they combine a large number of sensors and a processing unit in a relatively affordable device.

Future solutions must provide a wide ranging solution, attempting to cover all criteria with different sensors so as to create a "health monitoring partner"; a software solution that acquires the information, processes it, adapts it to different needs and sends it to several APP users.

It is important to distinguish between the users' aim with the system. Medical staff can receive parameters based on objective measurements that can help them to diagnose, but this information is not useful for a patient. Patients can receive health advice adapted to different degrees of frailty status in order to improve quality of life and even messages to motivate them to do all the tests with different sensors to improve the quality of acquired data.

Table 1
Comparison of systems. Empty is not covered, "X" partially covered, "XX" covered and "XXX" totally covered

	Phenotype criteria					Ecology	Variety of environments
	Unintentional weight loss	Self-reported exhaustion	Weakness	Slow walking speed	Low physical activity		
Sensors for nutritional habits	XX					XX	XXX
Smart shoes	XXX			XXX	XXX	XXX	XXX
Kinect sensors		XX	XX	XXX	XXX	X	X
Sit-to-stand and stand-to-sit systems		XX	XXX		X	X	X
Quiet standing sensors		XX	XXX		X	XX	XX
eFurniture and everyday home devices	XX	XXX	XXX	XXX	XXX	XX	XXX
Smartphone/smartwatch sensors		XX	XX	XXX	XXX	XX	XXX
Ambient videogames		XX	XX		XXX	XX	XX

Taking into account the ecology of sensors is another aspect to consider. The best way to obtain high quality information is to acquire it without the users noticing. For this reason, Table 1 includes the degree of compliance with this parameter for each system. All devices are relatively ecological because they are non-invasive and obtain information without contact or with little contact.

Nevertheless, the best options are developments without users involvement. From an ecological viewpoint, smart shoes are one of the best choices because they obtain information using a necessary object. However, systems based on Kinect or accelerometers for St-Si tests provide useful information and do not induce a high disturbance to users. In addition, these devices that do not need user intervention are not affected by the digital gap that affects the technological skills of users.

If the tool generates rejection, the users will not be motivated to use it, so systems based on smartphones or smartwatches that acquire information for frailty detection during ADL are an interesting choice. Smartphone penetration for elderly people is growing and the large number of sensors embedded in smart devices provides information during the whole day. Moreover, this dataset can be supplemented with data from the infrastructure of smart cities and knowledge from both sources about physical performance and activities during the day, feeding a frailty detection criteria based on technological metrics, enabling a novel system for frailty management in the future.

New developments should respect comfort for users and try to add sensors to everyday objects such as shoes, clothes, etc. Another option is contactless devices; for instance, ARPEGE has a Doppler radar inside a vase and obtains information without user engagement. This data collection is done during daily activities and in real time and the information is most valuable for frailty status measurement.

The last aspect reviewed in Table 1 is the environment where the device can perform the test or obtain information, and it is closely related to system ecology. Concepts such as Kinect sensors usually necessitate passing a test in an ambulatory environment with medical assistance and it is difficult to use in a home environment. Obviously, it is an easier tool than magnetic resonance, but smart shoes or smartphones are perfect in all environments. Researchers should tend toward solutions that can be suitable in several situations.

Another feature of the equipment presented in this work is that they are based on cheap and commonly used devices (IMUs, Kinect, etc.), so maintenance is not particularly a problem beyond the replacement of batteries in some systems. This is important so as not to induce discomfort in users or health staff with continuous maintenance visits.

12. Conclusion

Technology for healthcare is a vibrant market that attracts great interest both in users and in healthcare professionals. The development in technological devices with a wide range of biosensors and software APPs and their introduction into everyday life is closely related to people's interest in healthy life styles. For this reason, this field has been undergoing expansion during the last few years.

Furthermore, the ratio of elderly people is rising at the same time as technological expansion grows. This demographic change means that much more technical and human resources must be allocated to this sector. Technical solutions that do not require a healthcare professional's intervention can improve elderly people's assistance and reduce costs.

The relationship between frailty and technology still has a long way to go, but the two concepts will have to converge toward; a standard test battery based on metrics from technological devices that can be used as real instruments for frailty monitoring. This is the first challenge in attaining new frailty monitoring in an ecological and affordable way.

This work attempts to provide a starting point for new research which needs new ideas to achieve this first challenge, providing useful and accurate metrics for early frailty detection.

Once this goal is accomplished, the next step is to expand the devices and concepts described here to create completely new devices based on these new concepts that could bring a real revolution in healthcare for our future society.

Authors' contribution

F.A.G. has written the whole paper and he has systematically reviewed papers (with L.R.G.). L.R.G. and L.R.C. have advised about technical aspects related with photonic devices. C.F.V. and S.S.S. have advised about medical content of the document. S.D.V., E.M. and R.G.G. have advised about technical aspects related with accelerometers and web services. J.M.L.H. has coordinated the paper's content. All authors reviewed the manuscript.

Conflict of interest

Authors declare that there are no conflicts of interest.

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