Motor Activity Sensorics for mHealth Support of Human Resilience in Daily Life

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Abstract—**The quality of life depends on the human resilience to stresses and other negative impacts from the environment and society. We assume that the human resilience can be effectively supported by motor activity. The problem is that people reduce the motor activity (the human mobility) although they are potentially able to move (the human motility). In this paper, we consider human motor activity sensorics and study the concept of mobile Health (mHealth) system to digitally support the mobility of a person during her/his daily life. The sensorics is based on inertial sensors of a smartphone that accompanies the person. The smartphone evaluates various motor tests for the human activity. The collected statistics provide an interesting picture to motivate the person to more activity. We introduce the concept model that interrelates human resilience and motor activity. We discuss possible digital support of human resilience based on testing the human activity. In sum, this study contributes our concept of smartphone-based mHealth system that digitally supports the motor activity of a person in daily life subject to increase the human resilience.**

I. INTRODUCTION

One of the key goals of using digital technologies in healthcare and well-being is the quality of life (QoL) and the support of QoL improvement [1]. An essential factor for QoL is related with the human resilience to stresses and other negative impacts from the environment and society [2]. The human resilience refers to the property of a person to adapt to life's misfortunes and setbacks. The goal is to protect a person from various negative mental health conditions, such as depression and anxiety.

Negative impacts to mental health occur more and more frequently in our daily life, especially in urban areas where the speed of life processes is increasing. Let us focus on the human resilience problem in respect to human motor activity. According to World Healthcare Organization (WHO), physical inactivity is one of the significant risk factors for global mortality [3]. In particular, WHO reports that any decrease in motor activity leads to steady increasing the morbidity associated with hypokinesia, such as obesity, cardiovascular and respiratory disorders, diabetes mellitus, cognitive and mental disorders.

Another important factor is difficult conditions of the northern territories for human habitation, daily life and working life. Health status of people living in the north is of great importance due to chronic environmental stress and the increasing costs of daily and professional physical activity [4]. Cold-related discomfort typically limits everyday physical activity [5, 6]. It leads to mostly high cardiovascular and respiratory morbidity, and common morbidity in cold seasons [7], [8]. As a result, physically inactive behavior become more widespread.

Emerging information and communication technologies (ICT) provide an effective personalized mobile support based on Artificial Intelligence (AI) and Ambient Intelligence (AmI) [9]. The Healthcare 5.0 concept focuses on real-time patient monitoring, ambient control and wellness, and privacy compliance through assisted ICT like Internet-of-Things (IoT), Big Data, and mobile communication [1, 10]. In this paper, we consider the human resilience problem in respect to low daily physical activity of individuals. In particular, low physical activity is observed in elderlies and in younger generations. Note that the difficult conditions of northern area play an important role in making the physical activity low.

We expect that regular monitoring of motor activity can lead to construction of an individual picture of person's daily activity. Such a picture can be used as motivation to activity, thus supporting the human resilience. ICT for tracking physical activity can help not only in disease prevention; they can also be integrated into the national health system to improve public health databases, improve the quality and speed of healthcare service delivery. The expected result is improved QoL, as it happens in well-being [11].

The ICT support to regular activity monitoring and to motivation to activity can be implemented using mobile applications based on smartphone, e.g., see [12-17]. Various activity trackers on smartphones become of active use in our daily life [18]. Particular direction is sensorics based on inertial data for analysis of human gait and other forms of physical activity [14]. The assisted ICT support development and deployment of mobile health (mHealth) systems with an essential role of AmI and smart spaces [9, 19]. Our assumption is that smartphone senses the physical activity and evaluates the motor tests performed by the person. The collected statistics provide a summary picture motivating the person to physical activity. This scenario is non-medical, oriented to the use in common settings of daily or work life, no clinical instruments are used [17], [19]. The opportunity is enabled by the progress in consumer electronics as well as in IoT and AI.

The concept of AmI at-home Lab for human daily life was introduced in our previous work [19]. This paper makes the next step introducing our concept of smartphone sensor-based mHealth system to support human resilience by monitoring individual physical activity. The concept considers the motor activity as consisting of the two components: motility and mobility. The resilience is reduced to the opposite term called frailty. The latter denotes a multidimensional syndrome characterized by: 1) increased vulnerability, 2) reduced ability to tolerate physiological stress, including recovering from a stressor, 3) weakness, 4) slowness, 5) low physical activity, 6) weight loss and exhaustion [20, 21].

In the introduced concept, human acts as a sensor of own motor activity, similarly to human sensors in [22]. The mHealth system senses the physical activity (mobility) when a person (either frail, pre-frail, or non-frail individual) performs a motor test. Frailty indicators are evaluated, the report (decision) is delivered to the person. We expect that deployment of such resilience- or frailty-oriented human sensors will lead to increasing QoL, especially required in northern areas.

The rest of this paper is organized as follows. Section II introduces the problem domain of motor activity sensorics and our model to reduce the human resilience problem to an opposite problem–the human frailty problem. Section III overviews functional tests for motor activity, which can be used to evaluate the physical activity of individuals. Section IV considers our concept of smartphone-based mHealth system supported with our early experiments. Section V summarizes the key findings of this pilot study.

II. The Problem of Human Motor Activity

We consider the human motor activity as consisting of the two components: motility (the ability to actuate the movement independently) and mobility (the ability to change location in the physical environment). Low motor activity is typically a sequence of geriatric syndromes, although the motor activity is now become low in younger generations, living in urban areas and northern areas. Due to negative factors the frailty syndrome becomes essential in daily life, reducing the resilience and vitality. A possible way is to motivate people to physical activity.

A. Mobility, physical activity, and hypodynamia

Motor activity is a critical daily practice to all animals, not to mention humans, because it allows *actively* seek food and partners. Several terms with close, though still different meaning are used to characterize various aspects of the phenomenon of motor activity. One of them is *motility,* which means the ability to actuate the movement independently, which is based on the ability to contract muscles and to produce movements in joints, with help of internal sources of energy. Another important term is *mobility,* or the ability to change location in the environment or to move between two locations, for example, between the start and end/destination points. Then, the term *motion*, in *sensu lato*, refers to the progression of an object or subject in space, or progression of the entire big subject or object (waves, avalanche, air, planets on the sky, etc). Motion could be also understood as a state opposite to the state of *rest*. As such, motion refers to the state of restlessness of the entire object. Correspondingly, the term *movement* refers to a physically moving smaller object (or part of the object), such as a hand, forearm, leg, or the head.

To better understand the difference between motility and mobility, one can imagine an individual who is able to move but has little reason or motivation to do that. In other words, such a human has the ability to move (i.e., is characterized by motility), but is not able to transfer the body from one location to another one (i.e., does not have mobility). Thus, there is a conflict between these two features, which becomes most evident in the process of aging. Indeed, many neurologically healthy aged people, who can move and even do physical exercise, do not do so for several reasons (so-called "barriers", see further in the text). They are capable of motility, but not mobility.

Ultimately, this leads to the so-called "sedentary lifestyle" and, inevitably, to conditions such as "hypokinesia" and "hypodynamia". It should be noted that the term "hypokinesia" (decreased amount of movements) is strictly opposite to the term "hyperkinesia", and it is most often attributed to clearly pathological conditions (neurological diseases) [23]. Hence, with regard to healthy aging, it would be more appropriate to use the term "hypodynamia", or a decrease in strength or power.

In addition, there are several other terms, which denote specific aspects of human motor activity. Among them, are exercise and non-exercise physical activity (NEPA), and activities of daily living (ADL). Exercise physical activity stands for the activity, which is performed volitionally, regularly, purposefully, vigorously and according to a kind of forethought program, which is very similar to common sport training. Accordingly, NEPA [24], usually measured in hours, includes all daily living movements (in general sense) performed irregularly without a special plan. The state, which is opposite to physical activity, either the exercise or non-exercise one, is *physical inactivity*. Many processes contribute to physical inactivity [25, 26], e.g., poor peer support, lack of motivation, social stigma, lack of support in family, and barriers to exercise.

B. Geriatric syndromes

The so-called "geriatric syndromes" are clinical conditions in *older adults* that do not fall into specific *disease* categories [27]. Along with hypodynamia, the geriatric syndromes include other physiological (actually, pathophysiological) states/symptoms, such as sarcopenia, polypharmacy, malnutrition, depression, falls, frailty, dementia, etc. Thus, the geriatric syndromes appear as rather a phenotype, than a disease. Hypodynamia is associated with "sarcopenia", a term which describes the ageing related loss of skeletal muscle mass [28]. According to [27], in older people the incidence of sarcopenia, depression, dementia, falls, and frailty was 20-40%, polypharmacy - >50%, urinary incontinence - around 50%, malnutrition - around 10%, and it increases with age. Only 20% of individuals in 60-69 years age group did not have any of these syndromes and 48% of cases in ≥80 years had more than four syndromes.

C. Frailty, Resilience, and Vitality

The term "frailty" is a multidomain "umbrella" measure, which denotes a multidimensional syndrome characterized by the following features: 1) increased vulnerability, 2) reduced ability to tolerate physiological stress, including recovering from a stressor, 3) weakness, 4) slowness, 5) low physical activity, 6) weight loss and exhaustion [27,21,20,29]. In that sense, "frailty" denotes the state, which is generally opposite to the state "resilience", or the ability to counter stress, or to bounce-back" from stressors [2].

Similarly, according to scholarly literature, there are 5 frailty indicators [20, 21]: 1) unintentional weight loss (or a body mass index (BMI) <18.5 kg/m^2) 2) muscle weakness assessed by grip strength, adjusted for gender, 3) exhaustion, 4) slowness assessed by means of walking speed, adjusted for gender and standing height, and 5) low physical activity assessed with a weighted score of kilocalories expended per week calculated using the questionnaire, on the basis of each participant's report. The subject is classified as "frail" if less than 3 of the aforementioned indicators are present. Correspondingly, the subject is classified "pre-frail" if 1-2 indicators are present, and "non-frail" if no indicators are present.

Vitality (or "internal capacity") is another widely used new phenotypic concept, is becoming popular among healthcare professionals and doctors. The internal capacity design was recently defined by WHO as the totality of all the physical and mental abilities of an individual, including five areas: movement, vitality, cognitive abilities, psychological and sensory [30]. Vitality is associated with self-estimation of "liveliness" and feeling "full of energy", physical performance, vigor, or strength. Measuring "vitality" is challenging, as it has different aforementioned aspects. Vitality has unclear physiological nature, which makes its measurement problematic.

The frailty and sarcopenia are related syndromes, as they share in common such features as lower lean mass and reduced physical function [20], while malnutrition plays a key role in the pathogenesis of both frailty and sarcopenia, and vice versa [29]. Hypodynamia and sarcopenia are associated with muscle disuse, immobilization and chronic low-grade inflammatory activity [31]. In parallel, autonomic de-conditioning due to sedentary life-style, and cognitive decline take place with ageing. In addition, one should dissociate the effects of chronological aging *per se* on muscle characteristics from the non-chronological, or secondary, influence of lifestyle or disease processes.

In sum, aged people are under risk of practically inevitably coming of the geriatric syndromes, which potentially would lead to decreased mobility and quality of life, and, eventually, to social de-adaptation. To overcome these unfavorable conditions, the older people should engage in either exercise or non-exercise physical activity, and modify their nutrition.

Physical activity and correct nutritional support seem to be the only ways to prevent and slow the progression of sarcopenia, and hence frailty [32, 33]. Among all physical exercise interventions studied, *intensive resistance training* was found the most efficient to counter sarcopenia, including the very old geriatric patients [34]. Significant ameliorations (up to >50% strength gain) can be expected after six weeks of training at a rhythm of 2-3 sessions per week. From a preventive viewpoint, all elderly patients should be advised to start such an exercise program and continue it as long as possible. As for the pharmacological interventions to counter sarcopenia, which mostly include drugs with anabolic effects, their efficiency is doubtful [35].

D. Mobilization and barriers to start physical exercising

There are physical, behavioral, and psychosocial barriers [26, 36] to start physical exercising. Therefore, older subjects need a kind of personalized "mobilization", which can be designed as a service for encouragement, motivation, or mobilization. The service can be delivered using smartphone and IoT technology.

Prior to taking of exercise as a therapy, several important questions should be addressed [36], namely 1) type of exercise, 2) dosing and timing of exercise, and 3) implementation strategy. As for the type and dosing of exercise, higher-intensity aerobic exercise is regarded as the most efficient type of exercise for the elderly, including those with neurological diseases [34]. As for implementation of exercise, alike medicines, it must be adapted on a regular basis over the course of the disease to optimize the benefit [36].

In sum, we can conclude with the following. 1) Instant awareness on current level of resilience (frailty, vitality) through measuring informative physiological indicators along the exercise intervention. 2) Delivering the status to a customer would be a challenging technological problem to be addressed. Such aspects of the motor function, as muscle mass, muscle function (strength, endurance, coordination, contraction speed), and muscle performance are critical to evaluate frailty (resilience) in the elderly. As such, low mass, low function, and low performance are the target domains to be measured and assessed

Therefore, the aim of the present study was to seek for the most relevant, easy-to-do, albeit informative tests, tasks and tools, which can be arranged in a AmI-based environment to assess one's resilience to stresses or human frailty.

III. Motor Activity Testing

Numerous functional tests have already been invented to evaluate specific aspects of the motor and motor-cognition state of in varied target groups, including the old-age group [37]. A comprehensive comparative analysis of the most used functional tests is provided in [38]. We have divided tests into two categories: 1) tests that are performed in everyday life; 2) tests that require special conditions.

A. Everyday Life Tests

Such functional tests are performed during daily life of a given person. As a result, the person is focused on her/his personal activity, not on the motor activity exercise.

1) *Walking speed (WS), or gait speed (GS), test.* Measuring the WS over a short distance, for example, over 3-6 m, is an easier method to evaluate the frailty and resilience in clinical practice [37]. In addition, WS test is an objective parameter that can be evaluated repeatedly. Low WS (<0.8 m/s) is a good marker of frailty. Usually, WS is measured during the 3 m Timed Up-and-Go (TUG) test.

2) *Trail Walking Test (TWT).* In the real world, walking is usually performed under dual task conditions (with cognition load), which requires much attention to changing environmental features (furniture, other people in the room, pets, autos outdoors, etc) to avoid tripping, slipping and colliding, and to recover quickly from postural disturbances [39]. TWT was first introduced in [40] to address the circumstances of the real-world walking.

In addition, TWT allows to assess motor-cognitive interference [39]. The essence of the TWT method is to walk under change of direction and cognition conditions (from one cone marked with a flag to another, which are placed randomly at 15 positions in a 16 m^2 (4 ×4 m) area. The TWT consists of 3 different motion-cognition conditions. In a pure motor task (condition 1), the participants are asked to *follow a line* connecting 15 cones. In a motor-cognition task (condition 2) participants have to step on numbered targets in sequential and ascending order. In the most complex task (condition 3), the subject step on targets with an ascending alternating number-letter sequence. As in other motor-cognitive tasks, the participants are instructed to perform the tasks as quickly but accurately as possible.

3) *2-minute (2MWT), 6-minute walk (6MWT) test, and 10-meter walk test (10MeWT).* In the 6MWT, the participants were asked to walk "as far as possible" in the 6 min (no running was allowed) [41]. In 2MWT, the participants were instructed to "walk at your comfortable, usual pace". The distance covered in 2 and 6 min was used as a measure outcome in the 2MWT and 6MWT. In the 10MeWT, the GS is measured within a distance of 10 m. Usually, healthy older people (cal. 80 years old) walk with a speed 0,96 m/s [42], at 2MWT they walk 134.3–184.2 m, [43], and at 6MWT - 392-572 m [44].

B. Specialized Tests

This category of functional tests implies that people do not perform such tests by accident. To run these tests, one need to have a task to solve a specific problem. Examples include the following tests.

1) *Maximal step length (MSL)* is the ability to maximally step out and return to the initial position [38]. In addition, such MSL-related metric as RST (the time taken to step out and return in multiple directions as fast as possible) is often taken into account.

2) *Timed Up-and-Go (TUG)* test is a well-known and widely-used test of functional mobility [39]. To perform that test, individuals have to perform 5 sequential tasks: 1) to rise from a chair of standardized height (e.g., 46 cm high, sit-to-stand phase), 2) walk a fixed distance of 3 m, or Gait-Go phase, 3) turning by 180°, or U-turn, 4) walk back to the chair, or Gait-Come phase, and 5) sit down again with a turn, or Walk-to-Sit phase. The task allows to evaluate several distinct motor functions: 1) a transfer from standing to sitting and vice versa (postural transitions, anticipatory postural adjustments), gait characteristics during walking and turning (walking speed, gait), dynamic balance. In addition, the TUG test can be performed under cognition load, what is under dual tasking. This allows evaluating cognitive involvement as well. Altogether, this test allowed to assess basic mobility skill and strength, agility and balance [38, 45]. Smaller values (faster time) represent better performance at each phase of the TUG test.

3) *Four square step test (FSST)* was found to be a good predictor of falls, which appears as part of the aforementioned geriatric syndromes [46].

4) *Backward stepping (BS).* In that test, participants step back 3 meters, usually within 4-5 seconds [47]. One cannot regard that test as safe and easy-to-do for the use in elderly people in a non-laboratory environment.

5) *Tandem walk (TW*). The number of correct tandem steps subjects could perform with arms crossed and eyes closed in a series of 10 steps is tested [48]. This method seems to be non-safe and easy-to-do by older people in home environment.

6) *Performance oriented mobility assessment (Tinetti POMA).* POMA is a widely-used test battery, which allows predicting falls by assessment of gait and balance [49].

7) *miniBEST test* (a mini version of the BESTest) [50]. A 4-domain test battery, which allows assessing postural and anticipatory reactions, body orientation in space, gait, static and dynamic balance.

Tests 6) and 7) are considered as precise, valid and reliable outcome measures of mobility and motor performance in elderly. However, they consist of >15 separate tests and require 1-2 testers, which is not reliable for instant assessment of mobility.

In addition, such more advanced functional tests (called as tasks) as 1) car task (to open the door of the car, then to sit down in it, to open the door and to step out to resume the initial standing position), 2) sock task (to put on socks or a footwear), and 3) lift-and-carry test (to approach a shelf, then pick up a 4,5 kg weight, and to walk back) [14] are used to identify impairments of mobility under specific pathologies of the motor system. Also, a 5 Chair Sit-to-Stand (5CSS), Alternate Stepping (AS), and Timed Rapid Gate (TRG) tests are used [51].

IV. Concept of Smartphone-based mHealth System

The introduced mHealth system implements tracking random execution of tests from the first category. Nowadays, many people have smartphones. Such a smartphone has an IMU (inertial measurement unit) to sense and measure the motor activity. A smartphone is relatively powerful computing device to process the sensed data using AI methods, even for fast and volumetric data, e.g., see [52].

A. Scenario

The high-level scenario is the following. 1) Collecting data from smartphone sensors; 2) Recognition of basic user actions (e.g., walking, standing, sitting, lying); 3) Search among the basic actions for patterns, such as the motor tests discussed in Section III. For simplicity, we assume that the person is carried a smartphone on her/his belt.

Let us consider that low BMI, exhaustion, physical inactivity, slow walking speed, and muscle weakness constitute the so-called "frailty phenotype" [21, 20, 51]. These features can be detected by screening tests/tasks evaluated with cutoff values.

There are many methods of sensorics for tracking motor activity, e.g., see [53]. Basically, they collect data from the accelerometers and gyroscopes of smartphones. In many datasets, the number of features is measured in hundreds. We also plan to use such data, but first we need to select only the most important features to recognize the necessary types of activity (see Table I). At the output of this stage, we receive the collected data.

TABLE I. SYSTEM ACTIONS

Stage	Actions	Minimum output unit
Collecting and filtering data from a smartphone	Application launch	Acceleration along the axes x, y and z. Angular velocity along the x, y and z axes. Etc.
Activity Type Recognition	Applying machine learning algorithms such as decision trees	Type of activity: walking, standing, sitting etc.
Search for motion patterns (tests)	Passing through the time window, mapping a window in the data to a window in the test	The name of the test that the user passed. For example, *walking speed*
Analysis and recommendations	Comparison the results of the test passed by the user, with normal indicators, preparation of a recommendation	Report for the user on the level of his physical activity and recommendations (if necessary).

Let us consider the events the mHealth system should recognize. The answer to this question is given by the tests that the user will pass:

1. Walking speed tracks walking, so it is necessary to understand when the user is walking. It is also necessary to understand when the user stopped, for example, at a traffic light, so as not to include the stop in the test. In addition, each walking event must have a corresponding speed. It will be analyzed in the next step.

2. Trail Walking Test assumes that the user can interact with the environment. For example, he can bypass obstacles in the form of other people. Thus, we need to build a trajectory of movement in order to recognize when the user is turning.

3. 2-minute (2MWT), 6-minute walk contains not only walking, but also speed, like the first test. Also, different types of walking are possible. For example, the user may be in a hurry somewhere, and then such a pace cannot be considered usual. The opposite situation is also possible, when the user walks very slowly, because, for example, she/he enjoys nature. This pace of walking also cannot be considered usual. Long-term measurements (e.g., weekly) should be considered in order to determine the user's typical walking pace.

In sum, the main recognized features (physical activity states) are: *walking, standing position, walking speed* and *trajectory of movement*. The corresponding scenario is shown in Figure 1. We assume that within one second the person can be in one of these states (when passing tests). Let $S = \{s_1, s_2, s_3, \ldots, s_n\}$, be an array of states obtained after data analysis, n is the number of measurements. Outside of the test, the person can also sit and lie down. A number of states obtained from the analysis of motion types are transferred to the next stage.

Let the system have been running for 10 minutes. In this case, from the previous stage, we received an array S_n where n=600 (one for each second). Now we need to understand if the user performed any tests. We build a set of patterns $P = \{p_1, p_2, p_3, \ldots, p_m\}$ where m is a count of tests. Every test has length of the pattern. For example, the *Walking speed* test pattern assumes that the user walks for 6 seconds. In this case, the *pattern of a test* looks like this: p_t = [*walking, walking, walking, walking, walking, walking]*. In this case, the length of the test pattern $l_{pt} = 6$.

Further, we introduce a set of windows $W_P = \{w_{P1}, w_{P2}, w_{P3}, \ldots, w_{Pn-lpt}\}$, where for set P, $w_{pi} = \{s_i, s_{i+1}, s_{i+2}, \ldots, s_{i+lpt}\}$. Compare each position of the comparison window w_{pi} and the test pattern p_t. Then the measure of similarity Ψ_{wp} will be equal to $\Psi_{wp} = \frac{C}{lpt}$, where C is the number of identical elements of arrays w_{pi} and p_t at the same positions. We assume that the test is passed if $\Psi_{wp} \geq 0.9$.

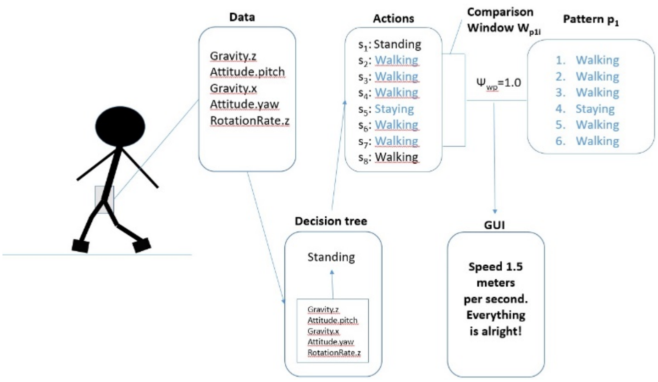

Fig. 1. Scenario of human gait sensing during test execution.

After receiving the test results, we can compare them with normal values. If the test results are within the normal range, then the application simply notifies the user about this. If deviations are present, the user is also notified of this. In addition to the test results, the application analyzes the general motor activity of a person. For example, if a person walks 15 minutes a day, then recommendation can motivate the person to walk more.

B. Screening tests and cutoff values for muscular performance in the elderly

In the existing literature, there are studies, which recommend cutoff values for muscle mass, muscle function and muscle performance measurements. For example, work

[54] recommends 7.0 kg of muscle mass per m^2 for men and 5.7 kg/m^2 for women (by using bioimpedance analysis), handgrip strength (<26 kg for men and <18 kg for women), and usual gait speed (<0.8 m/s). Similarly, the assessment of such aspects of muscle performance as grip strength and endurance was found reliable as a screening tool showing sufficient sensitivity [27]. In [51], the authors found that 1.24 m/s is a cutoff point for gait speed (GS) in elderly people.

Most community-dwelling older persons are able and willing to repeatedly assess their mobility and fall risk with MSL and GS tests [55]. Compliance of repeatedly self-measuring MSL and GS is good, as the median number of weekly measurements was 23.0 (88% of required 26) and 21.0 (81%) for MSL and GS, respectively.

Therefore, several simple (easy-to-do, safe, self-measured, reliable) motor tests are used in the field of frailty assessment in old-age population: 1) gait speed (cutoff values <0,8 m/s) as a marker of slowness, 2) maximal step length, and 3) chair rise time. In addition to GS and MLS, hand grip (a marker for weakness), and weight control could have formed a reliable battery to assess mobility and frailty in the elderly.

It was reported that data on as much as 10 strides (or, 20 steps) is sufficient to reliably characterize velocity and cadence of human's gait [56]. Ten strides roughly correspond to the distance of 10-15 meters. Having in the mind that, of all tests, *gait speed* has the strongest correlation with frailty and the highest diagnostic value [57], we can assume that characterization of gait speed (<0.8 m/s) at the distance of 10-15 m is sufficient to trace such feature of frailty in older subjects as slowness. Such test can be regarded as the simplest single measure that can replace the complex frailty assessment as a self-test for monitoring frailty at home or outdoors.

C. Enabler Technologes (smartphone-based)

Thus, gait speed, and, to a lesser degree, hand grip and BMI appear as the best indicators of frailty and, indirectly - resilience, in elderly people. There is a plenty of studies, which propose instruments to characterize human gait. Motion video-capture and force plates techniques are still regarded as "gold standard" methods to extract features from the human's gait [58]. However, the aforementioned method (gait speed evaluation at 10 m distance) does not require such sophisticated technique. Great progress has been made within the last decade, in inventing instrumented versions of TUG test (iTUG) [14]. In most of these versions, varied number and positions of custom or IMU-based sensors (usually, accelerometers) were used to discriminate between phases of TUG test [59, 60]. From the other hand, smartphones, as they also are equipped with IMU, are increasingly used to analyze the motor function in varied clinical and age groups [14]. Smarphones IMU allow reliably discriminate TUG test phases. Besides that, smartphones are promising as they are widespread and low-cost tool [61], [12], [62].

Self-administrable versions of iTUG (Self-TUG) are increasingly developed. In study [63], usability problems were identified (incorrect performance of the test, incorrect placement of the smartphone, etc.). Nevertheless, only less than one third of users make usability mistakes, which can be considered as promising. Still, Self-TUG and other self-conducted tests (e.g., Self-Sit-to-Stand or Self-Tandem) have some limitations, as subjects try to perform the test *as fast as possible* [13], which does not reflect real ADL. In addition, the self-test and clinical test, that is conducted in hospital conditions, differed in both time and performance quality [17].

The best way to avoid inference of the test conditions, either self- or clinically administered, is to make the test "incorporated" in the ADL to make it “invisible” for the subject. In particular, we propose that analyzing of gait speed during straightforward 10-meter walks during ADL, with the help of smartphone applications, would be the most easy-to-do informative approach to evaluate frailty in the elderly.

The smartphone is a core personalized part of the mHealth system. Activity Tracker applications provides a promising basic solution as they allow counting steps and evaluate length of walk in one min [16]. Walking is the commonest physical activity, and the approach supports monitoring the gait speed in real-life setting, without inference of self-testing. In addition, mHealth components (smartphone apps, physical activity trackers) have a significant effect in increasing physical activity, for example by 1850 steps [18], or 1126 step daily [64], which roughly equals 0,7-1 km. For most people walking at a moderate intensity approximates to 3000 steps in 30 min (100 steps in 1 min) [65].

D. Candidate functional tests and tasks to assess the motor performance

In sum, the phenotype-based approach to assess health and wellbeing of an individual looks promising and evolving. The characteristics of the motor activity, along with nutrition/metabolism and cognition, are likely the best markers of wellbeing (in the terms of vitality, frailty and resilience). Among the motor activity, fastness/slowness and strength/weakness are the best predictors of frailty.

Altogether, there is a variety of motor tests and their composition to tasks to evaluate the human mobility and motor performance, of which several have potential to invent high-throughput, easy-to-do and valid self-assessment systems (e.g., TUG test, gait speed and maximal length of steps, and 10-meter walk). Still, these can be reduced to the 10-meter walk test and gait speed assessment with help of a smartphone Activity Tracker.

In respect with aforementioned studies, simple tests can be used to evaluate the motor performance in the elderly. In addition, such simple tests are beneficial, because they do not create motivation/mobilization barriers to entry exercise or non-exercise physical activity. Indeed, complex motor tests (or tasks) can discourage the subject. Then, simple tests are easier to conduct methodologically and technically. Finally, simple tests can be easily evaluated in a IoT or AmI environment.

E. Early Experiments

The physical activity types were described in Table I above. The experiment aims at recognition the actions that a person performs. The following actions are recognized: walking, sitting, standing, lying, upstairs, downstairs.

We prepared ready-made data. The hypothesis was tested: is it possible to recognize human actions using a model trained on the gait samples of other people? We took a ready-made dataset [66] and construct a decision tree over the dataset. The trained model showed a recognition accuracy of no more than 80%. However, when the model was trained on the gait of the same person, the accuracy was always more 90%. There were not enough people in the original data. However, it was decided to individually train the model on the gait.

Smartphone Samsung Galaxy S5 was used. It has an accelerometer, gyroscope, and magnetometer. Each action took 15 seconds. Then a decision tree was built and actions were recognized. Action recognition accuracy of 98% was achieved. However, this high accuracy was achieved due to laboratory conditions. In the future, it is necessary to develop a training scheme that will not be too complicated, and which will allow the model to be trained. The accuracy of the model must be greater than 90%. Five parameters were used as initial data, which are shown in Figure 1. Our further plan for experiments is to recognize the steps performed by a person. Recognition algorithms can be used from [67-68].

V. Conclusion

This paper introduced a concept of smartphone-based mHealth system to perform and measure functional tests of human motor activity, to evaluate frailty indicators, and deliver the final information (decision) to either frail, pre-frail, or non-frail people. The measurements can be used to decrease human frailty syndrome, so increasing the human resilience through the motor activity. The system (as a mobile application) can provide motivation to the person to start more physical activity, to monitor the status and the progress.

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References

[1] Mohanta, B., Das, P. and Patnaik, S. Healthcare 5.0: A Paradigm Shift in Digital Healthcare System Using Artificial Intelligence, IOT and 5G Communication. 2019 International Conference on Applied Machine Learning (ICAML), 2019, pp. 191-196, doi: 10.1109/ICAML48257.2019.00044.

[2] Ryan, M, Ryznar, R. The molecular basis of resilience: a narrative review. Front Psychiatry. 2022 13:856998. doi: 10.3389/fpsyt.2022.856998.

[3] Bull, F.C. et al. World Health Organization 2020 guidelines on physical activity and sedentary behaviour. Br J Sports Med. 2020 Dec;54(24):1451-1462. doi: 10.1136/bjsports-2020-102955.

[4] Gronlund, C.J, Sullivan, K.P, Kefelegn, Y., Cameron, L., O'Neill, M.S. Climate change and temperature extremes: A review of heat- and cold-related morbidity and mortality concerns of municipalities. Maturitas. 2018 Aug;114:54-59. doi: 10.1016/j.maturitas.2018.06.002.

[5] Gerasimova-Meigal, L. Fedosova A., Meigal A. Hand skin temperature: A usability for health care services. Proceedings of the 18th Conference of Open Innovations Association FRUCT and Seminar on Information Security and Protection of Information Technology FRUCT-ISPIT. IEEE Computer Society, 2016. pp. 60-65. DOI 10.1109/FRUCT-ISPIT.2016.7561509.

[6] Gerasimova., L.I. Aggravated cold-induced vasoconstriction as premorbid sign of adaptation to Nordic conditions. Uchenye zapiski Petrozavodskogo gosudarstvennogo universiteta. 2008. No. 96, pp. 69-71.

[7] Demoury, C., Aerts, R., Vandeninden, B., Van Schaeybroeck, B., De Clercq, E.M. Impact of Short-Term Exposure to Extreme Temperatures on Mortality: A Multi-City Study in Belgium. Int J Environ Res Public Health. 2022 Mar 22;19(7):3763. doi: 10.3390/ijerph19073763.

[8] Ikäheimo, T.M., Jokelainen, J., Näyhä, S., Laatikainen, T., Jousilahti, P., Laukkanen, J., Jaakkola, J.J.K. Cold weather-related cardiorespiratory symptoms predict higher morbidity and mortality. Environ Res. 2020 Dec. 191:110108. doi: 10.1016/j.envres.2020.110108.

[9] Korzun, D.; Balandina, E.; Kashevnik, A.; Balandin, S.; Viola, F. Ambient Intelligence Services in IoT Environments. IGI Global, 2019. DOI: 10.4018/978-1-5225-8973-0.

[10] Saraswat, D. et al. Explainable AI for Healthcare 5.0: Opportunities and Challenges. IEEE Access, vol. 10, pp. 84486-84517, 2022, doi: 10.1109/ACCESS.2022.3197671.

[11] Zupkauskiene. J. et al. Changes in health-related quality of life, motivation for physical activity, and the levels of anxiety and depression after individualized aerobic training in subjects with metabolic syndrome. Hellenic Journal of Cardiology, vol. 66, 2022, pp. 41-51, doi: 10.1016/j.hjc.2022.04.003.

[12] Mellone, S.; Tacconi, C.; Chiari, L. Validity of a smartphone-based instrumented timed up and go. Gait Posture. 2012;36:163–5.

[13] Capecci, M; Pepa, L.; Verdini, F.; Ceravolo, M.G. A smartphone-based architecture to detect and quantify freezing of gait in Parkinson's disease. Gait Posture. 2016 50:28-33. doi: 10.1016/j.gaitpost.2016.08.018.

[14] Ishikawa, M.; Yamada, S; Yamamoto, K; Aoyagi, Y. Gait analysis in a component timed-up-and-go test using a smartphone application. J Neurol Sci. 2019 398:45-49. doi: 10.1016/j.jns.2019.01.023.

[15] Gür, F.; Gür, G.C.; Ayan, V. The Effect of the ERVE Smartphone App on Physical Activity, Quality of Life, Self-Efficacy, and Exercise Motivation for Inactive People: A Randomized Controlled Trial. European Journal of Integrative Medicine. Vol. 39, 2020, 101198, doi: 10.1016/j.eujim.2020.101198.

[16] Bentley, C.L. et al. The Use of a Smartphone App and an Activity Tracker to Promote Physical Activity in the Management of Chronic Obstructive Pulmonary Disease: Randomized Controlled Feasibility Study. JMIR Mhealth Uhealth. 2020 8(6):e16203. doi: 10.2196/16203.

[17] Mansson L, Bäckman P, Öhberg F, Sandlund J, Selling J, Sandlund M. Evaluation of concurrent validity between a smartphone self-test prototype and clinical instruments for balance and leg strength. Sensors. 2021;21:1765.

[18] Laranjo, L. et al. Do smartphone applications and activity trackers increase physical activity in adults? Systematic review, meta-analysis and metaregression. Br J Sports Med. 2021 55(8):422-432. doi: 10.1136/bjsports-2020-102892.

[19] Korzun,D., Borodin, A., Zavyalova, Yu., Meigal, A., and Gerasimova-Meigal, L. Ambient Intelligence At-Home Laboratory for Human Everyday Life. Int. J. Embed. Real-Time Commun. Syst. 10, 2 (Apr 2019), pp.117–134. doi: 10.4018/IJERTCS.2019040108.

[20] Fried, L.P. et al. Cardiovascular Health Study Collaborative Research Group. Frailty in older adults: evidence for a phenotype. J Gerontol A Biol Sci Med Sci. 2001 56(3):M146-56. doi: 10.1093/gerona/56.3.m146.

[21] Laur, C.V.; McNicholl, T.; Valaitis, R.; Keller, H.H. Malnutrition or frailty? Overlap and evidence gaps in the diagnosis and treatment of frailty and malnutrition. Appl. Physiol. Nutr. Metab. 2017;42:449–458. doi: 10.1139/apnm-2016-0652.

[22] Kostakos, V., Rogstadius, J., Ferreira, D., Hosio, S., Goncalves, J. Human Sensors. Participatory Sensing, Opinions and Collective Awareness. Understanding Complex Systems. 2017. Springer, Cham. doi: 10.1007/978-3-319-25658-0_4

[23] Schilder JC, Overmars SS, Marinus J, van Hilten JJ, Koehler PJ. The terminology of akinesia, bradykinesia and hypokinesia: Past, present and future. Parkinsonism Relat Disord. 2017 37:27-35. doi: 10.1016/j.parkreldis.2017.01.010.

[24] Snider J , Muller M , Kotagal V , Koeppe RA , Scott PJH , Frey KA , Albin RL , Bohnen NI (2015) Non-exercise physical activity attenuates motor symptoms in Parkinson disease independent from nigrostriatal degeneration. Parkinsonism Relat Disord 21, 1227–1231.

[25] Hirsch MA, Sanjak M, Englert D, Iyer S, Quinlan MM. Parkinson patients as partners in care. Parkinsonism Relat Disord. 2014;20(Suppl 1):S174–S179

[26] van der Eijk M, Faber MJ, Aarts JW, Kremer JA, Munneke M, Bloem BR. Using online health communities to deliver patient-centered care to

people with chronic conditions. Journal of medical Internet research. 2013;15:e115.

[27] Ates Bulut E, Soysal P, Isik AT. Frequency and coincidence of geriatric syndromes according to age groups: single-center experience in Turkey between 2013 and 2017. Clin Interv Aging. 2018 13:1899-1905. doi: 10.2147/CIA.S180281.

[28] Bautmans I, Van Puyvelde K, Mets T. Sarcopenia and functional decline: pathophysiology, prevention and therapy. Acta Clin Belg. 2009 64(4):303-16. doi: 10.1179/acb.2009.048.

[29] Cruz-Jentoft A.J., Baeyens J.P., Bauer J.M., Boirie Y., Cederholm T., Landi F., Martin F.C., Michel J.-P., Rolland Y., Zamboni M., et al. Sarcopenia: European consensus on definition and diagnosis: Report of the European Working Group on Sarcopenia in older people. Age Ageing. 2010;39:412–423. doi: 10.1093/ageing/afq034.

[30] Cesari M, Araujo de Carvalho I, Amuthavalli Thiyagarajan J, Cooper C, Martin FC, Reginster J-Y, et al. Evidence for The Domains Supporting The Construct of Intrinsic Capacity. J Gerontol A Biol Sci Med Sci 2018.

[31] Distefano, G.; Goodpaster, B.H. Effects of Exercise and Aging on Skeletal Muscle. Cold Spring Harb Perspect Med. 2018 8(3):a029785. doi: 10.1101/cshperspect.a029785.

[32] Phillips C. Lifestyle Modulators of Neuroplasticity: How Physical Activity, Mental Engagement, and Diet Promote Cognitive Health during Aging. Neural Plast. 2017:3589271. doi: 10.1155/2017/3589271.

[33] Jackson, P.A. et al. Promoting brain health through exercise and diet in older adults: A physiological perspective. J Physiol 2016, 594, 4485–4498. doi: 10.1113/JP271270.

[34] Schenkman, M. et al. Effect of high-intensity treadmill exercise on motor symptoms in patients with de novo Parkinson disease: A Phase 2 randomized clinical trial. *JAMA Neurol*. 2018, 75, 219-226. doi: 10.1001/jamaneurol.2017.3517.

[35] Burton LA, Sumukadas D. Optimal management of sarcopenia. Clin Interv Aging. 2010 Sep 7;5:217-28. doi: 10.2147/cia.s11473.

[36] Ellis, T., Rochester, L. Mobilizing Parkinson's disease: The future of exercise. *J. Parkinsons Dis.* 2018. 8(s1), S95-S100. doi: 10.3233/JPD-181489.

[37] Avram, R.L. et al. Functional tests in patients with ischemic heart disease. J Med Life. 2022 15(1):58-64. doi: 10.25122/jml-2019-0142.

[38] Bennell K, Dobson F, Hinman R. Measures of physical performance assessments: Self-Paced Walk Test (SPWT), Stair Climb Test (SCT), Six-Minute Walk Test (6MWT), Chair Stand Test (CST), Timed Up & Go (TUG), Sock Test, Lift and Carry Test (LCT), and Car Task. Arthritis Care Res (Hoboken). 2011 Nov;63 Suppl 11:S350-70. doi: 10.1002/acr.20538.

[39] Klotzbier TJ, Bühler K, Holfelder B, Schott N. Exploring motor-cognitive interference in children with Down syndrome using the Trail-Walking-Test. Res Dev Disabil. 2020 106:103769. doi: 10.1016/j.ridd.2020.103769.

[40] Schott N. Trail Walking Test zur Erfassung der motorisch-kognitiven Interferenz bei älteren Erwachsenen. Entwicklung und Überprüfung der psychometrischen Eigenschaften des Verfahrens [Trail walking test for assessment of motor cognitive interference in older adults. Development and evaluation of the psychometric properties of the procedure]. Z Gerontol Geriatr. 2015 48(8):722-33. German. doi: 10.1007/s00391-015-0866-3.

[41] Chan WLS, Pin TW. Reliability, validity and minimal detectable change of 2-minute walk test, 6-minute walk test and 10-meter walk test in frail older adults with dementia. Exp Gerontol. 2019 115:9-18. doi: 10.1016/j.exger.2018.11.001.

[42] Peters DM, Fritz SL, Krotish DE. Assessing the reliability and validity of a shorter walk test compared with the 10-Meter Walk Test for measurements of gait speed in healthy, older adults. J Geriatr Phys Ther. 2013 36(1):24-30. doi: 10.1519/JPT.0b013e318248e20d.

[43] Bohannon RW, Wang YC, Gershon RC. Two-minute walk test performance by adults 18 to 85 years: normative values, reliability, and responsiveness. Arch Phys Med Rehabil. 2015 96(3):472-7. doi: 10.1016/j.apmr.2014.10.006.

[44] Steffen TM, Hacker TA, Mollinger L. Age- and gender-related test performance in community-dwelling elderly people: Six-Minute Walk Test, Berg Balance Scale, Timed Up & Go Test, and gait speeds. Phys Ther. 2002 Feb;82(2):128-37. doi: 10.1093/ptj/82.2.128.

[45] Savva GM, Donoghue OA, Horgan F, O'Regan C, Cronin H, Kenny RA. Using timed up-and-go to identify frail members of the older population. J Gerontol A Biol Sci Med Sci. 2013 Apr;68(4):441-6. doi: 10.1093/gerona/gls190.

[46] Whitney SL, Marchetti GF, Morris LO, Sparto PJ. The reliability and validity of the Four Square Step Test for people with balance deficits secondary to a vestibular disorder. Arch Phys Med Rehabil. 2007 88(1):99-104. doi: 10.1016/j.apmr.2006.10.027.

[47] Bilek F., Demir C.F. Validity and reliability of the 3-meter backward walk test in mildly disabled persons with multiple sclerosis. Mult Scler Relat Disord. 2022 58:103532. doi: 10.1016/j.msard.2022.103532. Epub 2022 Jan 19. PMID: 35066275.

[48] Cohen. H.S. et al. Tandem walking as a quick screening test for vestibular disorders. Laryngoscope. 2018 128(7):1687-1691. doi: 10.1002/lary.27022.

[49] Tinetti, M.E. Performance-oriented assessment of mobility problems in elderly patients. J Am Geriatr Soc. 1986 34(2):119-26. doi: 10.1111/j.1532-5415.1986.tb05480.x.

[50] Horak, F. B.; Wrisley, D. M.; Frank J. The Balance Evaluation Systems Test (BESTest) to differentiate balance deficits. *Physical Therapy*, 2009, vol. *89*, pp. 484–498. https://doi.org/10.2522/ptj.20080071.

[51] Kim, M.J. et al. Mobility performance tests for discriminating high risk of frailty in community-dwelling older women. Arch Gerontol Geriatr. 2010 51(2):192-8. doi: 10.1016/j.archger.2009.10.007.

[52] Bazhenov, N.; Korzun, D.; Balandin, S. Smartphone-Oriented Development of Video Data Based Services. 23rd Conference of Open Innovations Association (FRUCT), 2018, pp. 62-68, doi: 10.23919/FRUCT.2018.8588068.

[53] H.-P. Liu, Y. -M. Chuang, C. -H. Liu, P. C. Yang and C. -S. Fuh, "Precise Measurement of Physical Activities and High-Impact Motion: Feasibility of Smart Activity Sensor System," in IEEE Sensors Journal, vol. 21, no. 1, pp. 568-580, 1 Jan.1, 2021, doi: 10.1109/JSEN.2020.3015392.

[54] Chen, L.K. et al. Sarcopenia in Asia: consensus report of the Asian Working Group for Sarcopenia. J Am Med Dir Assoc. 2014 15(2):95-101. doi: 10.1016/j.jamda.2013.11.025.

[55] Bongers KT, Schoon Y, Olde Rikkert MG. Feasibility of repeated self-measurements of maximum step length and gait speed by community-dwelling older persons. BMJ Open. 2016 Aug 5;6(8):e011538. doi: 10.1136/bmjopen-2016-011538.

[56] Schoon Y, Bongers K, Van Kempen J, Melis R, Olde Rikkert M. Gait speed as a test for monitoring frailty in community-dwelling older people has the highest diagnostic value compared to step length and chair rise time. Eur J Phys Rehabil Med. 2014 50(6):693-701.

[57] Hollman JH, Childs KB, McNeil ML, Mueller AC, Quilter CM, Youdas JW. Number of strides required for reliable measurements of pace, rhythm and variability parameters of gait during normal and dual task walking in older individuals. Gait Posture. 2010 32(1):23-8. doi: 10.1016/j.gaitpost.2010.02.017

[58] Zhou, L. et al. Validation of an IMU Gait Analysis Algorithm for Gait Monitoring in Daily Life Situations. Annu Int Conf IEEE Eng Med Biol Soc. 2020:4229-4232. doi: 10.1109/EMBC44109.2020.9176827.

[59] Salarian, A. et al. iTUG, a sensitive and reliable measure of mobility. IEEE Trans Neural Syst Rehabil Eng. 2010 18:303-10. doi: 10.1109/TNSRE.2010.2047606.

[60] Caronni, A. et al. Criterion validity of the instrumented Timed Up and Go test: A partial least square regression study. Gait Posture. 2018 61:287-293. doi: 10.1016/j.gaitpost.2018.01.015.

[61] Arkkukangas M. App-based strength and balance self-test in older adults: an exploratory study from a user perspective. BMC Res Notes. 2021 Sep 26;14(1):379. doi: 10.1186/s13104-021-05792-5. PMID: 34565455; PMCID: PMC8474945.

[62] Zhong R, Rau PLP. Are cost-effective technologies feasible to measure gait in older adults? A systematic review of evidence-based literature. Arch Gerontol Geriatr. 2020;87:103970

[63] Bergquist, R. et al. App-based Self-administrable Clinical Tests of Physical Function: Development and Usability Study. JMIR Mhealth Uhealth. 2020 8(4):e16507. doi: 10.2196/16507.

[64] Chaudhry UAR, Wahlich C, Fortescue R, Cook DG, Knightly R, Harris T. The effects of step-count monitoring interventions on physical activity: systematic review and meta-analysis of community-based randomised controlled trials in adults. Int J Behav Nutr Phys Act. 2020 17(1):129. doi: 10.1186/s12966-020-01020-8.

[65] Marshall, S.J. et al. Translating physical activity recommendations into a pedometer-based step goal: 3000 steps in 30 minutes. Am J Prev Med. 2009;36(5):410–5. doi: 10.1016/j.amepre.2009.01.021.

[66] Malekzadeh, M. (2020, November). Human Activity Recognition with Mobile Sensing, Version 4. Retrieved August 25, 2022 from

https://www.kaggle.com/code/malekzadeh/human-activity-recognition-with-mobile-sensing/notebook?scriptVersionId=47073836

[67] R. de Silva, J. Perera, C. P. Abeysingha and N. Abhayasinghe, "A Gyroscopic Data based Pedometer Algorithm with Adaptive Orientation," 2018 IEEE 14th International Conference on Control and Automation (ICCA), 2018, pp. 953-956, doi: 10.1109/ICCA.2018.8444198.

[68] S. Jayalath and N. Abhayasinghe, "A gyroscopic data based pedometer algorithm," 2013 8th International Conference on Computer Science & Education, 2013, pp. 551-555, doi: 10.1109/ICCSE.2013.6553971.