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First Approach to Automatic Performance Status Evaluation and Physical Activity Recognition in Cancer Patients

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***Abstract*—The evaluation of cancer patients' recovery is still under the big subjectivity of physicians. Many different systems have been successfully implemented for physical activity evaluation, nonetheless there is still a big leap into Performance Status evaluation with ECOG and Karnofsky's Performance Status scores. An automatic system for data recovering based on Android smartphone and wearables has been developed. A gamification implementation has been designed for increasing patients' motivation in their recovery. Furthermore, novel and without-precedent algorithms for Performance Status (PS) and Physical Activity (PA) assessment have been developed to help oncologists in their diagnoses.**

***Index Terms*—physical activity, performance status, cancer patients, Android, wearables, gamification, mHealth.**

I. Introduction

According to the World Health Organization, cancer is the plague of the XXI century. It has become the major cause of mortality and morbidity, with 14 million new cases and 8 million deaths related to cancer in 2012, affecting all the regions over the world. Moreover, these figures are expected to keep growing during the next years [1], [2].

One of the worst parts of facing cancer is the widely known aggressive impact of the treatment based on chemotherapy and radiotherapy [3]. The side effects stuck patients in a loop of asthenia and physical activity weakness that is hard to come out from [4]. Many studies have valued positively the effects of exercise in patients, improving survival probability [5], [6], [7], [8]. Furthermore, some apps and systems including gamification techniques have reported successful results in increasing users' physical activity in diverse areas like children obesity [9], chemotherapy-induced peripheral neuropathy affected cancer patients [10], general fitness [11], and some early proposals specially designed for adult and children cancer patients [12], [13], [14].

II. Motivation

Oncologists regularly use the Performance Status (PS) measurements like Karnofsky's PS (KPS) [3] and Eastern Cooperative Oncology Group PS (ECOG) [15] to evaluate the overall patient's status. These measurements serve, short-term, as a critical index to determine if a patient can handle a new session of treatment and, long-term, as a key pointer of the survival probabilities of the patient [16], [17], [18], [19]. Despite the relevance of the PS measure, there has always been some controversy around its applications due to the grades of subjectivity of each oncologist when evaluating patients. Different studies have determined a Kendal correlation coefficient of 0.75 of reliability when several oncologists evaluate the same patients, that is, 3 out of 4 oncologists categorize the same PS to the patient whilst the remaining one does not [20], [21]. There is an obvious need for more objectivity in the patients' evaluation.

There are also other tools like the International Physical Activity Questionnaire (IPAQ) that focus exclusively in the performed physical activity [22]. However, it is still applied in hospitals with outdated self-reported questionnaires. The patients need to remember all the activity done in a whole week, and besides, evaluate themselves the intensity of the exercise done.

On the other hand, we live nowadays in the era of the data and the Internet, where almost everybody in the world is connected via any sort of PC, smartphone or simply any other kind of mobile device, leading us to the brand new trend of the Internet of Things (IoT). Smartwatches and activity trackers are some of the technologies that compose the popular market of fitness and wearables that also deal with the concept of IoT [23]. Besides, the evaluations found in the literature support long-term evaluation of patients with photoplethysmography (PPG) for heart rate (HR) monitoring despite its need for improvement [24], [25]. Accelerometers have been used in the field for many kinds of physical activity evaluation such as steps counting in a day [26].

III. Objectives

The purpose of this project is double: to help oncologists in their diagnosis of PS with an automatic estimation of ECOG or

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KPS based in objective data, and to set the basic implementation of a gamified app to improve cancer patients' recovery and promote both their motivation and self-improvement control. The data will be provided by a biomonitoring system based on portable and wearable devices.

After an extensive art review and several interviews with specialists from the *Hospital Virgen de las Nieves (Granada, Spain)*, specifically oncologists and psychologists, the following needs are concluded:

1) Design the gamified system around a smartphone plus wearable system.
2) Implement patient's tracking with a smartphone-wearable system to obtain objective data.
3) Develop algorithms for automatic week-by-week IPAQ estimation.
4) Develop algorithms for automatic week-by-week ECOG and KPS estimation.
5) Focus on tendencies rather than absolute measurements. Support data visualisation for evolution tracking.

IV. Implementation

The technologies and designs implemented in the system are going to be described in this section.

A. Considerations for Design

The system has been carefully designed always following the recommendations from psychologists from the *Hospital Virgen de las Nieves (Granada, Spain)*; the psychological condition of patients found in the literature [27], [28]; and previous work on gamification [12].

1) Cancer patients' Psychology and Behaviour: One of the major problems of facing cancer is the treatment. Chemotherapy and radiotherapy cause both a long set of side effects which can lead the patients to reduce their physical activity due to the depressive state and the fatigue acquired. The patient always develops a series of cognitive and behavioural responses to the treatment from a cognitive triad: diagnostic vision, sense of control perceived and prognosis vision. Five facing styles are found: Fighting Spirit, Avoidance/Denial, Fatalism/Acceptance, Hopelessness/Abandonment, and Anxious Concern [27]. According to the studies found in the literature [29], [30], there is prevalence of Fighting Spirit along with moderate information research and ocassional Denial. However, one of the problems found with cancer patients' psychological condition is that society does not tolerate any sight of depressing moments for themselves, i.e. they cannot show any weakness in their recovery. Nonetheless, these moments are very necessary for their recovery and it is part of their defense behavioural mechanisms. Facing cancer is already a big pressure, so people or a biomonitoring system should understand the necessary emotional stages of the patient [27].

2) Gamification Purpose: The inclusion of gamification looks forward to improve the recovery of cancer patients by encouraging them to:

- Do more physical activity. Movement will be attached to most of the activities guided by this app.
- Do regular check-ins in the provided app.
- Keep track of the personal progress thanks to the data collected and the badges earned.
- Stay in touch more regularly with other patients through the exclusive and closed social network provided.

The use of game-elements along with the biomonitoring system will be focused on promoting both patients' extrinsic and intrinsic motivation. For this, a closed social network where patients with the highest KPS scores (60-100) and medical personnel is proposed. Optional open social media with tools like Twitter or Facebook are also foreseen. One of the keys to enhance patients' intrinsic motivation is to give them back some control of their treatment. Just waiting for diagnosis and analysis may be very harmful in a psychological way, so the gamified app will highlight all the achievements made by the patients on their own, such as fulfilling the quests given and remarking on the physical activity done during a day. Doctors, nurses and psychologists are also participants of the system, so the system will provide data of the performance of each patient individually. Physicians will be also key to integrate elder patients within the community the game mechanics create and give additional rewarding badges for every good analysis and after any clinical test or review.

3) Activity Loops:

a) Engagement Loop: Engagement is necessary to make patients feel comfortable when being part of the system. Then the engagement loop in Figure 1 keeps the patient within the system in each notification of badges, points and achievements. For the *onboarding*, in a introductory session of the benefits of making physical activity, social activities and positive thinking to fight cancer will be explained. Then, this gamified system will be introduced as a way to make it in a very easy way. Patients will also be informed about the continuous biomonitoring to provide objective measures to the physicians. The *scaffolding* will consist in starting the engagement loop. An assistant will guide the patients through the different quests and tasks to do after asking for their username. Charts and diagrams will give the information of the different available and realized achievements. There will also be a wall where the badges attached to the achievements collected to keep track of the progress from just a glance.

b) Progression Loops: Progression is this intangible sense of advance you feel when looking backwards at any point in your life (Figure 2). The elements described before, quests, missions, badges and achievements should make this possible in an enjoyable way. This activity tracking will be easily accessible for the patients to see their own progress, always highlighting the good results on the tendencies. Besides, there will be different experience points attached to each kind of activity:

- Physical activity: referred to the time stood up, the steps given or the intensity of activity performed.
- Social activity: referred to activities involving social interaction. This will be very important in the social community of patients.

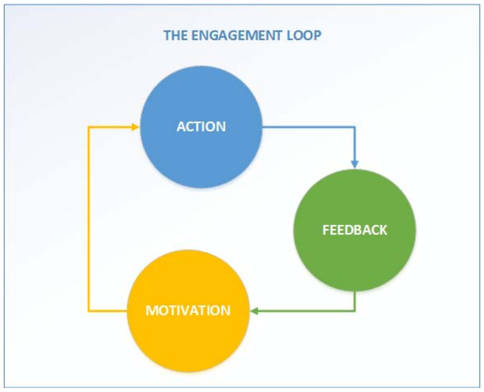

Fig. 1: Engagement Loop. Adapted from [31]

- Mental activity: referred to quests and missions that imply concentration activities.
- Reflexive activity: referred to quests and missions that imply deep insights.
- Emotional activity: referred to quests and missions that are related to the own or other people feelings.

Moreover, like in videogames, the patient will be able to beat *final bosses*, for example, when they pass a chemotherapy, radiotherapy or reduce the tumor volume.

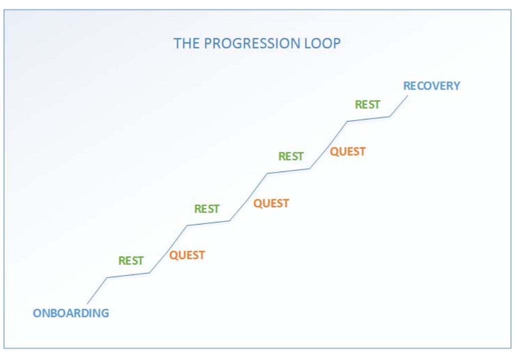

Fig. 2: Progression Loop. Adapted from [31]

4) Game-design Elements and Tools: To achieve the gamification purpose, the following elements are necessary:

- *Quests*. Missions or objectives for the patient to fulfill. They will be all related to health and physical activity. In Figure 3 a first approach to its implementation in the Android app *OncoHealth* has been done. To activate the activity the user would only need to tap on them to increase the counter.
- *Badges*. Achievements to earn in determined conditions, for example, for good physical activity performance in IPAQ score or rising up the step-count tendency.
- *Social media*. This will enable to build up a community where patients can fight in group.
- *Points*. Physical, Social, Mental, Reflexive and Emotional points attached to any activity.

B. *Patient's App*

It is necessary to collect the appropriate data for patients' evaluation. To support this, the Google Fit API offers a tool set that enables the data recording and subsequent querying plus other features related to the Google Fit environment. Consequently, the Recording API and the History API have been used among the different APIs provided [32]. First, the automatic recording of the selected data is activated with the Recording API, then the History API is set up into a service to query and pre-process the data requested. This is implemented in an Android app: *OncoHealth*.

1) Data Recorded: To infer IPAQ, ECOG and KPS the following data is required to be queried from the Google Fit API. A structure of the data purpose can be seen in Figure 4:

a) Heart Rate: HR can be monitored in two different modes, automatic and manual. In this project the automatic mode has been selected. The automatic mode is entirely controlled by the commercial activity tracker used, a Sony Smartband 2 SWR12. According to the tracking and the experiments done, the band tracks HR for 1 minute long after time intervals between 2 and 15 minutes, depending on the activity detected by the accelerometers of the wristband. Consequently, a non-regular sampling will force a post-processing to enable comparison with other measures. In this mode the battery lasts for 48 hours long. The automatic activation of HR monitoring when a sudden activity is detected makes this option suitable for the purpose of measuring the patients' tendencies along the time. For example, if the wristband user is in a still position, the monitoring will be activated in time intervals of 15 minutes; if suddenly the patient starts walking or moving, the SmartBand 2 will automatically start to measure HR. On the other hand, the continuous mode is controlled by the user,

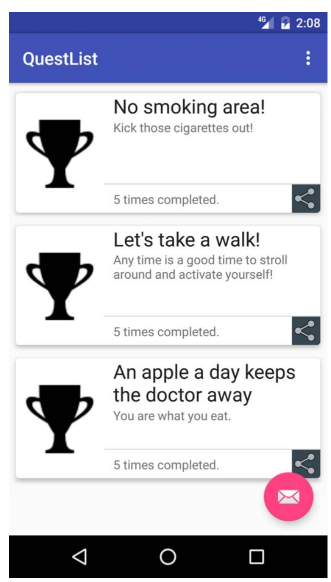

Fig. 3: Quest list in an Android ScrollView design.

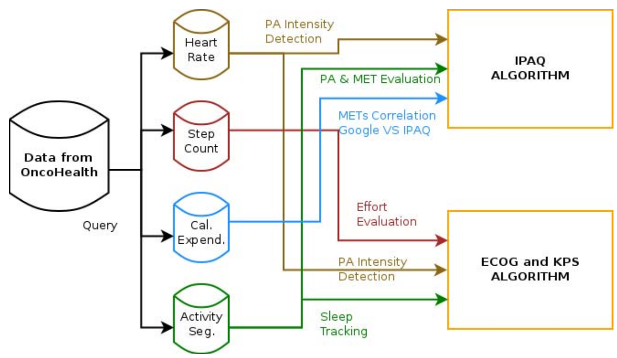

Fig. 4: Data Structure and utilization in IPAQ, ECOG and KPS algorithms.

activated manually by double clicking the button on the side of the wristband. Thereon a more reliable measure is gathered at the expense of reducing the battery duration to a maximum of 16 hours. The reason this mode is not selected is double, first because the automatic mode gives enough and significant data when monitoring for entire weeks long, and second since the battery draining is too high.

b) Steps Count: There is a continuous sampling frequency determined by the hardware itself, it combines data from the accelerometers of all the *smart* devices being carried on which are compatible with the Google Fit technology. Data will be ultimately bucked in fixed-length segments of 5 minutes.

c) Calories Expended: These data are used to compare the Metabolic Equivalent of Task (MET) activity measured with the IPAQ criteria against the Google Fit's algorithm. This Google Fit measure includes the Resting Metabolic Rate (RMR) whilst the IPAQ does not (Figure 6).

d) Activity Segments: Activity recognition is inferred from the accelerometers' data and HR monitoring. This enables to recognize still, walking, running, cycling and sleeping conditions used in the IPAQ and KPS-ECOG algorithms.

2) Android App: At first use, two things are going to be needed: to insert the patient's data and to give permissions for querying the data with the History API. This will result in the activation of a *service* to query the recorded data every hour.

The app is built around the two major objects and, consequently, two separated databases: the Patient's object, with all the necessary information to identify the subject, and the SmartBand-Data's object, with all the pre-processed information obtained from the History API query. The whole process summarized in Figure 5 will be activated every hour.

The obtention of the data from Google Fit has been done with the History API. In the *DataReadRequest* the raw data of the previous hour is aggregated in time buckets of 5 minutes. The *DataPoints* gathered have the following *DataTypes* referring to the time bucket defined:

a) AGGREGATE_STEP_COUNT_DELTA: steps given (int-count).

b) AGGREGATE_HEART_RATE_SUMMARY: average (float-bpm), min (float-bpm) and max (float-bpm) HR.

c) AGGREGATE_CALORIES_EXPENDED: calories expended (float - kcal).

d) AGGREGATE_ACTIVITY_SUMMARY: activity detected (int-enums), duration (int-ms) and num_segments (int-count).

With this distributed scheduling there is no perceptible drain of the smartphone's performance. The total Time of Execution (TE) of one hour query is $TE = (3.4 \pm 0.4)s$

V. Data Gathering and Processing

For the whole implementation of the algorithms an 18 days-long database has been used. A single subject has been considered for a preliminary test.

A. IPAQ Estimation

As an alternative to the self-reported IPAQ, the following algorithm is proposed for automatic evaluation. It is built upon the algorithm depicted in the IPAQ evaluation with data obtained from continuous biomonitoring [22]. It consists of:

1) *Database query*. The following data is queried:
   - Activity intensity based on HR and Karvonen Formula.
   - METs estimation for IPAQ.
2) *Frequency adaptation*. Since the frequency of the Activity intensity is higher than the HR monitoring, a frequency adaptation is necessary to compare data.
3) *Daily detection*. Divide the data day by day.

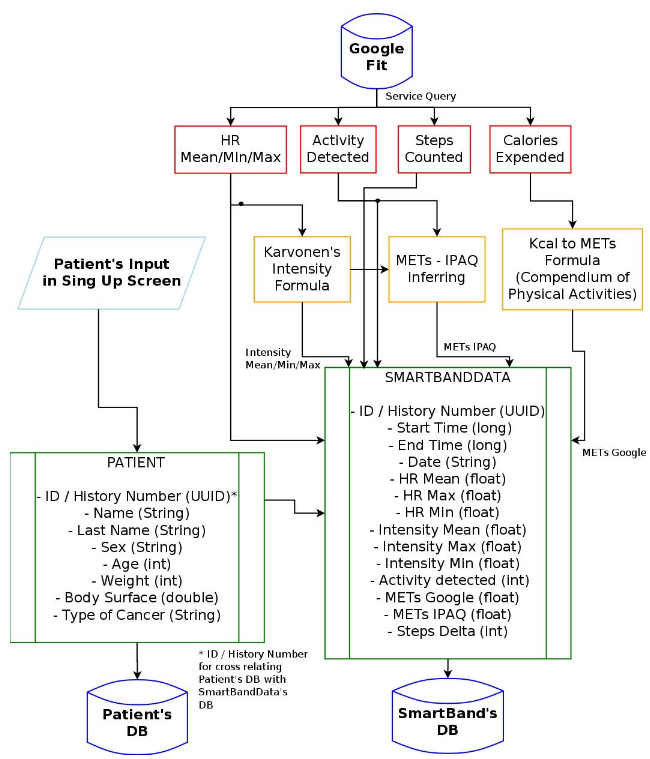

Fig. 5: OncoHealth main activity flowchart.

4) *Activity intensity and METs for IPAQ daily bucket*. The raw data gets organized in buckets of one day length. Both variables are composed by three different labels depending on the nature of the physical activity performed: *light*, *moderate* and *intense*.
5) *Activity intensity and METs for IPAQ cumulative week by week*. For each week, the IPAQ algorithm is evaluated as it is described in [22], classifying the patient as IPAQ 1, 2 or 3 depending on the amount of exercise detected.

One of the problems that Google's calorie expenditure estimation presents is that it always considers the RMR, so it points out calorie expenditure even when total resting is detected. The IPAQ does not take into account this kind of activity, therefore, to filter this, the IPAQ MET expenditure has been calculated strictly when the detected *activity* is different from *EXCEPTION*, *IN_VEHICLE*, *STILL*, *DEEP_SLEEP*, *LIGHT_SLEEP*, *REM_SLEEP* and *AWAKE_SLEEP* [33]. All those activities automatically are assigned with a zero-MET value, which means no physical activity at all. The *activities* that are enabled to calculate the MET expediture are *CYCLING*, *ON_FOOT*, *WALKING* and *RUNNING*, since most of physical activities imply on foot movement in different grades of intensity

The MET expenditure is calculated following the criteria proposed in [22], base upon the Compendium of Physical Activity [34]. The intensity of the activity is inferred directly from HR according to Karvonen's Formula [35]:

- *Light* intensity. $MET = 3.3 \cdot duration \ (MET \cdot min)$
- *Moderate* intensity. $MET = 4 \cdot duration \ (MET \cdot min)$
- *Vigorous* intensity. $MET = 8 \cdot duration \ (MET \cdot min)$
- *Cycling* intensity. $MET = 6 \cdot duration \ (MET \cdot min)$

A comparison of the METs inferred with IPAQ rules and with the Google Calorie Expenditure, transformed to METs, for a database along 18 days long, can be seen in Figure 6. A good Pearson correlation coefficient of 0.8505 is obtained with all the data, however, a few data points apart from the major tendency can still draw it back. These are just 49 data points over a total of 3385 in which Google detected activity and calorie expenditure whilst the IPAQ remained to zero. If these outliers are taken out the Pearson score rises up to 0.9665. These results validate the use of this IPAQ algorithm for exclusive physical activity detection in METs.

The time considered for the IPAQ activities is strictly the one attached to physical activity, that is, the time in which METs evaluated are higher than zero. The resulting time recorded along the 18 days can be seen in Figure 7. In the data presented the following activities can be highlighted to validate the algorithm:

1) Two one-hour-and-a-half-long paddle matches in days 10 and 17. The breaks and starting and ending times are correctly not detected as physical activity.
2) An hour-and-a-quarter-long music concert performed in day 12. The duration of the activity shown is quite accurately the time on stage.

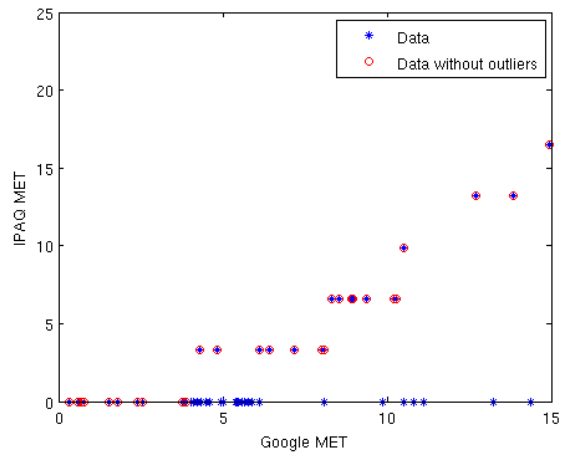

Fig. 6: METs calculation comparison between Google estimation and IPAQ algorithm.

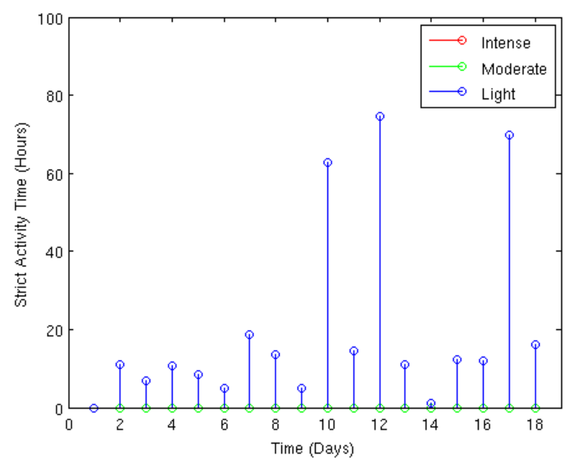

Fig. 7: Strict Light Activity Detection

The rest of the time a rather sedentary or low level activity performed is found. This leads to an IPAQ scoring of 1 (LOW) for each of the two weeks detected, which seems appropriate according to the sporadic exercise done.

B. ECOG and KPS Estimation

In this subsection the ECOG and KPS algorithm is presented. No precedent for automatic ECOG and KPS estimation algorithms was found in the literature review done. Unlike the IPAQ estimation, the PS measure does not focus strictly on the intensity of physical activity, it highlights the tendency and continuity of the exercise done, even if it is performed at a very low level of intensity. Thus, a more flexible concept of *light*, *moderate* and *vigorous* activities is necessary to measure the activities beyond absolute rest. It is important to notice that most of cancer patients tend to have long resting periods of time due to the physical weakness and fatigue acquired along the treatment.

At first, the time considered for *light* activity was strictly all the gathered with intensity in the interval $[0, 50)\%$ [36]. Since all the activity detected was within this category, it was necessary to add an extra step for absolute rest. The algorithm would now take into account the data in the interval $(X, 50)\%$ where $X = \{0, 1, 2, 3, 4, 5\}\%$. By using this extra division the algorithm is offering slightly different levels of restriction to the same measure of PS. The point is to detect any activity beyond absolute rest, so by using this extra division, the algorithm is offering different levels of the patient's activation through the HR detected beyond their Resting Heart Rate (RHR), the HR of a person just awake and within a neutrally temperate environment [37]. This will be specially important to detect if the patient is out of bed more than 50% of the waking hours available – gap between 2 and 3 ECOG 50 and 60 KPS, scores that may determine whether a patient can tolerate a new chemotherapy session for treatment or not [38].

Another objective measure was needed, the steps count. This extra data will help to evaluate the level of activity according to the total steps done day by day [39]. The following points conform the algorithm:

1) *Database query*. The following data is queried:
   - *Activity Detected* (AD).
   - *Activity Intensity* based on HR.
   - *Steps delta* counted in 5-min-long time buckets.
2) *Frequency adaptation*. Since the frequency of the AD is higher than the HR monitoring, a frequency adaptation is necessary to compare *Activity intensity* with AD.
3) *Daily detection*. It is applied to the following data:
   - *Activity intensity* and AD after frequency adaptation.
   - *Steps Delta*.
4) *Day-by-day Bucketing*. The raw data gets organized in buckets of one day length. It is divided in:
   - *Steps Delta*.
   - Sleep Tracking: *Light*, *deep*, *REM* and *awake* sleep. All conform the total sleeping time of each day.
   - *Activity intensity* with multiple division depending on the intervals defined for *light* intensity: $(X, 50)\%$ where $X = \{0, 1, 2, 3, 4, 5\}\%$.
5) *Calculation of the daily proportion of AD time*. It is applied to each of the divisions defined for *Light* activity, plus the *moderate* and *high* activity. The sleeping time detected is taken out of the proportion of every day. In Figure 8 the results are presented.
6) *Weekly segmentation*. ECOG and KPS rule base (Tables I and II) applied to the weekly segmented data.

The results are shown in Table III. The first week scores at 0% level with 90 KPS and 1 ECOG, higher than the rest of levels with 70 KPS and 2 ECOG; the second week strikes with 70 KPS and 2 ECOG for all the possibilities. This results were obtained using the optimistic filter of $X = 0\%$, and ensuring the prevalence of tendencies and the long term activity to score the KPS and ECOG estimations.

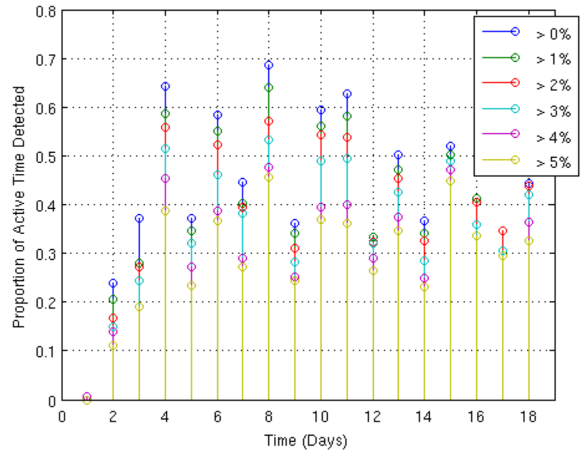

Fig. 8: Daily proportion of user's Active Time

VI. Conclusions

The recovery and evaluation of cancer patients is a major and global issue that has been clearly presented with needs for improvement. An entirely new approach to automatic PS evaluation without any precedent known has been proposed, and besides, the system makes the most of commercial devices in the wearable market thanks to the Google Fit integration. It is not only the relevance of the algorithms developed, but also the implementation with common and affordable components, like Android-based smartphones and activity trackers, what makes it directly applicable in the recent future. Many different goals have been successfully reached:

- A system involving several disciplines has been properly designed and implemented. A reasonable evaluation of the necessities of the project has been done according to the wearable and smart-devices market status and catalog. Several interviews with psychologists and oncologists from the hospital *Virgen de las Nieves (Granada, Spain)* has helped to achieve it.
- An extensive study of the *State of the Art* to the very different subjects tackled along the report has been done: cancer patient's recovery, Performance Status evaluation, Physical Activity assessment, Gamification and mHealth.
- Gamification techniques have been studied along with the most relevant cancer patients' psychological condition and a proper design has been developed.

To sum up, it is important to point out that this work emerges from the need for a suitable and objective evaluation of cancer patients by adapting the rather outdated estimation of KPS (1949) and ECOG (1960) scales to help oncologists in the PS evaluation and diagnoses.

VII. Future Work

This work is intended to be just the beginning of a long-term project. It has the potential to be tested directly to evaluation and validation with real patients. Furthermore,

RULE BASE				
IPAQ	**Proportion**	**Steps**	**ECOG**	**KPS**
3	>=0.5	5	0	100
		4	0	100
		3	0	100
		2	0	100
		1	0	100
	<0.5	5	0	100
		4	0	100
		3	0	100
		2	0	90
		1	1	90
2	>=0.5	5	0	100
		4	0	100
		3	0	100
		2	1	90
		1	1	80
	<0.5	5	0	100
		4	0	100
		3	1	90
		2	2	80
		1	2	70
1	>=0.5	5	1	90
		4	1	90
		3	2	80
		2	2	70
		1	2	60
	<0.5	5	2	70
		4	2	70
		3	3	60
		2	3	50
		1	4	40

TABLE I: Rule base for ECOG and KPS estimation.

LEGEND		
Steps Count	**Intensity**	
sc > 12.500	5	Very High
10.000< sc <12.500	4	High
7.500< sc <10.000	3	Normal
5.000< sc <7.500	2	Low
Sc <5.000	1	Very Low

IPAQ	Intensity
3	High
2	Moderate
1	Low

Proportion	Legend
>=0.5	More than 50% active time out of bed
<0.5	Less than 50% active time out of bed

ECOG	Legend
0	Best (Asymptomathic)
1	
2	...
3	
4	
5	Worst (Exitus)

KPS	Legend
100	Best (Asymptomathic)
90	
...	...
...	
10	
0	Worst (Exitus)

TABLE II: Rule Base's Legend.

	Week 1		Week 2	
HR Intensity	**ECOG**	**KPS**	**ECOG**	**KPS**
> 0 %	1	90	2	70
> 1 %	2	70	2	70
> 2 %	2	70	2	70
> 3 %	2	70	2	70
> 4 %	2	70	2	70
> 5 %	2	70	2	70

TABLE III: ECOG and KPS performance along two weeks with IPAQ 1 and different HR intensity margins.

several improvements and new leads of research are open to keep progressing. The most immediate steps to continue with are the following:

- Present the project to the Ethics Committee of the *Hospital Virgen de las Nieves (Granada, Spain)* to test the system with real patients. The Spanish Data Protection Law has been taking into account.
- Keep working on the gamified framework for the patients, developing an friendly app to interact with.
- In the ECOG and KPS estimation a typical Rule Base for Fuzzy Logic Controllers has been defined so it could be implemented. Besides, if there is availability of enough data, even Machine Learning algorithms could be applied to infer new rules non devised on a first sight.

To conclude, it is important to express the high value of this project and, with enough work, the eventual contribution to the society. This is not only because of its direct application to cancer patient's recovery, but also all the advances still to come in the mHealth field and the transition to this new medicine paradigm.

Acknowledgements

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