Smartphones as Multipurpose Intelligent Objects for AAL: Two Case Studies

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Abstract. The increasing adoption of smartphones among older adults, especially in most developed countries, suggests they can be used not only for personal communications, but also in the framework of Active and Assisted Living solutions. This paper addresses two case studies in which a smartphone, when equipped with a proper software application, may operate as an inactivity monitor, and a drug management assistant, respectively. Activity monitoring is carried out by targeting the user's interaction with the smartphone related to incoming, outgoing, and lost calls. In the latter case, an application processes images of drugs boxes captured by the smartphone camera, to automatically recognize the name of the drug, and inform the user about the corresponding prescription. Experimental results show this kind of approach is technically feasible and may provide satisfactory performance through a very easy interaction, thus supporting improved medication adherence by patients.

Keywords: Ambient assisted living · Mobile device · Activity monitoring · Drug management

1 Introduction

Several studies have shown the effectiveness and benefits of using mobile devices, such as tablets or smartphones, in Active and Assisted Living (AAL) applications, and in certain specific diseases treatment [1–3]. Mobile devices have the advantage of being intuitive, computationally powerful, personal, provided with high-resolution screens, rich of sensors (e.g. cameras, accelerometers and geo-positioning systems) and wireless interfaces (e.g. NFC, WiFi, Bluetooth, etc.), and portable, thanks to reduced size and weight. The personal nature of mobile

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phones suggests they are well suited for pervasive computing, but the data they are able to collect and process could be beneficially used in a wide range of context-aware applications, to automatically identify user's habits and provide structured knowledge [4].

Advances in smartphone applications technology, and their mass adoption, make these mobile devices an unprecedented vehicle to promote positive changes in users' habits, from reducing sedentary behaviors, to improving dietary choices and stimulating cognitive functionalities. The simple user-smartphone interaction that takes place when using the smartphone to communicate (i.e. to make calls or send messages) makes it possible to monitor different conditions, such as user's prolonged inactivity.

In [5], the feasibility of using smartphones for rheumatic diseases self-management interventions is widely discussed, while other studies, such as [6], show the benefits of using mobile devices, when dealing with people under treatment for addiction to drugs or alcohol. Self-monitoring of pain [7], and dietary intake to promote weight loss, are other possibilities of exploiting mobile devices in the healthcare arena. Just to mention an example, experimental results indicate that food records completed using digital tools are more acceptable to young women, than traditional paper-based methods, yet equally accurate [8]. Nevertheless, ICT-based solutions are sometimes inadequate for elderly or technologically inexperienced users. In fact, when designing a system for the self-management of health care or health status monitoring, a user-friendly interaction is essential, especially considering that the people who need it most, usually are affected by impairments or not familiar with technology [9]. In this paper, two examples of use of smartphones as intelligent multipurpose objects in AAL are presented.

The first case study relies in a software application that allows to use a smartphone as a personal assistant for inactivity detection, based on a multiple threshold analysis including incoming, outgoing, and lost calls. This way, the application may assess the behavior of a user (either a chronic disease patient or an old person) based on their interaction with the smartphone. The use of smartphones to monitor and stimulate physical activity has gained a great attention within the workplace context, as a tool to avoid prolonged sedentary behaviors by workers in modern workplaces [10], which may have dramatic impacts on their health conditions [11]. In this paper, a more general purpose inactivity detection application is addressed, which may be used in a home environment too.

In the second case study, a software application enabling the use of a smartphone as a personal assistant for drugs and therapy management is presented, which exploits the built-in camera of the device to capture a picture of the drug box, and processes the picture to automatically recognize the drug name and show details about it. This way, the specific information about the drug, such as active ingredients, intended purpose, method of use, dosage, contraindications, interactions and side effects, may be retrieved in a fast and easy way, by taking a picture of the package. The system also allows to check whether or not a drug is part of the user's therapy, by displaying required dosage and intake schedule.

The paper is organized as follows: Sect. 2 summarizes the relevant state-of-the-art in the use of smartphones as intelligent devices for personal assistance in AAL. The two use cases are discussed, in Sects. 3 and 4, respectively. Section 5 discusses the related experimental results, and finally Sect. 6 concludes the paper.

2 Background

Several applications aimed at monitoring how a smartphone is used are available from popular online repositories. The Apple (iTunes) mobile app store and Google Play mobile app store were searched for inactivity detection apps. The following search terms were used: *web browsing monitoring*, *incoming calls monitoring*, *incoming calls registering*, *incoming calls dashboard*, *incoming calls*, *logging*, *outgoing call*, *lost calls monitoring*, *SMS activity*, *SMS reporting*, and *SMS logging*. We excluded apps that were designed for call recording, SMS broadcasting and virus protection. In addition, data were collected using store description and the developer's website, including app name, functions, and developer information. Each app store was analyzed separately, as some apps were found in both mobile app stores. In line with this, the search terms yielded a total of 101 and 1058 unique apps, in the iTunes and Google Play app store, respectively. A total of 111 apps met the inclusion criteria, out of which 4 apps were available in iTunes, whereas 107 in the Google Play store. Finally, the included apps were segmented as presented in Table 1. In fact, the concept of inactivity may be observed from multiple and complementary perspectives, such as: web browsing monitoring, incoming, outgoing, and lost calls monitoring, and SMS activity monitoring. The web browsing monitoring aims to collect information about the Internet usage by capturing several parameters, such as time spent at each site, sites visited, and bandwidth consumed. Similarly, calls monitoring aims to obtain information on the phone activity in terms of time-stamp and contact of all the incoming, outgoing, and lost calls. Finally, the SMS activity aims to collect information about all the text messages issued or received by the user.

Table 1. Number of apps by topic.

Topic	iTunes	Google play
Web browsing monitoring	0	99
Incoming calls monitoring/registering/dashboard/logging	29	239
Outgoing calls	0	20
Lost calls monitoring	17	250
SMS activity/reporting/logging	55	450
	101	1058

The design of applications and systems for automatic visual recognition of drug boxes is still an open area, despite some proposals and ideas can be found in the literature. Typically, this kind of solutions is conceived to support impaired users, in order to improve their adherence to medication, reduce risks related to errors, and facilitate drug assumption. Benjamim et al. in [12] propose a system based on visual features matching applied to a captured picture of a drug box, to detect it and play audio files providing the user with information about dosage, indications and contraindications of the medication. Visually impaired subjects are supported in taking the right medicine at the time indicated in advance by the doctor. This system relies on a laptop and a connected web camera, to catch pictures of the drug boxes, and performs image processing by using a software developed for a Windows-based machine. Our proposal relies on the use of smartphones, avoiding the need for a personal computer at home and a web camera. This also facilitates image capturing, as the preview of the captured image is shown on the device screen, and it is easy to properly point the device with respect to the box, thanks to the reduced size and weight of the mobile device itself. In [13], an automated inspection system based on computer vision is presented, to inspect prescription drugs with press-through package (PTP). The system is designed to support pharmacists and decrease the rate of errors. This proposal targets different users from those we are interested in, who at home, are deemed not familiar with technology, and require very easy-to-use tools and intuitive interfaces. Yu et al. in [14] address a very complex issue, i.e. single pill recognition using imprint information. This is a quite tricky task, due to the huge variety of pill sizes, shapes, colors, and imprints. In the system herein presented, the drug boxes are subjected to automatic identification, not the single pills.

3 Inactivity Detection Application

At the current development stage, the proposed application for inactivity monitoring features a complete processing engine, i.e. the set of methods to perform inactivity detection, including calls monitoring, alarm notifications, and contacts management in terms of user's preferences contact short list.

As depicted in Fig. 1, the application is persistent in the background, which means after the smartphone's boot, the app is automatically launched in background mode (1. Start app). However, the user may access the application by selecting its icon from the list of installed applications. Since the application is launched, it triggers two main processes such as: the inactivity detection function (2), and the main menu navigator (3).

The inactivity detection is a cyclic service processed by the app, and it is defined by the following algorithm:

1. Start Hour is obtained from mean of the first incoming or outgoing call on the previous n days;
2. End Hour is obtained from mean of the last incoming or outgoing call on the previous n days;
3. The sleep period is defined as [Start Hour, End Hour];

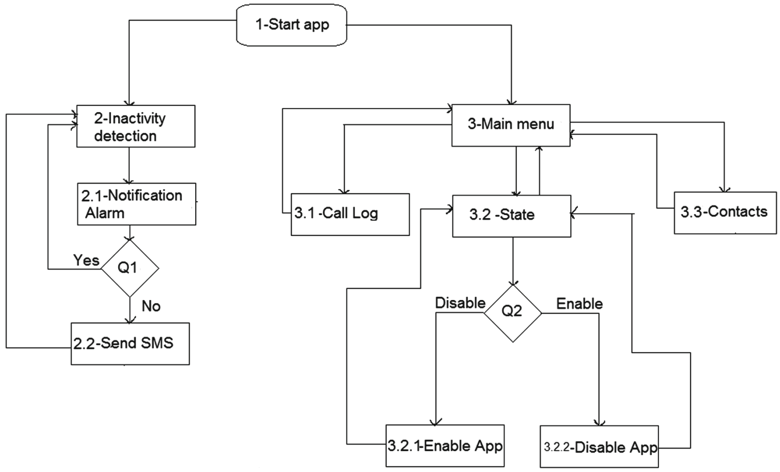

Fig. 1. Workflow of the inactivity detection app.

4. The awake period is defined as $[0...24] \notin$ [Start Hour, End Hour];
5. Maximum interval between calls, including incoming, outgoing calls on the previous n days, is obtained;
6. *if* awake period is *True* and (Current date-time) - (Last call (incoming, or outgoing) date-time) $>$ Maximum interval between calls, *then* Inactivity trigger;
   otherwise
7. *if* the number of consecutive t lost calls is achieved *then* Inactivity trigger.

The *inactivity trigger* means that the user is asked to press a confirmation button in the app (Q1). If this does not happen, the app sends a short message (SMS) to the preferred contact on the user's defined short list (2.2.). The t is a dynamic threshold defined by the user, and may vary from 0 to 100, meaning a percentage of lost calls over all the incoming and outgoing calls.

On the one hand, the app allows Create, Read, Update, and Delete (CRUD) operations on a user's defined contact list (3.3.). On the other hand, the app provides its status information (3.2.) including: daily mean incoming/outgoing calls, sleep period, maximum interval among calls, and app state. In addition, the user may explicitly enable (3.2.1.) or disable (3.2.2.) the app when it is disabled or enabled, respectively (Q2). Finally, a call log (3.1.) is provided including the time-stamp and contact number related with the incoming, outgoing, and lost calls.

4 Drugs Management Application

Both in the literature and in the market there are many ICT-based solutions that allow to obtain drug reference and prescribing material, but they are designed for the healthcare professionals [15]. On the contrary, the application presented in this paper is designed for the final end-users: it enables easy interaction with the device minimising the actions that need to be carried out. The mobile applications uses Optical Character Recognition (OCR) and a string matching algorithm, to detect the name of the drug from the captured image of its box.

OCR is a field of artificial intelligence and pattern recognition aimed at automatically decoding and interpreting the text depicted in an image. The application described here uses an appropriate open source library, called Tesseract [16]. One of the key aspects for the proper functioning of the application is the quality of the captured image: the more the image is defined and properly illuminated, the greater the system's ability to correctly recognize the name of the drug. To support this, the image should be taken by pointing the device camera in front of the drug package, so as not to undergo any rotation or inclination which would produce a non-horizontal projection of the text on the image. Another aspect to consider is the possible presence of dark edges in the picture, that could be interpreted as characters.

In order to ensure adequate performance from the OCR, and avoid the need of taking into account all the previous requirements at the same time, a computer vision library to pre-process and correct the captured image, is exploited. Through well known line detection algorithms, the main lines of the image have been identified. Many of them correspond to the box's edge, this way it is possible to calculate its orientation and rectify the picture so that the drug's name becomes perfectly horizontal.

Once the text is detected from the straightened image, an algorithm able to identify the most likely word (i.e. the correct one) is necessary. For this purpose, error correction and string matching techniques have been evaluated. There are several string matching algorithms designed for word processing, database querying, and search engine implementation. Among them, the Levenshtein algorithm, a well-known process used to determine similarity between two strings, is used [17]. The returned result is called Levenshtein distance, or edit distance, and represents the number of characters to be changed to achieve equality between the strings being compared. Edit operations can either be insertions, deletions, or substitutions of characters. For example, the edit distance between "ho*r*se" and "ho*u*se" is 1.

5 Experimental Results

The application for automatic recognition of drug boxes includes algorithms to perform image acquisition, pre-processing, text recognition, string matching, and data visualization.

According to a typical use case, when the user takes a picture of the drug package, the pre-processing algorithm detects the right orientation and rectifies the image. The rotated picture is fed into the OCR engine that outputs a text. This text could match exactly the real name of the drug, or could differ from it, due to errors in the OCR processing. The text provided by the OCR engine is compared to the name of all the drugs included in the Italian Drug Index, and based on the minimization of the Levenshtein distance computed by the algorithm, the most likely matching name is returned. At this point, the application sends a request to a server to obtain the details of that specific medicine. If it is included in the user's therapy, in addition to indications and contraindications, also the information on specific times and doses of assumptions defined for the user are shown.

As previously mentioned, Tesseract can not correctly recognize the text when the image provided as input is not properly illuminated, contains dark edges or is rotated with respect to the text. In Table 2, the outcome of tests performed in the laboratory environment in different conditions are shown. The text extracted by the OCR algorithm contains more errors when the image features an angled text, rather than the presence of a complex background, or dark borders. The strong misalignment case is certainly the most unfavorable situation for the application, because the system has not been able to recognize the text. This problem has been solved by introducing orientation recognition and picture rectification capabilities. Fig. 3 shows the OCR results for both the normal image, and the straightened one. Nevertheless, since Tesseract returns a string that does not correspond perfectly to the text in the image, the introduction of the Levenshtein algorithm has been fundamental to the proper functioning of the application, identifying within a file containing the names of more than 6,000 drugs, the most likely one. The complete application has been tested using four different drug boxes (see Fig. 4) in bright light conditions. Results are shown in Table 3.

Table 2. Tests performed on the same drug box in different conditions (see Fig. 2) without pre-processing and string matching algorithms, using an Android device equipped with built-in camera featuring 16 megapixels resolution.

Picture	Condition	Results
Figure 2(a)	Aligned picture, low light	94% chars detected, drug name partially recognized
Figure 2(b)	Slightly misaligned picture, normal light	100% chars detected, drug name correctly recognized
Figure 2(c)	Strongly misaligned picture, normal light	0% chars detected
Figure 2(d)	Dark edges in the picture	98% chars detected, drug name correctly recognized

The first line refers to a drug whose name is written in gold color (see Fig. 4(a)), it does not facilitate the detection of the text, however, more than half times the recognition has been successful. The second line refers instead to a drug whose box is very colorful and the text is underlined (see Fig. 4(b)); this prevents the proper recognition of the drug name, while the term "vitamin" reported under the name is recognized correctly, causing misunderstandings in

(a) Aligned picture

(b) Slightly misaligned picture

(c) Strongly misaligned picture

(d) Dark edges

Fig. 2. Pictures of the same drug box in different conditions related to Table 2.

OCR output:
m AmusCxo nominano I
Odluh www M manu

OCR output:
I f Diclofenac EG v
ATCMOMBOS commssn
Didofenoc Sod co P gmg
o a

Fig. 3. An example of OCR outputs for both normal and stretched pictures.

Table 3. Tests performed on 4 different drug boxes (see Fig. 4): for each drug, the success, failure, and misunderstanding percentages, and the number of performed tests are shown.

Drug	Success	Misunderstanding	Failure	Tests num.
Drug 1	53.85%	46.15%	0%	13
Drug 2	23.07%	38.46%	38.46%	13
Drug 3	84.61%	7.69%	7.69%	13
Drug 4	100%	0%	0%	13

the drug identification from the list of names. Graphics of the last two boxes, shown in Figs. 4(c) and (d), is very simple, thus, as expected, the results are highly positive.

Further tests are foreseen to evaluate the usability and acceptability of the proposed system by the target users, particularly the elderly in a real life scenario.

(a) Drug 1 (b) Drug 2 (c) Drug 3

(d) Drug 4

Fig. 4. Drug packages related to Table 3.

6 Conclusion

Well-being and good physical health are commonly associated to an active lifestyle, that also means being able to maintain stable social relationships and contacts with a specific group of fellows and relatives. As a consequence, the way a modern communication device such as a smartphone is used, to make calls or send messages, may reveal information on the activity or inactivity degree of the owner. This is a very hot topic in the Active and Assisted Living domain, and the application presented in this paper showed it is possible to unobtrusively gather information on the user's inactivity, by simply collecting data from the smartphone usage, through a simple though effective threshold-based algorithm.

Consistently with the increasing use of smartphones even among older adults, the number of apps aimed at supporting the user in organizing and taking their medications is also growing, across the dominant smartphone platforms. Most of them rely on a proactive behavior of the user, who is requested to interact with the device by answering questions or feeding data on medication assumption events. The application for drugs management presented in this paper adopts a different approach, that aims at minimizing or even avoiding the need for the user to input data or interact with the device, by resorting to the automatic processing and recognition of the drug box, through a picture captured by the smartphone camera. Despite some challenging issues that may occur, due to the way the picture is taken or to environmental conditions, the experimental results showed the technical feasibility of the approach, which is going to be complemented by future tests on usability in real-life conditions.

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