Annexes

A-Tech4SocialChange Article

Tech4SocialChange: Technology for all

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Abstract. Universities and other educational institutions are sometimes accused of not being involved in real world problems, focusing more on the scientifically value of the work produced and not on the humanitarian value. A way of encapsulating the second with the first is the main goal of the Tech4SocialChange that is described here. An innovative database/repository of challenges with real impact in the world is created and given access to people with skills and knowledge to tackle them. Also the work made by researches can be stored and used in a project and the researcher gets recognition for it by becoming referenced in that project. A web application has been built as a prototype for this process and can be accessed in www.tech4socialchange.org. It has been planned and developed by a team of students and researchers of the Department of Informatics Engineering of the University of Coimbra and is currently being constantly altered according to feedback received by the testers in the same team. This paper presents an application that aims to help people that face certain challenges every day and motivate those that have the skillset, to tackle these challenges, into doing so.

Keywords: social problems; university-society relation; innovation; entrepreneurs; problem solving;

1 Introduction

By taking advantage of the academic world, which is sometimes accused of not taking into account real world situations, and providing a database/repository of problems that have a real and direct impact in the lives of people someplace in the world, the means and/or knowledge to tackle these problems are provided. Tech4SocialChange's goal is to be this bridge that links universities to the problems affecting people around the world.

Researchers that sometimes struggle to find interesting subjects for their work get a database where they can consult and start building solutions to be applied in the real world. After publishing their work, they can also share it with the community, so it can be used in projects that have an impact.

Students are also an important part of this process. Typically, they have assignments in their courses that have a purely academic value. By letting students work on real world problems, the assignments would gain an increased value with real impact in the world, which also gives the student an increased value and knowledge for their professional career.

The problems can be submitted by anyone that faces or has knowledge of some kind of challenge or difficulty, in either their own or someone else's life, and that would like to see it solved/tackled by people with the skills to do so.

The process that leads to the solving of a problem is incremental. First it needs to be clear and well defined to let the solvers understand the context and needs of the problem. Next, based on the information provided about it, the solvers need to come up with ideas and develop a project that answers all or most of the problem's needs.

After this, a project must be chosen to be developed and applied in the real world. This choice must be made by the ones that are closer to the problem. In this case, they are the ones who submitted it in the first place. However, some people might not have the skills or knowledge to verify if a project actually responds to all of the requirements in the problem's description. For this situation, specialists are needed; they are people with experience in analyzing and verifying the requirements of a project and validating these in respect to the problem.

In this process, three types of users have been identified:

- Problem Makers create/submit problems.
- Problem Solvers come up with ideas and create projects with the intent of solving the problems.
- Problem Specialists have experience in matching a problem's needs and a project's requirements.

Also, all three types of users can help in the first phase (definition of a problem) by asking questions about the problem to the Problem Makers. In the second phase, the Problem Solvers use the information gathered to think up solutions and create projects. In the third phase, with the help of Problem Specialists that recommend projects to the Problem Makers, a decision has to be made about which of the proposed projects will be developed in the next phase to, ultimately, solve the problem.

The fourth phase is the actual development of the project. In this phase, a simple tracking method is provided with a task list. This list is updated every time a new step in the project planning is created or concluded. This way, the Problem Solvers can give feedback on the project's progress.

The fifth and final phase corresponds to the project in its final state: ready to be implemented and used in the real world. It is the responsibility of the project's team to evaluate if its final state has been reached.

The five phases can be better observed in Fig. 1 where each one is named respectively.

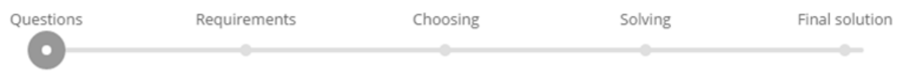

Fig. 1. Phases of a problem

To submit, and to help with the definition of the problem, some questions are provided in the beginning to the Problem Makers. These questions act as guidelines and must be answered before presenting the problem to the community:

- What problem do you want to solve? Or what do you want to change?
- Why does this problem exist?

- What is going to change in the world after the problem is solved?
- What product could be invented? What impact it should have?
- Is there a complete or partial solution to this problem? What is its limitation?
- Do you have something that might support a solution?

The first two guidelines aim to gather information about the environment in which the problem occurs. The next two are about what to expect of the solution to build and the impact that it will cause in response to the problem. The last two guidelines are optional and refer to the existing alternatives or solutions to the problem: why they don't apply to this problem in specific and if there are resources available that can be used in the final solution.

2 State of the art

There are already projects with the goal of tackling social problems and developing solutions to them. Tech4SocialChange innovates over these through a novel process of processing problems, which is described in section III.

2.1 HeroX

HeroX [1] is a profitable platform that allows anyone to create a competition and define the conditions for its completion. These competitions are funded by whoever launches them and are based on unsolved problems that are to be solved by combining crowdsourcing, competition and collaboration.

A challenge is an online competition where people all over the world have the opportunity to solve or build a solution. The winner gets prize money, awarded by the entity that created the competition. To help turn a problem into a challenge, some guidelines [2] are provided by HeroX:

- What problem do you want solved?
- Why does this problem exist?
- What breakthrough are you committed to creating?
- What is the "finish line" or bullseye?
- How long will this challenge last from day 1 to day "won"?

These competitions are managed by an HeroX team that takes care of team selection (they choose who enters the competition or not; the criteria for this choosing depends on the requirements initially set for the competition), management and judging.

To participate in a competition, the users must pay a fee; this ensures that the competitors are committed to finding a solution to the problem being tackled. It also creates a sense of assurance to the entities or groups funding these competitions.

A competition´s winning conditions are set on the beginning and are used by the HeroX team to determine the end victor.

The rights to the final solution can differ from challenge to challenge. They can be attributed to the developers, the creators of the competition, HeroX or put under some specific license.

2.2 OpenIDEO

It is a platform that allows for the splitting of the innovation process into phases and building on the ideas of people.

Challenges and programs are created, using crowdsourcing, as a means to tackle problems around the world.

A challenge can last from three to five months and is focused on a single issue that the community can work on and find and develop a solution. A program is a long-term partnership where a specific grand issue (climate change, for example) is tackled and numerous challenges, events or other activities are released [3].

All challenges require financial sponsorship to cover their own costs associated with managing and providing tech and community support. This approach is based on IDEOs design thinking. Tim Brown, CEO of IDEO, states that:

“Design thinking is a human-centered approach to innovation that draws from the designer's toolkit to integrate the needs of people, the possibilities of technology, and the requirements for business success.” [4].

This methodology uses skills people have but get overlooked by the standard/popular problem-solving methods. This concept allows for the final solution to be emotionally meaningful and also functional as it integrates feeling, intuition and inspiration with rational and analytical. There are three concepts to keep in mind: inspiration (is the problem or opportunity that motivates the search for solutions), ideation (process of generating, developing and testing ideas) and implementation (path that leads the project to the real world).

In the end, there is a selection of winners, chosen by the sponsor of the challenge and the OpenIDEO team. This selection is based on the challenge criteria and on the OpenIDEO team’s skills to implement it. All other ideas can be developed further and used/adapted on other challenges that meet their purpose.

2.3 Others

A. Innocentive

Innocentive uses crowdsourcing solutions that are built for business, social, policy, scientific and technical challenges. These challenges are competitions where the objective is to find a solution to a problem that a client (group or company) has submitted into Innocentive. This submission is based on some criteria, relevant information about the problem (Innocentive helps determining what is important or not) [5]. Also, the winner is determined by the entity that created the challenge and also the award. Innocentive can help with the winner selection but ultimately the decision is of who submitted the problem.

After a challenge ends, the whole solution is given to the entity, including the rights.

The problem solving network and tools that Innocentive already has presents a big motivation for groups, companies and other entities to submit their problems and have them being solved by other people. To the solvers (single individuals or teams), the prizes that are awarded are the main motivation to use Innocentive to work on the solving of problems presented in the platform.

B. CodeForAmerica

CodeForAmerica partners with local governments to build open-source technology and train groups of people to improve government services. It focuses on four key government services:

- Health and human services
- Economic development
- Safety and justice
- Communication and engagement

The way CodeForAmerica gets people and governments to participate is through a fellowship program. This program joins technologists and local governments across America for a year, while working full-time. During this period, the technologists become a part of the community, researching user needs, meeting with stakeholders and proposing solutions. This way, with collaboration from the government, it is possible to build technology that is user-centered and data-driven [6].

The final product of this fellowship is, generally, an early stage application that improves a government service or function. The period of fellowship is a way to encourage innovation and improve risk tolerance inside the government.

Every year, eight to ten governments are selected and twenty-four to thirty people are chosen to the fellowship program through a competitive selection. The government selected has to be in the United States and has to want to work on projects involving health, economic development, safety and justice. They also have to provide support to the technologists that are helping and also be able to support the work that these leave by the end of the fellowship.

To enlist in the fellowship as a fellow/technologist, an application has to be submitted through the page in the website of CodeForAmerica.

Usually a fellowship costs 440.000 dollars. Of this investment, 50% is covered by the local government, to cover for expenses of the team (benefits, travel, training, salary). The other half of the investment is raised by the government with the help of corporations, foundations and individuals, which helps cover the costs of management of the fellowship.

C. Hack4Good

Hack4Good [7] is an event where any technology enthusiast can participate.

Each event has problem as its main theme. The goal is to find a way to solve or change people's actions towards this problem. The event is global; in a single day, groups of people around the world gather to build prototypes that address different challenges inside the problem.

The problem is divided into challenges to let people focus on more specific issues instead of trying to find a solution to a broader one, like climate change. These challenges and the problem itself are set by NGOs, government organizations and experts in fields related to the problem.

Teams of solvers have one days to find a solution, create a prototype that tackles the problem and make a deep impact in the world. Judges, in each location, are made up of technological experts and are from fields related to the problem being addressed at the event.

The judging is based on the potential of impact that a solution might cause. After a first selection, a solution will move on to a judging at the global scale, competing with the best selected from other locations with different judges.

There is no specific prize for the winners. At 12 of September of 2014, where the theme was climate change, the solutions selected at the global scale were presented as a part of New York City Climate Change Event alongside with the United Nations Climate summit.

3 Tech4SocialChange

Students often have assignments with mere academic value. If these assignments could be directed to real world problems then not only it would serve as an increase in the assignment's value, but also as a real world work experience.

Teachers sometimes struggle to find exciting work subjects that incorporate all of the essential class material. Having a place where they could find projects or subjects that allow the students to come up with ideas to work on during the course would be a major help. This also works for researchers that have difficulties finding exciting subjects to apply their work, or even share their results with people involved in projects with a real or big impact in the world.

As such, all these people would be making the world a better place while improving the value of their own work. This is Tech4SocialChange´s audience and goal: to bring the academics' technical knowledge closer to solving the world's problems.

In this section we present a prototype (1) that implements the process presented in section I. This prototype consists on a web application that has the following main objectives:

- Create a user
- Create problems
- Create projects associated with problems
- Correctly manage the phases in which a problem is presently in
- Allow researchers to submit their work
- Reference researches in projects

2.1 User perspective

There are three roles already mentioned before: Problem Maker, Problem Solver and Specialist. In addition to these, there is the researcher. This last one is not a role but a type of user, as any user can submit research and thus be recognized as a researcher in the application.

A. Create user

To register a user, it is requested the input of the name of the user, an email to use in the login and a password.

After the registration, an email is sent to the address provided, asking the user to verify its account. This helps in identifying the active users in the application. If, after two days, the user doesn't activate his account, it is deleted.

When the activation is done, the user can login into the application with the email and passwords provided.

The first time the user logs in, it is prompted to choose whether it wants to become a Problem Maker or a Problem Solver, and if he wants to become a candidate to Problem Specialist. This choice can be viewed in Fig. 2.

Fig. 2. Choosing the type of user

B. Create problem

If the user chooses to become a Problem Maker, he can create a problem in the platform. To create the problem, only a title is asked initially. Problems have three states:

- Public, every user in the application has access to the problem
- Private, only the Problem Makers in the problem's team and the Problem Solvers in the solution's team can see the problem
- Draft, only the Problem Makers in the problem's team can see it

After submitting the title of the problem, its state is set to private and its phase to the first, with no deadline set.

The problem can be edited in the page shown in Fig. 3. This page asks for the title of the problem, a brief description (or pitch), keywords (which are used when searching for the problem and that represent the fields or subjects where the problem is inserted) and the deadlines for the Questions and Requirements phases. The first deadline must be set before the second and none of the two can be set before the present date.

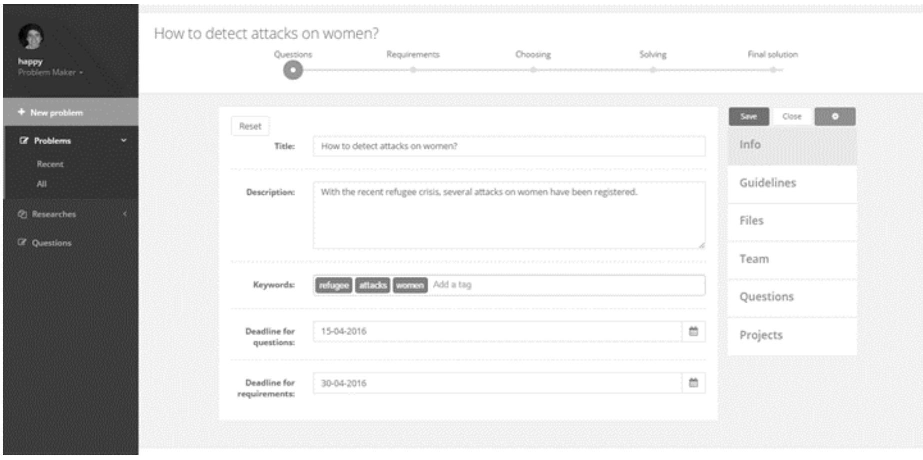

Fig. 3. Editing a problem

The guidelines used to define the problem can also be set in the page of Fig. 4. All the obligatory guidelines (the last two are optional) must be filled to set the problem public and be accessible by other users.

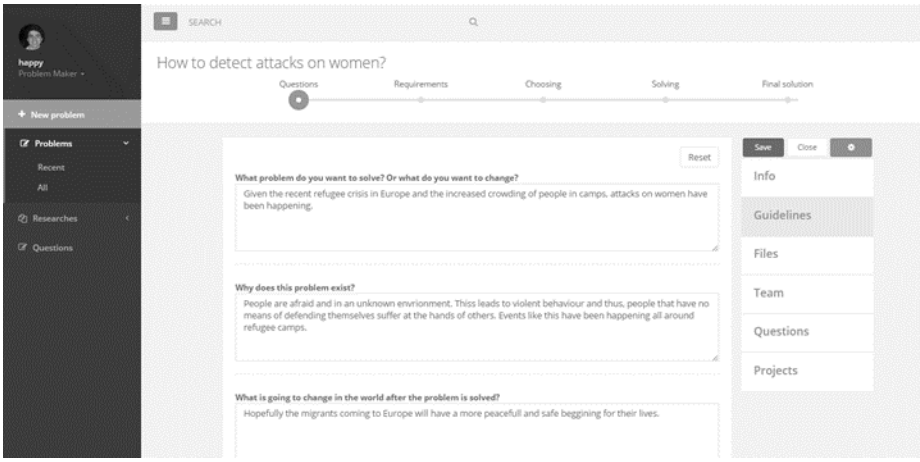

Fig. 4. Editing a problem

Files can be shared with team members and new members can be added to a problem. Another component that can be managed in the problem edit page, are the questions that are posted by users. In Fig. 5 questions are shown to be divided into answered and unanswered. A comment in an unanswered question can be marked as an answer and the question is moved to the corresponding list. The only users that can mark a comment as an answer are the Problem Makers in the problem's team.

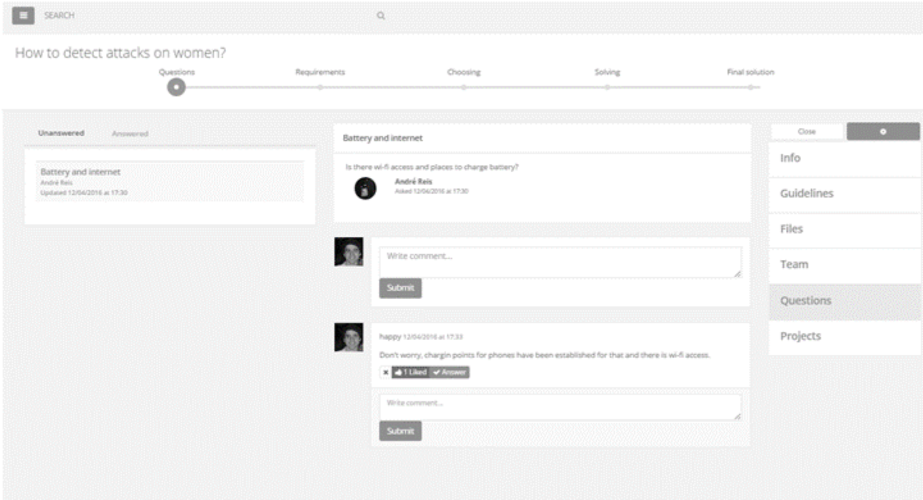

Fig. 5. Questions on problem edititng

When all the obligatory information is set, the problem can be set to public in the settings or editing pages.

The problem profile can now be seen by every user in the platform as it shown in Fig.6. At the top of the page, the problem's current phase is indicated.

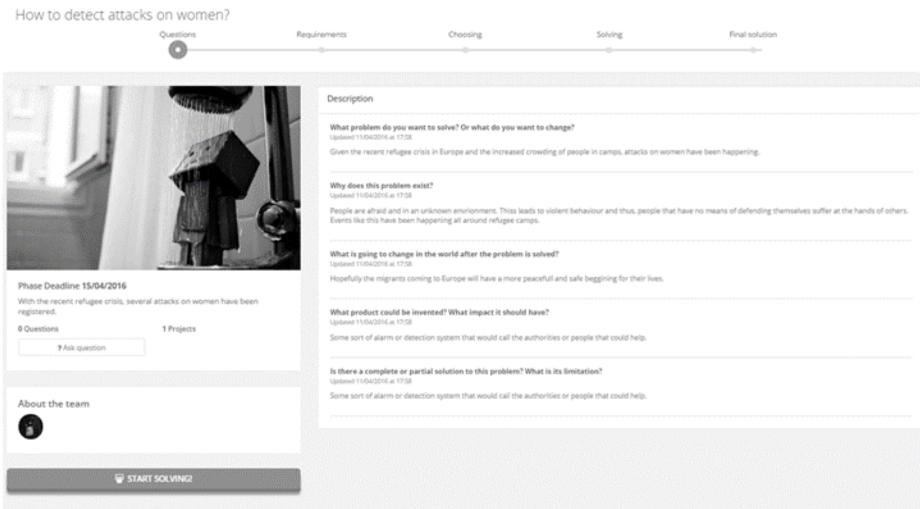

Fig. 6. Problem profile

C. Create project

A Problem Solver can only create a project if it is associated with a problem. This means that he first needs to access a problem profile in order to create an associated project.

Just like a problem, a project only needs the title to be created, being immediately set to private after its creation.

Following the creation is the editing page, in Fig. 7. This page allows the Problem Solver to edit the title and type a brief description (or pitch), keywords representing the subjects/fields where the project is inserted, a full description of the project and an estimated deadline for the completion of the development.

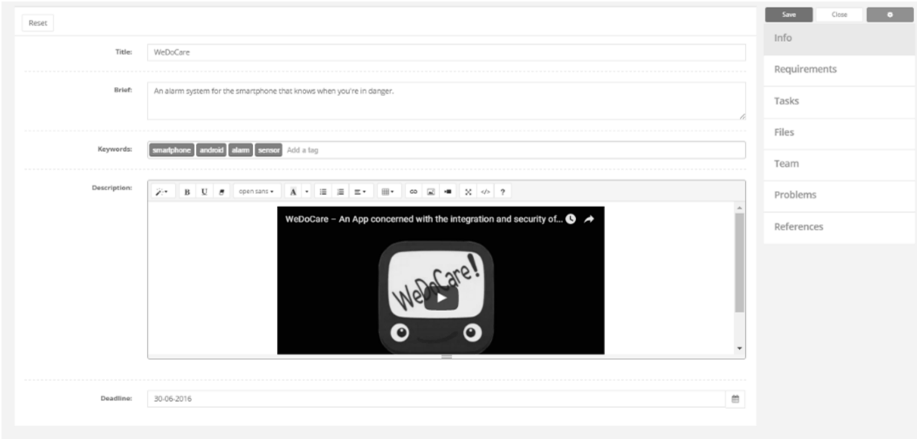

Fig. 7. Editing project

In the editing zone it is also possible to add the project's requirements, as seen in Fig. 8. These requirements are then shown in the project's public profile and can include images, video and text.

Fig. 8. Project requirements

The Problem Solvers working on the project can also manage the tasks involved in its development, like it is represented in Fig. 9. These tasks have three states: to-do, ongoing and completed. They can also be dragged from one of these lists to the other.

A task needs a title. In fact, it is the only obligatory field; it also possible to add a description, assign one or more persons from the team to complete the task and define a due date.

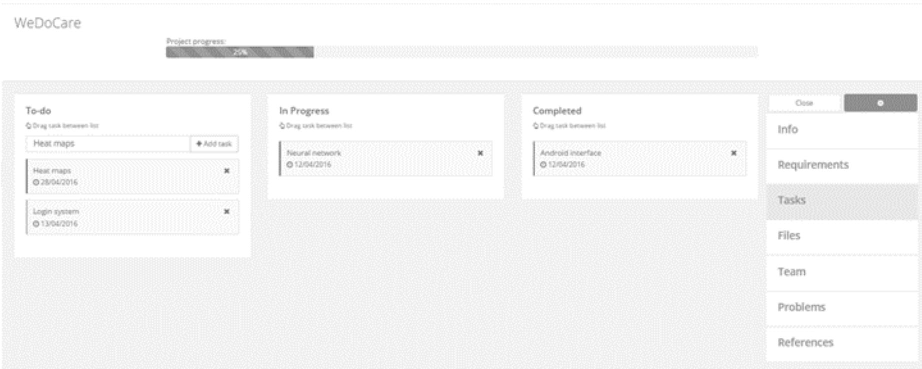

Fig. 9. Project tasks

Like a problem, files and new team members (Problem Solvers) can be added to the project. Also, the problems that the project is associated with (trying to solve) can be listed in the editing. Another component that can be listed are the researches being referenced by the project.

The project's state can be changed in the settings, although to make it public, the project needs a deadline (estimate) for its completion. Also in the settings it is possible to delete or leave the project.

If the project is public, then everyone can access its profile (Fig. 10). Here, the project's profile image (which can be set in the files area in the editing page), title, description, keywords, team and requirements are presented to the other users of the application.

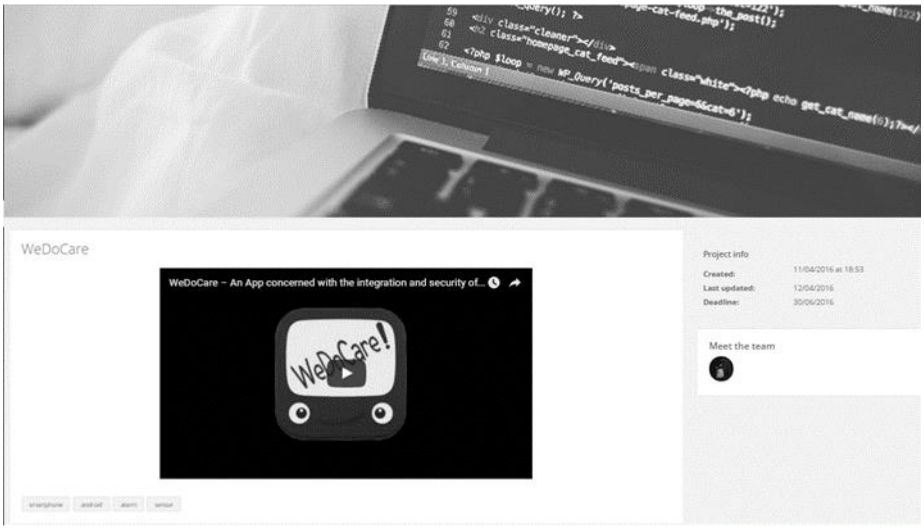

Fig. 10. Project profile

A Problem Specialist not belonging to the project's team can recommend the project as a solution, through the project's profile.

D. Create a research

Any user can create a research by only typing the title of the research. After a research is submitted, its editing area (shown in Fig.11) is made available, allowing the change and input of new information. Title, description and keywords to use in the search for this article can also be changed in this page. The research has two states, public and private. By default, the latter is enabled.

Fig. 11. Editing research

Files can also be uploaded to a research, although, contrary to problems and projects, these files are shared with the community and are considered attachments to the real research developed by the user.

Similarly, to problems and projects, new users can be added to the team of the research. Projects that referenced this research are also listed in the editing area.

When a project is set to public, its profile is provided and shown to other registered users. If the user accessing it is a Problem Solver, then an option to reference a particular research is enabled. Comments by other users can be left in the research's profile.

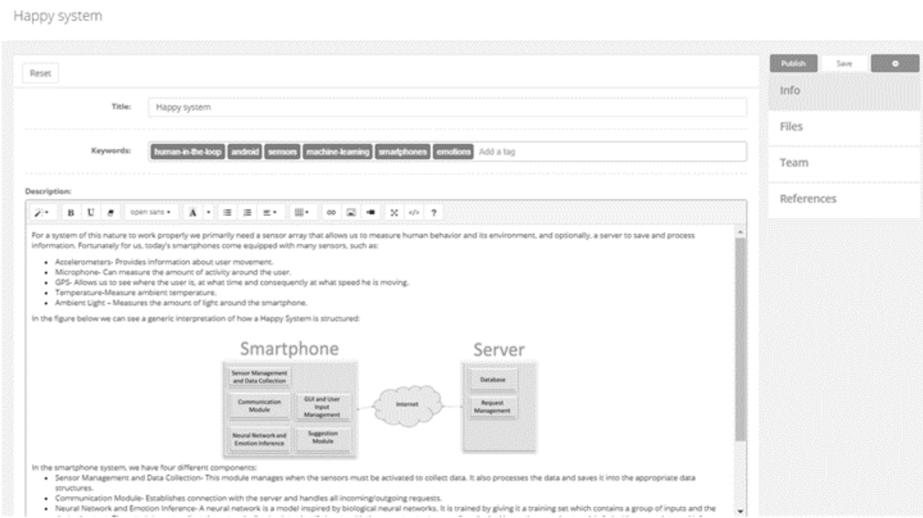

Fig. 12. Research profile

2.2 Comparison

Table 1 shows how similar aspects of two different platforms work in comparison to Tech4SocialChange. Even though others were studied, only two were included due to being the ones closest to the context of Tech4SocialChange.

Table 1. Comparison with state of the art

	Tech4SocialChange	***HeroX***	***OpenIDEO***
Audience	Students, teachers, geeks and researchers	Anyone with sponsorship	Anyone
Motivation of use	Have problems tackled by experienced people in various areas Work on problems that have a real impact in the world Have research work be applied in projects that impact people's lives	Monetary prizes Sharing of competition-based know-how, for a fee	Solutions need to be sponsored Work on problems that affect the real world
Problem/Project selection and support	Anyone can submit a problem Problem criteria is defined by community and submitters Submitters choose the final solution; they can ask for help that is provided by Problem Specialists Projects only advance to development after they have been chosen. This prevents wasting time and resources building a solution that is not used after	Only accepts challenges that are sponsored Provides guidelines to define the problem An HeroX team manages the competition HeroX team helps in the choosing of a solution. along with the creator of the competition	Only problems that are sure to become projects A team from OpenIDEO defines the criteria for the problem The submitter and the team of OpenIDEO choose the solution according to the challenge criteria and the skills needed to build the solution
What happens when a solution is chosen?	Delivered to the NGO or other entity that submitted the problem Projects can be further developed and used on other problems	Prizes are awarded to the winner and project stays idle	Solutions are delivered to the OpenIDEO team that builds it and delivers it to the problem submitter. The solvers stay idle

		as well as the project

HeroX allows for any sponsored entity to create a challenge/competition, which is normally based on a problem that the entity is currently facing. It provides management and counselling along the way for a certain fee. Also, to participate or access a challenge the user needs to pay, this ensures commitment and also helps in covering the costs of the competition.

OpenIDEO lets anyone submit a challenge or a social problem, to be evaluated and defined more clearly, ensuring that only problems that are sure to become projects are released to the community. Moreover, the selection process of solutions is based on OpenIDEO team's skills. This might result in a great solution being discarded.

Tech4SocialChange is aimed at a different audience, which is interested in the problem's context and the experience and recognition to be gained. Anyone can participate in submitting, defining and solving a problem. Even though prizes aren't awarded when a problem is solved, the Problem Solvers are given full recognition from Tech4SocialChange´s side.

Some additional features are also provided based on the audience:

- All problems and projects are stored in the system and are accessible at all times. Projects can be re-used in different problems.
- Projects that have not been chosen do not stay idle; Problem Solvers can further develop them and present them on other problems.
- A research repository is also provided, letting researchers and scholars submit their work where it can be used and referred in projects and receive comments or ideas that may contribute towards its further development.

However, there are some concepts from problem solving that were adapted from other platforms into Tech4SocialChange.

For example, OpenIDEO's methodology of using skills people have that would otherwise get overlooked by the standard/popular problem-solving methods was taken advantage of. This concept allows for the final solution to be emotionally meaningful and also functional as it integrates feeling, intuition and inspiration with rational and analytical support. There are three concepts to keep in mind: inspiration (is the problem or opportunity that motivates the search for solutions), ideation (process of generating, developing and testing ideas) and implementation (path that leads the project to the real world). The three concepts motivated the creation of the different phases that a problem undergoes until a solution is found.

Also, HeroX's understanding of problem criteria was used to learn the key guidelines on how to better define/explain a problem, previously mentioned in section I.

3 Innovative research issues

As it is important to make a link between the researcher's work and real-world problems, the same link may also be applied a company's projects. As such, a search engine that makes a matching between research, companies and problems is necessary. A first version of this function is being developed using ElasticSearch - an open-source, scalable, full-text search and analytics engine. It allows to store, search and analyze big volumes of data and is highly used in applications that have complex search requirements.

At a structural level, the matching is done with simple text, matching the titles and keywords that represent the areas or subjects that a certain project/research/problem is inserted on.

Another important research venue is that of the intellectual property of the projects developed. Currently, the projects that are submitted to Tech4SocialChange are completely open-source and anyone can make use of the information and the products made available by the Problem Solvers. Those that do not wish for others to access their work can do so by setting a project as either "private" or "draft" (the first option shares it only with other teams that work on target problem, the second shares it exclusively with the team of the project itself). However, this might not be ideal for companies that wish to participate in Tech4SocialChange. As such, improved models of intellectual property will be object of future study and applied to the prototype.

A related research objective is understanding the language that both companies, entrepreneurs and NGO's have and create a bridge between them: what terms and visual aids can be used to minimize the gap between these three?

There is an interesting approach, presented in [8], concerning web-based collective design platforms. These platforms make use of their community to design and build solutions. OpenIDEO and another platform, Quirky, are studied to determine the main values that such a platform needs in order to motivate users and enhance the quality and diversity of solutions that are built. Tech4SocialChange is such a platform and since the study used, as case study, one of the platforms in the state of the art, it is interesting to determine how these values apply in Tech4SocialChange, which focuses on the academia and social problems, and perhaps further improve these values and/or set new ones.

Another objective is creating a model of specialization in different areas. What this means is that Problem Specialists are not only people specialized in problem definition but can also be specialized in different areas, or subjects, and be recognized as such. This way, projects can receive support from users that have knowledge about their specific subjects. It is a way of introducing help to inexperienced people (students for example) from others with greater experience on the field. This results in both better project results and greater learning experiences for students.

To determine and select the experienced people (Problem Specialists), a points system is currently being developed, and refined, based on the events, actions and achievements of the users (e.g. having a project chosen as a solution).

Nowadays people's interests and lifestyle are increasingly more integrated into the Internet: the Internet Of Things (IoT) uses low-cost technology that has a high potential of solving people's everyday issues in an non-intrusive way. Using this information to better match Solvers and Specialists to problems and researches that have a bigger connection with them is another research objective. Motivate people to work on subjects that interest them more. This would obviously be a major asset to problem solving and help tackling the challenges presented by Problem Makers.

4 Conclusions

There is already a prototype of the application that can be accessed in www.tech4socialchange.org. It was developed by a team of students and researchers of the Department of Informatics Engineering of the University of Coimbra.

By allowing social problems to reach the academic world, we intend to not only solve them but also to approximate universities and institutions to real world situations and create many opportunities and cases of big impact in people's lives, in various parts of the world.

The next steps involve changes according to feedback being received by people that are helping in testing the prototype and also better support to tracking the contribution of people involved in problems, projects and researches.

An important link that it is hoped to be established is with entrepreneurship. How can Tech4SocialChange help the growth and establishment of entrepreneurs by finding situations in which their ideas and projects can be applied?

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Annex B-Wireless Sensors and Mobile Phones towards Green Behavior Article

Wireless Sensors and Mobile Phones towards Green Behavior

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Abstract - Mobile phones were developed with the general objective of supporting conversation. However, more and more people are using mobile phones for sensing and supporting their daily lives. With some signal and digital processing methods, every mobile phone could be used for sensing different activities or behaviors that people do every day. Increasingly, wireless sensor networks (WSNs) are being integrated with Mobile Phone Sensing and this trend will be seen mainly in urban environments. This represents an opportunity, since both WSNs and mobile phones have the potential of being applied in the search for "green solutions". That is, people-centric and environment-centric “green applications” can be developed to improve human life and the environment. It is interesting to relate these two types of applications in order to motivate people towards having a greener behavior. However, this leads to multiple challenges. This paper presents a vision about this integration and also an overview of these challenges. We will also show a case study and its implementation using the mobile phone as a FogPhone system, which aims to improve the people’s quality of life.

Index Terms— Mobile phone sensing, wireless sensor networks, human behavior, environment, FogPhone.

I. Introduction

THE number of mobile phones continues to grow. According to 4G Americas, in December 2015, there were 7.3 billons of mobile subscriptions around the world[1]; so that the number of mobile devices connected is greater than the number of people on Earth. For this reason the mobile phone is the most popular device in the world.

New technologies are now oriented to provide connectivity to people, things and applications through the Internet. The network that allows these facilities is the Internet of Things (IoT), which enables the exchange of data for intelligent applications and services to be developed. In accordance with 4G Americas, it is predicted that over 50 billion IoT devices will be

1 http://www.4gamericas.org/en/resources/statistics/statistics-global/

connected with around US $8.9 trillion in annual revenue by the year 2020 [1].

While WSNs were initially being developed as specialized hardware, their development in conjunction with mobile phone use is growing day by day. More and more sensors are integrated into mobile phones and there are many applications that are using the mobile phone for getting information about various variables, such as position, temperature, human behavior, etc. This research area is known as Mobile Phone Sensing (MPS) and it analyzes how the sensing of every-day activities and their environmental impact is possible through mobile phones. It integrates areas such as wireless sensor networks and web sensing.

Y. Xian et. al [2], show a survey of Mobile Phone Sensing systems, where several applications are analyzed and classified as either participatory or opportunistic sensing systems. In the work realized by N. Lane et. al. [3], a survey of Mobile Phone Sensing and its challenges are presented, together with a proposal of a simple architectural framework that uses the mobile phone as a single sensing system. Our contribution, on the other hand, focuses on presenting a vision about the integration of Wireless Sensor Networks with Mobile Phone Systems and how these can help to improve the lifestyle of people as well as their interaction with the environment, promoting environmentally conscious acts.

In section II, we will present the main notions about how the processing is localized in the edge devices or the Fog of Things, the main concept behind the integration of WSNs and mobile phones. Section III will describe the concepts of mobile phone sensing, the main sensors that exist in smartphones, some well-known applications and how WSNs are increasingly integrated into mobile phones. In the section IV, we will present our prototype of an emotionally-aware FogPhone system that attempts to positively impact people's day-to-day mood and the way people move around their city. Then, in section VI, we will show how human behavior can be inferred with the use of mobile phone sensing. The conclusions and guidelines for further work will be provided in the last section.

II. FOG OF THINGS

Cloud computing is responsible for the biggest change in the way people work, live and, mainly, do business in the recent years. It evolves the use of technology from an ownership paradigm to a subscription based and pay-per-use methodology. Based on three main service levels - Infrastructure, Platform and Software, it leverages the know-how on clustering and virtualization to provide elastic computing and storage services with high-availability assurance. In fact, cloud computing is nowadays the preferable platform for many business solutions. It does not require initial investments, resources are elastic and services are quickly deployed and available. Organizations are allowed to focus on the business model, leaving the management of infrastructures, platforms and software at the cloud's provider side.

However, today's devices, which make up the Internet of Things (IoT) and Cyber-Physical Systems (CPS), are becoming increasingly more heterogeneous, mobile and intelligent. Theoretically, everything from lightbulbs to fridges, microwaves and coffee machines will be soon connected to the Internet. In fact, some studies estimate that human beings will have an "Internet of Things" with 26 billion connected devices by 2020 [4]. These devices represent an untapped resource that is available on site; that is, it no longer makes sense to rely on distant service providers when we wish to communicate with neighbors to handle local tasks and information. Thus, an efficient cloud should "descend" to the network edge and become "diffused" among the client's devices in both mobile and wired networks, whenever necessary. This means that the traditional "cloud" architectures are "descending" to the network edge and becoming "Fog" (Fog of Things - FoT).

To date, as far as we know, few research has delved into investigating the integration of WSN with mobile phone systems within the cloud, supported by IoT architectures and shared approaches. Consequently, this paper analyzes the next generation of WSNs that are becoming more integrated with the personal mobile phones. This will require significant conceptual changes to the traditional cloud architecture, endowing it with new functionalities based on a fog paradigm. As far as extending the cloud to the IoT and CPSs is concerned, new advancements in the state-of-the-art need to be considered. Most of the current sensing techniques have to be investigated and adapted to the highly distributed and heterogenic environment of these embedded systems. The outputs of these techniques also need to "close the loop" and affect the way the embedded systems collaborate, in order to achieve dynamic levels of security/privacy and higher system performance. All of these tasks are highly challenging and, as a consequence, innovative solutions have to be found by promoting the use of this new generation of cloud through virtual environments that facilitate the construction of new applications and products.

The goal of this distributed cloud is to quickly assist local nodes by maintaining and using data locally, avoiding the cost and latencies of transmitting to a centralized cloud. Thus, the integration of WSN and mobile phone sensing benefits when processing and data storage tasks are performed on local devices; that is, these operations should be performed near the edge of the fog.

III. The Mobile Phone and Sensing components, Areas and Applications

The mobile phone works as a system of sensors that empowers the collection, processing and distribution of different types of information [1]. There are some challenges to consider when a mobile phone works as a system of sensors [2], like programmability, continuous sensing and phone context. In the case of the programmability, the challenge rests on the way of accessing the low-level sensors; however, the new mobile phone technologies offer open source platforms with easy access to their sensors. Background processing and multitasking can support the need for continuous sensing. So, the consumption of energy can be managed through low-energy algorithms. Finally, the phone context problem can occur when the user carries the phone in unexpected ways, which may affect the data collected by its sensors.

A. Sensors

Sensors provide information about parameters that enable the inference of human behavior. Many sensors are integrated in the mobile phone, like the GPS, accelerometer, gyroscope, digital compass, light and proximity (Fig. 1). Also there are other types of sensors such as the microphone and camera, which are general purpose and have a great potential in obtaining information about people's behavior. The combination of all of these sensors represents an opportunity to improve the collection of data about people and their environments. For example, the combination of accelerometer data and the information from the GPS allows us to know the mode of transportation of a user [2]. The human interaction with social networks enables us to infer information about the people's context.

Bluetooth and WiFi can be used as sensors for human activity recognition. These technologies allow the inference of social interaction with other people or can also be used to obtain the user's location.

Fig. 1. Sensors on a Mobile Phone

All mobile phones have a microphone; despite being rarely seen as a sensor; this component permits us to obtain a lot of information. In fact, we can develop many applications using sound to obtain information about the environment and the user. Through voice, a person can transmit moods or emotions. For example, we can know when a person is in a noisy site, which, in turn, can be correlated with changes in mood (loud environments can be stressful or joyful, depending on the context). Thus, it is possible to develop applications for mobile phones that use mobile phone sensors to improve the quality of human life or to infer human activity.

Figure 2 represents a block diagram illustrating the process of acquisition of information with a mobile phone using two sensors, the microphone and accelerometer. First, we need extract the feature selection of data collected by the microphone and accelerometer; then, we should enter to classification process based for example in mathematical algorithms for machine learning. With the microphone, we can know if the user is talking or not, while with the accelerometer may provide us with information about his activity (e.g. walking, running or sitting). Finally, we combine these results in the inference engine block and obtain as a result the human behavior information.

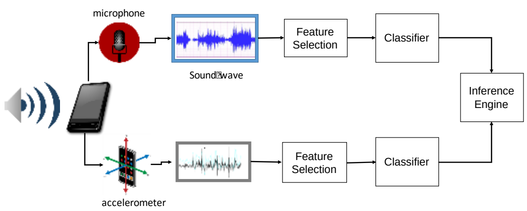

Fig. 2. Diagram of blocks for acquisition and obtained of information using the mobile phone sensors.

B. Areas

MPS can be applied in different areas, for example: health monitoring, traffic monitoring, commerce, environment monitoring, social interaction, monitoring human behavior and special purpose applications [2]. As presented by Yang Xiang, et. al. [2] a new concept named Urban Sensing defines systems based in sensors that collect data from the urban landscape and change the environment. These researches present sub-classifications of urban sensing: participatory sensing - where the user is directly involved in the sensing action, and opportunistic sensing - where user is not aware of active applications.

C. Applications

MPS not only offers information about human behavior, it also permits to help people. When we implement applications where information about the human state can be obtained, this information can be applied to improve or resolve people's problems; the idea is use technology for human service and for resolving different social issues. The following paragraphs describe two interesting examples of applications in the area of social interaction.

CenceMe is a participatory MPS system that was proved in the Dartmouth University. It uses the sensors in the mobile phone to classify different people events (e.g. walking, sitting) and states (e.g. happy, sad) and shared this information using online social networks such as Facebook or MySpace [5]. Also, this application obtained information about people's habits and their environment. The authors proposed the following process for the implementation of CenceMe:

- Sound samples were obtained through of the microphone. Discriminant analysis clustering was used to classify between talking and no talking.
- Accelerometer was used to determine the user's activity, such as sitting, walking, running and standing.
- Information about which people were around the user was obtained using Bluetooth technology.
- GPS provided the device's location.
- The phone's camera took photos when its keypad key was pressed or when a call was received.

EmotionSense [6] is an opportunistic MPS system for social and psychological studies that allowed the sensing of individual emotions as interactions in a social group, using the microphone, accelerometer and Bluetooth technology. This work was realized with social psychologists' collaboration. With the accelerometer, it was possible to infer the current activity (movement or non-movement). The system also detected other devices nearby using the Bluetooth interface. The localization of the user was obtained with GPS.

EmotionSense included two subsystems, the emotion detection and speaker recognition. The process was performed as follows:

- Speech data was obtained from the microphone and collected. Afterwards, each audio sequence was classified as silence or non-silence. This data could also be used to infer information about the user environment or sleep patterns.
- The emotion recognition was based on a Gaussian Mixture Model classifier. This information was tested with 5 emotion groups and used by social psychologists (happy, sad, fear, anger and neutral).

There are other works related to the integration of WSNs with mobile phones. The authors in [7] present an application that uses mobile phone sensors to collect information about air quality and climate. The mobile phone was connected to a central web system, which received and collected the data. This data was, in turn, processed in a cloud computing system. The application then provided the processed result for the user. Despite touching the subject, this work does not provide a Fog-like integration between WSNs and the mobile phone.

In [8] a prototype is presented that offered different means of integrating WSN nodes and smartphones. In a first case, they realized interconnection using IEEE 802.15.4 communications; in a second case, they used Bluetooth technology. However, the realization of the communication between the different platforms required hardware extensions for both cases.

There are many applications continuously being developed that obtain information about human behavior using the mobile phone as a sensing system. There also exist other applications that permit integration between Wireless Sensor Networks and mobile phones, but need additional hardware for adapting the communication protocols. However, a Fog-like approach could allow applications that integrate these technologies without the need for additional hardware. In fact, ideally these new applications can be oriented towards adapting the human behavior and dampen its effect on the environment.

D. Evolution of Mobile Phone Sensing

Advances in sensor technologies have led not only to an increase in WSNs but also to a proliferation of mobile phone with native sensors. This proliferation has vastly changed what we believe will be the future IoT, where WSN will work together with mobile phones. These integration domains will give the research community a massive flood of data that enables systems to leverage constantly sensed information and cyber resources to learn about the structure, human, environment, energy and resources.

The vision of our proposal is a future of integrated smart cities with mobile phones that can perceive (sense), understand (infer), and respond to/affect (influence) the humans within to improve their quality of life.

There are several people-centric or environment-centric sensing applications implemented in mobile phone systems. In the work of E. Macias et. al. [9] several such applications are presented. Research points towards a future of WSNs increasingly integrated with mobile phone sensors. The next generation of MPS should enable us to relate a person-centered application with the effects caused by human behavior in the environment. Their aim can be the inducing of changes in peoples' behavior for the conservation of the environment. Thus, we should integrate more external sensors that permit the monitoring of environments together with mobile phone sensing systems. This converts the traditional mobile phone to a fog-like device: the FogPhone.

In the FogPhone, the processing will be distributed in the edge devices and only certain information will be sent to the cloud. This is a new vision for new applications that can be developed on mobile phones that interact directly with WSNs.

For instance, with activities recognition results (walking, cycling or driving), it is possible to infer if a person uses public or private transport, or if this person prefers walking to a destination. Now, if this will relate to the level of pollution that is measured on the roads by a network of wireless sensors, we can influence and raise awareness in users, encouraging them to use environmental-friendly transportation.

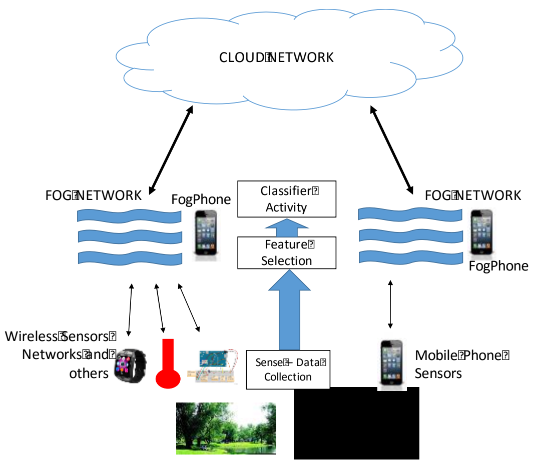

Fig. 3. Structure of Fog Network with a FogPhone

In the fig. 3, a general structure of a Fog Network using FogPhones is proposed, where the data collected from a network of wireless sensors, a smart watch or from the mobile phone sensors are processed on a FogPhone. This processing includes: feature selection and algorithms for activities classification.

IV. CASE OF STUDY AND IMPLEMENTATION

As we have discussed in the previous sections, mobile sensing and the Fog of Things have been evolving proportionally with smartphones. In fact, we are witnessing a tremendous increase in systems that sense various facets of human beings and their impact on surrounding environments. In particular, the detection of human emotions can lead to emotionally-aware applications that promote a greener behavior, to the benefit of everyone's daily lives.

In this section, we will present our implementation of an emotionally-aware FogPhone system that attempts to positively impact people's day-to-day mood and the way people move around their city, through the promotion of walking exercise. We found that previous research suggests that moderate walking exercise and the change of environments can have a significant impact on the improvement of mental health. In fact, changing from one place to another while walking provides several cognitive benefits such as improved memory, attention and mood [10].

Thus, we developed HappyWalk, an evolution of a prototype that we previously developed [11]. HappyWalk is based on a smartshirt and an Android application that takes advantage of walking to positively influence its users' mood. Data from the smartphone's sensors (accelerometer, microphone, location services) and the smartshirt's electrocardiogram are processed through a machine-learning algorithm to infer emotional states. A neural network infers the user's current emotion and uses this information to trigger suggestive feedback that motivates walking exercise, to positively affect mood. When negative emotions are detected, the application timely suggests green parks and other outdoor locations as walking destinations, while providing real-time information regarding each of these locations. Crowdsourcing data gathering is employed to determine the near real-time context of nearby points-of-interest (POI) that might be of interest to visit. This contextual information includes near real-time attendance and average mood at a certain location, being displayed through the use of heatmaps. HappyWalk's application flow is shown in fig. 4.

Current scientific knowledge does not yet have an exhaustive picture of all the factors influencing a person's emotions [12]. Nevertheless, for our case-study application, we intended to consider at least four general sources of data: environmental clues, body-movement, vital-signs and contextual information. Regarding environmental clues and body-movement, the accelerometer and microphone have been previously identified as effective sensors for identifying human context [13].

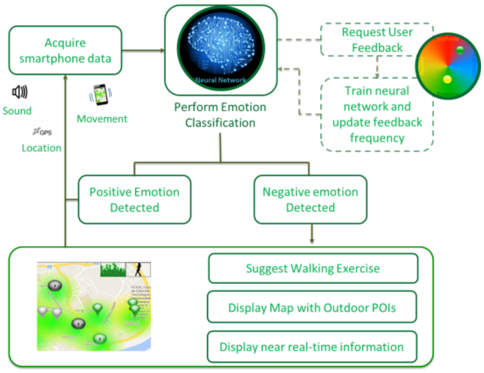

Fig. 4. HappyWalk's application flow

Thus, our application acquires raw data from these sensors, processes it through a simple classifier that performs a Fast Fourier Transformation and sums the Fourier coefficients. This sum gives the neural network an idea on the amount of background noise and movement detected by the smartphone. Vital-signs were acquired from a smartshirt[2] that relayed the user's ECG signal through Bluetooth, which was then processed to infer the current heart-rate. This value is directly fed to the neural network. In terms of context, most smartphones are equipped with a GPS, allowing us to know the geographical area where the user is located. The user's emotion is inferred once or twice an hour. The time between two sensory acquisitions is randomly determined within these constraints, in order to avoid user habituation.

In our current prototype, we consider four distinct moods: *euphoria*, *calmness*, *boredom* and *anxiety*. *Boredom* and *anxiety* are considered ***negative*** emotions, whereas *euphoria* and *calmness* are considered their ***positive*** counterparts. Users receive a notification when an emotion is detected and, by selecting it, the application opens and displays a feedback screen. (Fig. 5)

Fig. **5**. HappyWalk's feedback screen

The output representing the inferred emotion is shown as a yellow circle in a two-dimensional circular space containing the four emotions. The user can provide corrective feedback by dragging the yellow circle to a new position, now shown in green. This feedback initiates a neural network re-training process, which will reflect the correction in future inference tasks. After a considerable amount of training, and when the neural network begins to become accurate, the feedback notifications become progressively replaced with notifications suggesting walking exercise, whenever negative emotions are detected.

In HappyWalk, the mobile phone works as a FogPhone system. The data processing and classification are realized in this system in real-time. The FogPhone operates as master device

[2] VitalJacket: http://www.vitaljacket.com/

with the smartshirt, being a scalable system where more wireless sensors can be connected easily and without major alterations to the system.

Because of the limitations related to processing power and power consumption in our FogPhone system, we made several tests on our prototype to evaluate CPU and energy consumptions.

Figure 6 shows the energy consumption in our FogPhone system when the application sends a feedback request each one, two and four hours.

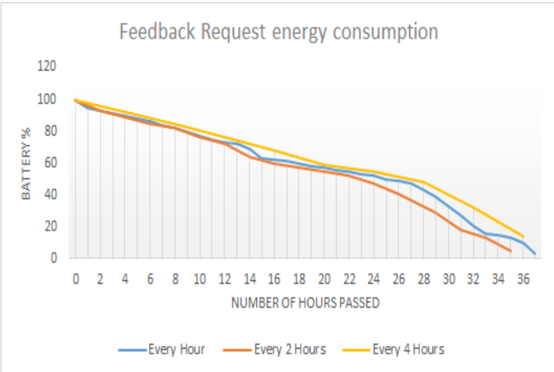

Fig. 6. Energy Consumption of HappyWalk

In our prototype, CPU consumption was measured using two configurations of neuronal networks. Firstly, it was used a neuronal network (4-3-2-2) with four inputs, two hidden layers (three and two neurons respectively) and two outputs. In the second case, the neuronal network worked with 4 inputs, 2 hidden layers (five neurons in each layer) and two outputs (4-5-5-2). These results are presented in the figure 7 and 8.

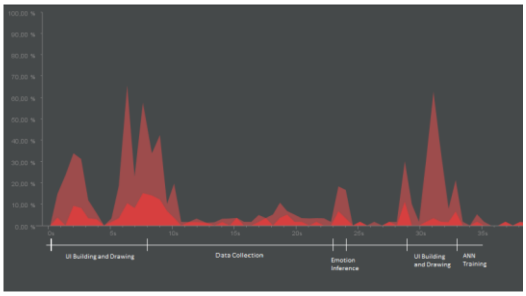

Fig. 7. CPU consumption with a configuration 4-3-2-2 of Neuronal Network

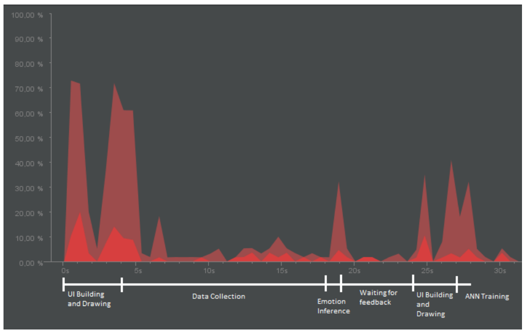

Fig. 8. CPU consumption with a configuration 4-5-5-2 of Neuronal Network

Due to the sensitivity of information acquired through the sensors, information from the microphone and from the accelerometer is not stored either in the device or on servers. However, analysis of the security and privacy will be made in future work.

Despite being merely a prototype, our HappyWalk implementation serves as a concrete example of a FogPhone system that relies on external sensors and the mobile phone's ones to motivate people towards healthier and greener behavior.

V. Monitoring of Human Behavior and Future Work

Diseases linked to the lifestyle we carry are the leading cause of death worldwide. In fact, diseases related to a sedentary lifestyle such as obesity, diabetes, hypertension, cardiovascular disease and myocardial infarction represent 60% of disease at a global scale. Most of these diseases are linked to the fact that we acquire an unhealthy lifestyle, both at a dietary level as well as a physical activity level. This is due to many reasons, but mostly unawareness when it comes to personal health [14]. A poor lifestyle can also be caused by depression, which is characterized by a loss of pleasure in daily activities (anhedonia), apathy, psychomotor (fatigue and feeling of weakness), sleep disturbances (most often insomnia) and appetite changes (most commonly loss of appetite). Depression frequently comes from psychosocial causes, i.e., the loss of a loved one or even a lack of friends which later leads to loneliness [15].

Our goal here is to identify individuals that lead a less favorable lifestyle, through mobile sensing and WSNs, and then try to minimize the risk factors by strengthening prevention and advising the user to a more controlled and beneficial lifestyle. This in turn will lead the user to a more positive state of well-being.

Well-being indicators are built upon four dimensions: sleep, physical activity, social interaction and overall emotional state. These indicators have a deep impact on our personal health [16]. For example, as mentioned above, social withdrawal is connected to depression. Positive health effects can be perceived when these wellbeing indicators are kept in healthy spectrums.

Physical Activity can be tracked easily using the smartphone's GPS and accelerometer. Nowadays there are a good deal of algorithms and libraries available for detecting the number of steps given during the day, kilometers ran or calories consumed in one's exercise. Thereat, we can then promote physical activity depending on the user's result [17].

How we feel is greatly influenced by how we sleep, thereby, sleep detection is important in our matter. Sleep detection is done by using a set of sensors/features combined, which include: light sensor, microphone (detecting silence), accelerometer (stationary feature), alarm clock feature, phone usage features (phone lock state/usage statistics) [18]. The model developed will soon estimate the amount of hours slept and thereon advise the user to clock in bed sooner.

To detect social interaction, GPS can be used to comprehend where the user is positioned. With the user's location we can later examine if the user is outgoing or reclusive. Because poor social life isn't only allied to the user's position, we have the microphone which can be used to detect conversations, also SMS, Call Logs and other messaging/call services that can also be taken into consideration [19]. This is important to improve life quality and social integration leading the user to a more fulfilled state of mind.

Other dimensions can also be used to determine our overall emotion, such as the weather. In fact, the weather is widely believed to influence people's mood [20].

Emotional state as anxiety, also influences the quality of human life. For this reason, it is important to have mechanisms that allow to detect when people are stressed, as well as we have applications that send a feedback with different activities that people can take to reduce their stress level. There are different mechanisms to detect the stress level of a person. For example, a psychological test can be applied to detect this. Also, there are some methodologies that use wearable sensors to measure physiological responses. Physiological parameters like the Galvanic Skin Response (GSR) and Heart Rate

(HR), can also be measured to determine the stress level. The wearable sensors localized in smart devices (e.g. smart-shirts, smartphones, smart bands, smart watches, etc.) allow one to obtain these measures and to infer stress levels in the people.

All of this leads to consider the mobile phone as a FogPhone system, where several wearable smart devices, will send physiological signals toward a FogPhone to infer the emotional state of people.

In conclusion, using these features, wearable sensors or mobilephone sensing, it is possible to infer emotional states and therefore provide the user with advice and more suitable approaches to improve his life quality, thus becoming a healthier and more active person.

VI. OPEN RESEARCH ISSUES

The development of Fog Phone systems is still young; thus, there exist a lot of unresolved issues and research challenges related to processing and storage capacity. To solve them, research needs to develop distributed algorithms that permit a low-power consumption and security mechanisms that avoid malicious attacks or theft of information.

Several challenges also arise from this distributed fog architecture that combines MPS and WSNs. Firstly, it is fundamental to setup the virtual infrastructure, namely to chose the distributed cloud supporting devices and to implement the distributed cloud services over heterogeneous devices, capable to transparently operate as one (building a tiny-virtual cluster). Secondly, it is necessary to distinguish and pre-process sensing data to determine which data will be kept in the local-distributed cloud and which data will be also sent to the centralized cloud. This pre-processing can be useful either to facilitate big data processing, by avoiding transmitting large amounts of raw data to a centralized data centre, or to deliver local data faster, with higher availability, security and control, among other benefits.

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C-HappyWalk Feedback Management Article

Managing User Feedback in Emotional Smartphones

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Abstract—Smartphones are becoming increasingly more intelligent as personal assistants. One important aspect of these systems is their ability to cope with human individuality: to do so, smartphones must be able to learn about their users. However, dynamic classification models are difficult to achieve since they cannot be fully trained prior to deployment and require a great deal of personalization. As far as we know, there is a lack of research that provides guidelines on how to manage the frequency of feedback requests. In this article, we attempt to study the impact in smartphone usability derived from requesting user feedback to train classifiers. To do so, we designed and implemented a smartphone app that periodically requests feedback to train an artificial neural network. The neural network attempts to understand its users mood, using the smartphone's sensors. We then performed several experiments to better understand the delicate balance between user experience, battery life and classifier accuracy. We found that the impact of feedback requests and neural network training tasks is minimal when compared with heavy location sensor usage. We also found that continued feedback requests may lead to greater emotional accuracy, possibly at the expense of user frustration.

Index Terms—Emotion Detection, Human-in-the-Loop Cyber- Physical Systems, Feedback Management, Smartphones

I. Introduction

A. Smartphones and HiTLCPSs

The smartphone has become an essential device for a considerable percentage of the population. They became much more than mobile phones: smartphones are pocket-sized computers that serve as personal assistants. They allow us to call each other, remind us of our appointments and tasks, can be used to send and receive email and connect us to our social networks of choice. At the same time, even the most basic and cheap smartphones are capable of processing considerable amounts of information. They also possess advanced sensors such as gyroscopes, accelerometers and digital compasses.

It is not a surprise, therefore, to realize that this ad- vancements spun a considerable amount of recent research dedicated to smartphone sensing [1] in the last few years. Their close proximity with their users' daily lives and their sensing capabilities make smartphones a privileged platform to create context-aware personal systems. In other words, it is possible to harness sensing data and process it through ma- chine learning algorithms to achieve some sort of user-centric intelligent action. This idea has previously been proposed in several research fronts. It has been used as part of the concepts of anticipatory mobile computing [2], people-centric sensing [3] and smartphone-based behavior change interventions [4], among others.

In fact, it is possible to see these context-aware smartphone- based systems as part of a larger group of human-aware systems. This is particularly important when considering that the Internet of Things (IoT) is upon us, bringing a potential huge amount of interconnected and associated devices. In terms of sensing applied to individual users, Bosch Sensory Swarms and the Qualcomm Swarm Lab at UC Berkeley estimate that the amount of sensors present in personal devices account for 1000 wireless sensors per person estimated to be deployed in the next 10 to 15 years [5]. Thus, smartphones will not be used in isolation; the entirety of the Internet will likely strive to become more "human-aware". This is the defining characteristic of "Human-in-the-loop" Cyber-Physical Systems (HiTLCPSs), where the human's emotions and actions become an inherent part of computational systems [6].

B. *The importance of classifier personalization in HiTLCPSs*

HiTLCPSs have a wide spectrum of applicability and it is difficult to categorize all possible examples of HiTL solutions from multiple domains. Nevertheless it is possible to expose the most basic steps associated to HiTL control. The first phase is known as data acquisition, where data is gathered from the smartphone sensors and / or from external devices. This data is then processed in the state inference stage where human actions and / or mood states are identified. In some cases, the prediction of future states can be attempted, based on historical data and the current state. Finally, in the actuation stage the system may perform certain actions based on the currently identified context.

One important aspect of many smartphone-based HiTLCPSs is how their state inference stage often requires an ability to learn. Unchanging classification models trained prior to deployment are not capable of coping with human individuality. Since smartphones are inherently personal devices, their state-inference techniques often require a great deal of personalization; that is, the smartphone adapts and learns about its particular user. Thus, personalized smartphone-based context-recognition is an area of considerable importance.

In fact, research has previously attempted to promote the personalization of existing classification models through different types of active or semi-supervised learning [7], and by incorporating inter-person similarity into the process of classifier training, allowing crowd-sourced sensor data to personalize classifiers [8]. The work in [9] attempted to adapting pre-trained activity recognition mechanisms to a particular person, based on limited labeled data and by using multiple classifiers. The use of smartwatches in combination with smartphones in order to detect different activities and contexts in which they occur was attempted in [10]. The authors used a supervised classifier together with a quantitative survey to understand the influence of different collected metrics and their use in the detection of user activities and contexts. Personalized and adaptive frameworks that incrementally learned from evolving data streams were also proposed [11].

The importance of adapting smartphone machine-learning techniques to particular users is also visible in areas other than activity recognition. For example, in the area of recommendation systems, the ability to quickly and accurately understand a particular consumer's desires allows companies to promote personalized advertisements and sales. Since consumers are influenced by the relevant information provided by the retailer, context-aware recommendation systems can have a considerable effect on consumerism dynamics. In [12], context-aware recommendation systems for smartphones were divided onto two modules to provide product recommendations. First, a simple RSSI Indoor localization module located the user position and detected the context information surrounding users.Second, a recommendation module provided effective product information for users through association rules mining. The system performed recommendation calculations pertaining to merchandise in the region of the user and passed on this information through the smartphone. Another example can be found in [13], where the authors managed to create a recommendation system to suggest smartphone applications. Bayesian networks processed data from several of the smartphone's sensors, including the accelerometer, light, GPS, time of day and date, to perform context-inference. From this information, the recommendation system was able to associate the user's context with application categories of interest. In a similar vein the authors in [14] proposed AppJoy, a system that also made personalized application recommendations; however, instead of using the smartphones' sensors to understand context, the system actually analyzed how the user interacts with his installed applications. AppJoy measured usage scores for each app, which were then used by a collaborative filter algorithm to make personalized recommendations: what the user does directly affects his application profiling.

As we have seen in the previous paragraphs, in some situations it is possible to obtain and train the machine-learning mechanism from nonintrusive feedback; such was the case in [14]. However, in many applications this is unfeasible; as we have seen in the previous paragraph, many HiTL smartphone applications require some degree of semi-supervised learning and manual labeling of training data [7], [8], [10].

Despite this, there is scarce research concerning the impact of requesting user feedback and training the classifier in the usability of the smartphone. As far as we know, there are no studies that attempt to provide guidelines on how often one should request user feedback to train the system, considering how this might affect the smartphone's battery life and the experience of the user.

We believe that it is important to have an understanding of the impact of requesting feedback in the design of new HiTL smartphone applications. To achieve good contextual analysis it is important to strike a delicate balance between user experience, battery life and classifier accuracy. Thus, this article presents a first attempt at studying the impact of user feedback in HiTL smartphone applications, with the following contributions:

- we present our own HiTL smartphone app: HappyWalk, a HiTLCPS that attempts to understand its users mood to present timely suggestions promoting social activities, such as walking exercises.
- we present studies that show how the frequency of signal collection and processing might affect the battery
- we present a study, based on a set of real-practical experiments. It shows how the frequency of feedback requests, followed by processing, can affect the accuracy of the machine-learning technique.

The rest of the article is organized as follows: section II presents our HappyWalk application; section III presents several evaluation studies regarding the smartphone's battery, user's mood and inference accuracy; finally, section IV dis- cusses the results and concludes the paper.

II. HAPPYWALK APP

It has been known that walking and having contact with natural environments provides several personal cognitive ben- efits, such as improved memory, attention, mood [15], [16] and also broader social benefits [17]. HappyWalk is a smartphone HiTLCPS (based on our previously presented work [18]) that takes advantage of this fact to positively influence mood.

By associating environmental clues with user provided feedback on his/her emotional state, the system becomes capable of presenting timely suggestions that promote walking exercise, in order to surpass negative moods. Figure 1 shows HappyWalk's HiTL control flow.

In its data acquisition process, the application periodically fetches data from the smartphone's sensors to know about the user's surroundings. This data is then processed and fed to a machine-learning mechanism, which attempts to infer the user's current state (e.g. his mood). This information is corrected through the user's feedback, which is used to train the learning mechanism so that it may be more effective in the future. As the application becomes more accurate, the

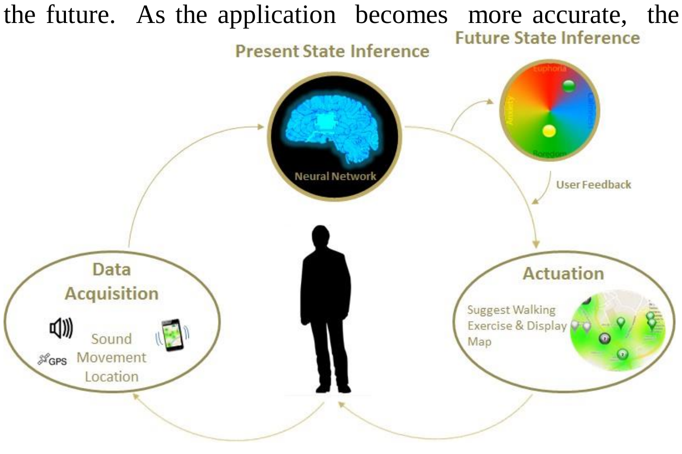

Fig. 1. HappyWalk's control flow

feedback requests are reduced in favor of fully automatic state inference. Finally the application actuates when negative emotional states are detected, by motivating the user to go for a walk, showing a map with near real-time contextual information about nearby points-of-interest (POI).

The system periodically sends its users' positioning and mood in an anonymous way to a central server, to be aggregated. Since we are dealing with possibly sensitive data, such as location and mood, one of the fundamental requirements of the design of our HiTL application was to respect the privacy of users. We considered this requirement through data anonymization, by generating pseudo-random identifiers. Thus, the identified states and location data are sent in an anonymous way to the server. This allows HappyWalk to display the real-time attendance (based on user location) and overall mood (based on average emotional data) at each POI through heatmaps with different colors. This information allows users to pick livelier areas (greater attendance and euphoric moods) or calmer areas (less attendance and calmer moods). All of this real-time information may provide the necessary motivation for walking and visiting places that the user feels are best for venting his emotional stress.

A. Sensor data and machine-learning

Current scientific knowledge does not yet have an exhaus- tive picture of all the factors influencing a person's emotions [19]. Nevertheless, for our example application, we intend to consider at least two general sources of data: location information, and contextual information. In order to avoid obligating the user to use additional hardware we limited our choice of sensors to those already provided by the smartphone device.

In terms of location, most smartphones are equipped with a GPS, allowing us to know the geographical area where the user is located. Regarding contextual information, the accelerometer and microphone have been previously identified as effective sensors for identifying human context [20]. Thus, our application will acquire raw data from these sensors, pro- cess it through simple classifiers. Figure 2 gives an overview of how the microphone and accelerometer processors were implemented.

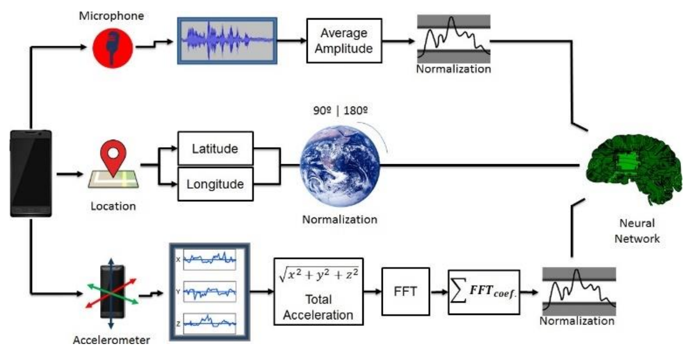

Fig. 2. HappyWalk's signal processing overview

Our classifiers use some concepts of signal processing. In particular, our microphoneProcessor calculates the average amplitude of the signal and normalizes this value within certain threshold values. These were merely indicative; we experimented to empirically determine values appropriate for our testing devices. The result provides an estimation on the amount of background noise in the environment surrounding the user.

For the accelerometer signal, we simply wanted to have an idea of the amount of movement of the smartphone, independently of its orientation. Thus, we first calculated the total acceleration from all axes (x,y,z) through the square root of the sum of their squared values. We then performed a simple Fourier analysis of the transformed signal and sum the associated fourier coefficients to access the amount of movement being produced. Again, the result is normalized within certain empirically derived threshold values.

The location coordinates were used directly. Thus, the application periodically processes data from the smartphone's microphone, accelerometer and location services.

As for the machine-learning technique, HappyWalk uses an artificial neural network (ANN) implemented through the Encog machine learning framework [21]. We used the same two hidden-layer configuration, the first containing three nodes and the second with two nodes, discussed in our previous work [18].

B. *Proposed feedback strategy*

A feedback request consists of three steps: data collection, user feedback and network training. Data collection consists of getting the data from the sensors described in the previous section and inferring the user's mood. After that, a notification appears asking the user for feedback. After the user provides feedback a training phase is initiated, where the feedback valued is used to train the network through resilient propagation. Figure 3 is a screenshot of the feedback menu. In it are two circles, a green and a yellow one. The yellow circle shows the mood inferred by the ANN and the green circle can be dragged by the user to a place that represents his current mood. After the user clicks the "This is how I feel"

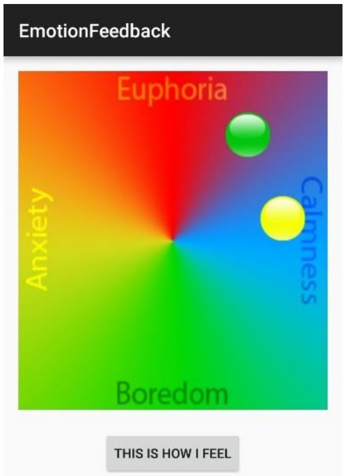

Fig. 3. HappyWalk's Feedback Menu

button, the ANN is trained with the new feedback, and will adjust its weights to improve its accuracy. From the figure, we can see that our emotional feedback is essentially a 2 axes plane: the X axis (width) corresponds to an Anxiety-Calmness value, whereas the Y axis (height) corresponds to an Euphoria-Boredom value.

It is known, from previous research, that an increase in feedback requests will, most likely, lead to greater user frustration [22]. If we repeatedly request user feedback, there is no point to our learning mechanism: the main focus of our HiTL app should be to become as unobtrusive as possible. As such, we want to minimize feedback requests by only performing them when necessary. We can achieve such strategy using a very simple algorithm:

```
void calculateNextFeedbackTime (double[] output,
    double[] idealOutput, β_previous) {
  /*Calculate the euclidean distance. This gives us
    an estimate on how accurate our last emotion
    inference was. */
  for (int i = 0; i<output.length; i++) {
      eucdist_current += √((output[i] − idealOutput[i])^2);
  }
  /* This weighted mean will be used to check if our
     neural network is performing well enough to
    trigger suggestions */
  eucdist_mean = eucdist_current * w_newEucDist +
      eucdist_mean * (1 − w_newEucDist);

  eucdist_max = √(output.length);
  /* we compute new "feedback time value" through a
    direct linear variation based on the weighted
    mean of the euclidean distance */
   β_new = β_max −
      (β_max − β_min)*
          eucdist_mean / eucdist_max;

  /* determine the actual time until the next
    feedback request through a weighted arithmetic
    mean */
  β_next = β_new * w_newEmoTime +
      β_previous * (1 − w_newEmoTime);

}
```

where:

- output and idealOutput - are arrays containing the ANN outputs and the user feedback, respectively;
- $\beta_{previous}$ - is the previous feedback period (previous value of β);
- $eucdist_{current}$ - is the euclidean distance between the last emotion inference and the corresponding user's feedback;
- $eucdist_{mean}$ - is a weighted mean calculated from pre- vious $eucdist_{current}$ values;
- $w_{newEucDist}$ - is a weight representing the impact of the newest $eucdist_{current}$ on $eucdist_{mean}$;
- $eucdist_{max}$ - is the maximum euclidean distance;
- β_{new} - is a temporary value computed from a direct linear variation based on $eucdist_{mean}$;
- β_{max} and β_{min}- are the maximum and minimum feedback periods, respectively;
- β - is the period until the next feedback request;
- $w_{newEmoTime}$ - is a weight representing the impact of β_{new} on β;

There are many interesting aspects of the proposed feedback mechanism. In particular, we would like to study the effects of different values of $w_{newEucDist}$ and $w_{newEmoTime}$ in future studies. However, we believe that an awareness of the impact of the final β value is crucial, before attempting to fine-tune our feedback strategy. As such, we present a study focused on this β value in the next section.

III. Evaluating feedback frequency

Every new generation of smartphones comes with more powerful processing capabilities, added functionalities and new Operating Systems. Usually, a trade-off of this evolution is a bigger power consumption. As a result, it is important to manage the app's background processing correctly in order to improve battery life. In this particular app, one of the things we wanted to discover was the relation between the smartphone's battery life with user feedback period, β.

There is a delicate balance between battery life and the amount of feedback requests done to the user; If we ask the user for feedback in a short time interval, the ANN will, most likely, increase its accuracy faster, but it will also drain the device's battery at a higher rate. On another hand, if we ask the user for feedback too often he can get annoyed and start to give inaccurate feedback. To better understand this balance, we performed two kinds of tests. On a first phase we conducted battery life-time testing with different values of β, to understand the impact that additional feedback requests and ANN training would have on the battery of the device. At the time of writing, we are still working on a second phase of tests, where we asked several volunteers to use the app with different values of β, to analyze how these might affect the accuracy of the system. We herein present some of the results from this "live" testing.

A. *Controlled battery life-time tests*

In this first testing phase, we decided to monitor power consumption caused by feedback requests and subsequent training of the ANN within a controlled environment. For this we used a Huawei ascend Y 201 Pro, which comes with a Cortex A-5 single core Processor (clocking at 800 MHz) with Android 4.0.3. Its approximate battery life is 72 hours and this value will be used as a reference throughout the analysis of our results. It is important to note that, for these tests we stopped all background services and apps to ensure that HappyWalk and Google Play Services are the only things running in the smartphone. The operation environment of the tests was also taken into account: all the tests were executed in the same place and using the same WI-FI access point, to avoid outliers in the results due to inconsistent Wi-Fi and GPS connections. To measure battery consumption we created two test suits: one used GPS and Wi-FI to discover the users location and the other only used Wi-FI. We also considered four different β time intervals to request user feedback: every one, two, three and four hours.

Instead of doing the tests manually, we added some code to automate this particular test suite: when a feedback request is received, the screen turns on, two random coordinates on the screen are picked and the button is clicked automatically. Methods were also added to retrieve the current level of the battery before and after the feedback request and send it to a server for statistical analysis.

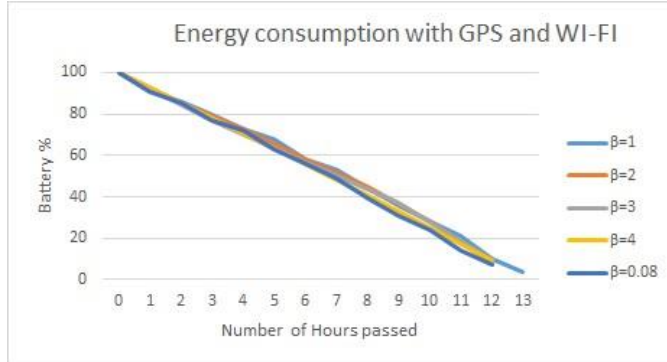

Fig. 4. Energy Consumption Experiments (GPS and WI-FI)

The results of the first test suite, shown in Figure 4, are quite surprising; The tests have a very approximate battery decay pattern, indicating that the user feedback process itself is not battery intensive, but the usage of both GPS and WI- FI for location discovery are, shortening battery life by 72%. To further validate this assumption, an extra test was created with a β of 0.08 (equivalent to 5 minutes). The results for this particular test validate the previous assumption, showing a very similar decay pattern.

These results tell us that the amount of feedback requests are not relevant to improve the smartphone's battery life, but the correct usage of GPS/WI-FI for location discovery is. This is further validated by the result of the second test suite:

As shown in Figure 5, using only WI-FI to discover the user's location, battery life is only decreased by 49% and for all the β tests battery decay follows the same pattern. With

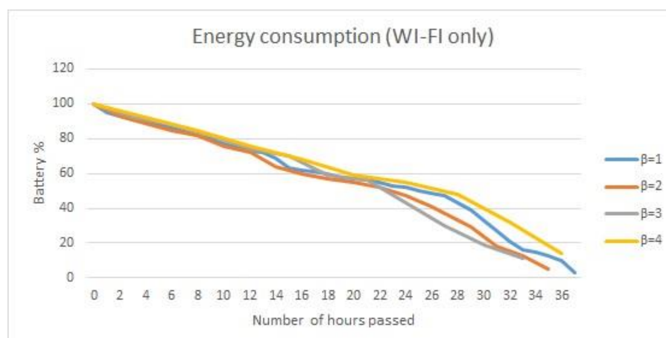

Fig. 5. Energy Consumption Experiments (WI-FI only)

these results we can focus on determining a β that provides better ANN accuracy rather than improving battery life.

B. *Live accuracy tests*

The accuracy of our ANN is an important part of this research. To evaluate its evolution, we installed HappyWalk in the smartphones of several tests subjects, with different values of β, and asked them to use HappyWalk during a period of at least one day for each β value. Each time the user provides feedback, the neural network is trained and the values of the feedback and the inferred result provided by the ANN are sent to and saved on a remote server. This will allow us to calculate the accuracy of our artificial neural networks for different frequencies of feedback requests. We are currently analyzing data coming from various subjects.

In this paper, we present some results consisting of data coming from two of those subjects, which have successfully completed the tests for $\beta = 1$. After the user gives his feedback (recall the feedback menu shown in figure 3) both the yellow and green circles coordinates are converted into two values, one for each axis. We shall refer to these values as:

- o_Y and o_X for the values inferred by the ANN.
- f_Y and f_X for the values given by the user.

These values are then used to calculate the Euclidean distance between two points using the following formula:

$$AN\,N\ accuracy = 1 - \sqrt{(o_Y - f_Y)^2 + (o_X - f_X)^2}$$

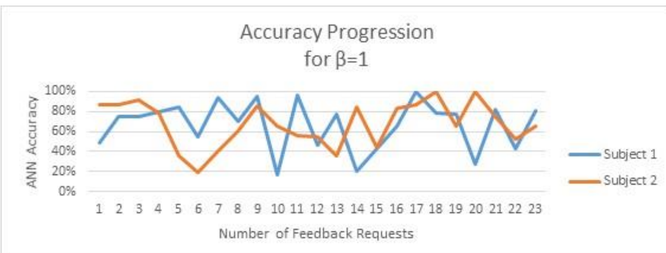

Fig. 6. Accuracy Progression for $\beta = 1$

Figure 6 represents the results for 24 hours of usage for the two subjects. We can observe that the accuracy varies greatly along this time interval ranging from 20% to almost 100%. This is expected in the beginning, as the network is still in training. With these results we calculated the trend lines for the accuracy progression of both subjects, shown in 7. This can give us a better comprehension on how the accuracy evolved over time.

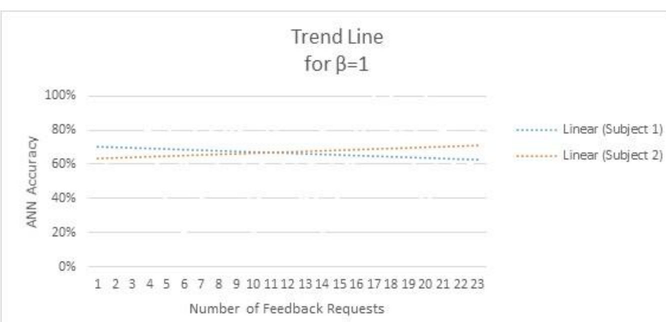

Fig. 7. Trend line for $\beta = 1$

The evolution of accuracy seems to be opposite between the two subjects. This difference can be explained by the fact that every person's personality and emotional states differ greatly, and that the network requires more time/data to learn how to correctly classify the four different emotions in our spectrum. Even so, the fact that the network can have 60% to 70% accuracy with only 24 feedback requests shows great promise.

IV. Conclusion

In this paper, we have proposed a dynamic feedback request strategy to train a personalized and emotionally-aware neural network for a HiTL smartphone app. We also studied the impact of the frequency of user feedback requests to better understand the balance between battery life and classifier accuracy. We found that the impact of feedback requests and neural network training tasks can be disregarded in comparison to the amount of energy used by location sensors. We also found indications that continued feedback might lead to greater emotional ANN accuracy, but additional experiments and data are needed before arriving to any definitive conclusions.

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