A Novel Middleware Solution to Improve Ubiquitous Healthcare Systems Aided by Affective Information

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***Abstract*—The arousal of emotion might have consequences for physical health is a broadly acknowledged idea. Therapy for depression, prevention for heart pathologies, and rehabilitation treatments for drug addiction are just a few examples of application domains that may benefit from technologies capable of monitoring, detecting, representing, and disseminating information pertaining to patients' physical and psychological/emotional states. However, the design and development of healthcare applications of this kind is a rather challenging issue that requires to integrate sensor infrastructures, which are able to detect changes in patients' physiological and emotional states, and of sharing this information to interested caregivers, such as professional medical staff, relatives, and friends. This paper proposes the Pervasive Environment for AffeCtive Healthcare (PEACH) framework, a middleware level support for affective healthcare that incarnates these ideas and describes its effective functions in a drug addiction treatment application scenario.**

***Index Terms*—Affective computing, healthcare network, pervasive computing, ubiquitous assistance.**

I. Introduction

HEALTHCARE spending indeed accounts for a significant fraction of the welfare budget of any country. In the years to come, the demographic compression, along with the increased number of senior members in the society will undermine economic sustainability of available healthcare systems. Wise and long-term welfare-oriented policies are mandatory to deal with this daunting challenge. However, to compensate effects and implications of demographic changes in the society, it is also necessary to identify suitable technology solutions capable of reducing healthcare costs, and at the same time, of improving healthcare services quality for citizens.

The widespread diffusion of low-cost portable/embedded devices, and the proliferation of wireless networking solutions offer unique opportunities to avoid/postpone patients hospitalizations, with positive impacts in social, emotional, and economic contexts. Impaired individuals, patients affected by chronic diseases or engaged in rehabilitation therapies may take full advantage from pervasive healthcare systems deployed close to where they live and move, with the main goals of increased independence, safety, and quality of life on the one hand, and of care cost-saving on the other hand [1].

Various research proposals have recently appeared in the literature that suggest the development of solutions, which are able to record and analyze patients' behavioral patterns, to monitor users' mobility, to assist individuals with special needs in their daily activities, such as self-care, etc. However, existing solutions [2]–[8] typically focus only on purely medical aspects of healthcare, and do not pay the required attention to emotional states of the patients. In fact, recent clinical evidences demonstrate how the arousal of emotions could influence the physical health through a number of symptoms and manifestations. Available evidences cast a light on psychophysical aspects, which need to be considered in healthcare service provisioning to promote rethinking of existing pervasive healthcare supports.

With the aforementioned considerations in mind, our research aims at investigating how to take full advantage of emotional aspects of care in ubiquitous healthcare with notable positive potential impacts in disease prevention, therapy, and rehabilitation. However, capturing emotional aspects in healthcare scenarios raises several challenging issues. How can we define, detect, model, and represent the emotional states of individuals? How can we use emotional information to improve healthcare applications? How, when, and whom should we propagate and/or delegate affective information? And finally, how can we identify suitable tradeoffs that keep into account all of these considerations?

To the best of our knowledge, it still seems impossible to provide one-fits-all solution able of covering the whole spectrum of healthcare application domains. Several researches [9], [10] have pointed out the need for user-centric design and for strong customization of pervasive healthcare solutions to better suit to actual patients' needs and pathologies. In order to meet the increasing complex needs and to customize mission critical functions of a modern healthcare system, middleware solutions can provide a viable solution to simplify the development of advanced medicare applications, by providing a set of basic facilities to manage and query sensors, to deal with intermittent wireless connectivity, to detect potentially dangerous situations, etc.

Based upon our previous research on pervasive healthcare [9], [10], this research work presents the *Pervasive Environment for AffeCtive Healthcare* (PEACH) framework, a context-aware middleware-level solution capable of integrating together sensors, able of detecting alterations of patients' psychophysical conditions, of aggregating sensing information, of detecting

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potentially dangerous situations for the patients, and in this case, capable of promoting and supporting the formation of groups of individuals willing to provide prompt assistance to the patient. This paper also describes a PEACH-enabled healthcare application within the drug rehabilitation application domain.

The remainder of this paper is organized as follows. Section II presents relevant related researches, whereas Section III identifies the major requirements and design guidelines that should be followed to support affective healthcare services. Section IV presents PEACH model, while Section V provides its system architecture and implementation insights on response group members selection. Section VI sets the presented work within a state-of-the-art field to evaluate the performance of PEACH. Concluding remarks follow in Section VII.

II. Related Research Work

Lately, a broad literature and relevant research proposals have started to investigate pervasive healthcare and affective computing. However, the convergence of pervasive healthcare and affective computing is still a relatively recent phenomenon, with only few pioneering research works available [9]–[12].

As a consequence, it appears natural for us to consider related researches both in affective computing and pervasive healthcare fields. It is not our goal to exhaustively summarize the state-of-the-art of the aforementioned research fields. Readers interested in complete coverage of pervasive healthcare and affective computing may refer to [11]–[13].

A. Affective Computing

So far, affective computing research has been mainly directed toward the investigation of innovative human–computer interaction models. The ultimate goal is to develop systems able of interacting with the users in a natural manner, by taking full advantage from the rich and multimodal human communication [14]. Affective computing-based user interaction approaches tend to recognize the role of nonsemantic communication, e.g., gesture, with the main advantage of tailoring human–computer interaction according to user behavioral changes rather than on the basis of plain user commands [15], [16].

Affective computing is an extremely challenging research area. The central issues in affective computing are representation, detection, and classification of users emotions.

1) Emotion Representation: Defining, modeling, and representing emotions are extremely challenging tasks. Several practical approaches to the aforementioned issues have been proposed within the psychology research field. In particular, the scientific literature proposes three main approaches to emotion representation, namely emotion description, dimensional description, and appraisal-based description.

Emotion description is a widespread emotion representation model both in psychology and in affective computing research fields. Emotion description models represent emotions in terms of discrete categories of basic emotional elements, such as happiness, sadness, fear, anger, disgust, and surprise [17]–[19]. The theoretical foundation of this approach lies in cross-cultural studies demonstrating that people can perceive basic emotions expressed by the others in the same manner and independently from their cultural and anthropological profiles. However, a list of basic emotions can only cover a tiny part of the rich set of emotional states that an individual experiences in everyday life. Nevertheless, the emotion description approach influences much affective computing, especially due to its intrinsic simplicity. As a consequence, the vast majority of studies in the field of affective computing aim at detecting and recognizing discrete emotion categories.

Relevant researches are currently starting to approach the emotion representation problem according to dimensional and appraisal-based models. However, the discouraging technical complexity of these approaches has strongly limited their practical adoptions. On the one hand, dimensional descriptions of emotions make it technically difficult to distinguish between different emotions, such as fear and anger, or to represent complex emotions, such as surprise [20], [21]. As a consequence, only oversimplified emotion representation models have been proposed so far [22], [23]. On the other hand, appraisal-based emotion representation approaches are still subject to fundamental research and only few research works are currently available in the scientific literature [24], [25].

2) Data Acquisition and Mapping of Emotions: Humans rely on their natural senses, e.g,. sight, touch, and hear, for estimating the current emotional states of the others. The mechanism that permits to understand people's emotional states is rather complex and often requires individuals to use their senses in combination to improve estimation accuracy. According to the aforementioned considerations, early research efforts in affective computing aimed at understanding human emotions by analyzing visual and speech data [26]. More recently, the availability of wearable sensing technologies has opened further possibilities for emotion detection.

Emotions usually induce physiological changes, which may be measured by employing biosensors. For example, fear increases heartbeat and respiration rates, causes palm sweating, etc. By monitoring these emotion-induced physiological signals, it is possible to recognize various emotional states of the users. Different wearable biosensors currently available on the market [e.g., EEG, electromyogram (EMG), ECG, electrodermal activity (EDA)] may play an important role in detecting emotion-induced physiological signals. Indeed, the availability of wearable and low-cost biosensors opens the possibility to monitor individuals' emotional reactions anywhere and at any time [27]. Wearable biosensing solutions are unobtrusive and can be integrated into commonly available objects in everyday life. For example, skin conductivity sensors, blood volume sensors, and respiration sensors may be integrated with shoes, earrings or watches, and T-shirts, respectively [28]. These sensors are capable of monitoring users under various daily conditions ranging from driving to home-based healthcare [29], [30].

Sensed emotion-related raw data obtained from sensors are indeed difficult to use in applications development. In addition, according to user needs, different sensors may be required. As a consequence, it is necessary to provide a suitable mechanism to map sensed data to emotion models. The main advantage is to free application developers from the need to take care of all the details related to raw data acquisition, aggregation, and emotion classification. Toward this goal, the vast majority of solutions in literature adopt emotion description models and rely on specific classification techniques to impose a precise mapping between sensed data and emotion categories. Support vector machines, hidden Markov model, and Fisher linear projection are examples of the different techniques that can be employed for mapping emotional data to emotion models [16], [31]. Notably, available researches exhibit high percentage of correctness in emotion detection [30], [32]–[35]. However, experimental evidences are often obtained in laboratories during controlled experiments, and only in recent times, the research is starting to address emotion detection in uncontrolled environments. Since emotions detection in uncontrolled environments is a challenging issue, the commonly adopted approach is to combine several different emotion-related sensing sources to improve the success ratio [36].

B. *Pervasive Healthcare and Affective Computing*

In recent times, several research efforts have been directed [1] toward realizing pervasive healthcare. In fact, the increased availability of relatively cheap commonly-on-the-shelf (COTS) mobile devices, sensors, and wireless networking solutions promotes design and development of ubiquitous assistance solutions that integrate wearable devices and smart environments to assist people affected by severe disabilities, to facilitate diagnosis of diseases, and to detect possibly occurring emergency situations. Furthermore, recent researches (e.g., [9]) have also started to investigate the link between wellness and social engagement of individuals. Along this line, few research works have started to investigate ubiquitous care networking supports to overcome social limitations imposed by illness and disability. Toward this goal, ubiquitous care networking proposals provide patients with communication artifacts and services specifically tailored to set them within the context of a rich social and emotional framework and to reduce their sense of loneliness.

1) Ubiquitous Assistance Solutions: A growing research interest both in academia and industry research circles has been recently directed toward ubiquitous assistance solutions. Available research prototypes permit constant in-house monitoring of patients' conditions, and often integrate alerting mechanisms to provide prompt responses to emergency situations. Proposals in literature show different incarnations of these basic ideas and aim at providing assistance to patients, especially elders, affected by diverse pathologies. The Honeywell Laboratories' Independent Life Style Assistant (ILSA) [37], and more recently numerous works, such as [38], [39], are notable examples of integrated smart environments. The main contribution of ILSA is to demonstrate the possibility to build an integrated ubiquitous assistance on the basis of relatively low-cost COTS components. In particular, ILSA adopts a multiagent architecture, where different agents are deployed that are able to support data monitoring via home-installed sensors. Collected data are then aggregated and processed by exploiting planning and machine learning techniques. Accordingly, further agents can assist individuals by controlling actuators deployed in their home environments. More in line with the basic ideas of affective computing, few solutions are promoting user-centric in-home assistance design approaches. For example, in [40] an interesting solution tailored for patients affected by dementia is proposed. The system adopts a vision-based patient monitoring approach to identify whether assisted individuals correctly perform basic daily activities, such as handwashing. Correct execution of activities is recognized by exploiting artificial intelligence (AI) and planning techniques, whereas a speech-based user interface is used to instruct patients on how to complete their activities. In the UbiSense system devised by Benny *et al.*, vision techniques are employed to identify changes in the users' posture, gait, and activities, thus allowing to detect dangerous situations, such as falls, in advance [41].

Recent researches aim at extending the support provided by ubiquitous assistance solutions, and at promoting patients' engagement in rich socioemotional relationships. Solutions of this class are collectively named as ubiquitous care networking solutions. Although the ubiquitous care networking research is still in its infancy, few relevant proposals are emerging that permit to identify the different stake-holders involved in patient care, to promote their engagement in care, and to favor the establishment and maintenance of strong social relations with the patient. A relevant extension to this basic model is presented in different research work, such as [9], [42], where context-aware middleware solutions are proposed for the creation and management of *ad hoc* assistance teams to provide emergency assistance to senior citizens in need of immediate help.

III. Pervasive and Affective Healthcare Requirements

Available proposals in literature are unquestionably an important step ahead for deploying pervasive healthcare systems. However, current solutions are still more proof-of-concept application prototypes to investigate single management aspects of affective computing and ubiquitous healthcare, rather than comprehensive frameworks for supporting the design, development, and deployment of anytime, anywhere healthcare services. The vast majority of literature proposals are built on top of the network layer and tend to provide dedicated support for specific applications. However, this approach has several shortcomings. Application designers can hardly reuse implemented supports in different application situations, e.g., to suit the needs of patients affected by different pathologies. As a consequence, it is necessary to design and develop a new support system from scratch, whenever it is necessary to implement a new application. In addition, building healthcare applications on top of the network layer can be tedious and error-prone because it is necessary to deal explicitly with all the issues related to users and devices mobility, intermittent connectivity, sensor data acquisition, and processing, etc. Middleware-level solutions for healthcare may offer interesting opportunities to master the complexity of healthcare. Middleware solutions could, for example, provide support for different service management details, such as user location detection and tracking, user profiling, acquisition of biosignals from sensors, etc. The main advantage is to provide application developers with a support that permit them to focus only on designing and developing the application logic, without the need for implementing low-level features. This significantly simplifies and accelerates application development. Designers may use the same middleware-level support in different ubiquitous and affective healthcare applications, thus encouraging applications interoperation and rapid prototyping.

To support affective healthcare in ubiquitous environments, we must account for context information, such as users affective states, physical conditions, physical allocation, etc. Toward this goal, middleware proposals should provide integrated support for context modeling, acquisition, and reasoning. Aside location-awareness, we need to take into account two other forms of context-awareness in affective healthcare scenarios, namely psychoemotional awareness and group awareness.

A. *Psychoemotional Awareness*

Psychoemotional awareness entails the whole information describing psychological and health condition of an individual, including his/her health status (such as blood pressure and temperature), gestures (signifying emotional conditions), and medical history. In the light of all these information, a context is created based upon which the system needs to dynamically determine whether the patient actually requires aid. For instance, from sensor readings exhibiting elevated blood pressure, temperature, and hormone levels may indicate a number of diseases. In addition, the visibility of other context information, such as different gestures of the patient, including abnormal hand movements, lack of coordination, self indulgence (e.g., the person talking to him/herself), and rapid eye movement, it is indeed possible to determine whether the patient is subject to abnormal emotional and physical conditions, such as the influence of alcohol or drugs.

B. *Group Awareness*

According to our previous research, and following to the detection of a psychoemotional anomaly of patient status and/or behavior, it is possible to promote the formation of *ad hoc* rescue teams comprising nearby volunteers willing to support the patient in need of help. For example, when the system tracks a person with certain physiological and affective symptoms of drug overdose or abuse, it can promptly respond by formulating caregiving groups to assist the victim and contacting the victim's relatives. In order to manage the group memberships, we cannot solely depend on preconceived information of the individuals and their devices that may be available to be included in the group. It is of utmost importance to present the users the opportunity to join or leave the group, and to use communications devices that support various forms of wireless connectivity. For example, at the event when a patient exhibits possible signs of drug abuse/overuse, a group comprising individuals in the vicinity of the incident may be created to provide prompt support to the victim. Such a group should be composed according to volunteers medical skills and may include people from all walks of life (e.g., people with limited medical skills, professional caregivers, family members, and even doctors currently located nearby) who emerge as rescuers.

Finally, the bystander apathy problem [43] needs to be addressed also. When a person apparently requires help, other people around that person usually voluntarily intervenes. This is commonly known as the bystander intervention. However, [43] reveals that help is surprisingly less likely to be provided if more people are present. In some cases, a large group of bystanders may indeed fail to assist a person who is in obvious need of help. In order to reduce such a bystander apathy problem, the context awareness should allow the novel middleware to formulate groups in such a manner in which the best volunteers are selected depending on the context at hand, while the other users are asked not to intervene.

IV. PEACH Framework

PEACH is a context-aware middleware solution that promotes and supports the development of emotional healthcare applications for pervasive computing environments. The PEACH framework (as shown in Fig. 1) provides a set of basic facilities for integrating wearable biosensors able of monitoring the patient's psychophysical conditions, of aggregating sensed data to detect situations, where prompt patient assistance is needed, and to compose and manage groups of volunteers willing to help the patient in emergency situations.

The PEACH framework recognizes the need to consider different management roles in emotional healthcare service provisioning. In PEACH, each patient is provided with a portable device, such as a personal digital assistant (PDA). In addition, patient conditions are monitored by exploiting different sensing entities (SEs). In case of emergency situations, a surveillance center (SC) is alerted, and a prompt response group composed of volunteers willing to help the patient is promoted. In particular, PEACH groups are based on the locality principle and group together volunteers allocated in proximity to the patient.

A. *Emergency Detection Model*

In PEACH, SEs are connected through a wireless body area network (BAN), to the user access terminal, which on its turns, provides suitable support for gathering and aggregating sensed data and to detect situations, where patient assistance is needed.

SEs may display heterogeneous nature and characteristics, ranging from simple wireless sensors to implantable devices, and should be chosen according to patient pathologies and requirements. Sensed data represent the psychoemotional context of the monitored patient. According to the patient's pathology, the SEs may monitor relevant emotion-related and physical information, such as patient's heartbeat, gesture, skin conductivity, etc. SEs not only sense patient context information but also continuously forward collected data to the PEACH support installed on the user access terminal, e.g., a PDA with smartphone features. According to collected SEs readings, the PEACH framework permits to aggregate context information and to detect the presence of a possibly imminent emergency state. In particular, emergency states are detected on the basis of

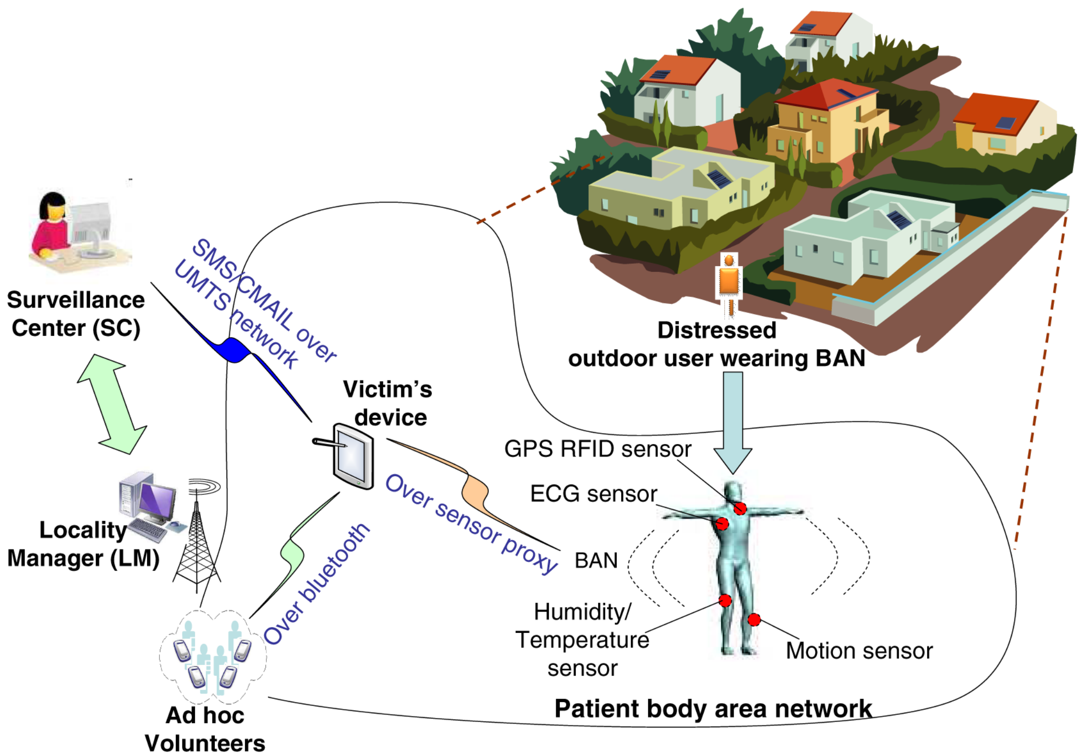


Fig. 1. Peach framework.

a multipleattribute decision-making algorithm (MADM), which is elaborated in Section V.

We here describe our emergency detection technique. Let us assume that a disease or an abnormal health condition (e.g., due to drug abuse) has developed in the patient's body. For example, diseases can vary diversely, from a simple outbreak of flu to a serious case of heart attack or appendicitis. Emotional abnormalities, on the other hand, may be illustrated with examples of panic attacks, paranoia, etc. In case of certain abnormalities, such as drug abuse or overuse, patients exhibit both physiological and emotional symptoms. Based on the set of observable symptoms, PEACH is able to estimate the probability of these various combinations of physiological and/or emotional disorders. It is to be noted here that this is not the focus of our paper. We are more interested in the communications aspects. Nevertheless, an overview of how PEACH may evaluate a possible disorder is given below.

Let us suppose that PEACH has a set of disorders and a set of observable symptoms, denoted by F_j and x_i^j, respectively, where $i = 1, 2, \ldots, n$ and $j = 1, 2, \ldots, m$. If the probabilities associated with the disorders, i.e., $p(F_j)$ are known, and further, if the symptoms $x_1^j, x_2^j, \ldots, x_l^j$, are known (where $\{1 \le l \le n\}$) for the jth disorder such that their conditional probabilities $p(x_1^j|F_j), p(x_2^j|F_j), \ldots, p(x_l^j|F_j)$ are statistically independent and known, then from Baye's rule, we have the following:

$$p(F_j|x_1 x_2, \ldots, x_n) = \frac{p(F_j x_1^j x_2^j, \ldots, x_l^j)}{p(x_1^j x_2^j, \ldots, x_l^j)}. \quad (1)$$

As a consequence of the assumed statistical independence of $p(x_1^j|F_j), p(x_2^j|F_j), \ldots, p(x_l^j|F_j)$, we have the following:

$$p(x_1^j x_2^j, \ldots, x_l^j) = \sum_{k=1}^{m} p(x_1^k|F_k) p(x_2^k|F_k) \ldots p(x_l^k|F_k) p(F_k) \quad (2)$$

and

$$p(F_j x_1^j x_2^j, \ldots, x_l^j) = p(x_1^j|F_j) \ldots p(x_l^j|F_j) p(F_j). \quad (3)$$

By substituting (2) and (3) into (1), we have

$$p(F_j|x_1 x_2, \ldots, x_n) = \frac{p(x_1^j|F_j) p(x_2^j|F_j) \ldots p(x_l^j|F_j) p(F_j)}{\sum_{k=1}^{m} p(x_1^k|F_k) p(x_2^k|F_k) \ldots p(x_l^k|F_k) p(F_k)} \quad (4)$$

where $p(F_k)$ and $p(x_i^j|F_j)$ represent the probability of having the kth disorder (i.e., physiological, emotional, or combined) and that of observing symptom x_i, given that the patient has the jth disorder (denoted by the functional value F_j), respectively.

In PEACH, the complexity of evaluating and storing the conditional probability $p(F_j|x_1 x_2, \ldots, x_n)$ increases exponentially with the increasing number of symptoms. By separating the set of n symptoms into $l(l \le n)$ reduces this complexity by formulating mutually independent subgroups of symptoms.

The right hand term of (4) is based on both $p(F_j)$ and $p(x_i^j|F_j)$. Since these two quantities are not known $a\ priori$, PEACH needs to obtain them by estimation, accuracy of which is indeed crucial. Hence, we carefully estimate $p(x_i^j|F_j)$ from the past history of various patients' syndromes and the

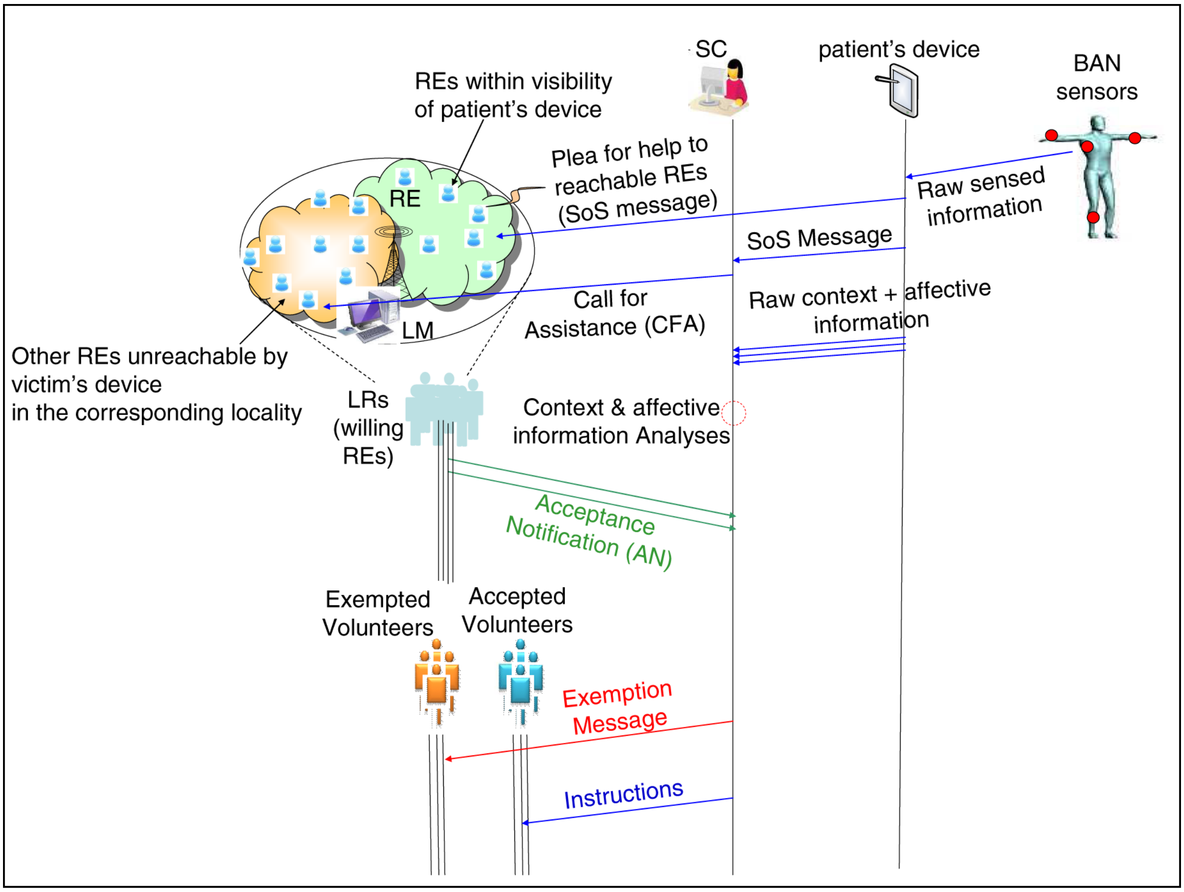


Fig. 2. Messages exchanged between different entities in PEACH framework upon detection of an emergency event.

associated diseases. For this purpose, we assume that y_j is the outcome of the observable symptom x_i^j given the system has the jth disorder F_j. The value of y_j is either zero or one, for not observing x_i^j with probability $(1 - p_j)$ and for observing x_i^j with probability p_j, respectively. The distribution of y_j is expressed in terms of a Bernoulli trial as follows:

$$f(y_j) = p_j^{y_j}(1 - p_j)^{1-y_j}, \qquad 1 \geq p_j \geq 0. \tag{5}$$

B. Emergency Response Model

Whenever PEACH detects a possibly dangerous situation, the patient access terminal promptly promotes suitable response operations. In particular, a response group of volunteers allocated nearby the patient is promptly composed. In addition, aggregated context information are forwarded to the SC by exploiting available networking support, e.g., Wi–Fi, general packet radio service (GPRS), or universal mobile telecommunications system (UMTS) networks. In the following the detail response group formation and management are discussed.

While the patient is roaming, his/her access terminal belongs, as a node, to a mobile *ad hoc* network (MANET) topology. When the patient's access terminal/PDA detects abnormal context information that are indicative of an emergency event, it sends plea for help to surrounding *ad hoc* peers. To discover these peers, the patient's device can employ Bluetooth technology that uses the free and globally available 2.4 GHz industrial scientific medical (ISM) radio band. This is unlicensed for low-power use and allows the patient's device to communicate with peer devices withing a range of 10–100 m. For increased range of communications, IEEE 802.11 *ad hoc* mode may also be employed. These peers in the concerned locality (i.e., in the locality of the patient) are called roaming entities (REs). As demonstrated in Fig. 2, the patient's device sends plea for help to the REs within its visibility. This emergency notification message issued by the patient's PDA is referred to as Save Our Souls (SOS) throughout this paper. However, there may be a number of undiscovered REs in the corresponding locality that are unreachable by the victim's device. In order to include all the REs in an effective manner, PEACH uses the local manager (LM) entities. For each locality, a LM is deployed in the access point. Upon handoff, a device switches to the new access point of the new locality, and this information is delegated and stored in the LM of the corresponding locality. In the mean time, the patient's PDA also notifies a SOS to the SC regarding the event (e.g., by writing a short messaging service or by placing an emergency call to the SC). On the other hand, the REs representing the roaming individuals, who are positioned in the same locality as the victim and have been requested by the victim's PDA for assistance, also apprise the SC whether they intend to assist the victim or not through acceptance notification (AN) messages. The SC then finds out the available REs in the concerned locality by contacting with the LM of this locality and issues a call for assistance (CFA) message to the rest of the REs, which were not discovered and contacted by the victim's device. The contents of a CFA message include basic personal information of the victim, such as his age and sex, his current location, his physical and cognitive characteristics, the kind of assistance he requires, his current health status (e.g., high blood pressure, eye-popping conditions, etc. that are typical of drug overdoses).

An RE who demonstrates willingness to help the patient by dispatching an AN message to the SC is referred to as a local rescuer (LR). Each LR is identified by a unique user identifier dubbed as UID. The AN message consists of the LR's UID, current position, and the estimated time frame within which he/she may be able to arrive at the target spot. Each LR is obviously a subscriber of the PEACH service. An LR may be a family member, friend, or neighbor of the victim, or may also be a total stranger (e.g., from a common pedestrian to a professional caregiver/medical specialist). SC stores the profile information of every LR, including his/her identity, current physical location, medical background, and track record in providing timely assistance to victims. The devices subscribed by LRs are trusted by the SC so that they may discover, join, and leave dynamic rescue groups. An LR that joins a particular group is also able to fetch from the SC the visibility information and also the profiles of other members in this group who are located nearby. In this way, PEACH avoids the situation, where the patient's PDA would have to provide information to all the peers in the locality, which would 1) flood the network with redundant information increasing congestion and communications delay; and 2) exhaust valuable battery power of the patient's PDA that should remain switched on as long as possible. In addition, PEACH also facilitates message exchanges among the *ad hoc* group members (i.e., the LRs), thereby allowing them to collaborate swiftly to assist the victim.

From here on, we describe the functionality of the SC, main task of which is coordinating the tasks that follow an emergency situation, i.e., formation of rescue groups based on best possible LRs and also handing out information to the selected LRs' devices regarding possible courses of action. While formulating emergency response groups, the SC has to take into account the bystander apathy problem. The bystander apathy, also known as Genovese syndrome, is the psychological phenomena among the LRs in which an LR is less likely to intervene in an emergency situation when a large number of other LRs are also present at the scene. Such a bystander apathy can potentially lead to the victim being not attended at all, even in the presence of a large number of volunteering LRs. PEACH framework allows SC to mitigate the bystander effect as much as possible. To this end, the SC first categorizes the type of emergency situation that is at hand and also determines the necessary course of actions. Second, it takes into consideration the profile information, expertise, and experience of each of the willing LRs. Based on these information, the SC selects the LRs who are best suited to respond to this particular type of emergency scenario. Thus, the SC creates an assistance group (synonymous to rescue group, volunteer group, and emergency response group) comprising the potentially best LR candidates only. When the SC finds out the most suitable LRs by executing a MADM algorithm (detailed implementation of this is provided in the following section), it issues a notification to them. Meanwhile, it provides them with information on how to access the victim's current location and also guides them on what kind of assistance may be required. It should be noted here that formulating a response group is indeed a challenging MADM problem. Solutions to this problem requires tradeoffs pertaining to the victim's pathological conditions, distance of a LR from the victim's current location, his medical expertise, etc. In PEACH, each victim support unit is uniquely identified by a group identifier (GID) and a profile that includes information on the victim's identity, his pathologies, his contact information and home address, his family members, current location (e.g., whether he is in distress at home or outside, whether he has been moved by others after he succumbed to illness), etc.

It is worth stressing that assigning group formation duties to SC can provide several advantages. From the technical perspective, our model permits to reduce traffic congestion on patient's locality. In fact, PEACH does not require potential helpers to distribute their profile information to the patient device to promote the formation of a response group. In addition, our approach does not overload patient's devices to solve complex MADM problems. Finally, the envisioned solution to the group formation problem can provide a suitable basis to mitigate the effect of bystander apathy. In fact, upon reception of an invitation to join a response group, a potential helper is able to actually understand the need to promptly act.

V. Implementation of the PEACH Architecture

We here present PEACH architecture and implementation insights. Our solution provides all basic facilities needed for managing a BAN-based sensing platform able of continuously monitoring patient's psychoemotional states. In addition, our solution also integrates a group management support, which is able of composing groups of individuals willing to provide prompt help to the patient when it is needed. Groups are composed both on the basis of the current physical locations of the users' devices and the expertise of the users in terms of their medical skills, as well as prior caregiving experiences.

Fig. 3 illustrates the PEACH middleware architecture consisting of three layers, namely the monitoring and assistance (MA), response management (RM), and group communications (GC) layers, implemented on top of the Java virtual machine (JVM).

A. PEACH MA Layer

The PEACH MA layer provides the needed support to collect and aggregate the raw context information (representing patient's psychophysical context) from the deployed sensors over the BAN of the monitored patient, to aggregate sensed data, and to detect whether the patient is in need of help.

Due to the need to customize and also to (possibly) update the sensing infrastructure frequently, according to patient's evolving needs, the MA layer is implemented on top of OSCAR [44], an open service gateway initiative (OSGi) compliant support. OSGi facilitates software life-cycle management and permits

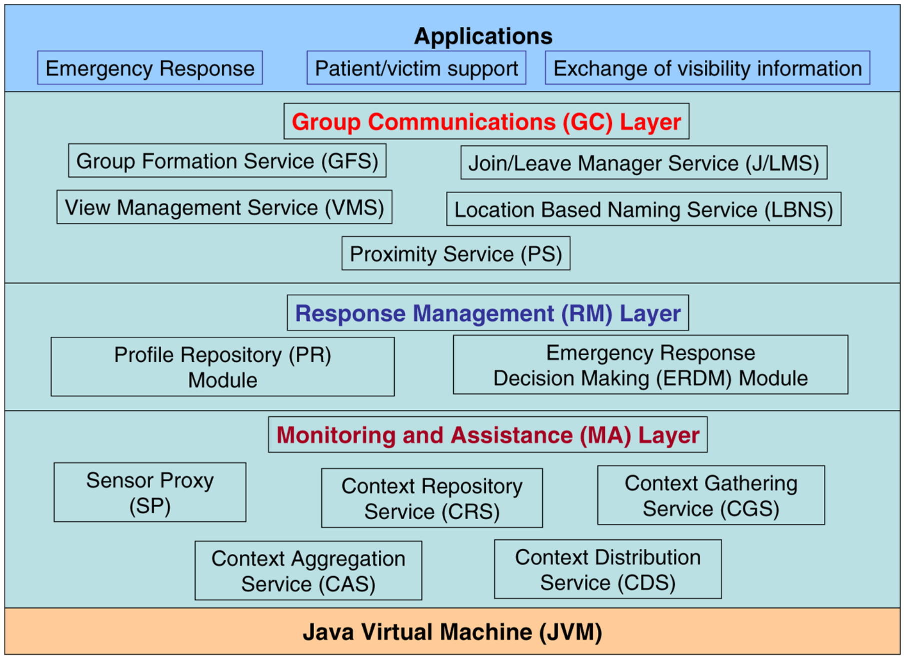


Fig. 3. Modular implementation of PEACH.

to upgrade our service infrastructure easily, without requiring major changes on the application layer.

The main services composing the MA layer are depicted in Fig. 3 and include: context gathering service (CGS), sensor proxy (SP), context aggregation service (CAS), context repository service (CRS), and context distribution service (CDS).

CGS is in-charge of collecting psychoemotional context data from deployed SP instances. Each SP is statically associated to a specific sensor and is in-charge of sampling sensed data at regular intervals. The time between consecutive samples depends on sensor characteristics. For example, while monitoring for drug overuse, patient temperature can be sampled every ten minutes, whereas blood pressure should be sampled more frequently, e.g., every minute. After obtaining context information from the SP, CGS forward them to CRS and CAS, which are in-charge of storing collected information and of aggregating them according to application requirements and patient's pathologies, respectively. In particular, CAS is also in-charge of detecting whether the patient is under an immediate threat and whether prompt help is required. To this end, CAS compares the aggregated context information with a previously formulated user/patient-profile, which is stored in the patient's access terminal. This profile typically contains patient's basic information (e.g., name, address, and family members) and also his/her pathological information (e.g., regular heartbeat rate, respiration rate, temperature, etc.). Based on the profile, CAS can interpret the baseline conditions for the patient-specific pathologies. Detection of threats is performed on the basis of the comparison between this conventional profile of the patient that establishes the value of sensed parameters when his/her psychophysical status is normal, with the sensed data. If significant alterations in sensed data are detected, then PEACH assumes an imminent medical threat to the patient. As a consequence, CAS coordinates with services of RM and GCs layers to trigger a suitable emergency response.

B. PEACH RM Layer

The RM layer provides the needed support to promote the formation of groups of volunteers according to a multiplicity of criteria, such as their physical allocation, medical skills, and patient's pathologies. In particular, RM provides basic services to receive emergency notifications from the MA layer, to gather information needed for forming a response group, and to identify a set of potential helpers to invite to the newly formed emergency response group.

Fig. 3 depicts the main RM layer services, i.e., emergency response decision making (ERDM) service and profile repository (PR).

Following to these emergency notifications, ERDM begins promoting the formation of a group of responders, who are willing to help the patient (i.e., who become LRs), and are within a close proximity of the patient (i.e., are found to be colocated with the LM via the proximity service (PS), which has the visibility of nearby individuals). To identify the best suited responders to help the patient, ERDM sees if the potential rescuers are indeed nearby and obtains their profiles information by coordinating with the PS and PR, respectively. ERDM then faces with a MADM problem in terms of the LRs' current locations, skills, medical expertise, history of previous rescue attempts, etc. In order to solve this problem, for each LR, LR_k that subscribes to the PEACH service, a set of attributes $(X_{k,j}, j \epsilon \{1, 2, \ldots, t\})$ is assigned, as shown in Table I. These attributes include: 1) the expertise and skills of the LRs; 2) their history records in providing assistance; and 3) the trust levels that SC associates with them. SC constantly updates and maintains these attributes.

TABLE I
FORMAT OF LRs PROFILES

LR ID (LR_i)	Attribute 1, X_1	Attribute 2, X_2	Attribute 3, X_3		Attribute t, X_t
LR_1	$X_{1,1}$	$X_{1,2}$	$X_{1,3}$		$X_{1,t}$
LR_2	$X_{2,1}$	$X_{2,2}$	$X_{2,3}$		$X_{2,t}$
LR_3	$X_{3,1}$	$X_{3,2}$	$X_{3,3}$		$X_{3,t}$
.	.	.	.	.	
.	.	.	.	.	
.	.	.	.	.	
LR_N	$X_{N,1}$	$X_{N,2}$	$X_{N,3}$		$X_{N,t}$

TABLE II
EMERGENCY LEVELS AND THEIR ASSOCIATED PARAMETERS

Emergency Level	Attribute 1, X_1	Attribute 2, X_2		Attribute t, X_t	Action Time	Acceptance Threshold	Waiting Timeout
e_1	$w_{1,1}$	$w_{1,2}$		$w_{1,t}$	θ_1	γ_1	τ_1
e_2	$w_{2,1}$	$w_{2,2}$		$w_{2,t}$	θ_2	γ_2	τ_2
.	.	.	.	.	.	.	.
.	.	.	.	.	.	.	.
.	.	.	.	.	.	.	.
e_M	$w_{M,1}$	$w_{M,2}$		$w_{M,t}$	θ_M	γ_M	τ_M

The PEACH implementation assumes that there are M emergency levels predefined at the SC. As shown in Table II, for each emergency level e_i ($i\epsilon\{1, 2, \dots M\}$) and each attribute X_j ($j\epsilon\{1, 2, \dots, t\}$), SC assigns a weight $w_{i,j}$ and three additional parameters, namely the minimum response time within which the victim should be assisted, the acceptance threshold for selecting LRs, and the maximum waiting time SC should wait for receiving AN messages from the LRs, denoted by θ_i, γ_i, and τ_m, respectively.

Whenever potential rescuers are selected, ERDM forward them a request to join the group. The request to join message includes information, such as the GID associated with this group, a set of instructions to attend the patient, last confirmed location of the patient, information pertaining to the shortest route to access the victim, etc.

ERDM awaits for acknowledgments (i.e., AN messages in Fig. 2) from potential helpers during a timeout period of τ_m. When either τ_m expires or the system receives the responses from at least the required number of skillful and/or nonskilled helpers for this emergency level, ERDM sorts out the helpers based on the information within their AN messages (e.g., physical proximity and availability of the LRs) and also based on the minimum response time (θ_i), specific to the emergency level. Out of these already sorted LRs, only those with attributes that satisfy the following condition are selected to assist the victim:

$$A_k W_m = \sum_{p=1}^{t} X_{k,p} w_{m,p} \geq \gamma_m \tag{6}$$

where A_k and W_m represent the vector of attributes of LR$_k$ and the weight vector associated with the emergency level (i.e., $W_m = \{w_{m,1}, w_{m,2}, \dots, w_{m,t}\}$), respectively.

Thus, when the set of volunteers willing to help the patient is determined, ERDM coordinates with the GCs layer to enable group collaboration.

C. PEACH GC Layer

Based on the ANGELAH middleware [10], we envision the GC layer, which presents the LRs, selected by the RM layer, to become rescuers. As illustrated in Fig. 3, the GC layer consists of group formation service (GFS), join/leave manager service (J/LMS), view manager service (VMS), location-based naming service (LBNS), and PS modules. By coordinating these various modules, the GC layer provides important functionalities to compose, dissolve, and manage emergency response groups in wireless environments.

As mentioned earlier, the PS module, installed at LM, helps the ERDM entity of RM layer to find who are nearby (i.e., the UIDs of neighboring users of the patient). Following an emergency event, ERDM coordinates with the GFS module (also installed at LM) to promote a new rescue group. GFS receives profiles information of both the patient and selected LRs, and coordinates with the LBNS module that arbitrarily generates and assigns the concerned GID and UIDs. A selected LR is then invited to join the group using the J/LMS instance deployed on his/her portable device.

The VMS is an important module in the GC layer because of its role in creating, maintaining, and disseminating group views to this newly formed group members. Each view consists of the list of group members (i.e., in terms of their UIDs/IP addresses retrieved by PS) and their profiles information. PS monitors the availability of the group members by sending them advertisement messages periodically. When the latency between subsequent advertisements to a particular member exceeds a threshold (determined by taking into consideration factors, such as the average number of responders within a locality, their mobility patterns, and the surface of the locality), PS considers that individual to be disconnected. Whenever the PS finds a rescuer to join, disconnect, or permanently quit the group, it accordingly updates the view.

The previously described interactions among the various entities, groups, and services in PEACH aimed at forming a rescue group are depicted in Fig. 4.

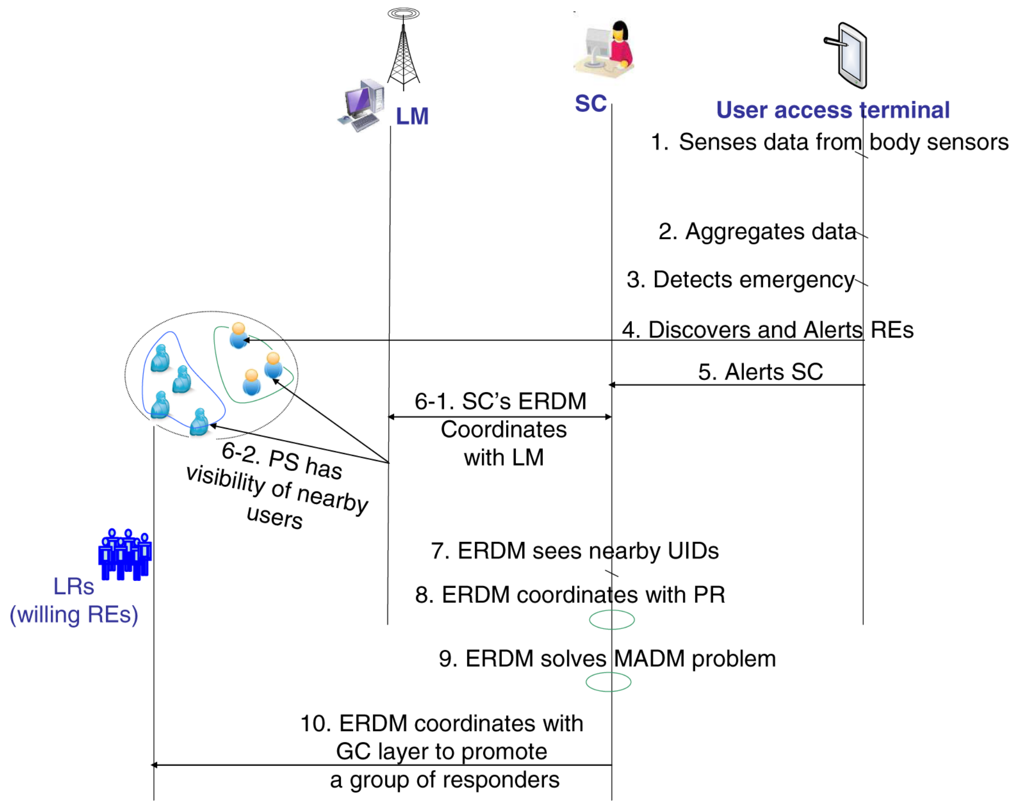


Fig. 4. Interaction among the PEACH entities and services for promoting a responders group.

VI. PEACH at Work in a Drug Addiction Scenario

To demonstrate the feasibility of our approach, we implemented an application prototype on top of PEACH to detect drug overdoses and promote support groups to provide assistance to victims.

A. Experimental Settings

Our experimental scenario acknowledges the need to consider several roles, namely patient, rescuer, and SC roles.

Patients are provided with Xybernauts MA-V, laptop like wearable devices. Each patient device installs Linux, J2SE 1.5, and a subset of PEACH services of the MA layer. Patients devices are also equipped with a UMTS networking support to interact with the remote SC in the case of emergency. In addition, patients' devices are also connected to several sensors via Bluetooth connectivity. In particular, in our scenario, and without lack of generality, we consider Global Positioning System (GPS) location support, along with several biosensors. In particular, our test-bed setting includes blood pressure sensors, respiration sensors, and skin conductivity sensors. Sensors are selected on the basis of the application scenario. In fact, in drug overdose avoidance domains, it is necessary to consider the following symptoms using the deployed sensors:

1) x_1: rapid and/or irregular heartbeats;
2) x_2: elevated pulse rate;
3) x_3: elevated blood pressure;
4) x_4: slowed breathing;
5) x_5: rise in body temperature;
6) x_6: rise in sweat in the palms;
7) x_7: tremors, jitters, or shakes of hands, feet, or head;
8) x_8: change/rise in hormone levels;
9) x_9: poor coordination, tripping, spilling, bumping into things, and other passers-by;
10) x_{10}: large or small (dilated) pupils;
11) ....

Clearly enough, according to patient's needs, it is also possible to enrich the sensing platform by considering further elements. However, in our experiments, we have reduced monitoring to only the key symptoms, namely x_1 to x_5 for keeping the number of biosensors, and the interaction between the patient device and the deployed sensors as low as possible. It is worth noticing that in order to provide a suitable support for interaction between potential users and the remote SC, potential helpers' devices are also equipped with UMTS support for maintaining continuous remote connectivity.

In our test-bed setting, potential helpers are equipped with wireless-enabled iPAQ PDAs, running Linux, Java SE 1.4, along with GC layer PEACH services. Moreover, hands-free communications through JAVA speech application programming interfaces (APIs) on top of the IBM via voice speech engine are provided.

In our settings, we have also deployed a SC composed of one PC running Linux and J2SE 1.5. The SC also runs the PEACH services belonging to the RM and GC layers for assessing and responding to plea for help from the concerned patients, and for promoting *ad hoc* assistance teams, respectively. In addition, for each locality, a PC is configured as an LM, which operates on

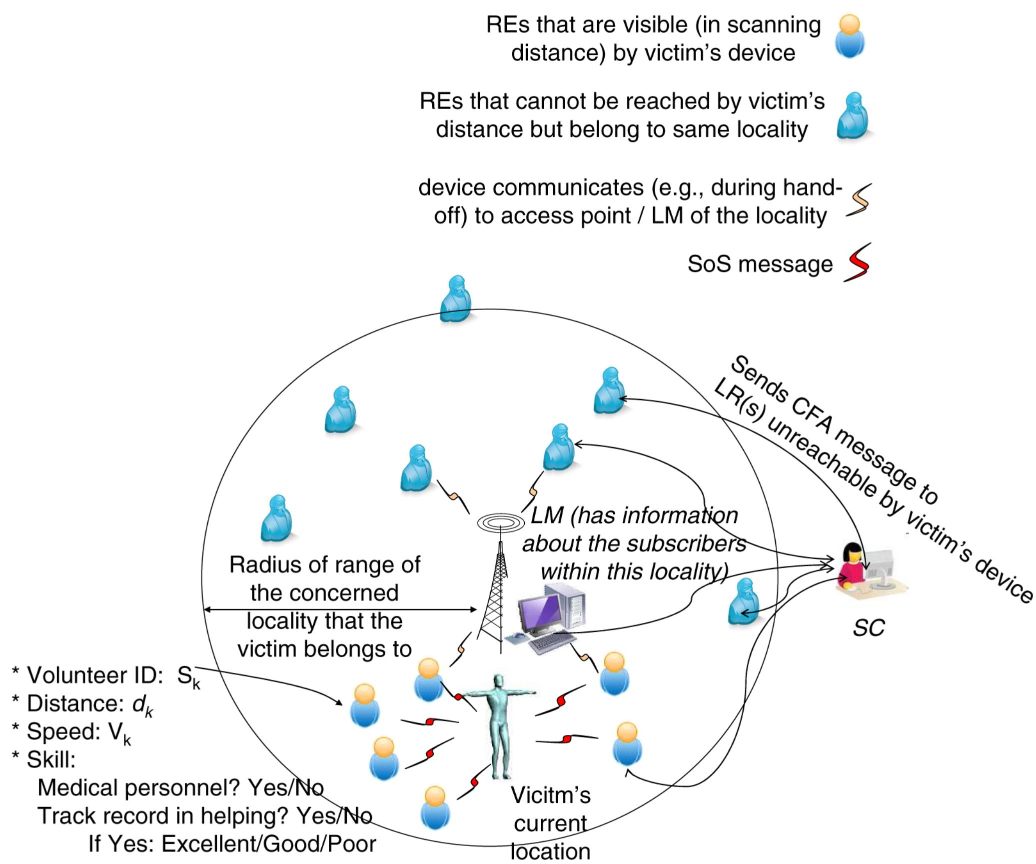


Fig. 5. Sample experimental scenario.

Linux and consists of the PS entity, which is implemented by binding the PC with the local access point.

Patient's and potential helpers' devices are connected via a MANET. In particular, the network is based on IEEE 802.11 standards. In addition, without lack of generality, in our scenario IP addresses are statically determined at deployment time, and the "*ad hoc* on-demand distance vector" (AODV) protocol provides the needed network routing support.

B. Formation of Rescue Teams

The patient's device and the RE devices, upon entering a locality, switch to the concerned access point and LM. When an abnormal situation (generally understood in terms of a function of the exhibited symptoms and physical, as well as emotional conditions of the patient) comes into notice by the user's device, it changes to the *ad hoc* mode and sends SOS messages to the discovered portable devices of the nearby PEACH subscribers (see Fig. 5) who may be either skilled (e.g., doctors, medical officers, and trained first-aid givers) or nonskilled (simple passersby without any prior medical/healthcare training). In order to construct a realistic scenario, the REs' devices are placed at varying distances from the victim, e.g., from just a few meters (within eye distances) to 100 m. The REs that are thus contacted by the victim and are willing to come in aid of the patient become LRs and accordingly report to the SC. Meanwhile, the victim's device also contacts the SC. The SC then contacts the LM of the corresponding locality to obtain information regarding the REs unreachable by the patient's device. The SC issues CFA messages to these REs. Upon receiving the willing LRs' confirmations about assisting the patient, the SC then proactively promotes the formation of a rescue group. First, the SC uses its PS to advertise its online availability. Meanwhile, it uses GFS, in concert with LBNS, to create the appropriate GIDs and UIDs, and accordingly sets up group profiles. The J/LMS modules installed in the portable devices of the LRs sense the advertisements and invite the selected LRs to join the group while discarding the nonselected LRs by sending them a negative message. When a LR joins this new group via J/LMS, VMS provides in the group view with the LR's profile information, current location, estimated time of arrival at the scene, etc. The GID and UID of the new group member, along with the updated view, are returned to this new member. It is worth mentioning that the view-based concept is rather dynamic in nature and context-dependent views may indeed change to incorporate variations in collocated pedestrians (who turned into rescuers) while the victim awaits assistance.

The nonselected LRs are provided with a negative message. By this way, the system attempts to proactively avert possible bystander effects. Upon receiving emergency signals for assistance by the SC, the applications installed on the selected LRs' devices require them (the respective LRs) to explicitly respond to this event. The SC that receives acknowledgments from the willing LRs build a list of volunteers, who are indeed ready to help. In our PEACH implementation, the application at an LR-end keeps playing an emergency beep at an increasing volume up to the point where the user explicitly accepts or rejects to offer assistance. Our observations from previous work [9] have indicated that such sound-signal-based implementations indeed function well in clearly informing the passersby that it is not a drill, i.e., an emergency situation is at hand and their assistance is needed on an urgent basis.

C. Experimental Results and Lesson Learned

PEACH induces different forms of overheads. We here report the main result obtained in PEACH experimentation. In particular, we here first discuss PEACH responsiveness in group formation. We define responsiveness as the amount of time needed to compose a group of responders following to the emergency notification. Responsiveness is a critical aspect to consider in our system. In fact, PEACH is required to promote the formation of response groups in a short amount of time, thus facilitating prompt help to the patient. Then, we consider battery degradation on mobile nodes. Battery degradation should be considered as a crucial aspect in anywhere, anytime assistance, since both patients and potential users assumed to be able to take advantage of their devices. Finally, we report our evaluations on memory requirements over mobile terminals to demonstrate that the imposed overhead in terms of memory use permits the deployment of PEACH applications even on resource constrained portable devices.

1) PEACH Responsiveness: In our experiments, we have considered one patient, 20 potential responders, and a single SC. We constructed our experiments by relying on students' help and we deployed our system on a campus setting. The experiment required students to hold the PDA and to freely roam around the campus. Several emergency situations were simulated over the patient devices and the amount of time needed for the students to notice the incident, join the group, and arrive at the scene of incident was measured. A staff member was in-charge of controlling the patient's access terminal and to simulate emergency situations in different localities at arbitrary times. Emergency conditions were simulated by executing an *ad hoc* software component on the patient device to add abnormalities to the sensed data acquired from the biosensors.

Based on the collected results, upon detecting an emergency event, the patient device takes only few milliseconds to alert the SC. On average, one second is required to gather information pertaining to potential helpers allocated in the proximity of the patient. Finally, the average time that SC takes to gather users profile information and to compose a group is found to be approximately three seconds. However, in our experiments, it takes few minutes to let the users actually notice and respond to the invitation to join the response group. In particular, group formation needs about two minutes in our experiments. Two additional minutes are required for all selected helpers to reach the location, where the patient is placed.

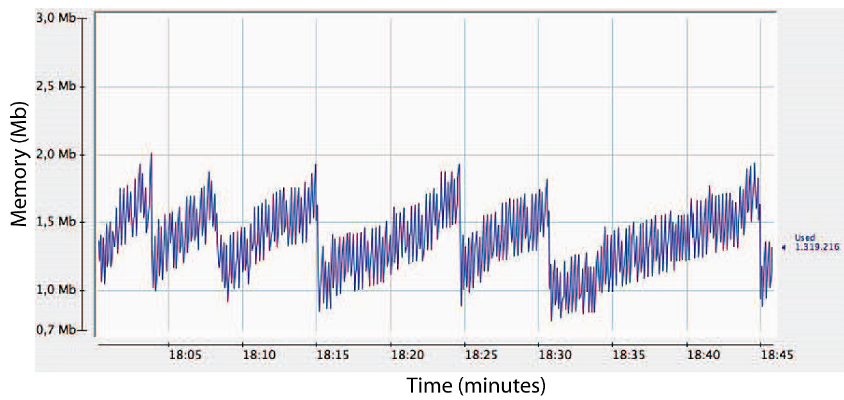
In addition, we have also evaluated PEACH responsiveness in a large-scale scenario. Due to the practical difficulties of deploying a large scale MANET topology, we adopt a simulation-based approach. In particular, our simulations are built on top of the network simulator (ns-2) [45]. We simulate an IEEE 802.11 based network deployed in 1 km^2 area. Our simulations include one patient in need of help along with several potential helpers. Both the patient and potential helpers are also connected via a UMTS link to a ns-2 agent, which acts as the SC.

The time required to compose a response group depends on the number of potential helpers allocated in patient's locality. As a consequence, the time needed to promote a responders' group varies from few seconds in the case of 50 simulated potential helpers, to tens of seconds in the case of 100 nodes, up to few minutes in the case of 500 deployed nodes. These results do not take into account the time needed for the potential helpers to notice the incident and to react accordingly, but demonstrate the suitability of our approach even for large scale MANET environments.

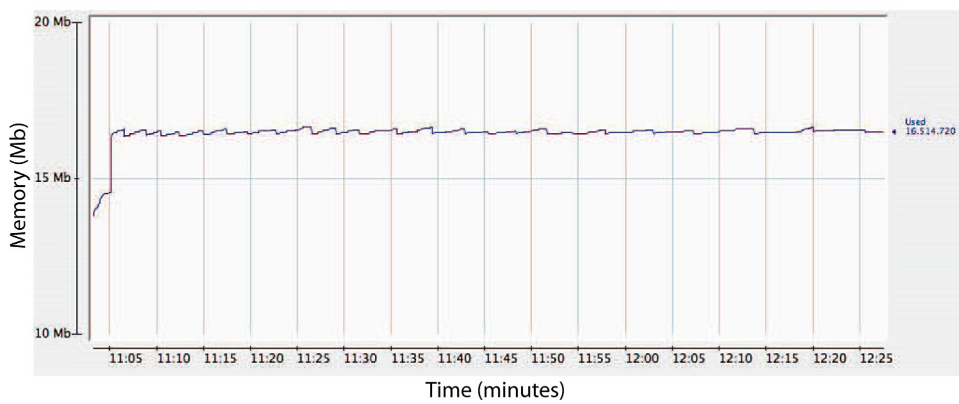
2) Battery Degradation: Another critical aspect to consider in mobile healthcare applications is battery degradation. In fact, it is necessary to provide solutions able of operating anywhere and anytime. Battery degradation can be determined both by computation and networking. PEACH aims at reducing computation needs on portable devices. In fact, the computation to solve a MADM problem needed for group formation is moved on a fixed server operated within the SC. In addition, PEACH protocols minimize, as much as possible, the network cost by reducing the need for communicating large amounts of data between entities running over mobile terminals. However, despite the energy efficient approach adopted in designing the protocol, communications overheads still remain as the main contributor to battery degradation in PEACH.

In particular, the distribution of group views over the MANET network requires both senders and receivers to consume a fraction of their available battery budgets. To investigate this issue, we installed our PEACH application over ten Apple iBook that operate as potential responders and are connected through a MANET. We made several tests by varying the time between consecutive group view disseminations ranging from few tens of seconds, up to few minutes. The resulting average battery life is between 3:30 and 4:40 hours. This result demonstrates a scarce impact of our solution on the overall device energy budget. A similar consideration is applicable to the patient device.

3) Memory Requirements: Finally, we investigate the memory requirements at the individual devices that run PEACH. For this purpose, we consider one out of the three LR devices, subscribed with PEACH, in a locality. By using JConsol profiling tool, we obtain the necessary data for a relatively long time, and then, evaluate the memory requirements of the considered LR device over time as depicted in Fig. 6. Fig. 6(a) demonstrates that the total amount of the used heap memory varies between 0.8 and 2.1 MB. The average value in this case lies around 1.3 MB. On the other hand, Fig. 6(b) takes into account nonheap memory involving data, code, and stack. As this plot shows the nonheap memory over time approaches a consistent value of approximately 16.5 MB. These results clearly demonstrate the viability of installing the PEACH group management services onto a PDA or a smartphone.



(a)



(b)

Fig. 6. Memory usage over time on a particular LR device. (a) Heap memory. (b) Nonheap memory.

VII. Conclusion

Anywhere and anytime healthcare services for the monitored subjects (e.g., patients, drug abusers, etc.) require novel group management solutions. In this paper, we have proposed PEACH, which is a novel framework for quickly formulating and managing *ad hoc* rescue groups in the same locality as the victim's so that they may perform rescue operations and provide life-saving assistance to the victim. Unlike previous approaches, PEACH considers probabilistic functions of roaming victims' physiological and affective symptoms for detecting a potentially emergency situation. A case study of the PEACH framework was envisioned for victims of drug abuse/overuse in an outside test-bed environment. The sensors deployed in the patient's BAN gather and aggregate raw information, and channel them to the victim's device, which aggregates the context information and compares it with previously stored profile information of the patient to detect potentially hazardous situations. We have designed and developed prototypes to be used in responders' PDAs, which are contacted by the victim's device asking for emergency help. Through practical test beds and also via simulations, we have evaluated the performance of PEACH in terms of its responsiveness, battery consumption, and memory use at the rescuers' devices. The empirical results demonstrate that the proposed PEACH framework is viable and will stimulate further research work to extend the current prototype along manifold directions.

By adopting a modular approach in designing and implementing PEACH, we have left scopes for further modules with additional functionalities to be easily inserted into its middleware. Future works in this direction demand investigation into security pertaining to privacy, sensitive healthcare information, etc. To this end, we are currently working on extending PEACH services to integrate modules that will ensure data integrity, privacy, and also nonrepudiation. In future, we expect to develop PEACH to transparently handle more complex scenarios, intricate symptoms and gestures, and process huge volumes of context information.

References

[1] P. Bellavista, D. Bottazzi, A. Corradi, and R. Montanari, "Challenges, opportunities and solutions for ubiquitous eldercare," DEIS University of Bologna Tech. Rep., Oct. 2005.

[2] P. Salovey, A. J. Rothman, J. B. Detweiler, and W. T. Steward, "Emotional states and physical health," *Amer. Psycol.*, vol. 55, no. 1, pp. 110–121, Jan. 2000.

[3] W. Katon and M. D. Sullivan, "Depression and chronic medical illness," *J. Clin. Psychiatry*, vol. 51, pp. 3–11, 1990.

[4] W. Katon, "Depression: Relationship to somatization and chronic medical illness," *J. Clin. Psychiatry*, vol. 45, pp. 4–11, 1984.

[5] G. L. Maddox, "Some correlates of differences in self-assessment of health status among the elderly," *J. Gerontol.*, vol. 17, pp. 180–185, 1962.

[6] R. Tessler and D. Mechanic, "Psychological distress and perceived health status," *J. Health Soc. Behav.*, vol. 19, pp. 254–262, 1978.

[7] N. A. Cummings and W. T. Follette, "Brief psychotherapy and medical utilization," in *The Professional Psychologist Today*, H. Darken, Ed. San Francisco, CA: Jossey-Bass, 1976, pp. 165–174.

[8] K. Jones and T. Vischi, "Impact of alcohol, drug abuse, and mental health treatment on medical care utilization: Review of the research literature," *Med. Care*, vol. 17, pp. 1–82, 1979.
[9] D. Bottazzi, A. Corradi, and R. Montanari, "Context-aware middleware solutions for anytime and anywhere emergency assistance to elderly people," *IEEE Commun. Mag.*, vol. 44, no. 4, pp. 82–90, Apr. 2006.
[10] T. Taleb, D. Bottazzi, M. Guizani, and H. Nait-Charif, "ANGELAH: A framework for assisting elders at home," *IEEE J. Sel. Areas Commun.*, vol. 27, no. 4, pp. 480–494, May 2009.
[11] U. Varshney, "Pervasive healthcare and wireless health monitoring," *J. Mobile Netw. Appl.*, vol. 12, no. 2–3, pp. 113–127, Mar. 2007.
[12] J. E. Bardram and H. B. Christensen, "Pervasive computing support for hospitals: An overview of the activity-based computing project," *IEEE J. Pervasive Comput.*, vol. 6, no. 1, pp. 44–51, Mar. 2007.
[13] D. Trossen, D. Pavel, G. Platt, J. Wall, P. Valencia, C. A. Graves, M. S. Zamarripa, V. M. González, J. Favela, E. Lövquist, and Z. Kulcsár, "Sensor networks, wearable computing, and healthcare applications," *IEEE J. Pervasive Comput.*, vol. 6, no. 2, pp. 58–61, Jun. 2007.
[14] Z. Zeng, M. Pantic, G. I. Roisman, and T. S. Huang, "A survey of affect recognition methods: Audio, visual, and spontaneous expressions," *IEEE Trans. Pattern Anal. Mach. Intell.*, vol. 31, no. 1, pp. 39–58, Jan. 2008.
[15] A. Oikonomopoulos, P. Ioannis, and M. Pantic, "Spatio-temporal salient points for visual recognition of human actions," *IEEE Trans. Systems, Man, Cybern. B, Cybern.*, vol. 36, no. 3, pp. 710–719, Jun. 2006.
[16] J. Healey and R. W. Picard, "Digital processing of affective signals," presented at the ICASSP, Seattle, WA, May 12–15, 1998.
[17] P. Ekman, "About brows: Emotional and conversational signals," in *Human Ethology.* Cambridge, U.K.: Cambridge Univ. Press, pp. 169–202, 1979.
[18] P. Ekman, W. Friesen, and P. Ellsworth, "What emotion categories or dimensions can observers judge from facial behavior?" in *Emotion in the Human Face*, P. Ekman, Ed. New York: Cambridge Univ. Press, 1982, pp. 39–55.
[19] P. Ekman, *Emotion in the Human Face*, 2nd ed. New York: Cambridge Univ. Press, 1982.
[20] P. J. Lang, M. K. Greenwald, M. M. Bradley, and A. O. Hamm, "Looking at pictures: Affective, facial, visceral and behavioral reactions," *Psychophysiology*, vol. 30, pp. 261–273, 1993.
[21] J. A. Russell, "A circumplex model of affect," *J. Pers. Soc. Psychol.*, vol. 39, pp. 1161–1178, 1980.
[22] C. Pelachaud, E. Bevacqua, G. Caridakis, K. Karpouzis, M. Mancini, C. Peters, and A. Raouzaiou, "Mimicking from perception and interpretation," presented at the Enactive Interfaces: Enaction Complexity, Montpellier, France, Nov. 20–21 2006.
[23] J. G. Taylor and N. F. Fragopanagos, "The interaction of attention and emotion," *J. Neural Netw.*, vol. 18, no. 4, pp. 353–369, 2005.
[24] K. R. Scherer, "Appraisal theories," in *Handbook of Cognition and Emotion*, T. Dalgleish and M. Power Editions, Eds. Chichester, England: Wiley, 2005, pp. 637–663.
[25] D. Sander, D. Grandjean, and K. R. Scherer, "A systems approach to appraisal mechanisms in emotion," *J. Neural Netw.*, vol. 18, pp. 317–352, 2005.
[26] Z. Zeng, M. Pantic, G. I. Roisman, and T. S. Huang, "A survey of affect recognition methods: Audio, visual and spontaneous expressions," presented at the Int. Conf. Multimodal Interfaces (ICMI), Nagoya, Japan, Nov. 12–15, 2007.
[27] J. T. Cacioppo, "Introduction: Emotion and health," in *Handbook of Affective Stress*, 1st ed. London, U.K.: Oxford Univ. Press, 2003.
[28] C. Dara, L. Monetta, and M. D. Pell, "Vocal emotion processing in Parkinson's disease: Reduced sensitivity to negative emotions," *Brain Res.*, vol. 1188, pp. 100–111, 2007.
[29] J. Healey and R. W. Picard, "Detecting stress during real-world driving tasks using physiological sensors," *IEEE Trans. Intell. Transp. Syst.*, vol. 6, no. 2, pp. 156–166, Jun. 2005.
[30] R. W. Picard, "Affective medicine: Technology with emotional intelligence," in *Future of Health Technology*, R. G. Bushko, Ed. Amsterdam, The Netherlands: IOS Press, 2001.
[31] C. D. Katsis, G. Ganiatsas, N. Katertsidis, and D. I. Fotiadis, "Emotional understanding using a wearable multisensorial platform," in *Proc. Improving the Quality of Health Information: An Internat. Perspective, Proc. ISHIMR*, P. D. Bamidis *et al.*, Eds., 2005, pp. 188–197.
[32] J. A. Healey, "Wearable and automotive systems for affect recognition from physiology," Ph.D. thesis, MIT, Cambridge, MA, May 2000.
[33] A. Haag, S. Goronzy, P. Schaich, and J. Williams, "Emotion recognition using bio-sensors: First steps towards an automatic system," presented at the Affective Dialogue Systems, Tutorial and ResearchWorkshop, Kloster Irsee, Germany, Jun. 14–16 2004.
[34] F. Nasoz, K. Alvarez, C. L. Lisetti, and N. Finkelstein, "Emotion recognition from physiological signals for presence technologies," *Int. J. Cogn., Technol. Work, Spec. Issue Presence*, vol. 6, no. 1, pp. 1–32, 2003.
[35] K. Kim, S. Bang, and S. Kim, "Emotion recognition system using short-term monitoring of physiological signals," *Med. Biol. Eng. Comp.*, vol. 42, pp. 419–427, 2004.
[36] Online Emotion Recognition. (2010, Feb.). [Online]. Available: http://affect.media.mit.edu
[37] K. Z. Haigh, L. M. Kiff, J. Myers, V. Guralnik, C. W. Geib, J. Phelps, and T. Wagner, "The independent lifestyle assistant (I.L.S.A.): AI lessons learned," presented at the 16th Innovative Appl. Artif. Intell. Conf. (IAAI), San Jose, CA, Jul. 2004.
[38] F. D. Mola, G. Cabri, N. Muratori, R. Quitadamo, and F. Zambonelli, "The UbiMedic framework to support medical emergencies by ubiquitous computing," *Int. Trans. Syst. Sci. Appl.*, vol. 1, no. 1, pp. 15–26, 2006.
[39] C. Pesto, L. Selavo, Y. Chen, J. Ko, J. H. Lim, A. Terzis, A. Watt, J. Jeng, B. Chen, K. Lorincz, and M. Welsh, "Wireless medical sensor networks in emergency response: Implementation and pilot results," presented at the 2008 IEEE Int. Conf. Technol. Homeland Security, Waltham, MA, May 2008.
[40] A. Mihailidis, B. Carmichael, and J. Boger, "The use of computer vision in an intelligent environment to support aging-in-place, safety, and independence in the home," *IEEE Trans. Inf. Technol. Biomed.*, vol. 8, no. 3, pp. 238–247, Sep. 2004.
[41] B. P. Lo, J. L. Wang, and G. Z. Yang, "From imaging networks to behavior profiling: Ubiquitous sensing for managed homecare of the elderly," presented at the 3rd Int. Conf. Pervasive Comput., Munich, Germany, May 2005.
[42] D. Bottazzi, R. Montanari, and A. Toninelli, "Context-aware middleware for anytime, anywhere social networks," *IEEE Intell. Syst.*, vol. 22, no. 5, pp. 23–32, Sep./Oct. 2007.
[43] B. Latane and J. Darley, "Bystander apathy," *Amer. Scientist*, vol. 57, pp. 244–268, 1969.
[44] Oscar, an open source OSGi implementation. (2010, Feb.). [Online]. Avaliable: http://oscar-OSGi.sourceforge.net
[45] The Network Simulator – ns-2. (2010, Feb.). [Online]. Avaliable: http://www.isi.edu/nsnam/ns/

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A Novel Middleware Solution to Improve Ubiquitous Healthcare Systems Aided by Affective Information

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***Abstract*—The arousal of emotion might have consequences for physical health is a broadly acknowledged idea. Therapy for depression, prevention for heart pathologies, and rehabilitation treatments for drug addiction are just a few examples of application domains that may benefit from technologies capable of monitoring, detecting, representing, and disseminating information pertaining to patients' physical and psychological/emotional states. However, the design and development of healthcare applications of this kind is a rather challenging issue that requires to integrate sensor infrastructures, which are able to detect changes in patients' physiological and emotional states, and of sharing this information to interested caregivers, such as professional medical staff, relatives, and friends. This paper proposes the Pervasive Environment for AffeCtive Healthcare (PEACH) framework, a middleware level support for affective healthcare that incarnates these ideas and describes its effective functions in a drug addiction treatment application scenario.**

***Index Terms*—Affective computing, healthcare network, pervasive computing, ubiquitous assistance.**

I. Introduction

HEALTHCARE spending indeed accounts for a significant fraction of the welfare budget of any country. In the years to come, the demographic compression, along with the increased number of senior members in the society will undermine economic sustainability of available healthcare systems. Wise and long-term welfare-oriented policies are mandatory to deal with this daunting challenge. However, to compensate effects and implications of demographic changes in the society, it is also necessary to identify suitable technology solutions capable of reducing healthcare costs, and at the same time, of improving healthcare services quality for citizens.

The widespread diffusion of low-cost portable/embedded devices, and the proliferation of wireless networking solutions offer unique opportunities to avoid/postpone patients hospitalizations, with positive impacts in social, emotional, and economic contexts. Impaired individuals, patients affected by chronic diseases or engaged in rehabilitation therapies may take full advantage from pervasive healthcare systems deployed close to where they live and move, with the main goals of increased independence, safety, and quality of life on the one hand, and of care cost-saving on the other hand [1].

Various research proposals have recently appeared in the literature that suggest the development of solutions, which are able to record and analyze patients' behavioral patterns, to monitor users' mobility, to assist individuals with special needs in their daily activities, such as self-care, etc. However, existing solutions [2]–[8] typically focus only on purely medical aspects of healthcare, and do not pay the required attention to emotional states of the patients. In fact, recent clinical evidences demonstrate how the arousal of emotions could influence the physical health through a number of symptoms and manifestations. Available evidences cast a light on psychophysical aspects, which need to be considered in healthcare service provisioning to promote rethinking of existing pervasive healthcare supports.

With the aforementioned considerations in mind, our research aims at investigating how to take full advantage of emotional aspects of care in ubiquitous healthcare with notable positive potential impacts in disease prevention, therapy, and rehabilitation. However, capturing emotional aspects in healthcare scenarios raises several challenging issues. How can we define, detect, model, and represent the emotional states of individuals? How can we use emotional information to improve healthcare applications? How, when, and whom should we propagate and/or delegate affective information? And finally, how can we identify suitable tradeoffs that keep into account all of these considerations?

To the best of our knowledge, it still seems impossible to provide one-fits-all solution able of covering the whole spectrum of healthcare application domains. Several researches [9], [10] have pointed out the need for user-centric design and for strong customization of pervasive healthcare solutions to better suit to actual patients' needs and pathologies. In order to meet the increasing complex needs and to customize mission critical functions of a modern healthcare system, middleware solutions can provide a viable solution to simplify the development of advanced medicare applications, by providing a set of basic facilities to manage and query sensors, to deal with intermittent wireless connectivity, to detect potentially dangerous situations, etc.

Based upon our previous research on pervasive healthcare [9], [10], this research work presents the *Pervasive Environment for AffeCtive Healthcare* (PEACH) framework, a context-aware middleware-level solution capable of integrating together sensors, able of detecting alterations of patients' psychophysical conditions, of aggregating sensing information, of detecting

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potentially dangerous situations for the patients, and in this case, capable of promoting and supporting the formation of groups of individuals willing to provide prompt assistance to the patient. This paper also describes a PEACH-enabled healthcare application within the drug rehabilitation application domain.

The remainder of this paper is organized as follows. Section II presents relevant related researches, whereas Section III identifies the major requirements and design guidelines that should be followed to support affective healthcare services. Section IV presents PEACH model, while Section V provides its system architecture and implementation insights on response group members selection. Section VI sets the presented work within a state-of-the-art field to evaluate the performance of PEACH. Concluding remarks follow in Section VII.

II. Related Research Work

Lately, a broad literature and relevant research proposals have started to investigate pervasive healthcare and affective computing. However, the convergence of pervasive healthcare and affective computing is still a relatively recent phenomenon, with only few pioneering research works available [9]–[12].

As a consequence, it appears natural for us to consider related researches both in affective computing and pervasive healthcare fields. It is not our goal to exhaustively summarize the state-of-the-art of the aforementioned research fields. Readers interested in complete coverage of pervasive healthcare and affective computing may refer to [11]–[13].

A. Affective Computing

So far, affective computing research has been mainly directed toward the investigation of innovative human–computer interaction models. The ultimate goal is to develop systems able of interacting with the users in a natural manner, by taking full advantage from the rich and multimodal human communication [14]. Affective computing-based user interaction approaches tend to recognize the role of nonsemantic communication, e.g., gesture, with the main advantage of tailoring human–computer interaction according to user behavioral changes rather than on the basis of plain user commands [15], [16].

Affective computing is an extremely challenging research area. The central issues in affective computing are representation, detection, and classification of users emotions.

1) Emotion Representation: Defining, modeling, and representing emotions are extremely challenging tasks. Several practical approaches to the aforementioned issues have been proposed within the psychology research field. In particular, the scientific literature proposes three main approaches to emotion representation, namely emotion description, dimensional description, and appraisal-based description.

Emotion description is a widespread emotion representation model both in psychology and in affective computing research fields. Emotion description models represent emotions in terms of discrete categories of basic emotional elements, such as happiness, sadness, fear, anger, disgust, and surprise [17]–[19]. The theoretical foundation of this approach lies in cross-cultural studies demonstrating that people can perceive basic emotions expressed by the others in the same manner and independently from their cultural and anthropological profiles. However, a list of basic emotions can only cover a tiny part of the rich set of emotional states that an individual experiences in everyday life. Nevertheless, the emotion description approach influences much affective computing, especially due to its intrinsic simplicity. As a consequence, the vast majority of studies in the field of affective computing aim at detecting and recognizing discrete emotion categories.

Relevant researches are currently starting to approach the emotion representation problem according to dimensional and appraisal-based models. However, the discouraging technical complexity of these approaches has strongly limited their practical adoptions. On the one hand, dimensional descriptions of emotions make it technically difficult to distinguish between different emotions, such as fear and anger, or to represent complex emotions, such as surprise [20], [21]. As a consequence, only oversimplified emotion representation models have been proposed so far [22], [23]. On the other hand, appraisal-based emotion representation approaches are still subject to fundamental research and only few research works are currently available in the scientific literature [24], [25].

2) Data Acquisition and Mapping of Emotions: Humans rely on their natural senses, e.g,. sight, touch, and hear, for estimating the current emotional states of the others. The mechanism that permits to understand people's emotional states is rather complex and often requires individuals to use their senses in combination to improve estimation accuracy. According to the aforementioned considerations, early research efforts in affective computing aimed at understanding human emotions by analyzing visual and speech data [26]. More recently, the availability of wearable sensing technologies has opened further possibilities for emotion detection.

Emotions usually induce physiological changes, which may be measured by employing biosensors. For example, fear increases heartbeat and respiration rates, causes palm sweating, etc. By monitoring these emotion-induced physiological signals, it is possible to recognize various emotional states of the users. Different wearable biosensors currently available on the market [e.g., EEG, electromyogram (EMG), ECG, electrodermal activity (EDA)] may play an important role in detecting emotion-induced physiological signals. Indeed, the availability of wearable and low-cost biosensors opens the possibility to monitor individuals' emotional reactions anywhere and at any time [27]. Wearable biosensing solutions are unobtrusive and can be integrated into commonly available objects in everyday life. For example, skin conductivity sensors, blood volume sensors, and respiration sensors may be integrated with shoes, earrings or watches, and T-shirts, respectively [28]. These sensors are capable of monitoring users under various daily conditions ranging from driving to home-based healthcare [29], [30].

Sensed emotion-related raw data obtained from sensors are indeed difficult to use in applications development. In addition, according to user needs, different sensors may be required. As a consequence, it is necessary to provide a suitable mechanism to map sensed data to emotion models. The main advantage is to free application developers from the need to take care of all the details related to raw data acquisition, aggregation, and emotion classification. Toward this goal, the vast majority of solutions in literature adopt emotion description models and rely on specific classification techniques to impose a precise mapping between sensed data and emotion categories. Support vector machines, hidden Markov model, and Fisher linear projection are examples of the different techniques that can be employed for mapping emotional data to emotion models [16], [31]. Notably, available researches exhibit high percentage of correctness in emotion detection [30], [32]–[35]. However, experimental evidences are often obtained in laboratories during controlled experiments, and only in recent times, the research is starting to address emotion detection in uncontrolled environments. Since emotions detection in uncontrolled environments is a challenging issue, the commonly adopted approach is to combine several different emotion-related sensing sources to improve the success ratio [36].

B. Pervasive Healthcare and Affective Computing

In recent times, several research efforts have been directed [1] toward realizing pervasive healthcare. In fact, the increased availability of relatively cheap commonly-on-the-shelf (COTS) mobile devices, sensors, and wireless networking solutions promotes design and development of ubiquitous assistance solutions that integrate wearable devices and smart environments to assist people affected by severe disabilities, to facilitate diagnosis of diseases, and to detect possibly occurring emergency situations. Furthermore, recent researches (e.g., [9]) have also started to investigate the link between wellness and social engagement of individuals. Along this line, few research works have started to investigate ubiquitous care networking supports to overcome social limitations imposed by illness and disability. Toward this goal, ubiquitous care networking proposals provide patients with communication artifacts and services specifically tailored to set them within the context of a rich social and emotional framework and to reduce their sense of loneliness.

1) Ubiquitous Assistance Solutions: A growing research interest both in academia and industry research circles has been recently directed toward ubiquitous assistance solutions. Available research prototypes permit constant in-house monitoring of patients' conditions, and often integrate alerting mechanisms to provide prompt responses to emergency situations. Proposals in literature show different incarnations of these basic ideas and aim at providing assistance to patients, especially elders, affected by diverse pathologies. The Honeywell Laboratories' Independent Life Style Assistant (ILSA) [37], and more recently numerous works, such as [38], [39], are notable examples of integrated smart environments. The main contribution of ILSA is to demonstrate the possibility to build an integrated ubiquitous assistance on the basis of relatively low-cost COTS components. In particular, ILSA adopts a multiagent architecture, where different agents are deployed that are able to support data monitoring via home-installed sensors. Collected data are then aggregated and processed by exploiting planning and machine learning techniques. Accordingly, further agents can assist individuals by controlling actuators deployed in their home environments. More in line with the basic ideas of affective computing, few solutions are promoting user-centric in-home assistance design approaches. For example, in [40] an interesting solution tailored for patients affected by dementia is proposed. The system adopts a vision-based patient monitoring approach to identify whether assisted individuals correctly perform basic daily activities, such as handwashing. Correct execution of activities is recognized by exploiting artificial intelligence (AI) and planning techniques, whereas a speech-based user interface is used to instruct patients on how to complete their activities. In the UbiSense system devised by Benny *et al.*, vision techniques are employed to identify changes in the users' posture, gait, and activities, thus allowing to detect dangerous situations, such as falls, in advance [41].

Recent researches aim at extending the support provided by ubiquitous assistance solutions, and at promoting patients' engagement in rich socioemotional relationships. Solutions of this class are collectively named as ubiquitous care networking solutions. Although the ubiquitous care networking research is still in its infancy, few relevant proposals are emerging that permit to identify the different stake-holders involved in patient care, to promote their engagement in care, and to favor the establishment and maintenance of strong social relations with the patient. A relevant extension to this basic model is presented in different research work, such as [9], [42], where context-aware middleware solutions are proposed for the creation and management of *ad hoc* assistance teams to provide emergency assistance to senior citizens in need of immediate help.

III. PERVASIVE AND AFFECTIVE HEALTHCARE REQUIREMENTS

Available proposals in literature are unquestionably an important step ahead for deploying pervasive healthcare systems. However, current solutions are still more proof-of-concept application prototypes to investigate single management aspects of affective computing and ubiquitous healthcare, rather than comprehensive frameworks for supporting the design, development, and deployment of anytime, anywhere healthcare services. The vast majority of literature proposals are built on top of the network layer and tend to provide dedicated support for specific applications. However, this approach has several shortcomings. Application designers can hardly reuse implemented supports in different application situations, e.g., to suit the needs of patients affected by different pathologies. As a consequence, it is necessary to design and develop a new support system from scratch, whenever it is necessary to implement a new application. In addition, building healthcare applications on top of the network layer can be tedious and error-prone because it is necessary to deal explicitly with all the issues related to users and devices mobility, intermittent connectivity, sensor data acquisition, and processing, etc. Middleware-level solutions for healthcare may offer interesting opportunities to master the complexity of healthcare. Middleware solutions could, for example, provide support for different service management details, such as user location detection and tracking, user profiling, acquisition of biosignals from sensors, etc. The main advantage is to provide application developers with a support that permit them to focus only on designing and developing the application logic, without the need for implementing low-level features. This significantly simplifies and accelerates application development. Designers may use the same middleware-level support in different ubiquitous and affective healthcare applications, thus encouraging applications interoperation and rapid prototyping.

To support affective healthcare in ubiquitous environments, we must account for context information, such as users affective states, physical conditions, physical allocation, etc. Toward this goal, middleware proposals should provide integrated support for context modeling, acquisition, and reasoning. Aside location-awareness, we need to take into account two other forms of context-awareness in affective healthcare scenarios, namely psychoemotional awareness and group awareness.

A. *Psychoemotional Awareness*

Psychoemotional awareness entails the whole information describing psychological and health condition of an individual, including his/her health status (such as blood pressure and temperature), gestures (signifying emotional conditions), and medical history. In the light of all these information, a context is created based upon which the system needs to dynamically determine whether the patient actually requires aid. For instance, from sensor readings exhibiting elevated blood pressure, temperature, and hormone levels may indicate a number of diseases. In addition, the visibility of other context information, such as different gestures of the patient, including abnormal hand movements, lack of coordination, self indulgence (e.g., the person talking to him/herself), and rapid eye movement, it is indeed possible to determine whether the patient is subject to abnormal emotional and physical conditions, such as the influence of alcohol or drugs.

B. *Group Awareness*

According to our previous research, and following to the detection of a psychoemotional anomaly of patient status and/or behavior, it is possible to promote the formation of *ad hoc* rescue teams comprising nearby volunteers willing to support the patient in need of help. For example, when the system tracks a person with certain physiological and affective symptoms of drug overdose or abuse, it can promptly respond by formulating caregiving groups to assist the victim and contacting the victim's relatives. In order to manage the group memberships, we cannot solely depend on preconceived information of the individuals and their devices that may be available to be included in the group. It is of utmost importance to present the users the opportunity to join or leave the group, and to use communications devices that support various forms of wireless connectivity. For example, at the event when a patient exhibits possible signs of drug abuse/overuse, a group comprising individuals in the vicinity of the incident may be created to provide prompt support to the victim. Such a group should be composed according to volunteers medical skills and may include people from all walks of life (e.g., people with limited medical skills, professional caregivers, family members, and even doctors currently located nearby) who emerge as rescuers.

Finally, the bystander apathy problem [43] needs to be addressed also. When a person apparently requires help, other people around that person usually voluntarily intervenes. This is commonly known as the bystander intervention. However, [43] reveals that help is surprisingly less likely to be provided if more people are present. In some cases, a large group of bystanders may indeed fail to assist a person who is in obvious need of help. In order to reduce such a bystander apathy problem, the context awareness should allow the novel middleware to formulate groups in such a manner in which the best volunteers are selected depending on the context at hand, while the other users are asked not to intervene.

IV. PEACH Framework

PEACH is a context-aware middleware solution that promotes and supports the development of emotional healthcare applications for pervasive computing environments. The PEACH framework (as shown in Fig. 1) provides a set of basic facilities for integrating wearable biosensors able of monitoring the patient's psychophysical conditions, of aggregating sensed data to detect situations, where prompt patient assistance is needed, and to compose and manage groups of volunteers willing to help the patient in emergency situations.

The PEACH framework recognizes the need to consider different management roles in emotional healthcare service provisioning. In PEACH, each patient is provided with a portable device, such as a personal digital assistant (PDA). In addition, patient conditions are monitored by exploiting different sensing entities (SEs). In case of emergency situations, a surveillance center (SC) is alerted, and a prompt response group composed of volunteers willing to help the patient is promoted. In particular, PEACH groups are based on the locality principle and group together volunteers allocated in proximity to the patient.

A. *Emergency Detection Model*

In PEACH, SEs are connected through a wireless body area network (BAN), to the user access terminal, which on its turns, provides suitable support for gathering and aggregating sensed data and to detect situations, where patient assistance is needed.

SEs may display heterogeneous nature and characteristics, ranging from simple wireless sensors to implantable devices, and should be chosen according to patient pathologies and requirements. Sensed data represent the psychoemotional context of the monitored patient. According to the patient's pathology, the SEs may monitor relevant emotion-related and physical information, such as patient's heartbeat, gesture, skin conductivity, etc. SEs not only sense patient context information but also continuously forward collected data to the PEACH support installed on the user access terminal, e.g., a PDA with smartphone features. According to collected SEs readings, the PEACH framework permits to aggregate context information and to detect the presence of a possibly imminent emergency state. In particular, emergency states are detected on the basis of

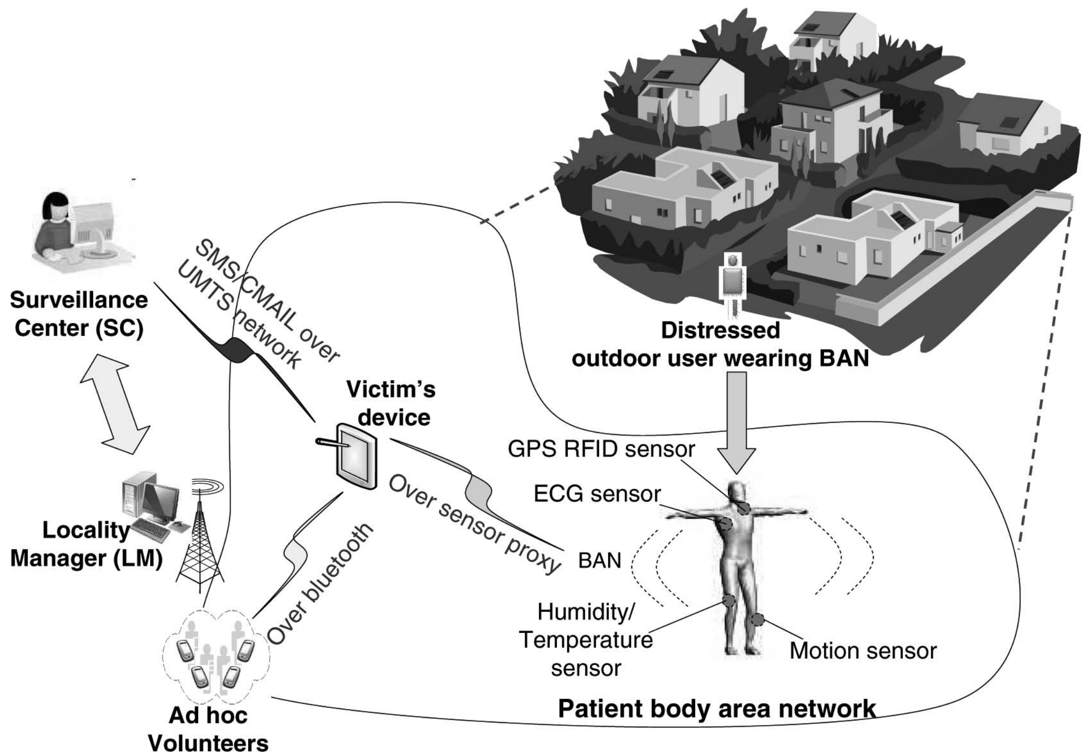

Fig. 1. Peach framework.

a multipleattribute decision-making algorithm (MADM), which is elaborated in Section V.

We here describe our emergency detection technique. Let us assume that a disease or an abnormal health condition (e.g., due to drug abuse) has developed in the patient's body. For example, diseases can vary diversely, from a simple outbreak of flu to a serious case of heart attack or appendicitis. Emotional abnormalities, on the other hand, may be illustrated with examples of panic attacks, paranoia, etc. In case of certain abnormalities, such as drug abuse or overuse, patients exhibit both physiological and emotional symptoms. Based on the set of observable symptoms, PEACH is able to estimate the probability of these various combinations of physiological and/or emotional disorders. It is to be noted here that this is not the focus of our paper. We are more interested in the communications aspects. Nevertheless, an overview of how PEACH may evaluate a possible disorder is given below.

Let us suppose that PEACH has a set of disorders and a set of observable symptoms, denoted by F_j and x_i^j, respectively, where $i = 1, 2, \ldots, n$ and $j = 1, 2, \ldots, m$. If the probabilities associated with the disorders, i.e., $p(F_j)$ are known, and further, if the symptoms $x_1^j, x_2^j, \ldots, x_l^j$, are known (where $\{1 \leq l \leq n\}$) for the jth disorder such that their conditional probabilities $p(x_1^j|F_j), p(x_2^j|F_j), \ldots, p(x_l^j|F_j)$ are statistically independent and known, then from Baye's rule, we have the following:

$$p(F_j|x_1 x_2, \ldots, x_n) = \frac{p(F_j x_1^j x_2^j, \ldots, x_l^j)}{p(x_1^j x_2^j, \ldots, x_l^j)}. \quad (1)$$

As a consequence of the assumed statistical independence of $p(x_1^j|F_j), p(x_2^j|F_j), \ldots, p(x_l^j|F_j)$, we have the following:

$$p(x_1^j x_2^j, \ldots, x_l^j) = \sum_{k=1}^{m} p(x_1^k|F_k) p(x_2^k|F_k) \ldots p(x_l^k|F_k) p(F_k) \quad (2)$$

and

$$p(F_j x_1^j x_2^j, \ldots, x_l^j) = p(x_1^j|F_j) \ldots p(x_l^j|F_j) p(F_j). \quad (3)$$

By substituting (2) and (3) into (1), we have

$$p(F_j|x_1 x_2, \ldots, x_n) = \frac{p(x_1^j|F_j) p(x_2^j|F_j) \ldots p(x_l^j|F_j) p(F_j)}{\sum_{k=1}^{m} p(x_1^k|F_k) p(x_2^k|F_k) \ldots p(x_l^k|F_k) p(F_k)} \quad (4)$$

where $p(F_k)$ and $p(x_i^j|F_j)$ represent the probability of having the kth disorder (i.e., physiological, emotional, or combined) and that of observing symptom x_i, given that the patient has the jth disorder (denoted by the functional value F_j), respectively.

In PEACH, the complexity of evaluating and storing the conditional probability $p(F_j|x_1 x_2, \ldots, x_n)$ increases exponentially with the increasing number of symptoms. By separating the set of n symptoms into $l(l \leq n)$ reduces this complexity by formulating mutually independent subgroups of symptoms.

The right hand term of (4) is based on both $p(F_j)$ and $p(x_i^j|F_j)$. Since these two quantities are not known $a\ priori$, PEACH needs to obtain them by estimation, accuracy of which is indeed crucial. Hence, we carefully estimate $p(x_i^j|F_j)$ from the past history of various patients' syndromes and the

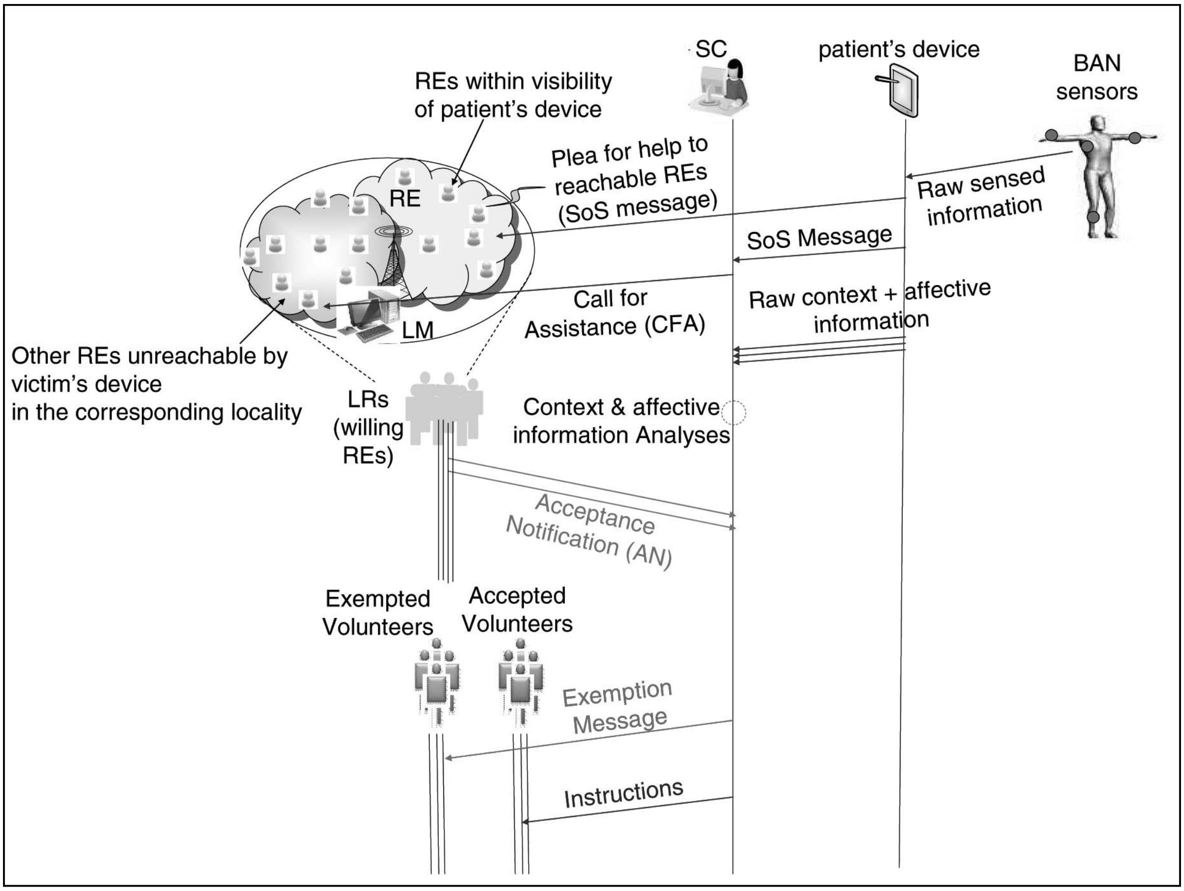

Fig. 2. Messages exchanged between different entities in PEACH framework upon detection of an emergency event.

associated diseases. For this purpose, we assume that y_j is the outcome of the observable symptom x_i^j given the system has the jth disorder F_j. The value of y_j is either zero or one, for not observing x_i^j with probability $(1 - p_j)$ and for observing x_i^j with probability p_j, respectively. The distribution of y_j is expressed in terms of a Bernoulli trial as follows:

$$f(y_j) = p_j^{y_j}(1 - p_j)^{1-y_j}, \qquad 1 \geq p_j \geq 0. \tag{5}$$

B. Emergency Response Model

Whenever PEACH detects a possibly dangerous situation, the patient access terminal promptly promotes suitable response operations. In particular, a response group of volunteers allocated nearby the patient is promptly composed. In addition, aggregated context information are forwarded to the SC by exploiting available networking support, e.g., Wi–Fi, general packet radio service (GPRS), or universal mobile telecommunications system (UMTS) networks. In the following the detail response group formation and management are discussed.

While the patient is roaming, his/her access terminal belongs, as a node, to a mobile *ad hoc* network (MANET) topology. When the patient's access terminal/PDA detects abnormal context information that are indicative of an emergency event, it sends plea for help to surrounding *ad hoc* peers. To discover these peers, the patient's device can employ Bluetooth technology that uses the free and globally available 2.4 GHz industrial scientific medical (ISM) radio band. This is unlicensed for low-power use and allows the patient's device to communicate with peer devices withing a range of 10–100 m. For increased range of communications, IEEE 802.11 *ad hoc* mode may also be employed. These peers in the concerned locality (i.e., in the locality of the patient) are called roaming entities (REs). As demonstrated in Fig. 2, the patient's device sends plea for help to the REs within its visibility. This emergency notification message issued by the patient's PDA is referred to as Save Our Souls (SOS) throughout this paper. However, there may be a number of undiscovered REs in the corresponding locality that are unreachable by the victim's device. In order to include all the REs in an effective manner, PEACH uses the local manager (LM) entities. For each locality, a LM is deployed in the access point. Upon handoff, a device switches to the new access point of the new locality, and this information is delegated and stored in the LM of the corresponding locality. In the mean time, the patient's PDA also notifies a SOS to the SC regarding the event (e.g., by writing a short messaging service or by placing an emergency call to the SC). On the other hand, the REs representing the roaming individuals, who are positioned in the same locality as the victim and have been requested by the victim's PDA for assistance, also apprise the SC whether they intend to assist the victim or not through acceptance notification (AN) messages. The SC then finds out the available REs in the concerned locality by contacting with the LM of this locality and issues a call for assistance (CFA) message to the rest of the REs, which were not discovered and contacted by the victim's device. The contents of a CFA message include basic personal information of the victim, such as his age and sex, his current location, his physical and cognitive characteristics, the kind of assistance he requires, his current health status (e.g., high blood pressure, eye-popping conditions, etc. that are typical of drug overdoses).

An RE who demonstrates willingness to help the patient by dispatching an AN message to the SC is referred to as a local rescuer (LR). Each LR is identified by a unique user identifier dubbed as UID. The AN message consists of the LR's UID, current position, and the estimated time frame within which he/she may be able to arrive at the target spot. Each LR is obviously a subscriber of the PEACH service. An LR may be a family member, friend, or neighbor of the victim, or may also be a total stranger (e.g., from a common pedestrian to a professional caregiver/medical specialist). SC stores the profile information of every LR, including his/her identity, current physical location, medical background, and track record in providing timely assistance to victims. The devices subscribed by LRs are trusted by the SC so that they may discover, join, and leave dynamic rescue groups. An LR that joins a particular group is also able to fetch from the SC the visibility information and also the profiles of other members in this group who are located nearby. In this way, PEACH avoids the situation, where the patient's PDA would have to provide information to all the peers in the locality, which would 1) flood the network with redundant information increasing congestion and communications delay; and 2) exhaust valuable battery power of the patient's PDA that should remain switched on as long as possible. In addition, PEACH also facilitates message exchanges among the *ad hoc* group members (i.e., the LRs), thereby allowing them to collaborate swiftly to assist the victim.

From here on, we describe the functionality of the SC, main task of which is coordinating the tasks that follow an emergency situation, i.e., formation of rescue groups based on best possible LRs and also handing out information to the selected LRs' devices regarding possible courses of action. While formulating emergency response groups, the SC has to take into account the bystander apathy problem. The bystander apathy, also known as Genovese syndrome, is the psychological phenomena among the LRs in which an LR is less likely to intervene in an emergency situation when a large number of other LRs are also present at the scene. Such a bystander apathy can potentially lead to the victim being not attended at all, even in the presence of a large number of volunteering LRs. PEACH framework allows SC to mitigate the bystander effect as much as possible. To this end, the SC first categorizes the type of emergency situation that is at hand and also determines the necessary course of actions. Second, it takes into consideration the profile information, expertise, and experience of each of the willing LRs. Based on these information, the SC selects the LRs who are best suited to respond to this particular type of emergency scenario. Thus, the SC creates an assistance group (synonymous to rescue group, volunteer group, and emergency response group) comprising the potentially best LR candidates only. When the SC finds out the most suitable LRs by executing a MADM algorithm (detailed implementation of this is provided in the following section), it issues a notification to them. Meanwhile, it provides them with information on how to access the victim's current location and also guides them on what kind of assistance may be required. It should be noted here that formulating a response group is indeed a challenging MADM problem. Solutions to this problem requires tradeoffs pertaining to the victim's pathological conditions, distance of a LR from the victim's current location, his medical expertise, etc. In PEACH, each victim support unit is uniquely identified by a group identifier (GID) and a profile that includes information on the victim's identity, his pathologies, his contact information and home address, his family members, current location (e.g., whether he is in distress at home or outside, whether he has been moved by others after he succumbed to illness), etc.

It is worth stressing that assigning group formation duties to SC can provide several advantages. From the technical perspective, our model permits to reduce traffic congestion on patient's locality. In fact, PEACH does not require potential helpers to distribute their profile information to the patient device to promote the formation of a response group. In addition, our approach does not overload patient's devices to solve complex MADM problems. Finally, the envisioned solution to the group formation problem can provide a suitable basis to mitigate the effect of bystander apathy. In fact, upon reception of an invitation to join a response group, a potential helper is able to actually understand the need to promptly act.

V. Implementation of the PEACH Architecture

We here present PEACH architecture and implementation insights. Our solution provides all basic facilities needed for managing a BAN-based sensing platform able of continuously monitoring patient's psychoemotional states. In addition, our solution also integrates a group management support, which is able of composing groups of individuals willing to provide prompt help to the patient when it is needed. Groups are composed both on the basis of the current physical locations of the users' devices and the expertise of the users in terms of their medical skills, as well as prior caregiving experiences.

Fig. 3 illustrates the PEACH middleware architecture consisting of three layers, namely the monitoring and assistance (MA), response management (RM), and group communications (GC) layers, implemented on top of the Java virtual machine (JVM).

A. PEACH MA Layer

The PEACH MA layer provides the needed support to collect and aggregate the raw context information (representing patient's psychophysical context) from the deployed sensors over the BAN of the monitored patient, to aggregate sensed data, and to detect whether the patient is in need of help.

Due to the need to customize and also to (possibly) update the sensing infrastructure frequently, according to patient's evolving needs, the MA layer is implemented on top of OSCAR [44], an open service gateway initiative (OSGi) compliant support. OSGi facilitates software life-cycle management and permits

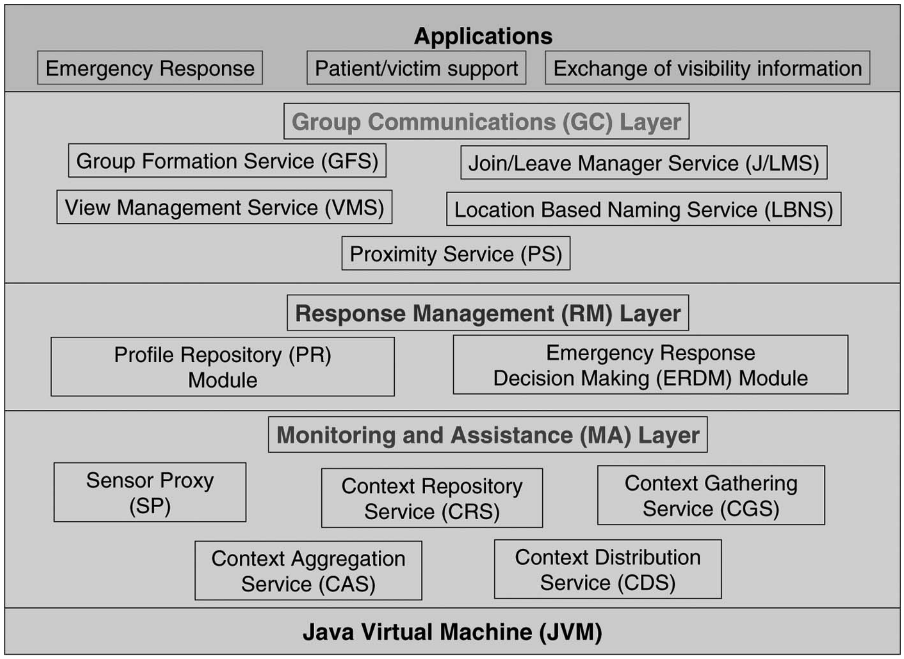

Fig. 3. Modular implementation of PEACH.

to upgrade our service infrastructure easily, without requiring major changes on the application layer.

The main services composing the MA layer are depicted in Fig. 3 and include: context gathering service (CGS), sensor proxy (SP), context aggregation service (CAS), context repository service (CRS), and context distribution service (CDS).

CGS is in-charge of collecting psychoemotional context data from deployed SP instances. Each SP is statically associated to a specific sensor and is in-charge of sampling sensed data at regular intervals. The time between consecutive samples depends on sensor characteristics. For example, while monitoring for drug overuse, patient temperature can be sampled every ten minutes, whereas blood pressure should be sampled more frequently, e.g., every minute. After obtaining context information from the SP, CGS forward them to CRS and CAS, which are in-charge of storing collected information and of aggregating them according to application requirements and patient's pathologies, respectively. In particular, CAS is also in-charge of detecting whether the patient is under an immediate threat and whether prompt help is required. To this end, CAS compares the aggregated context information with a previously formulated user/patient-profile, which is stored in the patient's access terminal. This profile typically contains patient's basic information (e.g., name, address, and family members) and also his/her pathological information (e.g., regular heartbeat rate, respiration rate, temperature, etc.). Based on the profile, CAS can interpret the baseline conditions for the patient-specific pathologies. Detection of threats is performed on the basis of the comparison between this conventional profile of the patient that establishes the value of sensed parameters when his/her psychophysical status is normal, with the sensed data. If significant alterations in sensed data are detected, then PEACH assumes an imminent medical threat to the patient. As a consequence, CAS coordinates with services of RM and GCs layers to trigger a suitable emergency response.

B. *PEACH RM Layer*

The RM layer provides the needed support to promote the formation of groups of volunteers according to a multiplicity of criteria, such as their physical allocation, medical skills, and patient's pathologies. In particular, RM provides basic services to receive emergency notifications from the MA layer, to gather information needed for forming a response group, and to identify a set of potential helpers to invite to the newly formed emergency response group.

Fig. 3 depicts the main RM layer services, i.e., emergency response decision making (ERDM) service and profile repository (PR).

Following to these emergency notifications, ERDM begins promoting the formation of a group of responders, who are willing to help the patient (i.e., who become LRs), and are within a close proximity of the patient (i.e., are found to be colocated with the LM via the proximity service (PS), which has the visibility of nearby individuals). To identify the best suited responders to help the patient, ERDM sees if the potential rescuers are indeed nearby and obtains their profiles information by coordinating with the PS and PR, respectively. ERDM then faces with a MADM problem in terms of the LRs' current locations, skills, medical expertise, history of previous rescue attempts, etc. In order to solve this problem, for each LR, LR_k that subscribes to the PEACH service, a set of attributes $(X_{k,j}, j\epsilon\{1, 2, \ldots, t\})$ is assigned, as shown in Table I. These attributes include: 1) the expertise and skills of the LRs; 2) their history records in providing assistance; and 3) the trust levels that SC associates with them. SC constantly updates and maintains these attributes.

TABLE I
FORMAT OF LRS PROFILES

LR ID (LR_i)	Attribute 1, X_1	Attribute 2, X_2	Attribute 3, X_3		Attribute t, X_t
LR_1	$X_{1,1}$	$X_{1,2}$	$X_{1,3}$		$X_{1,t}$
LR_2	$X_{2,1}$	$X_{2,2}$	$X_{2,3}$		$X_{2,t}$
LR_3	$X_{3,1}$	$X_{3,2}$	$X_{3,3}$		$X_{3,t}$
.	.	.	.	.	
.	.	.	.	.	
.	.	.	.	.	
LR_N	$X_{N,1}$	$X_{N,2}$	$X_{N,3}$		$X_{N,t}$

TABLE II
EMERGENCY LEVELS AND THEIR ASSOCIATED PARAMETERS

Emergency Level	Attribute 1, X_1	Attribute 2, X_2		Attribute t, X_t	Action Time	Acceptance Threshold	Waiting Timeout
e_1	$w_{1,1}$	$w_{1,2}$		$w_{1,t}$	θ_1	γ_1	τ_1
e_2	$w_{2,1}$	$w_{2,2}$		$w_{2,t}$	θ_2	γ_2	τ_2
.	.	.	.	.	.	.	.
.	.	.	.	.	.	.	.
.	.	.	.	.	.	.	.
e_M	$w_{M,1}$	$w_{M,2}$		$w_{M,t}$	θ_M	γ_M	τ_M

The PEACH implementation assumes that there are M emergency levels predefined at the SC. As shown in Table II, for each emergency level e_i ($i\epsilon\{1, 2, \ldots M\}$) and each attribute X_j ($j\epsilon\{1, 2, \ldots, t\}$), SC assigns a weight $w_{i,j}$ and three additional parameters, namely the minimum response time within which the victim should be assisted, the acceptance threshold for selecting LRs, and the maximum waiting time SC should wait for receiving AN messages from the LRs, denoted by θ_i, γ_i, and τ_m, respectively.

Whenever potential rescuers are selected, ERDM forward them a request to join the group. The request to join message includes information, such as the GID associated with this group, a set of instructions to attend the patient, last confirmed location of the patient, information pertaining to the shortest route to access the victim, etc.

ERDM awaits for acknowledgments (i.e., AN messages in Fig. 2) from potential helpers during a timeout period of τ_m. When either τ_m expires or the system receives the responses from at least the required number of skillful and/or nonskilled helpers for this emergency level, ERDM sorts out the helpers based on the information within their AN messages (e.g., physical proximity and availability of the LRs) and also based on the minimum response time (θ_i), specific to the emergency level. Out of these already sorted LRs, only those with attributes that satisfy the following condition are selected to assist the victim:

$$A_k W_m = \sum_{p=1}^{t} X_{k,p} w_{m,p} \geq \gamma_m \tag{6}$$

where A_k and W_m represent the vector of attributes of LR$_k$ and the weight vector associated with the emergency level (i.e., $W_m = \{w_{m,1}, w_{m,2}, \ldots, w_{m,t}\}$), respectively.

Thus, when the set of volunteers willing to help the patient is determined, ERDM coordinates with the GCs layer to enable group collaboration.

C. PEACH GC Layer

Based on the ANGELAH middleware [10], we envision the GC layer, which presents the LRs, selected by the RM layer, to become rescuers. As illustrated in Fig. 3, the GC layer consists of group formation service (GFS), join/leave manager service (J/LMS), view manager service (VMS), location-based naming service (LBNS), and PS modules. By coordinating these various modules, the GC layer provides important functionalities to compose, dissolve, and manage emergency response groups in wireless environments.

As mentioned earlier, the PS module, installed at LM, helps the ERDM entity of RM layer to find who are nearby (i.e., the UIDs of neighboring users of the patient). Following an emergency event, ERDM coordinates with the GFS module (also installed at LM) to promote a new rescue group. GFS receives profiles information of both the patient and selected LRs, and coordinates with the LBNS module that arbitrarily generates and assigns the concerned GID and UIDs. A selected LR is then invited to join the group using the J/LMS instance deployed on his/her portable device.

The VMS is an important module in the GC layer because of its role in creating, maintaining, and disseminating group views to this newly formed group members. Each view consists of the list of group members (i.e., in terms of their UIDs/IP addresses retrieved by PS) and their profiles information. PS monitors the availability of the group members by sending them advertisement messages periodically. When the latency between subsequent advertisements to a particular member exceeds a threshold (determined by taking into consideration factors, such as the average number of responders within a locality, their mobility patterns, and the surface of the locality), PS considers that individual to be disconnected. Whenever the PS finds a rescuer to join, disconnect, or permanently quit the group, it accordingly updates the view.

The previously described interactions among the various entities, groups, and services in PEACH aimed at forming a rescue group are depicted in Fig. 4.

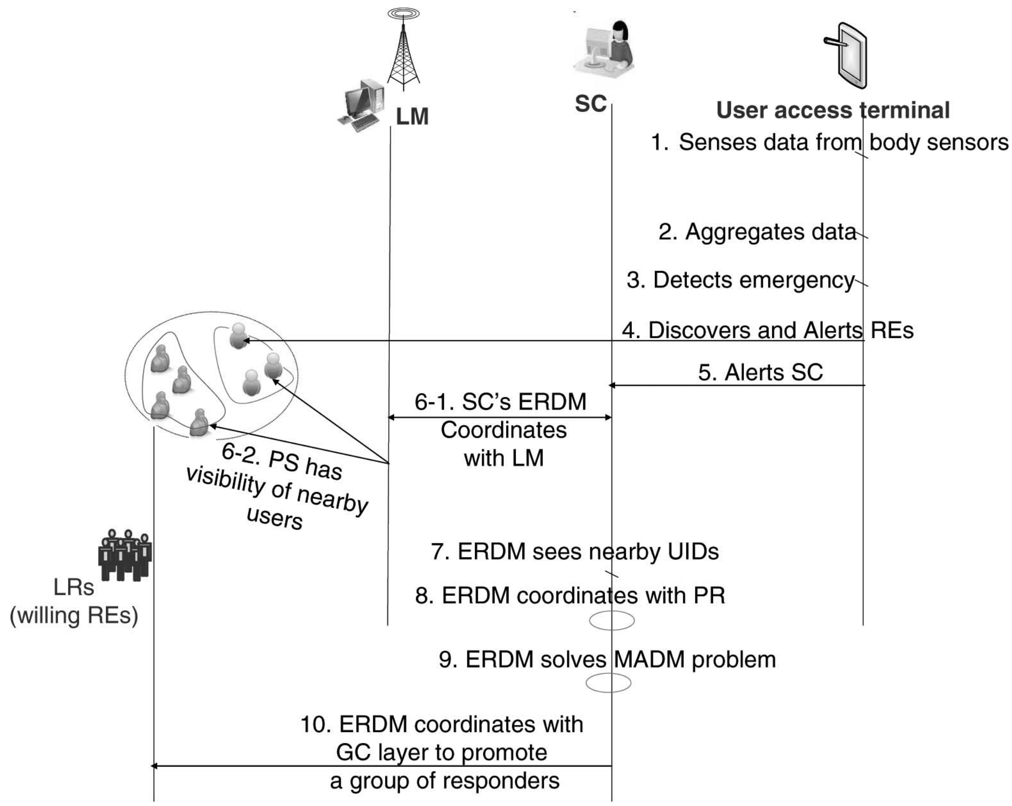

Fig. 4. Interaction among the PEACH entities and services for promoting a responders group.

VI. PEACH at Work in a Drug Addiction Scenario

To demonstrate the feasibility of our approach, we implemented an application prototype on top of PEACH to detect drug overdoses and promote support groups to provide assistance to victims.

A. Experimental Settings

Our experimental scenario acknowledges the need to consider several roles, namely patient, rescuer, and SC roles.

Patients are provided with Xybernauts MA-V, laptop like wearable devices. Each patient device installs Linux, J2SE 1.5, and a subset of PEACH services of the MA layer. Patients devices are also equipped with a UMTS networking support to interact with the remote SC in the case of emergency. In addition, patients' devices are also connected to several sensors via Bluetooth connectivity. In particular, in our scenario, and without lack of generality, we consider Global Positioning System (GPS) location support, along with several biosensors. In particular, our test-bed setting includes blood pressure sensors, respiration sensors, and skin conductivity sensors. Sensors are selected on the basis of the application scenario. In fact, in drug overdose avoidance domains, it is necessary to consider the following symptoms using the deployed sensors:

1) x_1: rapid and/or irregular heartbeats;
2) x_2: elevated pulse rate;
3) x_3: elevated blood pressure;
4) x_4: slowed breathing;
5) x_5: rise in body temperature;
6) x_6: rise in sweat in the palms;
7) x_7: tremors, jitters, or shakes of hands, feet, or head;
8) x_8: change/rise in hormone levels;
9) x_9: poor coordination, tripping, spilling, bumping into things, and other passers-by;
10) x_{10}: large or small (dilated) pupils;
11) ....

Clearly enough, according to patient's needs, it is also possible to enrich the sensing platform by considering further elements. However, in our experiments, we have reduced monitoring to only the key symptoms, namely x_1 to x_5 for keeping the number of biosensors, and the interaction between the patient device and the deployed sensors as low as possible. It is worth noticing that in order to provide a suitable support for interaction between potential users and the remote SC, potential helpers' devices are also equipped with UMTS support for maintaining continuous remote connectivity.

In our test-bed setting, potential helpers are equipped with wireless-enabled iPAQ PDAs, running Linux, Java SE 1.4, along with GC layer PEACH services. Moreover, hands-free communications through JAVA speech application programming interfaces (APIs) on top of the IBM via voice speech engine are provided.

In our settings, we have also deployed a SC composed of one PC running Linux and J2SE 1.5. The SC also runs the PEACH services belonging to the RM and GC layers for assessing and responding to plea for help from the concerned patients, and for promoting *ad hoc* assistance teams, respectively. In addition, for each locality, a PC is configured as an LM, which operates on

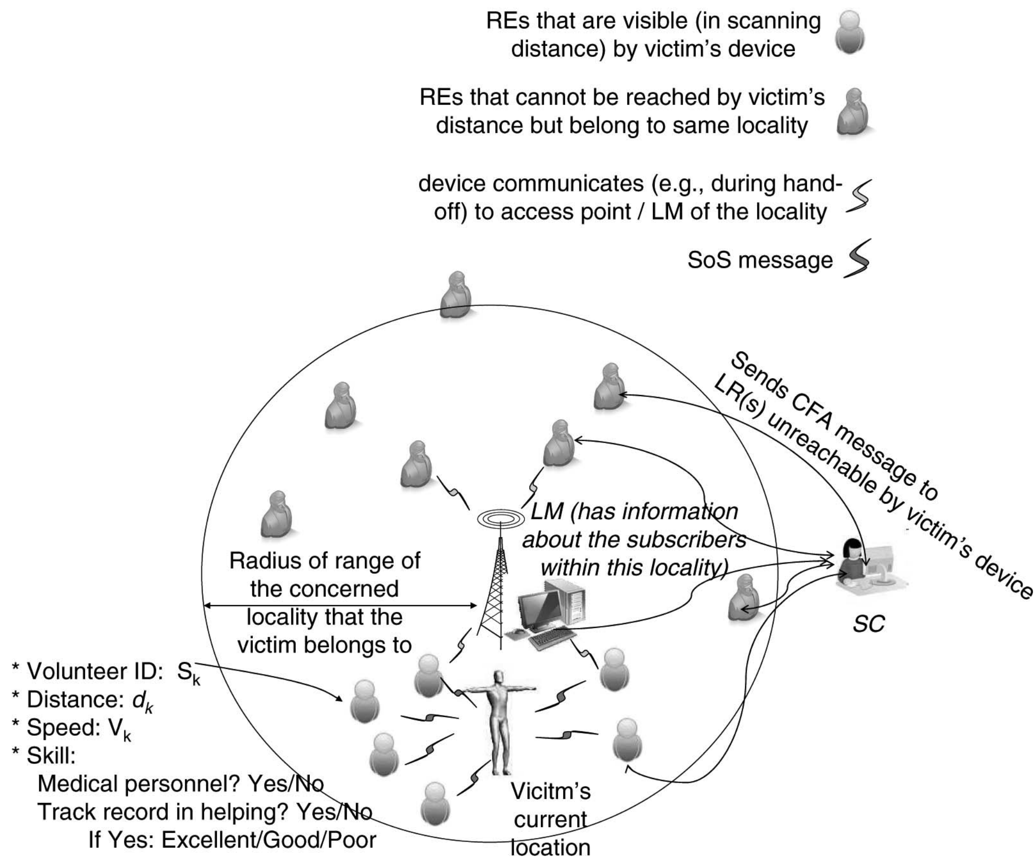

Fig. 5. Sample experimental scenario.

Linux and consists of the PS entity, which is implemented by binding the PC with the local access point.

Patient's and potential helpers' devices are connected via a MANET. In particular, the network is based on IEEE 802.11 standards. In addition, without lack of generality, in our scenario IP addresses are statically determined at deployment time, and the "*ad hoc* on-demand distance vector" (AODV) protocol provides the needed network routing support.

B. Formation of Rescue Teams

The patient's device and the RE devices, upon entering a locality, switch to the concerned access point and LM. When an abnormal situation (generally understood in terms of a function of the exhibited symptoms and physical, as well as emotional conditions of the patient) comes into notice by the user's device, it changes to the *ad hoc* mode and sends SOS messages to the discovered portable devices of the nearby PEACH subscribers (see Fig. 5) who may be either skilled (e.g., doctors, medical officers, and trained first-aid givers) or nonskilled (simple passersby without any prior medical/healthcare training). In order to construct a realistic scenario, the REs' devices are placed at varying distances from the victim, e.g., from just a few meters (within eye distances) to 100 m. The REs that are thus contacted by the victim and are willing to come in aid of the patient become LRs and accordingly report to the SC. Meanwhile, the victim's device also contacts the SC. The SC then contacts the LM of the corresponding locality to obtain information regarding the REs unreachable by the patient's device. The SC issues CFA messages to these REs. Upon receiving the willing LRs' confirmations about assisting the patient, the SC then proactively promotes the formation of a rescue group. First, the SC uses its PS to advertise its online availability. Meanwhile, it uses GFS, in concert with LBNS, to create the appropriate GIDs and UIDs, and accordingly sets up group profiles. The J/LMS modules installed in the portable devices of the LRs sense the advertisements and invite the selected LRs to join the group while discarding the nonselected LRs by sending them a negative message. When a LR joins this new group via J/LMS, VMS provides in the group view with the LR's profile information, current location, estimated time of arrival at the scene, etc. The GID and UID of the new group member, along with the updated view, are returned to this new member. It is worth mentioning that the view-based concept is rather dynamic in nature and context-dependent views may indeed change to incorporate variations in collocated pedestrians (who turned into rescuers) while the victim awaits assistance.

The nonselected LRs are provided with a negative message. By this way, the system attempts to proactively avert possible bystander effects. Upon receiving emergency signals for assistance by the SC, the applications installed on the selected LRs' devices require them (the respective LRs) to explicitly respond to this event. The SC that receives acknowledgments from the willing LRs build a list of volunteers, who are indeed ready to help. In our PEACH implementation, the application at an LR-end keeps playing an emergency beep at an increasing volume up to the point where the user explicitly accepts or rejects to offer assistance. Our observations from previous work [9] have indicated that such sound-signal-based implementations indeed function well in clearly informing the passersby that it is not a drill, i.e., an emergency situation is at hand and their assistance is needed on an urgent basis.

C. Experimental Results and Lesson Learned

PEACH induces different forms of overheads. We here report the main result obtained in PEACH experimentation. In particular, we here first discuss PEACH responsiveness in group formation. We define responsiveness as the amount of time needed to compose a group of responders following to the emergency notification. Responsiveness is a critical aspect to consider in our system. In fact, PEACH is required to promote the formation of response groups in a short amount of time, thus facilitating prompt help to the patient. Then, we consider battery degradation on mobile nodes. Battery degradation should be considered as a crucial aspect in anywhere, anytime assistance, since both patients and potential users assumed to be able to take advantage of their devices. Finally, we report our evaluations on memory requirements over mobile terminals to demonstrate that the imposed overhead in terms of memory use permits the deployment of PEACH applications even on resource constrained portable devices.

1) PEACH Responsiveness: In our experiments, we have considered one patient, 20 potential responders, and a single SC. We constructed our experiments by relying on students' help and we deployed our system on a campus setting. The experiment required students to hold the PDA and to freely roam around the campus. Several emergency situations were simulated over the patient devices and the amount of time needed for the students to notice the incident, join the group, and arrive at the scene of incident was measured. A staff member was in-charge of controlling the patient's access terminal and to simulate emergency situations in different localities at arbitrary times. Emergency conditions were simulated by executing an *ad hoc* software component on the patient device to add abnormalities to the sensed data acquired from the biosensors.

Based on the collected results, upon detecting an emergency event, the patient device takes only few milliseconds to alert the SC. On average, one second is required to gather information pertaining to potential helpers allocated in the proximity of the patient. Finally, the average time that SC takes to gather users profile information and to compose a group is found to be approximately three seconds. However, in our experiments, it takes few minutes to let the users actually notice and respond to the invitation to join the response group. In particular, group formation needs about two minutes in our experiments. Two additional minutes are required for all selected helpers to reach the location, where the patient is placed.

In addition, we have also evaluated PEACH responsiveness in a large-scale scenario. Due to the practical difficulties of deploying a large scale MANET topology, we adopt a simulation-based approach. In particular, our simulations are built on top of the network simulator (ns-2) [45]. We simulate an IEEE 802.11 based network deployed in 1 km^2 area. Our simulations include one patient in need of help along with several potential helpers. Both the patient and potential helpers are also connected via a UMTS link to a ns-2 agent, which acts as the SC.

The time required to compose a response group depends on the number of potential helpers allocated in patient's locality. As a consequence, the time needed to promote a responders' group varies from few seconds in the case of 50 simulated potential helpers, to tens of seconds in the case of 100 nodes, up to few minutes in the case of 500 deployed nodes. These results do not take into account the time needed for the potential helpers to notice the incident and to react accordingly, but demonstrate the suitability of our approach even for large scale MANET environments.

2) Battery Degradation: Another critical aspect to consider in mobile healthcare applications is battery degradation. In fact, it is necessary to provide solutions able of operating anywhere and anytime. Battery degradation can be determined both by computation and networking. PEACH aims at reducing computation needs on portable devices. In fact, the computation to solve a MADM problem needed for group formation is moved on a fixed server operated within the SC. In addition, PEACH protocols minimize, as much as possible, the network cost by reducing the need for communicating large amounts of data between entities running over mobile terminals. However, despite the energy efficient approach adopted in designing the protocol, communications overheads still remain as the main contributor to battery degradation in PEACH.

In particular, the distribution of group views over the MANET network requires both senders and receivers to consume a fraction of their available battery budgets. To investigate this issue, we installed our PEACH application over ten Apple iBook that operate as potential responders and are connected through a MANET. We made several tests by varying the time between consecutive group view disseminations ranging from few tens of seconds, up to few minutes. The resulting average battery life is between 3:30 and 4:40 hours. This result demonstrates a scarce impact of our solution on the overall device energy budget. A similar consideration is applicable to the patient device.

3) Memory Requirements: Finally, we investigate the memory requirements at the individual devices that run PEACH. For this purpose, we consider one out of the three LR devices, subscribed with PEACH, in a locality. By using JConsol profiling tool, we obtain the necessary data for a relatively long time, and then, evaluate the memory requirements of the considered LR device over time as depicted in Fig. 6. Fig. 6(a) demonstrates that the total amount of the used heap memory varies between 0.8 and 2.1 MB. The average value in this case lies around 1.3 MB. On the other hand, Fig. 6(b) takes into account nonheap memory involving data, code, and stack. As this plot shows the nonheap memory over time approaches a consistent value of approximately 16.5 MB. These results clearly demonstrate the viability of installing the PEACH group management services onto a PDA or a smartphone.

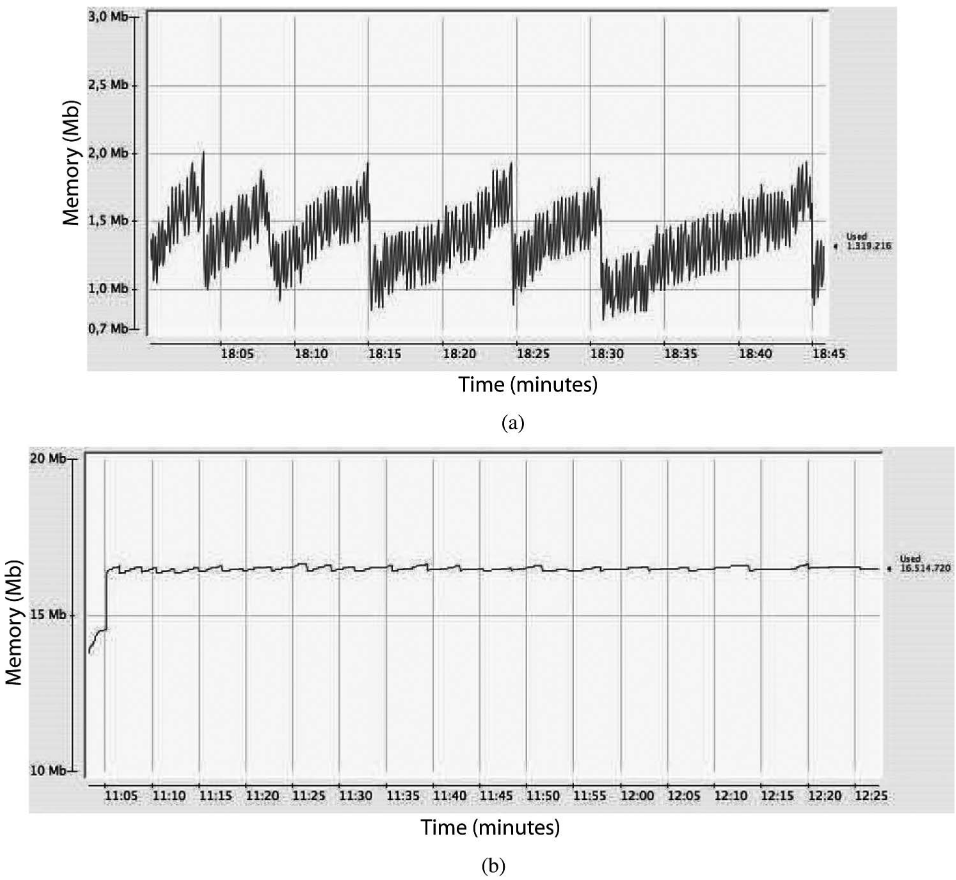

Fig. 6. Memory usage over time on a particular LR device. (a) Heap memory. (b) Nonheap memory.

VII. Conclusion

Anywhere and anytime healthcare services for the monitored subjects (e.g., patients, drug abusers, etc.) require novel group management solutions. In this paper, we have proposed PEACH, which is a novel framework for quickly formulating and managing *ad hoc* rescue groups in the same locality as the victim's so that they may perform rescue operations and provide lifesaving assistance to the victim. Unlike previous approaches, PEACH considers probabilistic functions of roaming victims' physiological and affective symptoms for detecting a potentially emergency situation. A case study of the PEACH framework was envisioned for victims of drug abuse/overuse in an outside test-bed environment. The sensors deployed in the patient's BAN gather and aggregate raw information, and channel them to the victim's device, which aggregates the context information and compares it with previously stored profile information of the patient to detect potentially hazardous situations. We have designed and developed prototypes to be used in responders' PDAs, which are contacted by the victim's device asking for emergency help. Through practical test beds and also via simulations, we have evaluated the performance of PEACH in terms of its responsiveness, battery consumption, and memory use at the rescuers' devices. The empirical results demonstrate that the proposed PEACH framework is viable and will stimulate further research work to extend the current prototype along manifold directions.

By adopting a modular approach in designing and implementing PEACH, we have left scopes for further modules with additional functionalities to be easily inserted into its middleware. Future works in this direction demand investigation into security pertaining to privacy, sensitive healthcare information, etc. To this end, we are currently working on extending PEACH services to integrate modules that will ensure data integrity, privacy, and also nonrepudiation. In future, we expect to develop PEACH to transparently handle more complex scenarios, intricate symptoms and gestures, and process huge volumes of context information.

References

[1] P. Bellavista, D. Bottazzi, A. Corradi, and R. Montanari, "Challenges, opportunities and solutions for ubiquitous eldercare," DEIS University of Bologna Tech. Rep., Oct. 2005.

[2] P. Salovey, A. J. Rothman, J. B. Detweiler, and W. T. Steward, "Emotional states and physical health," *Amer. Psycol.*, vol. 55, no. 1, pp. 110–121, Jan. 2000.

[3] W. Katon and M. D. Sullivan, "Depression and chronic medical illness," *J. Clin. Psychiatry*, vol. 51, pp. 3–11, 1990.

[4] W. Katon, "Depression: Relationship to somatization and chronic medical illness," *J. Clin. Psychiatry*, vol. 45, pp. 4–11, 1984.

[5] G. L. Maddox, "Some correlates of differences in self-assessment of health status among the elderly," *J. Gerontol.*, vol. 17, pp. 180–185, 1962.

[6] R. Tessler and D. Mechanic, "Psychological distress and perceived health status," *J. Health Soc. Behav.*, vol. 19, pp. 254–262, 1978.

[7] N. A. Cummings and W. T. Follette, "Brief psychotherapy and medical utilization," in *The Professional Psychologist Today*, H. Darken, Ed. San Francisco, CA: Jossey-Bass, 1976, pp. 165–174.

[8] K. Jones and T. Vischi, "Impact of alcohol, drug abuse, and mental health treatment on medical care utilization: Review of the research literature," *Med. Care*, vol. 17, pp. 1–82, 1979.
[9] D. Bottazzi, A. Corradi, and R. Montanari, "Context-aware middleware solutions for anytime and anywhere emergency assistance to elderly people," *IEEE Commun. Mag.*, vol. 44, no. 4, pp. 82–90, Apr. 2006.
[10] T. Taleb, D. Bottazzi, M. Guizani, and H. Nait-Charif, "ANGELAH: A framework for assisting elders at home," *IEEE J. Sel. Areas Commun.*, vol. 27, no. 4, pp. 480–494, May 2009.
[11] U. Varshney, "Pervasive healthcare and wireless health monitoring," *J. Mobile Netw. Appl.*, vol. 12, no. 2–3, pp. 113–127, Mar. 2007.
[12] J. E. Bardram and H. B. Christensen, "Pervasive computing support for hospitals: An overview of the activity-based computing project," *IEEE J. Pervasive Comput.*, vol. 6, no. 1, pp. 44–51, Mar. 2007.
[13] D. Trossen, D. Pavel, G. Platt, J. Wall, P. Valencia, C. A. Graves, M. S. Zamarripa, V. M. González, J. Favela, E. Lövquist, and Z. Kulcsár, "Sensor networks, wearable computing, and healthcare applications," *IEEE J. Pervasive Comput.*, vol. 6, no. 2, pp. 58–61, Jun. 2007.
[14] Z. Zeng, M. Pantic, G. I. Roisman, and T. S. Huang, "A survey of affect recognition methods: Audio, visual, and spontaneous expressions," *IEEE Trans. Pattern Anal. Mach. Intell.*, vol. 31, no. 1, pp. 39–58, Jan. 2008.
[15] A. Oikonomopoulos, P. Ioannis, and M. Pantic, "Spatio-temporal salient points for visual recognition of human actions," *IEEE Trans. Systems, Man, Cybern. B, Cybern.*, vol. 36, no. 3, pp. 710–719, Jun. 2006.
[16] J. Healey and R. W. Picard, "Digital processing of affective signals," presented at the ICASSP, Seattle, WA, May 12–15, 1998.
[17] P. Ekman, "About brows: Emotional and conversational signals," in *Human Ethology.* Cambridge, U.K.: Cambridge Univ. Press, pp. 169–202, 1979.
[18] P. Ekman, W. Friesen, and P. Ellsworth, "What emotion categories or dimensions can observers judge from facial behavior?" in *Emotion in the Human Face*, P. Ekman, Ed. New York: Cambridge Univ. Press, 1982, pp. 39–55.
[19] P. Ekman, *Emotion in the Human Face*, 2nd ed. New York: Cambridge Univ. Press, 1982.
[20] P. J. Lang, M. K. Greenwald, M. M. Bradley, and A. O. Hamm, "Looking at pictures: Affective, facial, visceral and behavioral reactions," *Psychophysiology*, vol. 30, pp. 261–273, 1993.
[21] J. A. Russell, "A circumplex model of affect," *J. Pers. Soc. Psychol.*, vol. 39, pp. 1161–1178, 1980.
[22] C. Pelachaud, E. Bevacqua, G. Caridakis, K. Karpouzis, M. Mancini, C. Peters, and A. Raouzaiou, "Mimicking from perception and interpretation," presented at the Enactive Interfaces: Enaction Complexity, Montpellier, France, Nov. 20–21 2006.
[23] J. G. Taylor and N. F. Fragopanagos, "The interaction of attention and emotion," *J. Neural Netw.*, vol. 18, no. 4, pp. 353–369, 2005.
[24] K. R. Scherer, "Appraisal theories," in *Handbook of Cognition and Emotion*, T. Dalgleish and M. Power Editions, Eds. Chichester, England: Wiley, 2005, pp. 637–663.
[25] D. Sander, D. Grandjean, and K. R. Scherer, "A systems approach to appraisal mechanisms in emotion," *J. Neural Netw.*, vol. 18, pp. 317–352, 2005.
[26] Z. Zeng, M. Pantic, G. I. Roisman, and T. S. Huang, "A survey of affect recognition methods: Audio, visual and spontaneous expressions," presented at the Int. Conf. Multimodal Interfaces (ICMI), Nagoya, Japan, Nov. 12–15, 2007.
[27] J. T. Cacioppo, "Introduction: Emotion and health," in *Handbook of Affective Stress*, 1st ed. London, U.K.: Oxford Univ. Press, 2003.
[28] C. Dara, L. Monetta, and M. D. Pell, "Vocal emotion processing in Parkinson's disease: Reduced sensitivity to negative emotions," *Brain Res.*, vol. 1188, pp. 100–111, 2007.
[29] J. Healey and R. W. Picard, "Detecting stress during real-world driving tasks using physiological sensors," *IEEE Trans. Intell. Transp. Syst.*, vol. 6, no. 2, pp. 156–166, Jun. 2005.
[30] R. W. Picard, "Affective medicine: Technology with emotional intelligence," in *Future of Health Technology*, R. G. Bushko, Ed. Amsterdam, The Netherlands: IOS Press, 2001.
[31] C. D. Katsis, G. Ganiatsas, N. Katertsidis, and D. I. Fotiadis, "Emotional understanding using a wearable multisensorial platform," in *Proc. Improving the Quality of Health Information: An Internat. Perspective, Proc. ISHIMR*, P. D. Bamidis *et al.*, Eds., 2005, pp. 188–197.
[32] J. A. Healey, "Wearable and automotive systems for affect recognition from physiology," Ph.D. thesis, MIT, Cambridge, MA, May 2000.
[33] A. Haag, S. Goronzy, P. Schaich, and J. Williams, "Emotion recognition using bio-sensors: First steps towards an automatic system," presented at the Affective Dialogue Systems, Tutorial and ResearchWorkshop, Kloster Irsee, Germany, Jun. 14–16 2004.
[34] F. Nasoz, K. Alvarez, C. L. Lisetti, and N. Finkelstein, "Emotion recognition from physiological signals for presence technologies," *Int. J. Cogn., Technol. Work, Spec. Issue Presence*, vol. 6, no. 1, pp. 1–32, 2003.
[35] K. Kim, S. Bang, and S. Kim, "Emotion recognition system using short-term monitoring of physiological signals," *Med. Biol. Eng. Comp.*, vol. 42, pp. 419–427, 2004.
[36] Online Emotion Recognition. (2010, Feb.). [Online]. Available: http://affect.media.mit.edu
[37] K. Z. Haigh, L. M. Kiff, J. Myers, V. Guralnik, C. W. Geib, J. Phelps, and T. Wagner, "The independent lifestyle assistant (I.L.S.A.): AI lessons learned," presented at the 16th Innovative Appl. Artif. Intell. Conf. (IAAI), San Jose, CA, Jul. 2004.
[38] F. D. Mola, G. Cabri, N. Muratori, R. Quitadamo, and F. Zambonelli, "The UbiMedic framework to support medical emergencies by ubiquitous computing," *Int. Trans. Syst. Sci. Appl.*, vol. 1, no. 1, pp. 15–26, 2006.
[39] C. Pesto, L. Selavo, Y. Chen, J. Ko, J. H. Lim, A. Terzis, A. Watt, J. Jeng, B. Chen, K. Lorincz, and M. Welsh, "Wireless medical sensor networks in emergency response: Implementation and pilot results," presented at the 2008 IEEE Int. Conf. Technol. Homeland Security, Waltham, MA, May 2008.
[40] A. Mihailidis, B. Carmichael, and J. Boger, "The use of computer vision in an intelligent environment to support aging-in-place, safety, and independence in the home," *IEEE Trans. Inf. Technol. Biomed.*, vol. 8, no. 3, pp. 238–247, Sep. 2004.
[41] B. P. Lo, J. L. Wang, and G. Z. Yang, "From imaging networks to behavior profiling: Ubiquitous sensing for managed homecare of the elderly," presented at the 3rd Int. Conf. Pervasive Comput., Munich, Germany, May 2005.
[42] D. Bottazzi, R. Montanari, and A. Toninelli, "Context-aware middleware for anytime, anywhere social networks," *IEEE Intell. Syst.*, vol. 22, no. 5, pp. 23–32, Sep./Oct. 2007.
[43] B. Latane and J. Darley, "Bystander apathy," *Amer. Scientist*, vol. 57, pp. 244–268, 1969.
[44] Oscar, an open source OSGi implementation. (2010, Feb.). [Online]. Avaliable: http://oscar-OSGi.sourceforge.net
[45] The Network Simulator – ns-2. (2010, Feb.). [Online]. Avaliable: http://www.isi.edu/nsnam/ns/

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