Ambient intelligent framework for modelling critical medical events based on context awareness

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ABSTRACT

With the rapid pace of communication technology, the modern communication system still encounters challenges in meeting the dynamic requirements of users. Facilitating emergency services for patients without a caretaker side by is quite challenging. This work contributes a solution towards state-of-the-art research problems by introducing a novel architecture using collaboration, coordination and user activity detection using contextual information. A prototype is built and experiment is carried out to emphasize the importance of real-time activity-based context awareness in ambient intelligence (AmI) applications. The primary contributions of this work are introduction of novel architecture and usage of both static and dynamic activity-based contextual parameters. The secondary contribution of this model is to integrate ambient intelligence with context awareness to offer higher accuracy in determining the critical condition of a patient. Initially, analytical models are built using the context-based attributes that consider both clinical and non-clinical entities based on the minimal and essential vital information of patient. This paper further discusses the experimental model, which is highly cost-efficient both from an operational and usage viewpoint. Different assessment environments have been used for assessing the performance of the model.

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1. INTRODUCTION

The eminent and potential theory of ambient Intelligence was coined to shape a vision of future computing technology to provide services based on the presence of intelligence from the surrounding environment [1], [2]. Ambient intelligence (AmI) is also characterized by i) potentiality in multiple device integration on a given environment, ii) should provide a specific service in context to the user only, iii) should be highly customizable, and iv) should be highly pervasive while providing the services [3]. Pervasiveness refers to the presence of a specific form of a computing environment saturated with various forms of intelligent devices and networking devices directly or indirectly connected to the human interface. Although the technology is very novel, and few commercialized products or applications have evolved in the consumer market, this kind of technology is also associated with various functional dependencies. The first dependency to formulate ambient Intelligence is to work on processing data acquisition and processing using various forms of sensors, nanotechnology, and smart devices. This paper will show that wireless sensor networks have played a significant role in designing ambient Intelligence. The sensor nodes are usually considered nodes that collect ambient information. Then, such information is processed and transmitted to a central unit for analyzing the processed data. Multiple forms of information are gathered from multiple sensors to formulate contextual data. Interestingly, the role of sensors is more in generating contextual data in ambient intelligence. The second critical dependency of ambient intelligence is fail-proof and interoperable communication media over various networking structures. The third critical dependency of this technology is the need for intelligent systems (or agents) incorporated with context awareness. The final dependency of this form of technology is to ensure optimal security in the services being rendered to the user [4]. However, besides these features, ambient intelligence is also tagged with various other characteristics. The distinct characteristics of ambient intelligence are self-sufficiency, effective distribution, and faster response rate with wide supportability of collaboration with various other entities.

The prime research issue is based on the practical supportability of existing context awareness concerning reliability. An area of emergency health care services has developed highly due to modern technology adoption [5]. However, it is pretty challenging to meet an emergency-based situation characterized by a higher degree of severity for the patient immediately by any existing technological advancement. This is due to constraints not directly connected with the clinical perspective [6]. Some attributes are precise patient health information at an instantaneous time or proximity of medical staff from the patient at the time of emergency. Such a condition may eventually give rise to improper computation, leading to improper formulation of treatment strategies. Hence, the facilitation of healthcare services during an emergency is often characterized by certain constraints that could be life-threatening [7]. The availability of wearable devices assists in capturing information associated with health statistics; however, the primary challenge is to disseminate the information on time by scaling the condition of emergency [8], [9]. All these challenges must be addressed precisely to incorporate the reliability of disseminating healthcare services during emergency conditions. Apart from this, different ambient sensors may offer ambiguous or noisy data, which makes it quite computationally challenging to perform interpretation [10]. From the viewpoint of contextual awareness towards activity detection, there is a higher degree of variations associated with user activity with a lack of personalization and adaptation, thereby making it quite challenging to construct a universal model [11]–[15]. Another significant challenge is constructing a comprehensive contextual model towards an activity determination system by integrating information from multiple sources [16]–[20]. Further, a dynamic environment always acts as an impediment towards effective implications of the model functioning.

There are current literatures with different approaches towards ambient intelligence and context awareness have been carried out. Vodyaho *et al*. [21] have presented a mechanism for aggregating data using ambient technology to construct a proper structure for managing data. Michalakis *et al*. [22] have developed a context modelling framework to create a unique middleware system involving context awareness. From the perspective of healthcare applications, Zon *et al*. [23] have investigated the adoption of context awareness-based schemes and found that still existing methodologies are in the nascent stage of development. A similar emphasis on using context awareness-based methodologies in healthcare is investigated by Christopoulou [24]. The study model presented by Altulyan *et al*. [25] discusses a healthcare-based notification system where productively computed suggestions are yielded to address the uncertainty attribute associated with the healthcare system. The adoption of artificial intelligence (AI) towards developing context awareness is reported by Al-Saedi *et al*. [26], where various methodologies linking to the usage of sensing systems have been presented. Bolek and Romanova [27] have investigated varied forms of indicators that potentially affect ambient intelligence systems within an organization, considering a specific geographical region-specific case study. Feller *et al*. [28] have investigated situational awareness to influence the accuracy of the diagnosis process for making accurate decisions. The work carried out by Machado *et al*. [29] has developed a mechanism to offer an assistive care system towards people who have Alzheimer's disease using ambient intelligence. The study has used an ontology-based context prediction scheme.

The prime contribution of the proposed study is to design a simplified and novel architecture of an ambient intelligent-based health monitoring system harnessing the potential of context awareness and AmI. This manuscript showcases the healthcare services that call for emergency attention. The proposed system is designed and a prototype is built that enables the personnel to provide medical services in emergencies to the patients distressed with critical health condition. The value-added contribution of the system is its mechanism of integration of various context filtering techniques, as well as formulation of the belief system that designs the proposed framework. The following section discusses the research methodology deployed for this purpose.

2. METHOD

The core purpose of the proposed design methodology is to present a service provisioning scheme based on context awareness and an ambient intelligence approach. The baseline architecture discussed in [30], [31] has been used in the design of the proposed model using different forms of contexts for identification of emergency clinical conditions, e.g., accidental fall, stroke, and heart attack. The system acquires data from sensors before subjecting it to analytical operation. The steps involved in building the system are designing the context model, developing a precise collaboration scheme and performing essential coordination among various entities, as shown in Figure 1.

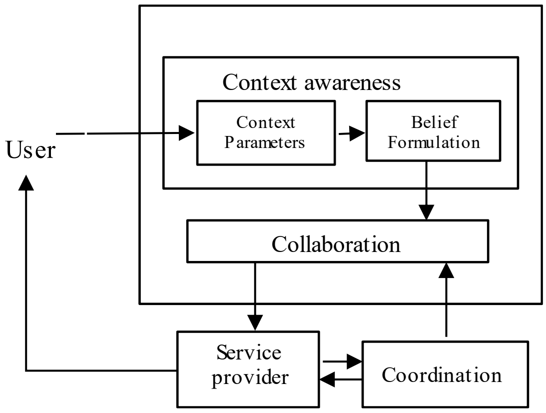


Figure 1. Schematic diagram of proposed system

According to Figure 1, it can be seen that there are three essential sets of operations being performed by modules of context awareness followed by the formulation of belief by collaboration module. In contrast, the coordination module acts as a bridge of interaction with the service provider and the collaboration module. The term context in the proposed study module is characterized by information acquired from the individual on a specific perspective, viz. i) information related to the condition and state of the psychological aspect of an individual, and ii) information of varied physical activity performed by an individual viz. jumping, running, sitting, and walking. From the viewpoint of ambient intelligence, the different entities of contextual information involve two types of classes viz. i) appropriate positional information of an individual derived from the global positioning system (GPS)-based devices, and ii) vital stat information of an individual, e.g. temperature and heart rate. The proposed study model considers extracting temperature information classified into the physical body and room temperature mapping with ambient intelligence.

2.1. Context acquisition

The study model considers the extraction of associated information on human body position. For this purpose, the model uses three-dimensional axes-based data mapping in an accelerometer [30]. A specific sampling frequency is utilized for this purpose, while the empirical formulation of the positioning of the body can be presented as (1),

$$P = (P_x, P_y, P_z) \tag{1}$$

In (1), the attributes $P_A = (P_A^0, P_A^1, \ldots, P_A^{M-1})$ and $A = (x, y, z)$ is the acceleration vector of an axis, and M is the magnitude of the temporal sequence. As the proposed study has considered a higher set of contexts and uses ambient intelligence, context-based parameters must be defined as precisely as possible. Therefore, the system defines the cumulative positioning but differentiates the time from each other. Therefore, we will classify the positioning into $(P_N + 1)$ sections similar in length, and then every two adjunct sections construct up the frame, which is thereby represented as F_P,

$$F_P = \{(f_x, f_y, f_z)||(x, y, z)\epsilon Z\} \tag{2}$$

$$f_A = (f_A^0, f_A^1, \ldots, f_A^{M_s.2-1}), A = (x, y, z) \tag{3}$$

$$f_A^n = P_A^{M_s Z+n}, n = 0,1,2, \ldots., M_s.2 - 1 \tag{4}$$

In (2)-(4), $M_s = [M/P_N + 1]$ is the magnitude of a context, and therefore each adjunct frames have context-magnitude overlap. Therefore, the proposed study considers the featured-type set ψ that illustrates the properties of the context-based parameters using ambient intelligence in our study by considering a subset

$C_F = \{c(^i)\}$ where i is a set of natural numbers from 1 to n. Component c illustrates one context of positioning based on a single axis in a spatial direction. As it is known that the accelerometer has three axes and we consider a total of C_N context per assumptions, all the contexts can be integrated to formulate a vector with dimension $D_{vector} = 3 \times n \times C_F$. Therefore, the context using an accelerometer can be formulated as (5):

$$C_{Acc} = \{C_{x,o}^{(1)}, C_{y,0}^{(1)}, C_{z,0}^{(1)}, \ldots, C_{x,P_N-1}^{(n)}, C_{y,P_N-1}^{(n)}, C_{z,P_{N-1}}^{(n)}\} \quad (5)$$

Looking into (5), it can be said that considering more frames that define the context of an individual will give better detailing and reasoning in ambient intelligence services. It is to be noted that this form of data/event availability is solely non-deterministic as it is all about human-uncertain behavior. However, the proposed study model can extract all the necessary information almost instantly at the time of occurrence of an event.

2.2. Capturing context from GPS

The implementation of the proposed system is carried out considering an open-source platform of Android environment with the deployment of a location-based inbuilt package (*android.location*) for considering the acquisition of services purely based on location. This has two functional parts: a) user side and b) attendee side. The user side module extracts appropriate positional information of the user is reported at attendee device using Google Maps. This provides periodic updates of the user location.

The method towards identifying the position of the user based on their mobile device is carried out considering multiple sets of parameters as follows: i) *Service_Provider_Param*: This parameter facilitates the operation of service providers using global positioning system for the mobile device owned by the user, ii) *Instantaneous_Minimum_Time_Param*: This is the duration involved for the arrival of any notification captured in the form of milliseconds, iii) *Least_Distance_Param*: This parameter represents the spatial distance between the user and service provider in the form of meters, iv) *Listener_Param*: This parameter is responsible for updating the change of location information of an individual where a specific java method is used for differentiating the change in position (*LocationChanged()*).

The parameter *Least_Distance_Param* is deployed by the system to perform activation of the coordination module to explore the positional information associated with the patient and service provider or emergency medical staff. The study also considers that this mobile application is also in possession of mobile devices by the emergency medical staff, who can seamlessly monitor the real-time status of the patient requiring emergency services. It will eventually mean that the emergency medical staff can also evaluate the distance between them and the system-reported patient encountering a critical clinical condition. The distance information is acquired in the form of latitude and longitude to offer accuracy in the location exploration process. The system performs consistent listening of the incoming information of tracked location information, context-based information, and other associated network-related location information. Owing to the adoption of multiple sensors, the system aggregates multi-sensory data from the individual to define the maximal degree of the context for the criticality state. Deploying navigational services and GPS-based information from an ambient intelligence perspective accomplishes the contextual awareness of location information. The situational information of the position is obtained by the accelerometer for the individual.

Further, a higher degree of context is formulated by the GPS tracking system that also consists of situation-related context data, proximity distance, phone number, residential information, the blood group, age and name of an individual. The sensors capture all the contextual information related to the critical clinical situation. In contrast, the sensors are assumed to be linked with devices with the wireless standard of IEEE 802.15 family that is further deployed for forwarding the notification with the aid of the existing service provider using a Java-based messaging application programming interface (API) to the available emergency medical staff.

It is to be noted that the proposed study considers that there is a specific department of medical staff who are meant to serve the patients who are system-reported to be in critical condition and need immediate medical assistance. However, not all the medical emergency staff members may be available to cater to the dynamic demand instantly owing to various practical reasons (higher journey time not enough to serve the critical patient or already engaged in servicing other patients). In such circumstances, the system sorts the selection of attending medical staff allocation based on distance from the reported patient. Upon arrival of the emergency message on the devices of the emergency medical staff, they set their route aligning with the GPS-related information obtained from the system followed by last-time criticality assessment based on evaluated contextual information. The emergency medical staff member undertakes two anticipated sets of actions to meet the demand of that critical hour viz. i) undertake instantaneous action: under this approach, the emergency medical staff only opt for an option to reach the patient location as the only set of action, and

ii) undertake monitoring of patient's condition: this situational approach calls for a second look into the patient's clinical information for further confirming the criticality of the situation by the emergency medical staff members. The members can ask for more information to judge the severity of the patient's clinical condition, and the members can offer remote diagnosis-based service, which could save significant amounts of travel time to reach the patient. The proposed scheme assumes that wearable devices are transceivers to facilitate such a form of remote medical services.

2.3. System design

The essential units of the proposed study model involve aggregating the contextual information and analyzing the system-generated request for emergency services. In contrast, collaborative units facilitate assigning the sync and allocation of emergency medical staff. This provides the context-aware provisioning system with the potential to provide user-required services and also enhances the trust and confidence in the service provided. The proposed system considers context awareness in ambient intelligence where the system user will be furnished with the emergency medical service exactly matching their real-time clinical condition. To increase the preciseness of the data collection, the proposed system considers exponential usage of the context parameters to furnish precise and reliable contextual information to the user at the correct time and appropriately so that the individual can use the information. It was also seen that most of the prior work on ambient intelligence concerning the healthcare system majorly adopts on-demand strategies. In contrast, our technique is entirely proactive, where the user will be independent of participation in any sophisticated computation and information processing. The proposed ambient intelligent (AmI) scheme's critical success factor is data processing followed by data classification. One of the significant needs of the AmI scheme is to establish a correct correlation between all the associated clinical (heart rate, temperature, physical activity) and non-clinical data (name, phone number, and address). If the correlation can exist precisely between the various types of the context captured from the devices (accelerometer and Android mobile device), a secondary potential or competence factor of the proposed system can be evolved automatically. It was also seen from the literature that some of the work conducted in the healthcare system uses classifiers to classify the captured clinical data. However, it should be noted that the processing of such data in emergency medical situations could not be guaranteed because of the inclusion of the learning and training phase of such algorithms. Hence, we avoid using such algorithms as they do not meet the need for ambient intelligence in emergency medical conditions. The proposed study is conducted under three basic modules, which are discussed below.

2.3.1. Context awareness in AmI

This is the preliminary module of the proposed framework in AmI, where the context design is formulated. The core idea of this module is to extract contextual information associated with activities. The extraction of context information is done from AmI. The basic formats of the context parameter design are shown in Figure 2.

Location	Time	Heart Rate	DOB, Blood Group	Temperature
Longitude, Latitude	20-06-2013, 2000 Hrs	100 beats 120 beats	19-06-1980, O+ve	Ambient Temperature, Body Temperature

Figure 2. Adopted sample format of disseminated data with context parameters

The prime purpose of the context parameter is to identify the attributes of the ambient intelligent system that will be processed using the wireless mobile network. The framework is equipped with a request analysis unit that specifically identifies the user, and their respective contexts are extracted, and the system formulates beliefs based on it. The request collection & request refinement unit provides the user identity (ID) to the context information and observation module and starts aggregating the contextual information. The aggregation for context starts collecting mainly the following forms of contextual information: e.g. i) location, ii) time, iii) heart rate, iv) date of birth, and v) temperature context parameters of the specified user. The system considers the usage of two microprocessors for data collection. The module to process the user's request proactively filters the user's request based on the belief obtained from contextual data and the monitoring unit. Finally, the filtered request accomplished from the request analysis unit is used for the collaboration module that specifically chooses a definite service considering many detailed specifications. The elaborated context parameters are exhibited in Figure 3.

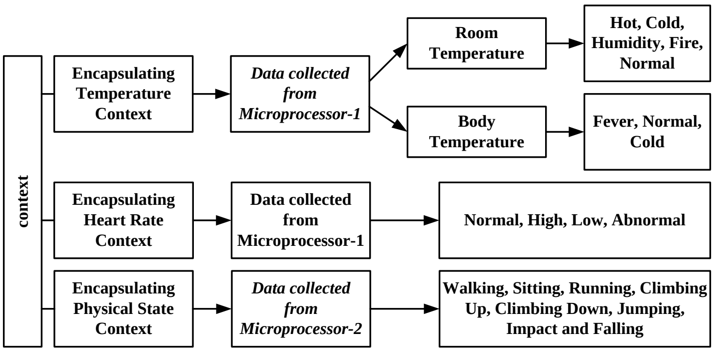


Figure 3. Design of adopted context

The context information of the proposed study is illustrated as $C_p(n) = \{c_{i1}, c_{i2}, \ldots\ldots, c_{ik}\}$, where $n \epsilon Z$, where $C_p(1)$ signifies location parameters, $C_p(2)$ signifies time parameters, $C_p(3)$ signifies heart rate parameters, $C_p(4)$ signifies Temperature parameters, and $C_p(5)$ signifies data captured from accelerometer parameters. Using our previous framework [30], context-based parameters of the individual will be extracted. Finally, the monitoring unit will check for relevant information about the users' context, thereby mechanizing various observations. Ultimately the request collection and refinement unit performs processing of query-based approach of request filtering. Finally, the user proactive request adopts AmI to forward the clinical information to the destined medical assistants in proximity using a GPS incorporated over the Android handheld device.

2.3.2. Collaboration in AmI

The prime purpose of the collaboration unit will be to identify the requirement classification of collaboration required to incorporate ambient intelligence in our context-based system. This module also incorporates the scrutiny of various context-based information collected from accelerometers. The system connected with sensors primarily for capturing heartbeat and body temperature connected to control units will quantify the context as per the belief formulated, and thereby, the specific service will be provisioned based on the emergency. Three operational blocks are majorly meant for i) the selection of collaborators, ii) furnishing constructive suggestions, and iii) the mechanism for vendor selection. The recommendation unit acquires the specification of the collaboration and refined request in the proposed study, thereby recommending specific services. The system adopts user-based collaborative filtering for services based on proximity and rating of the emergency as per the belief scores of the individual. The system allows the higher set of specifications for the remote medical assistant to understand the ill person's current situation thoroughly and to seek the request specific information from the ill person about the observatory set of vital stats, if necessary. After receiving the information from the wearable device of the ill-person using IEEE 802.15 to the Android handset, the system checks the availability of the medical assistant using a GPS navigational system. Using the formulation of the grading factor, the proposed study statistically prioritizes the ill person's emergency condition. The grading factor is defined as:

$$Gf_k = \sum_{i=1}^{n} NF_{ki}\, SF_{ki} \tag{6}$$

In (6), the variable N is the nearest medical assistant available within the proximity. The user emergency condition is captured using neighborhood factor (NF), and similarity factors can be evaluated based on accelerometer context. The product of the similarity factor SF with the neighborhood factor and the product yielding from this multiplication will be sequenced in decreasing order of NF. In the presence of N number of suggestions, the system performs a ranking of the services using *Gf*, where *Gf* possesses a component with identity k that is iterated for n sequences (6). The system finally considers the highest value of *Gf* as the suitable services as the highest prioritized recommendation. It is to be noted that this module is specifically designed for the remotely located medical assistant so that they can get an accurate visualization of the criticality of the emergency condition of the person. All the actions the medical assistant takes are based on information furnished by this module.

2.3.3. Coordination in AmI

The success of the availability of the services from the remotely located medical assistant entirely depends on collaboration and coordination. Without coordination, it may play a significant role in avoiding such unwanted circumstances. The block diagram of the coordination scheme in the proposed AmI is exhibited in Figure 3. For this purpose, the module is designed considering two essential attributes in the coordination system, e.g. pre-work coordination and post-work condition. Pre-work condition is a list of emergency service requests that are unattended. This list is considered public access and authorized to be checked by the available medical assistant, who can check and decide whether to attend to the emergency. It happens that multiple available remotely located medical assistants reach the single message of the emergency clinical condition, and all of the medical assistants rush to the same scene. Therefore, we strongly felt that real-time group communication The medical assistant may choose to deny the emergency in case they are currently attending an emergency or are located far enough to reach the destination of the emergency at an appropriate time. Once the medical assistant successfully attends the emergency, the current call record will be reposited on post-work coordination. Accessing the list of post-work conditions has two benefits, e.g. i) the medical assistant will have the clinical record or record about the report of an urgent situation that might be highly beneficial in future if the request originated from the same ill individual and attended by a different medical assistant, and ii) it also acts as updates for the other medical assistant who can refer the list and check the current condition of request.

3. RESULT ANALYSIS

The development of the proposed system is designed and experimented with using a laboratory prototype. A body area network (BAN) was deployed for capturing the patient's clinical information concerning the specific location for performing monitoring activity. BAN collects precise information about blood pressure, heart rate, motion as well as temperature of the human body. The system avoids using any invasive implants. The adopted sensors are cheap, readily available, and more accessible for experiments. The system also includes a prototype for filtering and enhancing the signal strength. The hardware components used for the prototype are cheaper and with low power requirements. The assessment of the proposed study model is carried out in real-time method. At the same time, the captured sensory information is disseminated using analogue-to-digital converters connected to the core microcontroller. A liquid-crystal display (LCD) screen is connected to the prototype for visualizing the patient's body temperature and pulse rate. The dissemination of digital data is carried out via Bluetooth or using the cellular data service of the user's handheld device. The assessment is carried out for a specific interval to record the captured sensory data. The prototype consistently monitors the acquired data while a notification is generated when encountering abnormalities in the readings of sensory data. It is already known that the human heart exhibits 72 beats per minute in normal conditions. In terms of our experiment, knowing the higher and lower limits of the beats is required. Hence, the system considers 50 and 90 as lower and higher limits of heartbeat coinciding with bradycardia and tachycardia. The sensory readings in digital form are captured in an exact manner that is less influenced by the physical activity performed by the patient, nor is it dependent on its location. The complete monitoring of the patient's clinical status is carried out by concurrently observing the temperature and heartbeat of the patient at the same time. The scheme mainly uses temperature and heartbeat sensors to acquire the patient's vital stats. A patient with an age range of 20 to 40 years bears a minimum pulse rate of 140 beats per minute and a maximum pulse rate of 170 beats per minute. The maximum pulse rate for patients aged 20 to 40 is 140 beats per minute, while the minimum pulse rate for the same age range is 115 beats per minute. The prototype considers body temperature and heartbeat as the core status attributes of a patient's health.

Further, a provision of recording the acquired sensory information concurrently is also facilitated in a proposed scheme meant to benefit the emergency medical staff to observe the maximum level of information. The scheme also facilitates retaining all the recorded information in a specific directory, which can be used for future analysis where the medical data can be queried considering the time and date of reporting. The reverse functionality is also provided, where the monitored data can be analyzed in real time without storing it. More information on the mobile application prototype is also facilitated in a proposed scheme where information associated with the installation date and time-based activity on the application can be monitored. It also facilitates editing the emergency contact number. The proposed prototype also facilitates the application running in the background while the live application can be exited simultaneously. This operation is carried out by seeking permission from the user.

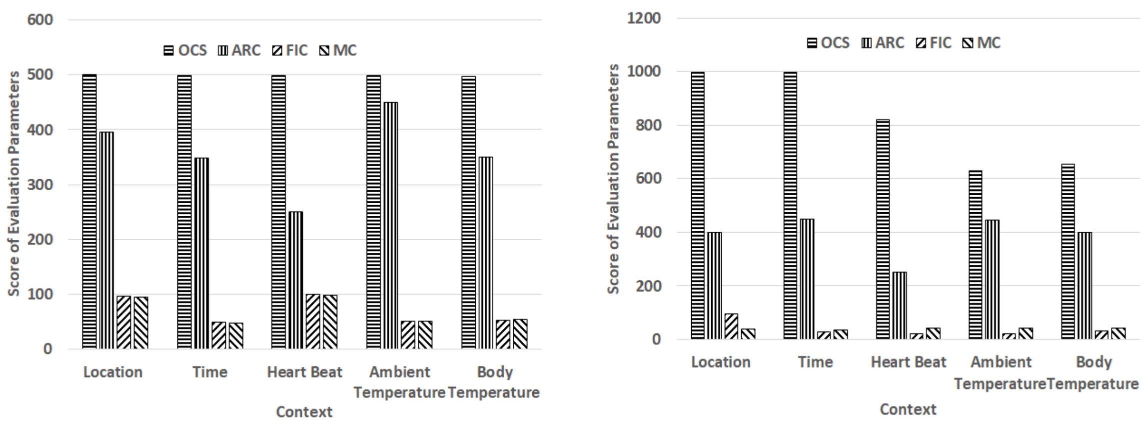
For result analysis, we consider some false positive cases: i) for location and time context: wrong setting/configuration with GPS, defective navigational service, profile not appropriately updated in the application. ii) heart rate context: illusive physical activity, e.g. waving legs sitting on a chair, Yoga activities related to cardiac muscles, excitement due to non-emergence cause, iii) temperature context: temperature sensor node not appropriately connected, and water drop on ambient sensor node will detect as fall in water. Multiple false positives have been considered while performing real-time experiments; however, a few significant false positives are mentioned above. We also preferred to perform the effectiveness analysis considering four specific evaluation factors, e.g. i) actual recognized context (ARC) in terms of real-time context, ii) falsely identified context (FIC) in terms of context that does not possess any critical emergency condition, iii) missing context (MC) in terms of ignored context, and iv) original context score (OCS) are taken as primary input data for result analysis. The empirical formulations of the adopted performance metrics are as (7) to (9):

$$CIR = ARC/OCS \tag{7}$$

$$ECIR = FIC/(ARC + FIC) \tag{8}$$

$$NCIR = MC/ARC \tag{9}$$

The expression (7), (8), (9) represents context identification rate (CIR), error in context identification rate (ECIR), and non-context identification rate (NCIR). As indicated, these parameters are evaluated for the five context parameters in the proposed study. The proposed study was evaluated considering the preliminary phase (<1 Hour) and terminated in the sharp 10th Hour after the wearable device was connected to the subject body. The experiment is performed on 25 individuals with different physical conditions to check the accuracy and effectiveness of the system. It can be seen that with the increase of time, the false positives are reduced, and the actual capturing of the data and context identification rate tremendously maximizes, as evident from Figures 4-5. The prime reason for false positives in the preliminary phases shoots up due to the adaptability of the wearable device with physical activity. However, with the availability of 5G services and IEEE 802.15 standard, the emergency request is given swiftly to remote medical assistant. Hence, the reliability of the services can be assured. The proposed system is energy efficient. Figures 4(a) and 4(b) show the system evaluation in the end phase compared with the preliminary phase results, OCS is dominant, and FIC is feeble for relatively less ARC.



(a) (b)

Figure 4. The system evaluation done in: (a) preliminary phase and (b) end phase

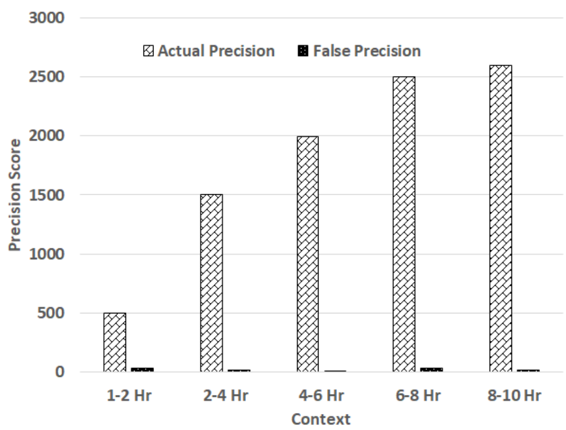


Figure 5. Evaluation of actual precision and false positives

4. CONCLUSION

This paper has presented an experimental prototype that targets the acquisition of contextual information to deliver emergency medical services in varied forms for patients with sudden critical clinical conditions. The hardware used in the proposed experimental design is relatively cost-effective and supports the real-time analysis and dissemination of critical clinical information. The contribution of this model is that it offers a belief system using varied forms of clinical data to undertake decisions in the most simplified way with better control over computation time as well. Interestingly, the communication overhead for sensor-based clinical data aggregation and dissemination is carried out by filtering the raw data to converge with contextual data. In contrast, the data pattern matches with criticality events using belief parameters. Another significant contribution of the proposed prototype is that it conserves a significant amount of power utilization by switching the mode of operation of the processor and peripherals, reducing the sampling rate under normal conditions which plays a key role in maximizing the lifespan of the battery to 6.2 weeks. Average power consumption rate of 1.8 mW.

Further, the processing and dissemination of aggregated contextual information is rendered seamlessly acquiring the belief information. However, data transmission speed and usage of channel capacity will be one dependent factor towards facilitating clinical information dissemination to emergency medical staff that originates from the handheld device of a patient/user. Hence, the adoption of 4G or 5G-based network services is highly recommended for the adoption of network-based services to offer faster data rate transmission. The future direction of this work will be towards further adopting a more complex environment and more challenging data transmission environment in real-time for optimizing the ambient intelligent system for clinical services.

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