International Journal of Pervasive Computing and Communications

Contextual case-based reasoning applied to a mobile device

Djamel Guessoum, Moeiz Miraoui, Chakib Tadj,

Received 27 November 2016
Revised 12 June 2017
Accepted 16 June 2017

Contextual case-based reasoning applied to a mobile device

Djamel Guessoum
Ecole de Technologie Superieure, Notre-Dame Ouest, Montreal, Quebec, Canada
Moeiz Miraoui
Higher Institute of Applied Science and Technology, Universite de Gafsa, Gafsa, Tunisia, and
Chakib Tadj
Ecole de Technologie Superieure, Notre-Dame Ouest, Montreal, Quebec, Canada

Abstract

Purpose – This paper aims to apply a contextual case-based reasoning (CBR) to a mobile device. The CBR method was chosen because it does not require training, demands minimal processing resources and easily integrates with the dynamic and uncertain nature of pervasive computing. Based on a mobile user's location and activity, which can be determined through the device's inertial sensors and GPS capabilities, it is possible to select and offer appropriate services to this user.

Design/methodology/approach – The proposed approach comprises two stages. The first stage uses simple semantic similarity measures to retrieve the case from the case base that best matches the current case. In the second stage, the obtained selection of services is then filtered based on current contextual information.

Findings – This two-stage method adds a higher level of relevance to the services proposed to the user; yet, it is easy to implement on a mobile device.

Originality/value – A two-stage CBR using light processing methods and generating context aware services is discussed. Ontological location modeling adds reasoning flexibility and knowledge sharing capabilities.

Keywords Services, GPS, Context-awareness, Mobile device, Case-based reasoning, Pervasive computing

Paper type Research paper

1. Introduction

Technological advances in the collection of contextual information (smartphone, social media, etc.) have resulted in the proliferation of context-aware applications aimed at offering relevant services to a user by adapting a service's behavior to changes in the environment. The origin of the term "context awareness" is attributed to Schilit and Theimer (1994) who asserted that context sensitivity is "the ability of a mobile application and/or of a user to discover and react to changing situations".

Before continuing this discussion, it is necessary to define the term "context" and to clarify how this concept differs from the terms "contextual information" and "situation". According to (Brézillon and Pomerol, 1999), context is a set of contextual data (e.g. time, location) that can be used in a decision-making process. Schilit *et al.* (1994) considered context to have three important aspects in response to the following questions: Where are you? Who is with you? What resources are available nearby? The authors thus categorized context according to six factors. The first three factors relate to the human component,

International Journal of Pervasive Computing and Communications
Vol. 13 No. 3, 2017
pp. 282-299

1742-7371
DOI 10.1108/IJPCC-11-2016-0056

namely, information concerning the user (e.g. clothing, biophysical conditions), the social environment (e.g. proximity to other people) and user tasks (e.g. smart tasks). The remaining three factors relate to the physical environment, namely, location, infrastructure (e.g. resources, communication) and environmental conditions (e.g. noise, light and climatic conditions).

Abowd *et al.* (1999) whose definition is cited most frequently, defines context as any information that can be used to characterize the situation of an entity (person, object or physical computing). This definition clearly resembles that of Schilit *et al.* (1994) because context is considered a set of data collected from a user environment (person), physical environment (physical object) or system environment. The characterization of these environments is the purpose of data collection. This rather generalized definition does not specify the nature of what may compel (constrain) the resolution of a problem.

The present study is based on works by Meissen *et al.* (2005) and Kayes *et al.* (2014) in which context is considered a snapshot or an instantiation of all context variables (e.g. contextual information such as location, temperature…) at a specific moment in time. Context thus differs from situation, which is the result of introducing semantic relations between these parameters (e.g. being at home, on the phone) and which may be a series of contexts that do not change over time. Studies on contextual models have shown that a user's location, identity, time and activity are the most important parameters that determine the type of service to provide to a user (Yuan and Herbert, 2014; Benazzouz, 2011; Bolchini *et al.*, 2007).

Case-based reasoning (CBR), which can be applied to machine learning, is a method that solves a common problem based on known solutions to similar problems encountered in the past. We chose to use CBR because it allowed us to save an initial number of cases containing the specific contexts and their corresponding services to a "seed" case base. These cases serve as a reference to be compared with a new case or a current context to identify the most similar case encountered in the past and to subsequently provide appropriate services to the user. The proposed services are then updated in a second stage that filters these services based on information obtained for the current context (e.g. battery level, ambient light conditions…). This service adaptation method is the main contribution of the present paper.

The CBR method presents the following main advantages: It does not require prior knowledge of the new problem field, does not involve training, demands minimal processing resources (Kofod-Petersen and Aamodt, 2003), is capable of solving problems in poorly defined fields and easily integrates with the dynamic and uncertain nature of pervasive computing (Öztürk and Aamodt, 1998). CBR originated in the cognitive sciences, specifically in research on human memory (Schmid and Richter, 2006). Unlike most problem-solving methodologies in artificial intelligence (AI), CBR is memory-based; it thus relies on the human use of remembered problems and solutions as a starting point for solving new problems (Schank, 1983).

The literature proposes several definitions of the CBR cycle that are in agreement with the cycle described in (Kolodner, 1996), which can be summarized as follows:

- *Case retrieval*: A new case consists of a request containing a problem that is similar to the cases stored in the case base. The case (or cases) most similar to the request is then retrieved from the case base.
- *Adapting (reusing) the solution*: The retrieved cases and solutions are adapted to fit the solution.
- *Assessing the solution*: The fit of the adapted solution is evaluated.

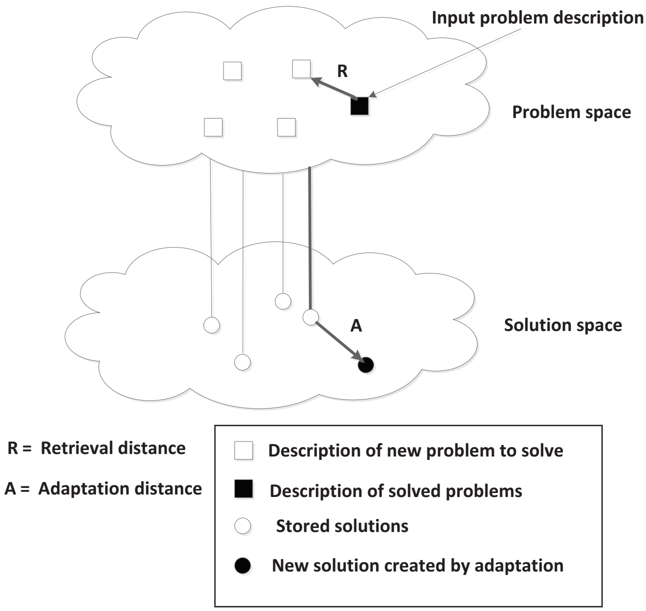
- *Updating the case base*: If the retrieved/adapted solution is acceptable, it will be added to the case base.

CBR uses analogy to solve new problems based on the concept that "similar problems have similar solutions" (Leake and Jalali, 2014). Thus, if a case is a pair (*P*, *S*), where *P* is a problem and *S* is the solution to the problem, and if (*P*, *S1*) and (*P*, *S2*) then *S1* = *S2* (Richter, 1995). Initially, cases containing the description of a problem (see "problem space" in Figure 1) and the corresponding validated solution for a specific field (see "solution space" in Figure 1) are carefully selected and then saved to a "seed" case base. The solution to a new problem in the same field is based on comparing the new problem description with the description of stored cases: The cases (or case) with the most similar descriptions are retrieved based on the minimum retrieval distance R (Figure 1), so that their solutions can be applied to the new problem. Cases extracted during the retrieval phase that are considered unsuitable require adaptation. The adaptation stage uses the minimum adaptation distance A (Figure 1) between the extracted case(s) and the new case.

The present paper is organized as follows: Section 2 presents related research and highlights the originality of our approach. Section 3 presents the proposed method for the adaptation of services based on CBR. Section 4 describes the experimental setup and the application of the two-stage service filtering process. Conclusions are presented in Section 5.

2. Related work

In pervasive computing, the adaptation of services is a dynamic process wherein services are offered either reactively to a user in response to a change in context or proactively by predicting a change in context and acting accordingly (Guessoum *et al.*, 2015; Sancho, 2010).



Source: Adapted from De Mantaras *et al*. (2005)

Figure 1.
Relationship between problem and solution spaces in CBR

Several definitions are proposed in the literature; the most general definition (Efstratiou, 2004) generalizes the concept of adaptation for mobile equipment and context-aware applications in a pervasive computing system, based on the premise that an application or system is adaptive when it changes its behavior in response to a change in context (this change occurs in either the context or in the equipment resources).

Nicklas and Henricksen (2008) categorized the adaptation of context-aware applications into four classes:

(1) the selection of information and services;

(2) the presentation of information and services;

(3) the automatic execution of a service for a user; and

(4) the labeling of contexts for later retrieval.

The main objective of the service adaptation process is to suggest the most appropriate service(s) to a user. The present study used the CBR method (for reasons stated above) to adapt services on a mobile device according to a user's current context. In general, CBR systems have incorporated contextual information as an adjunct to information previously acquired in a specific field to improve performance of similarity calculations during the retrieval phase by reducing case search volume (Nwiabu *et al.*, 2011; Montani, 2011; Lee and Lee, 2007), and to categorize the retrieved cases according to the relevance of the proposed solutions as well as adapt those solutions to a user's personal constraints (Montani, 2011; Lotfy and Salem, 2010; Pla *et al.*, 2014; Kofod-Petersen and Aamodt, 2009). This contextual information varies depending on the field of application. Note that this contextual information (location, temperature, humidity, lighting conditions, user profile, etc.) has always been used separately (Song *et al.*, 2013; Kwon and Sadeh, 2004). Furthermore, for rare cases in which contextual information has been used to describe an entire case, this use was limited by the field of application [smart home (Ma *et al.*, 2005), museum visits – LISTEN project (Zimmermann, 2003)].

Most studies using contextual information in conjunction with CBR have incorporated context into the cases to represent a past learning experience specific to the context for which this past experience can be used to determine the relevance of the proposed solution (Leake and Jalali, 2014; Pantic, 2005). Context is used as additional information for a given field of application in the various stages of CBR (retrieve, reuse, revise and retain) (Figure 2) (Kofod-Petersen and Aamodt, 2009; Leake and Jalali, 2014). In Gouttaya and Begdouri (2011), the authors used the ECA (event, condition and action) structure of active rules for adaptation but neglected the time factor of an event or of a change in context. In Zimmermann (2003), context was considered to represent a description of the problem, and the solution was regarded as the appropriate recommendation. The discretization of the continual acquisition of contextual attributes is transferred to a case in CBR.

Published research that considers context and uses CBR as a machine-learning method to select services (see "case representation" in Figure 2) can be classified into two categories:

(1) studies in which context (contextual information) is used as additional information for the case structure; and

(2) studies in which a case represents a specific context.

In both categories, the proposed services result from the retrieval/adaptation phase, and there is no guarantee that these services will be the most appropriate options. The present paper proposes a two-stage retrieval and service-filtering process to improve the relevance of the services offered to the user. Moreover, the study used methods that require minimal

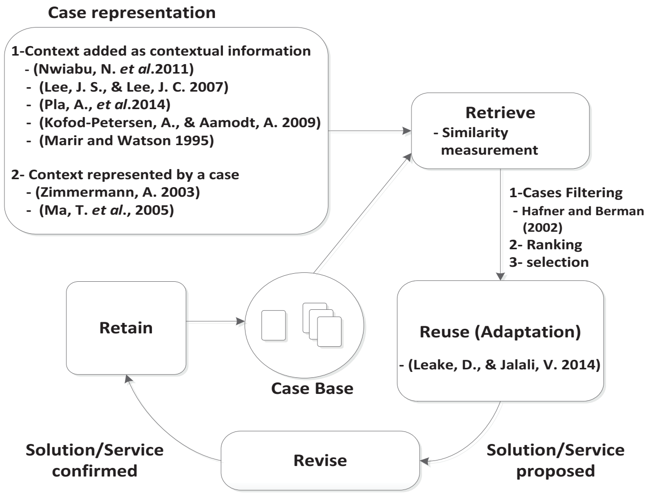


Figure 2.
Context and the CBR cycle

processing resources: CBR for the learning phase, the Wu and Palmer similarity measure to identify similarities between different user locations, the Euclidean distance to determine similarities between various user activities and the overlap coefficient to measure similarities for the contextual information attribute "time".

3. Our approach

The proposed approach is based on the following hypothesis analogous to the assumption that "similar problems have similar solutions" (Leake and Jalali, 2014), which forms the basis of CBR: "In a context-aware pervasive computing system, similar services are provided in similar contexts/situations". To apply the same methodology to a pervasive system, we thus sought to answer the following question: Based on our knowledge of the user's current context/situation, what is the most appropriate service we can provide to the user?

As mentioned previously, we chose CBR over other reasoning and AI inference techniques because it offers advantages that fit our target application and it fulfills the following requirements: The CBR cycle

- does not require training;
- demands minimal processing resources (Kofod-Petersen and Aamodt, 2003); and
- easily integrates with the dynamic and uncertain nature of pervasive computing (Knox *et al.*, 2010).

Based on the CBR cycle, the proposed approach intends to provide appropriate customized services to smartphone users. This approach is summarized in Figure 3.

Before presenting the CBR cycle, we first describe the representation of cases used in the present study.

4. Case representation

A case is a description of a problem and its corresponding solution. In general, the three techniques for presenting cases most often found in the literature (Watson, 1999) are:

(1) *Flat organization*: This simple organizational technique retrieves on a case-by-case basis and works well for small case bases.
(2) *Clustered organization*: Cases are stored in clusters of similar cases, which allow easy cluster selection for matching; however, this technique requires a complex algorithm to add/delete cases.
(3) *Hierarchic organization*: A hierarchic organization groups cases that share the same characteristics. Cases are organized in the form of a structured network of categories possessing semantic relationships. This type of organization permits a precise and rapid retrieval of cases; however, new cases are relatively difficult to add or delete.

The selection of contextual information used to represent a case is limited by several factors: the types of sensors current smartphones are equipped with, the processing power of current smartphone technology, the available storage capacity and the potential constraints of processing parallel requests (Incel *et al.*, 2013).

Studies on contextual models have shown that a user's location, identity, time and activity are the most important parameters that determine the type of service to provide. In many cases, these parameters correlate strongly: An activity can, for example, be determined according to the user's location (e.g. if the location is L = restaurant, the activity is A = eating) (Phithakkitnukoon *et al.*, 2010; Zhu and Sheng, 2011); it can be determined by using the smartphone's inertial or GPS sensors (e.g. the speed at which a user is moving can reveal whether the user is walking, running or using another means of transportation) (Incel *et al.*; Chon and Cha, 2011); and finally, an activity can be determined based on which functionality of the smartphone is being used (messaging, calling, browsing and playing games) (Chon and Cha, 2011). Accelerometers, gyroscopes and GPS sensors constitute an effective means of inferring even complex human behavior and identifying significant locations in people's everyday lives (at work, at home, at the coffee shop). (The techniques used to acquire this information have been described elsewhere (Schmid and Richter, 2006; Cao *et al.*, 2010).

Table I provides an overview of the typical case structure (case = context, service) that follows from the preceding arguments.

The chosen case structure is hierarchic (Figure 4), permitting rapid access to the various attributes (Ma *et al.*, 2005) as well as facilitating retrieval.

The case description is composed of a user's location, time and phone usage. The selection and classification of appropriate services is the subject of future work; here, we have focused our attention on services chosen specifically to explain the proposed approach.

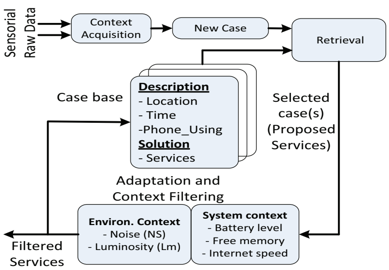


Figure 3.
Context acquisition and service filtering

			Collected data
1. Location			
	Description		
Location_eating	Restaurant, bakery, coffee shop		– location
Location_education	University, college, institute, school		– speed
Location_entertainment	Indoor	Cinema, bowling theater	– accel.x/y/z
	Outdoor	Stadium	(mean, SD, VAR)
Location_variable	Motorized	Car, bus, plane, train, subway	
	Non_motorized	Walking, running, biking	
Location_home, Location_recreational, Location_shopping, Location_work, Location_ government, Location_worship			
2. Time			– date
	daytime, nighttime, week day, week end		– time
3. Phone_Usage			– phone usage
	messaging, calling, browsing, gaming, nil		
Services			
	Services = (rt, rv, pm, lm, apps)*		

Notes: * rt = ring tone, rv = ringer volume, pm = phone mode, lm = luminosity, apps = recommended applications

Table I.
Case structure

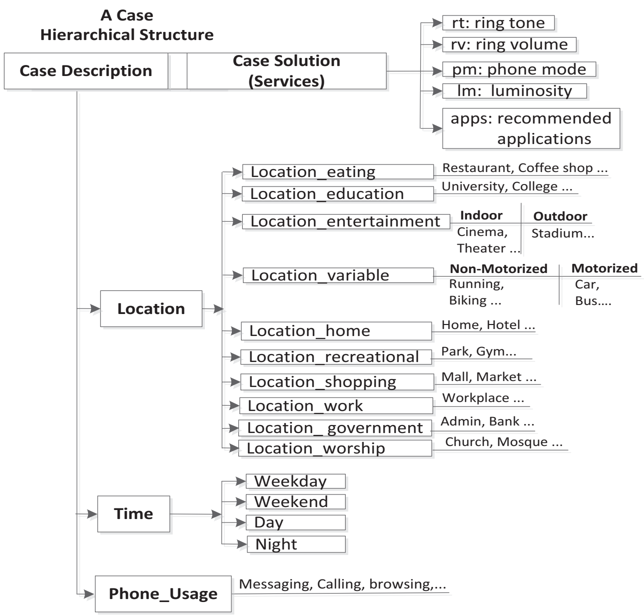


Figure 4.
Hierarchic structure of a case

5. Context acquisition

The following sensors can be used to obtain contextual data with a smartphone (Incel *et al.*, 2013): accelerometer, gyroscope, camera, GPS, Bluetooth, Wi-Fi, microphone, digital compass, ambient light and proximity sensors. The user's location, the current time and characteristics retrieved from the accelerometer, and the gyroscope are determined during the acquisition phase. If one of these characteristics matches a closely defined condition, then a new case is detected and the CBR cycle is initiated (e.g. if the current location differs from the previous location, which was "home", then the newly detected case contains the current location, the acquisition time and the characteristics obtained from the accelerometer and the gyroscope).

The context acquisition stage consists in retrieving the structural and statistical characteristics of the samples collected from the sensors (mean, variance, etc.). Time and frequency constitute the two main types of characteristics. Temporal characteristics are used most often because of their computational simplicity, in particular with respect to calculating the mean, the variance (VAR), and the standard deviation (SD) (Shoaib *et al.*, 2015).

5.1 Service filtering

The retrieval phase of the CBR cycle yields a case (or multiple similar cases) with *n* services. An adaptation or contextual filtering module filters these services according to relevance based on current smartphone resources and the environmental context (such as lighting conditions, noise levels, etc.) and by using a rule-based system (*if* context *then* service).

6. Case retrieval and similarity measure

It is important to choose similarity measures that meet the requirements of the CBR process because the nature of the selected measure affects the quality of the cases obtained during the retrieval phase (Gabel and Stahl, 2004). It has been shown that the efficiency of the retrieval process for cases that are similar to the new case depends on two factors (Zang *et al.*, 2008):

(1) the type of similarity chosen; and

(2) the organizational structure of the cases.

In CBR, the global approach to measuring the similarity between cases is primarily based on calculating local similarities between attributes, which can be customized for each case base (Richter and Weber, 2013). The global similarity [equation (1)] can then be calculated based on these local similarities by weighting each attribute:

$$Similarity(Case_{new}, \quad Case_{old}) = \frac{\sum_{i=1}^{n} w_i \times Sim\left(a_i^{Case_{new}}, \quad a_i^{Case_{old}}\right)}{\sum_{i=1}^{n} w_i} \tag{1}$$

where W_i is the weight of the attribute a_i, $\mathrm{a}_\mathrm{i}^{\mathrm{Case_{new}}}$ is the attribute i of the new case, and $\mathrm{a}_\mathrm{i}^{\mathrm{Case_{old}}}$ is the attribute i of the existing case in memory. Given the conditions of the present study, the limited resources of mobile devices were an important consideration for the selection of a suitable local similarity measure. We chose the semantic similarity measure proposed by Wu and Palmer (1994) [equation (2)] because of its ease of calculation and its applicability to user location and phone usage taxonomies (Figures 5 and 6):

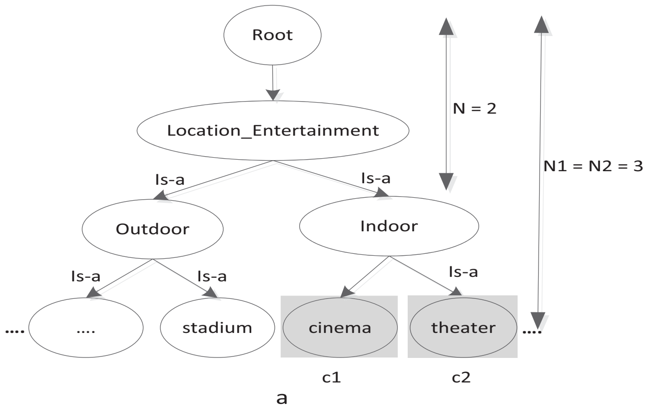


Figure 5.
Wu and Palmer similarity measure

$$sim_{WP}(c1, c2) = \frac{2N}{N1 + N2} \tag{2}$$

where N is the number of edges between the taxonomy root and the LSC (least common subsumer) of the concepts $c1$ and $c2$, $N1$ is the number of edges between the root and $c1$, and $N2$ is the number of edges between the root and $c2$.

7. Experimental method

The CBR cycle was performed with the open-source software application myCBR, a similarity-based retrieval tool and software development kit (SDK). The application was developed at the CBR center of the German Resource Center for Artificial Intelligence (DFKI, www.dfki.de) in partnership with the School of Computing and Technology at the University of West London, UK (www.ewl.ac.uk). The standalone version of myCBR allowed us to acquire the necessary cases to construct an initial case base through csv (comma-separated values) files. It was also used to store cases, calculate similarities and retrieve the best matches. In myCBR, similarities are calculated at the attribute level (local similarity) as well as at a global level (global similarity) (Roth-Berghofer *et al.*, 2012). The myCBR SDK 3.0.1 BETA version was used to acquire the case base, retrieve the best matches and calculate the similarities.

A case description consists of raw data collected through the smartphone sensors (daily routine locations, current time and mode of smartphone usage). The selection criteria for each characteristic are described in the following.

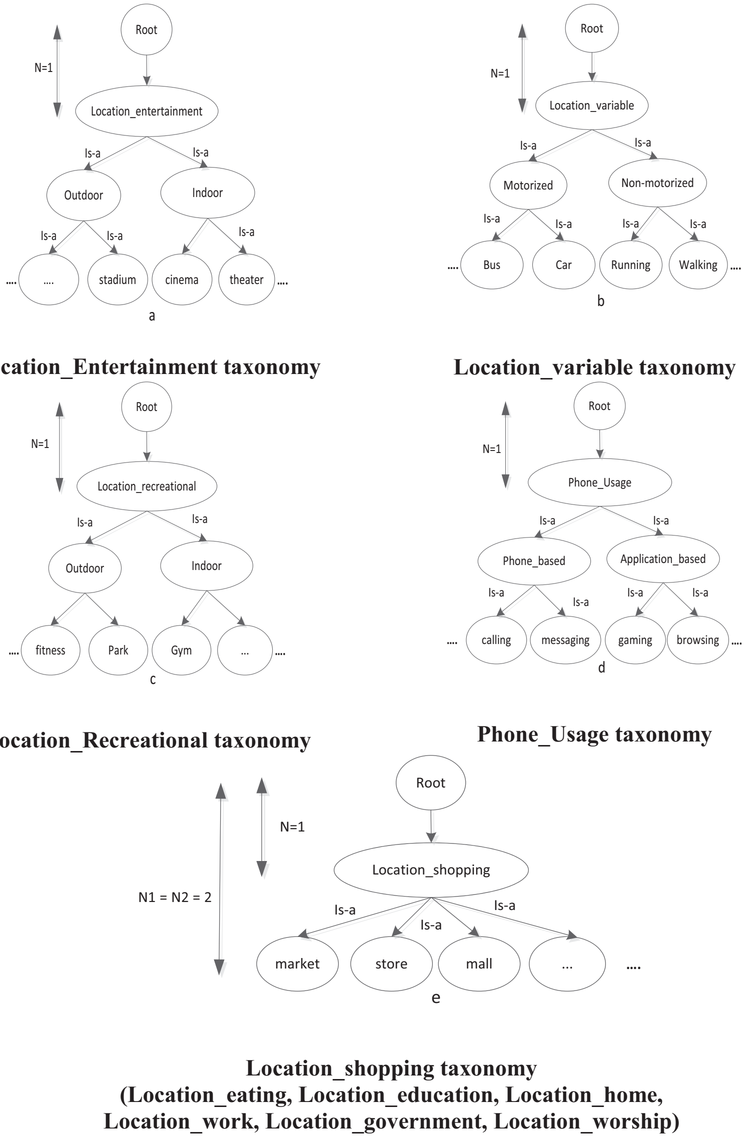
7.1 Daily routine locations

For a typical case, the description is composed of three groups of parameters: The user's location, the current time and the mode of smartphone usage. The kinds of locations and selected activities that make up a typical case (Figure 4) were borrowed from Incel *et al.* (2013), in which typical inferred activities were classified into six categories according to their objectives and in accordance with the state of the art in activity recognition:

(1) *cat. 1*: locomotion (walking, running);

(2) *cat. 2*: mode of transportation (bus, car);

(3) *cat. 3*: sporting activities (biking, etc.);



Note: (a) Location_entertainment taxonomy; (b) location_variable taxonomy; (c) location_recreational taxonomy; (d) phone_usage taxonomy; (e) location_shopping taxonomy (location_eating, location_education, location_home, location_work, location_government, location_worship)

Figure 6.
Taxonomies of the symbolic attributes "location" and "phone usage"

(4) *cat. 4*: health related activities (rehabilitation, etc.);
(5) *cat. 5*: daily/routine activities (shopping, eating); and
(6) *cat. 6*: smartphone usage (texting, browsing).

In addition, we incorporated the work of Phithakkitnukoon *et al.* (2010) who assigned daily and routine activities linked to a person's location to nine categories: eating (restaurant, bakery, coffee shop), shopping (mall, store, market), entertainment (theater, bowling alley, night club), recreational (park, gym, fitness), educational (university, college, school, institute), work (workplace), home (home, hotel), variable (bus, car, subway, plane, train, running, walking, biking) and worship (church, mosque, synagogue). Each group of parameters is associated with a set of services in the form Services = (rt, rv, pm, lm, apps), where each service is identified by an integer. Services = (1, 2, . . .10), (rt = ring tone = rt1, rt2, rt3), (rv = ringer volume = vibration only, low, medium, high), (pm = phone mode = normal, power saver), (lm = luminosity = low, medium, high) and (app = online apps, offline apps, app update, AVscan, ebook, TV program, bus schedule, course schedule).

Table II shows the "seed" case base, which is composed of ten initial cases corresponding to the ten identified location categories (Location_Eating, Location_Entertainment, Location_Recreational, etc.).

7.2 Activity recognition parameters

Among the multitude of available public data sets, we chose the simple yet comprehensive data set provided in Shoaib *et al.* (2013). This data set was used to select the parameters that describe a user's physical activity based on data obtained through the inertial sensors of a smartphone. The data were collected by three smartphone users (male, 25-30 years old, equipped with a Samsung Galaxy S2) for six physical activities (walking, running, sitting, standing, walking upstairs, walking downstairs) with a duration of 3-5 min per activity.

The following smartphone sensors were used to collect the data: the accelerometer (x/y/z, measured in m/s^2), the magnetometer (x/y/z, measured in micro Tesla units, μT) and the gyroscope (x/y/z, measured in rad/sec). An activity recognition algorithm running on MATLAB revealed that it is possible to identify the activities in the data set based on accelerometer characteristics – mean, standard deviation (SD) and variance (VAR) (Table III).

The similarity measure between two physical activities is given by:

$$sim\ (act1,\ act2) = \frac{1}{1 + dist\ \ (act1, act2)}$$

Case name	Location	Time	Weekday	Phone using	Services
Case 1	Home	Night	Weekday	Gaming	1
Case 2	Workplace	Day	Weekday	Nil	2
Case 3	Cinema	Night	Weekend	Nil	3
Case 4	Church	Day	Weekend	Nil	4
Case 5	School	Day	Weekday	Browsing	5
Case 6	Car	Day	Weekday	Nil	6
Case 7	Admin	Day	Weekday	Calling	7
Case 8	Park	Day	Weekend	Gaming	8
Case 9	Restaurant	Night	Weekend	Nil	9
Case 10	Mall	Day	Weekend	Messaging	10

Table II.
Initial case base

where *dist* (*act*1, *act*2) is the Euclidean distance between the activities *act1* and *act2*, given by:

$$dist \quad (act1, act2) = \sqrt{\left(Acc_{x,y,z}(act1) - \quad Acc_{x,y,z}(act2)\right)^2}$$

7.3 Similarity calculation
Local similarity attributes are of two types:

7.3.1 Similarities of the symbolic attributes "location" and "phone usage". Figure 6(a)-6 (d) shows the taxonomies applicable to a user's location and phone usage. Location taxonomies (Location_shopping, Location_eating, Location_education, Location_home, Location_work, Location_government, Location_worship) are shown in Figure 6(e).

The following demonstrates how the similarity measure is typically applied to the taxonomy, using the location "Location_Entertainment" as an example (Table IV):

$$sim(cinema, cinema) = 1, \quad sim(cinema, stadium) = \frac{2N}{N1 + N2} = \frac{1}{3} = 0.33$$

where N = 1, N1 = 3, N2 = 3 :

$$sim_{wp}(cinema, theater) = \frac{2N}{N1 + N2} = \frac{4}{6} = 0.66$$

where N = 2, N1 = 3, N2 = 3

7.3.2 Similarities of the "time" attribute. Similarities between the symbolic attributes of "time" are calculated using the overlap similarity measure (Stanfill and Waltz, 1986):

$$sim(time_{new}, time_{old}) = \begin{cases} 1 & if \quad time_{new} = time_{old} \\ 0 & Else \end{cases} \tag{4}$$

		Subject 1 Walking	Running	Standing	Sleeping
Subject 2	*Walking*	0.899	0.562	0.817	0.630
Subject 5	*Running*	0.680	0.722	0.604	0.436
Subject 10	*Standing*	0.756	0.484	0.912	0.747
Subject 14	*Sleeping*	0.629	0.375	0.775	0.782

Table III. Similarity of physical activities

	Nil	Stadium	Cinema	Bowling	Theater
Nil	0.0	0.0	0.0	0.0	0.0
Stadium	0.0	1.0	0.25	0.25	0.25
Cinema	0.0	0.25	1.0	0.66	0.66
Bowling	0.0	0.25	0.66	1.0	0.66
Theater	0.0	0.25	0.66	0.66	1.0

Table IV. Similarities between locations "location_ entertainment"

7.4 Application

We used the graphical interface of myCBR 3.0.1 for the initial phase (storing of the ten seed cases in the case base), to calculate the similarities between (randomly generated) new cases and cases in memory and to retrieve the best match.

An example of the CBR cycle including, the retrieval of the best match cases, services retrieved, services filtered (recommended to the user) and database updating is given below:

- *Initial query*: Case 11 (Table V)
- *Retrieval of best match case with Similarity Score*:
  - [name = case10, location = mall, time = day, weekday = weekend, phoneUsing = messaging], Similarity = 0.52
  - [name = case3, location = cinema, time = night, weekday = weekend, phoneUsing = nil], Similarity = 0.58
  - [name = case9, location = restaurant, time = night, weekday = weekend, phoneUsing = nil], Similarity = 0.82

Case 9 will be selected and the retrieved services are shown in Figure 7.

7.4.1 Services filtering. A rule set – BatteryRule, FreeMemoryRule, InternetSpeedRule, LuminosityRule and NoiseRule – was used to filter and adapt the services derived from the environmental context (noise level, NS; and Luminosity, LM) and the system context (free memory, FM; battery level, BL; internet connection speed, IS) (Table VI).

Each rule is implemented through the filter Service (Collection < Service>, UserContext) function. Services retrieved during the retrieval phase become the input to the function, and filtering is achieved by deleting (*exclude*) or changing (*add*) services based on the user's context (Figure 7).

The application was tested with 50+ cases, and some of the results are shown in Table VII. The services provided to the user correspond to the user's location, current time, smartphone usage and current context.

If the new case differs from all other cases in the case base (sim ($Case_{new}$, $Case_{old}$) < 1), then the case base is updated to include the new case $Case_{new}$ with the following structure:

$$Case_{new} : \{\text{Description} \quad (\text{Location, time, phone}_{\text{using}})_{new}, \text{ Services} = (\text{services})_{filtred}\}.$$

Parameter name	Value
Case name	Case11
Location	Restaurant
Time	Night
Weekday	Weekend
Phone using	Messaging
Context parameters	
Battery level	High
Luminosity	Medium
Free memory	Medium
Noise level	Low
Internet connection speed	High

Table V. Example of a new case

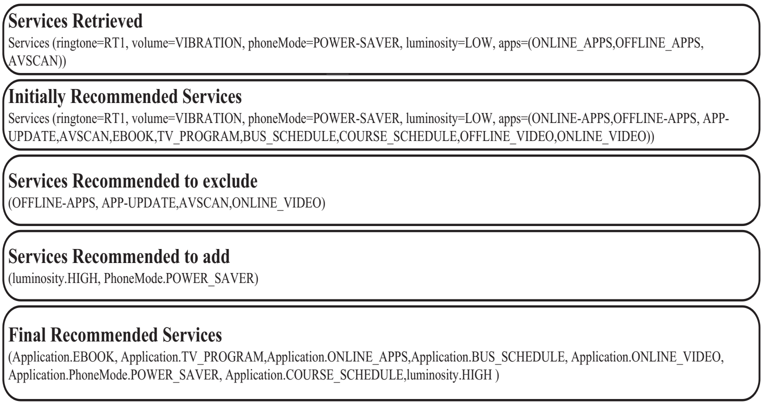


Figure 7.
Retrieved and filtered services

Filtering rule	Description
Noise level based	Rule1: IF *NS* = high THEN *RINGTONE* = vibration
Luminosity based	Rule2: IF *LM* = low THEN *LUMINOSITY* = high
Battery level based	Rule3: IF *BL* = low THEN *MODE* = power saver
Battery level and free memory based	Rule4: IF *BL* = low OR *FM* = LOWTHEN EXCLUDE (offline games, offline video, apps update, AVscan)
Internet connection based	Rule5: IF *IS* = low THEN EXCLUDE (online video, online games)

Table VI.
Filtering rules

The two-stage service adaptation process (similarity measurement and contextual filtering) consists in providing real services that are adapted to the user's current context. For example, for Case 1, the user is sending a message in a cafeteria at night on a weekday. The best match found in the case base is Case 9 containing the set of services = 9, which includes updating applications and scanning for viruses. However, neither of these two actions is initiated because of filtering rule 4 (BL = low). A classification of services according to available smartphone resources and current user context is critically important to create cases that are more relevant and to define filtering rules that provide a more relevant connection between the context and the proposed service.

8. Conclusion

We applied the CBR process to mobile devices (smartphones) using the devices' built-in sensors to adapt services provided to a user according to the user's location, current time, and smartphone usage. The similarity measure by Wu and Palmer was used to correspond to the target application. Our approach provides a basis for the implementation of adaptive systems involving lightweight context-sensitive services in the field of resource-limited devices such as smartphones. Further research will be necessary to investigate topics such as choosing and classifying the services a smartphone can provide to a user, updating the case base and defining adaptation and filtering rules.

Table VII.
Retrieval and filtering results

New case	Best match case	Service retrieved	Context	Services filtered
Cafeteria, night, Weekday, messaging	Sim = 0.83 Smartphone9 = Restaurant, night, Weekend, nil	Services = 9, Ring tone = rt2, Ringer volume = vibration, Phone mode = power saver, luminosity = medium, Apps = apps update, AV scan	BL = low IS = high FM = low LM = high NS = low	Apps = apps update, AV scan Removed by rule 4 BL = low
University, day, weekday, messaging	Sim = 0.85 Smartphone5 = school, day, weekday, browsing	Services = 4, Ring tone = rt2, Ringer volume = medium, Phone mode = normal, luminosity = medium, apps = bus schedule, course schedule	BL = high IS = low FM = low LM = high NS = low	No filtered services
Theater, day, Weekend, nil	Sim = 0.88 Smartphone3 = Cinema, night, weekend, nil	Services = 3, Ring tone = rt3, Ringer volume = vibration, Phone mode = power saver, luminosity = medium, apps = agenda, games	BL = low IS = low FM = high LM = high NS = low	Apps = games Removed by rule 4 BL = low IS = low
Market, day, Weekend, calling	Sim = 0.85 Smartphone10 = mall, Day, weekend, messaging	Services = 5, Ring tone = rt2, Ringer volume = high, Phone mode = normal, luminosity = medium, apps = online apps, offline, apps, agenda, games	BL = low IS = high FM = low LM = low NS = high	Apps = games, online apps, offline apps, Removed by rule 4,5 BL = low, FM = low Ring volume changed to: vibration NS = high Removed by rule 1
Bus, day, weekday, gaming	Sim = 0.85 Smartphone6 = car, Day, weekday, nil	Services = 6, Ring tone = rt1, Ringer volume = high, Phone mode = power saver, luminosity = medium, apps = agenda	BL = high IS = low FM = low LM = low NS = low	No filtered services

References

Abowd, G.D., Dey, A.K., Brown, P.J., Davies, N., Smith, M. and Steggles, P. (1999), "Towards a better understanding of context and context-awareness", *Handheld and Ubiquitous Computing*, Springer, Berlin Heidelberg, pp. 304-307.

Benazzouz, Y. (2011), "Découverte de contexte pour une adaptation automatique de services en intelligence ambiante", Doctoral Dissertation, Ecole Nationale Supérieure des Mines de Saint-Etienne.

Bolchini, C., Curino, C.A., Quintarelli, E., Schreiber, F.A. and Tanca, L. (2007), "A data-oriented survey of context models", *ACM Sigmod Record*, Vol. 36 No. 4, pp. 19-26.

Brézillon, P. and Pomerol, J.C. (1999), "Contextual knowledge and proceduralized context", *Proceedings of the AAAI-99 Workshop on Modeling Context in AI Applications*, *Orlando, Florida*, AAAI Technical Report, American Association for Artificial Intelligence.

Cao, X., Cong, G. and Jensen, C.S. (2010), "Mining significant semantic locations from GPS data", *Proceedings of the VLDB Endowment*, Vol. 3 Nos 1/2, pp. 1009-1020.

De Mantaras, R.L., McSherry, D., Bridge, D., Leake, D., Smyth, B., Craw, S. and Keane, M. (2005), "Retrieval, reuse, revision and retention in case-based reasoning", *The Knowledge Engineering Review*, Vol. 20 No. 3.

Chon, J. and Cha, H. (2011), "Lifemap: a smartphone-based context provider for location-based services", *IEEE Pervasive Computing*, No. 2, pp. 58-67.

Efstratiou, C. (2004), "Coordinated adaptation for adaptive context-aware applications", Doctoral Dissertation, Lancaster University United Kingdom, p. 173.

Gabel, T. and Stahl, A. (2004), "Exploiting background knowledge when learning similarity measures", *Advances in Case-Based Reasoning*, Springer, Berlin Heidelberg, pp. 169-183

Gouttaya, N. and Begdouri, A. (2011), "The quality integrating data mining with case based reasoning for personalized adaptation of context-aware applications in pervasive environments", *Colloquium in Information Science and Technology (CIST)*, IEEE, Fez, pp. 13-14.

Guessoum, D., Miraoui, M. and Tadj, C. (2015), "Survey of semantic similarity measures in pervasive computing", *International Journal on Smart Sensing and Intelligent Systems*, Vol. 8 No. 1, pp. 125-158.

Incel, O.D., Kose, M. and Ersoy, C. (2013), "A review and taxonomy of activity recognition on mobile phones", *BioNanoScience*, Vol. 3 No. 2, pp. 145-171.

Kayes, A.S.M., Han, J. and Colman, A. (2014), "PO-SAAC: a purpose-oriented situation-aware access control framework for software services", *Advanced Information Systems Engineering*, Springer International Publishing, Thessaloniki, pp. 58-74.

Knox, S., Coyle, L. and Dobson, S. (2010), Using ontologies in case-based activity recognition.

Kofod-Petersen, A. and Aamodt, A. (2003), "Case-based situation assessment in a mobile context-aware system", *Proceedings of AIMS2003, Workshop on Artificial Intgelligence for Mobil Systems*, *Seattle*.

Kofod-Petersen, A. and Aamodt, A. (2009), "Case-based reasoning for situation-aware ambient intelligence: a hospital ward evaluation study", *Case-Based Reasoning Research and Development*, Springer, Berlin Heidelberg, Seattle, pp. 450-464.

Kolodner, J.L. (1996), "Making the implicit explicit: clarifying the principles of case-based reasoning", *Case-Based Reasoning: Experiences, Lessons and Future Directions*, AAAI Press, Menlo Park, pp. 349-370.

Kwon, O.B. and Sadeh, N. (2004), "Applying case-based reasoning and multi-agent intelligent system to context-aware comparative shopping", *Decision Support Systems*, Vol. 37 No. 2, pp. 199-213.

Leake, D. and Jalali, V. (2014), "Context and case-based reasoning",*Context in Computing*, Springer, New York, NY, pp. 473-490.

Lee, J.S. and Lee, J.C. (2007), "Context awareness by case-based reasoning in a music recommendation system", *Ubiquitous Computing Systems*, Springer, Berlin Heidelberg, pp. 45-58.

Lotfy, A.E.A.M. and Salem, A. (2010), "A breast cancer classifier based on a combination of case-based reasoning and ontology approach", *Proceedings of the 2010 International Multiconference on Computer Science and Information Technology (IMCSIT)*, *Wisla*, IEEE, pp. 3-10

Ma, T., Kim, Y.D., Ma, Q., Tang, M. and Zhou, W. (2005), "Context-aware implementation based on CBR for smart home wireless and mobile computing", *IEEE International Conference on Networking and Communications*, *Montreal, Quebec* (WiMob'2005), IEEE, Vol. 4, pp. 112-115.

Meissen, U., Pfennigschmidt, S., Voisard, A. and Wahnfried, T. (2005), "Context-and situation-awareness in information logistics", *Current Trends in Database Technology-EDBT 2004 Workshops*, pp. 335-344, Springer, Berlin Heidelberg.

Montani, S. (2011), "How to use contextual knowledge in medical case-based reasoning systems: a survey on very recent trends", *Artificial Intelligence in Medicine*, Vol. 51 No. 2, pp. 125-131.

Nicklas, D. and Henricksen, K. (2008), "Context modeling and reasoning: key concepts for Pervasive computing", *5th IEEE Workshop on Context Modeling and Reasoning (CoMoRea'08) @PerCom, Hong Kong*, IEEE, 17 or 21 March 2008.

Nwiabu, N., Allison, I., Holt, P., Lowit, P. and Oyeneyin, B. (2011), "Situation awareness in context-aware case-based decision support", *IEEE First International Multi-Disciplinary Conference onCognitive Methods in Situation Awareness and Decision Support (CogSIMA)*, *Miami Beach, FL*, IEEE, pp. 9-16.

Öztürk, P. and Aamodt, A. (1998), "A context model for knowledge-intensive case-based reasoning", *International Journal of Human-Computer Studies*, Vol. 48 No. 3, pp. 331-355.

Pantic, M. (2005), *Introduction to Machine Learning and Case-Based Reasoning*, Imperial College, London.

Phithakkitnukoon, S., Horanont, T., Di Lorenzo, G., Shibasaki, R. and Ratti, C. (2010), "Activity-aware map: identifying human daily activity pattern using mobile phone data", *Human Behavior Understanding*, Springer, Berlin Heidelberg, pp. 14-25.

Pla, A., Coll, J., Mordvaniuk, N. and López, B. (2014), "Context-aware case-based reasoning", *Mining Intelligence and Knowledge Exploration*, Springer International Publishing, Cork, pp. 229-238.

Richter, M.M. (1995), "On the notion of similarity in case-based reasoning", *Proceedings of the ISSEK94 Workshop on Mathematical and Statistical Methods in Artificial Intelligence*, *Springer*, *Vienna*, pp. 171-183.

Richter, M.M. and Weber, R.O. (2013), *Case-Based Reasoning*, A Textbook, 546, Springer Berlin Heidelberg.

Roth-Berghofer, T., Sauer, C., Garcia, J.A.R., Bach, K., Althoff, K.D. and Agudo, B.D. (2012), "Building case-based reasoning applications with myCBR and COLIBRI studio", *Proceedings of the UKCBR 2012 Workshop*, *University of Brighton, UK*.

Sancho, G. (2010), "Adaptation d'architectures logicielles collaboratives dans les environnements ubiquitaires", Contribution à l'interopérabilité par la sémantique, "*Doctoral Dissertation*", Université des Sciences Sociales-Toulouse I.

Schank, R.C. (1983), *Dynamic Memory: A Theory of Reminding and Learning in Computers and People*, Cambridge University Press, New York, NY.

Schilit, B.N. and Theimer, M.M. (1994), "Disseminating active map information to mobile hosts", *Network, IEEE*, Vol. 8 No. 5, pp. 22-32.

Schilit, B., Adams, N. and Want, R. (1994), "Context-aware computing applications", *First Workshop on Mobile Computing Systems and Applications, WMCSA 1994*, IEEE, Washington, DC, pp. 85-90.

Schmid, F. and Richter, K.F. (2006), "Extracting places from location data streams", *UbiGIS 2006 – Second International Workshop on Ubiquitous Geographical Information Services, Workshop at GIScience 2006*, Munster.

Shoaib, M., Scholten, H. and Havinga, P.J. (2013), "Towards physical activity recognition using smartphone sensors", *Ubiquitous Intelligence and Computing, 2013 IEEE 10th International Conference on and 10th International Conference on Autonomic and Trusted Computing (UIC/ATC), IEEE, Vietri sul Mere*, pp. 80-87.

Shoaib, M., Bosch, S., Incel, O.D., Scholten, H. and Havinga, P.J. (2015), "A survey of online activity recognition using mobile phones", *Sensors*, Vol. 15 No. 1.

Song, M.R., Moon, J.Y. and Bae, S.H. (2013), "A design and implement contexts- aware case based u-health system", *International Journal of Bio-Science and Bio-Technology*, Vol. 5 No. 5.

Stanfill, C. and Waltz, D. (1986), "Toward memory-based reasoning", *Communications of the Acm*, Vol. 29 No. 12, pp. 1213-1228.

Watson, I. (1999), "Case-based reasoning is a methodology not a technology", *Knowledge-Based Systems*, Vol. 12 No. 5, pp. 303-308.

Wu, Z. and Palmer, M. (1994), "Verbs semantics and lexical selection", *Proceedings of the 32nd Annual Meeting on Association for Computational Linguistics, Association for Computational Linguistics*, *Las Cruces*, pp. 133-138.

Yuan, B. and Herbert, J. (2014), "Context-aware hybrid reasoning framework for pervasive healthcare", *Personal and Ubiquitous Computing*, Vol. 18 No. 4, pp. 865-881.

Zang, M.A., Gray, A., Hobbs, M. and Pohl, J.G. (2008), "Similarity assessment techniques", *Proceedings of InterSymp-2008: The 20th International Conference on Systems Research*, *Informatics and Cybernetics*, *Baden-Baden*.

Zhu, C. and Sheng, W. (2011), "Motion-and location-based online human daily activity recognition", *Pervasive and Mobile Computing*, Vol. 7 No. 2, pp. 256-269.

Zimmermann, A. (2003), "Context-awareness in user modelling: requirements analysis for a case-based reasoning application", *Case-Based Reasoning Research and Development*, pp. 718-732. Springer, Berlin Heidelberg.

Further reading

Shet, K.C. and Acharya, U.D. (2012), *A New Similarity Measure for Taxonomy Based on Edge Counting*, arXiv preprint arXiv:1211.4709, International Journal of Web & Semantic Technology (IJWesT), Vol. 3 No 4.

Corresponding author

Djamel Guessoum can be contacted at: djamel.guessoum.1@ens.etsmtl.ca