Expert Systems with Applications 39 (2012) 5774–5783

Contents lists available at SciVerse ScienceDirect

Expert Systems with Applications

journal homepage: www.elsevier.com/locate/eswa

Single activity sensor-based ensemble analysis for health monitoring of solitary elderly people

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ARTICLE INFO

Keywords:
Activity context
Elderly
Model-based reasoning
Remote health monitoring

ABSTRACT

Public health monitoring for solitary elderly people must be implemented in a particularly economic way because of their low-income status. The aim of this paper is to propose a model-based method combined with conventional reasoning methods such as multiple regression and the boosting strategy. The role of model-based reasoning is to generate secondary situational information from activity data gathered at home. Current health condition information is then provided as part of an activity-based smart management system for health monitoring. Only one activity sensor per house is considered. In this paper, we also discuss how the Korean government has actually applied this method in smart-care services for more than ten thousand solitary elderly people. The experiments are conducted based on the u-care system, which is composed of an activity sensor connected to a remote server using a wireless sensor network. The remote server includes multi-agents which analyze and diagnose current health conditions.

1. Introduction

Electronic-care (e-care) systems for elderly people allow them to live more sustainable lives in their own preferred space (Finking, 2008). Self-sustainability lessens caregivers' labor burden and saves on the cost of e-care services. The main goals of electronic-care systems are to maintain the physical and/or mental health of elderly people, and to complement the deficiencies of health care at home. Better quality at reduced cost is also desirable (Axisa et al., 2005). These goals are typically accomplished by means of a series of procedures: environmental data acquisition, data storage, analysis and decision-making, and collecting feedback from users.

With the advent of a variety of sensors, context-aware services, which refers to a system that automatically acquires information about the physical environment and adapts its service provision accordingly, are being used in intelligent systems such as ubiquitous health (u-health) services.

Although u-health systems are now widely available, there remains some room for improvement in terms of economic viability. First, gathering and managing all sensed data takes a lot of time and money, even though the service target is only one person. An efficient data-summarizing algorithm or compression method is necessary for economically sustainable recording. Second, there are trade-offs between service accuracy and cost: for greater accuracy in measuring health conditions, it is necessary to install many mobile devices and sensors, which may not be economically feasible, especially for those who are living on smaller incomes. Hence, minimizing the number of installed devices and sensors while preventing a decrease in service quality in areas such as context prediction accuracy is one of the desirable goals. Hence, we focus on single-sensor monitoring systems in this paper.

Activity sensors interpret human behavior, providing useful information on the degree of physical and psychological health comfortably and seamlessly. Since activity information is dynamic by nature and collected continuously, meaningful secondary context information can be extracted from it. Thus, most u-care systems have adopted activity sensors.

However, activity context data *per se* is not sufficient to provide extended services. Because it is a sort of time series data, we can extract from it more meaningful and higher abstract information, which is likely to be useful in health monitoring services. In addition, most activity information is not used alone, but in combination with other types of context data, which are obtained from different devices or sensors. Algorithms which improve the quality of service using activity sensor data alone have not yet been developed.

Moreover, although it is possible to predict human health conditions using activity data, such as movement counts collected by an activity sensor installed in a living space or ward, it is very hard to estimate normal or abnormal status accurately. For example, even if the data show that an elderly person is exhibiting less physical activity, it is difficult to distinguish whether he or she is really in trouble, or just absent from home or sleeping normally. Therefore,

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doi:10.1016/j.eswa.2011.11.090

a service provider must check whether the person is in difficulty or not. More effort spent monitoring in person results in a cost-ineffective system. It is therefore desirable to improve the quality of activity sensor-based context interpretation, rather than just enhancing sensing precision.

The purpose of this paper is to propose a method which generates secondary situation information from activity data as part of an activity-based smart management system (health monitoring system). The model-based reasoning method proposed in this paper is combined with conventional health condition reasoning methods, such as multiple regression analysis and the boosting strategy. Accordingly, a context prediction method is proposed to improve the accuracy of diagnosing a person's state of health with a single activity sensor. The algorithm used here is actually currently being implemented in a nation-wide public u-care system for 15,000 elderly people. The experiment is conducted with actual activity data to show the feasibility of the proposed method.

The remainder of this paper is organized as follows. The state-of-the-art of activity-based context-aware services and health care systems is described in section two. In section three, the main idea and algorithm of the health monitoring method are described. The performance of the proposed method is demonstrated via an experiment with actual cases, outlined in section four. Lastly, concluding remarks and future research issues are discussed in the final section.

2. Related work

2.1. Activity-based context-aware services

Observing and measuring the context of physical activity is important in a variety of application domains such as sport, education and health care. Numerous activity observation systems have been developed, mainly based on direct observation, such as SOFIT and SOPARC (McKenzie, Cohen, Sehgal, Willianson, & Golinelli, 2006; McKenzie, Sallis, & Nader, 1991). Physical activity can be measured by heart rate, oxygen consumption, accelerometers, and pedometers.

Activity context information is very useful for providing intelligent and automatically acquired secondary context information such as episodic, social and purpose information (Ferdous, Eluru, Bhat, & Meloni, 2010). So far, several ways of acquiring high-level context information through activity data have been proposed. The matchmaking method requires analysis of past patterns and comparison with a series of currently recognized activity data derived from activity sensors. Second, the rule-based approach utilizes predefined rules provided by experts to recognize various events from activity data. For example, the ECR rule-matching method is a typical example of rule-based context identification (Ipina, 2001). Markov processing is based on the causal probability between the current situation and what happens next under the assumption that users behave according to habit (Si, Kawahara, Morikawa, & Aoyama, 2005). If Markov processing can be applied, it would be possible to predict what will happen in the future and even longer-term, which would aid in providing proactive service. Context prediction by machine learning is another useful way to increase prediction accuracy automatically. For example, DCAP of THEMUSS, a classification method, acquires vital signs and other signs, then generates discriminating knowledge, which is used to determine if a person's status is normal or abnormal, and estimates the probability of him or her having a specific disease.

Context-aware systems using Artificial Intelligence (AI) techniques are useful to record habits and behaviors without disturbing people's daily activities. These intelligent techniques help to diagnose abnormal behaviors or disorders (Chan et al., 1998).

Activity context information is also useful to build competitive context-aware services in mobile web searches (Hattori, Tezuka, & Tanaka, 2006), postural control (Rasku, 2009), and mental health services (McCormick et al., 2009). Making full use of such information will improve the quality of context-aware services and eventually expand their application, making current computer-based systems and services more competitive than previous systems which do not apply it.

2.2. Health care systems for monitoring the elderly

Recently, the proportion of deaths at home rather than outdoors has increased, especially in the elderly. To cope with this issue, activity and health monitoring systems for the elderly or patients at home have been implemented in an effort to avoid fatal accidents. One of the useful services a ubiquitous health care system can provide is measurement of activity. To acquire activity context data, the conventional method of direct observation has often been adopted. The Alkisa Project developed a platform which remotely inspects the health status of the elderly at home, and then prescribes adequate support (Noury & Rumeau, 2006). However, the system still has the limitation that a caregiver must often directly intervene.

Recently, to minimize such direct intervention, some health care systems have adopted ubiquitous computing technology which includes context-aware capability. PROSAFE detects events or motions using various kinds of sensors, including multiple activity sensors, which monitor the indoor lives of elderly people. The embedded software informs the caregiver if the current activity pattern is similar to previously recorded patterns (Chan, Campo, Laval, & Esteve, 2002). Activity sensors provide more intimate information about the elderly than image detection sensors. NIAIST, a national health care project in Japan, developed an aware home system which monitors people's everyday lives and automatically sends abnormal activity information to the corresponding hospital.

Context-aware activity-based systems typically contain built-in devices or sensors to acquire user context information with some sort of measuring module. Activity sensing has been done in several ways. Various kinds of wearable sensors attached to the body or clothes of an elderly person have been utilized. ETRI offers a home-wide situation-aware system which consists of chest or wrist-wearable sensors, health care equipment and a personal area network (PAN). Health care equipment allows users to perform self-diagnosis based on blood pressure, blood glucose levels and other body-sensing information, which is sent from sensor devices through PAN. If necessary, the results are transmitted to the service provider (Kang, Kang, Lee, Ko, & Lee., 2010). However, this wearable computing-based activity sensing can feel burdensome and unnatural, especially to the elderly, simply because it limits their activities. Non-attached devices nearby provide an alternative way to monitor the user's activity. The U-Bed is an example of such a device. Posture can be analyzed using a smart vision technique like UbiSense to identify abnormal activity patterns. However, it does not identify responsive actions, but focuses only on recognition and interpretation (UbiSense project, 2010).

A hybrid approach can improve the quality of activity sensing. Using 167 sensors simultaneously, including wearable sensors installed at home, the Smart Home Osaka project acquires context information about who, when, what and where, and can simultaneously watch the activities of five people at home. It recognizes thirteen kinds of activities: sleep, washing, eating, cooking, dishwashing, cleaning, resting, bathing, toilet, going out, reading, office working, and moving. In order to do this, a variety of sensor signals and activities are linked. Furthermore, the system detects abnormal signals, unusual behavior patterns, slow response or deterioration of the activity rhythm. This project is a typical system using a large number of simple sensors (Tapia, 2004). The robot technique is another type of hybrid approach. UKARI of Japan proposed a u-home system with robot-based interaction for the elderly to improve the user interface (Yamazaki, 2006). The issue of the robot's location was resolved by letting him carry an RFID tag, while the sensors were embedded in the home.

Sometimes activity data are combined with other types of context information. For example, the u-health system of Seoul National University College acquires heart rate and activity context information from u-devices such as the U-Bed, U-Couch and U-Toilet Seat, and must be attached so that it does not interfere with the patient's lifestyle (Shin et al., 2007). It detects small changes in physical activity through sensitive loadcell sensors. Detecting patient movement is performed by IR-based sensors installed in living spaces such as the kitchen, front door, living room and bedrooms. Another example, the U-Health Smart Home project at POSTECH, is working on ways to acquire activity context information on the residential elderly directly and in an unconstrained manner (Kim et al., 2010). To do so, ontology technology is used to obtain high-level context information related to activity levels to aid in making normality decisions. In sum, collecting activity data conveniently is crucial for activity-based health care systems.

However, to increase the economic viability of life care systems, further development is still needed. One of the main causes of cost-ineffective care service lies in the number of sensors and resulting huge amount of sensor data. To avoid this problem, a data-summarizing algorithm or compression method can make long-term recording more viable. Configuring systems in a complicated environment which requires many sensors and devices for only a few people is not economically reasonable, especially if the application service does not require high-end sensing accuracy. In general, life care services for normal people are less sensitive than health care services for patients who need sophisticated medical care. In the former case, economic viability is more important than measurement accuracy.

3. Methodology

3.1. Overall framework

The framework of the proposed method is shown in Fig. 1. The goal of the proposed system is to estimate the user's health status as unobtrusively as possible based on his or her activity context. The system consists of four phases: sensing, analyzing, diagnosing and service recommendation.

The activity sensor is attached in an appropriate space to collect data about the user's degree of activity periodically. Activity data obtained each time, and the serial number of the sensor, are safely transmitted to the analyzing agent through a gateway, maintaining privacy and security. The serial number of the sensor can be encrypted if necessary. The analyzing agent searches the profile of the people in the smart space according to the sensor's ID, and the past activity information during a specified time period is loaded from the context history. Based on that history, the first inference is performed to interpret the activity using the model base, which stores the various modules and rules to interpret the activity count and can be extended as much as necessary. A set of inference results from the derived individual module and set of rules is then sent to a diagnosing agent, which performs a comprehensive analysis. The diagnosing agent has a pattern base, which is used to interpret the current activity pattern by selecting one past pattern which is the most similar to the current activity pattern. Then the agent makes a decision as to the user's current activity status and health condition, and whether or not further intervention is needed.

How the model-based reasoning results are combined with diagnosis knowledge is shown in Fig. 2. First the model is formulated *a priori* based on a series of context data stored in the context history. Model identification techniques, such as time series analysis and data mining methods, may be applied. Then the formulated model is instantiated by applying real values to the corresponding coefficients of the formulated model. With the model instance, model-based reasoning is then executed to produce higher-level and dynamic context information. Finally, diagnosis is performed based on the two types of context: the higher-level and dynamic context provided by the model-based reasoning, and the static context in the user profile. In this paper, a rule-based approach is selected to represent the diagnosis knowledge.

If necessary, the result is sent to the recommendation agent to respond to the request. The recommendation agent selects the most appropriate service(s) for the recovery and informs the user or caregiver.

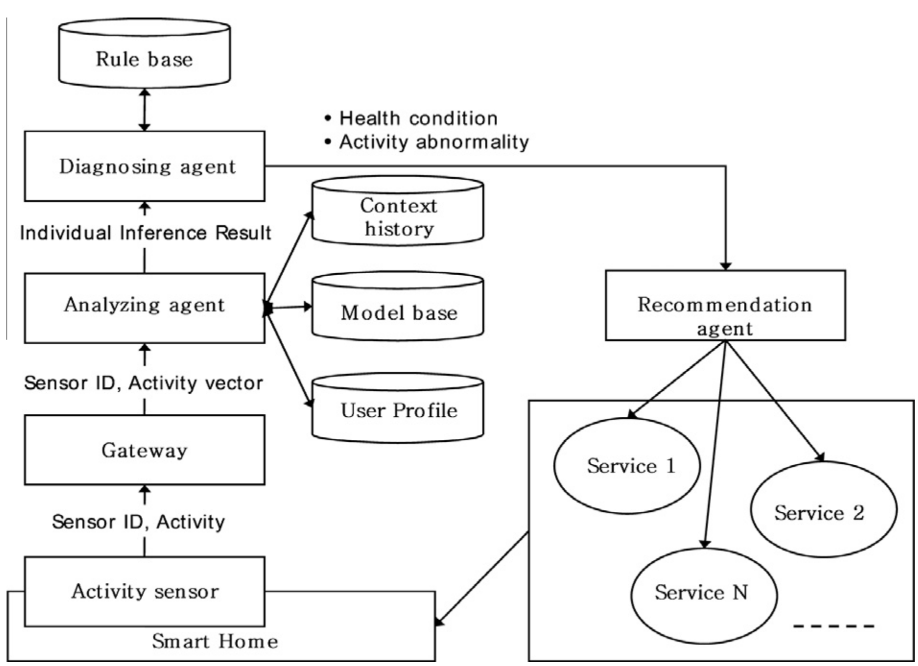

Fig. 1. Overall framework.

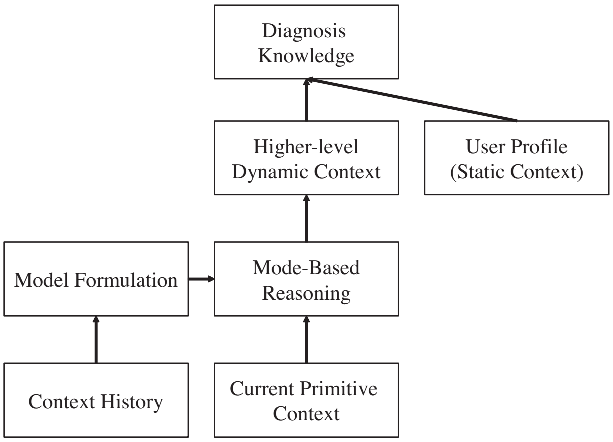

Fig. 2. Model-based reasoning.

To show the feasibility of the proposed method, it is applied to an actual life care system for the elderly in a living space. The individual rule estimates the activity count based on personal profile data about gender, age, and history of physical activity. Other models were also developed. The inference results are coded with six scales.

3.2. Generating individual rules from the user profile

The individual rules are generated from user profile information on gender, age and medical history, as follows.

Step 1 (*an* estimation rule for each situation): In the currently obtained set of context information for learning, $C = \{c_{ij},\ o_j | i = 1, \ldots, M,\ j = 1, \ldots, N\}$, where i and j indicates each individual situation and context which characterizes a situation, respectively. At this point, a causal relationship between $c_{.j}$ and $o_{.}$ is estimated for j as an individual situation. If both c and o are nominal scale variables, the highest value is adopted through a ratio analysis.
Step 2: $f_j : c_{.j} \rightarrow o_{.}$ is obtained for all j and then saved in the individual rule base.

3.3. Model-based reasoning for individual rule generation

The model-based reasoning approach is to use a pre-defined knowledge-based time series model to determine an activity data pattern which is beyond the normal range. Accuracy of the estimation depends substantially on the quality of the model. However, in many cases, model accuracy may not be satisfactory as it is. In this paper, the following two models are considered.

3.3.1. Inactive duration model

This model decides if a person is active or not based on a series of data. If the degree of activity is less than a threshold level for more than a specific duration, then the activity context is estimated as 'inactive' based on the model.

3.3.2. Activity pattern change model

Suppose that there is an activity pattern change when state $\delta_t = y_t - y_{t-1}$ is more than a certain threshold, while $\theta_t = y_t / y_{t-1}$ is less than another certain threshold, and at the same time $d_t = \sqrt{y_t^2 + y_{t-1}^2}$ is less than a certain amount. In this case, it may be determined that there is a sudden slowdown following normal activity. In other words, this is an analysis of the phase transition point: if two clusters are found in different areas, and only a small amount of activity data is located between the two clusters, then the model decides that the activity pattern is abnormal, and that the user may be rapidly declining or inactive. The activities of the previous time frame and those right afterward are not different; both have stayed in the active state.

3.4. Pattern generation using individual rules

When the inference results are determined by the profile or models described above, the association of these analysis results produces a pattern of multiple attributes. The method of generation follows below.

Step 1: The status levels normal, suspect and abnormal are analyzed for each factor at each unit of time. The factors include gender, location, age, disease history, normality with trend, normality with pattern change, normality with inactivity, and normality with inactive duration.
Step 2: Aggregate the estimation values by each factor and create a vector form.
Step 3: In the optimal rule base, the rule must be found which has a vector exactly matched with the above vector. If there is more than one matching vector, then the rule which contains the most frequently appearing vector would be selected. If the frequency is higher than a constant τ_1, then the conclusion would be the result of the rule; otherwise, the decision would be pended.
Step 4: If an exactly matched rule does not exist, then the most similar rule would be found. At this point, greater weight is placed on agreement with the results yielded from the analyses of normality with trend, normality with pattern change, normality with inactivity, and normality with inactive duration. When the most similar rules are found, the rule with the highest frequency is selected. If the frequency is more than a constant $\tau_2 (\tau_2 \geqslant \tau_1)$, the result is predicted by the rule. Otherwise, when the frequency is τ_2, the decision would be pended. τ_1 and τ_2 can be adjusted by the users.

4. Implementation: activity sensor-based u-care system

4.1. Overall description

In this paper, we apply the method of the u-care system actually being implemented by the Korean government since 2008. More than 15,000 elderly people now benefit from this activity-sensor-based context-aware system. However, one of the concerns of the existing u-care system is that utilizing a methodology with activity data alone is not sufficient to analyze effectively the status of solitary elderly people. In this system, the activity level is decided by simply comparing the cumulative average activity level with the current activity level for each person. In not a few context-aware services, context data come sequentially from sensors over time. In other words, specific time series data, in which the independent variable is time and the dependent variable is a specific context attribute such as activity level, are entered. However, in this case, the traditional learning and inference methods, including case-based reasoning and Artificial Neural Networks (ANN), are difficult to apply easily because they have only one independent variable. Therefore, in order to improve u-care systems, other than just applying various analyses using time series data, a higher-level context identification method is needed to analyze the current state and then predict the future state of solitary elderly people.

4.2. Current system

The home is equipped with a gas leak detector, gateway, absence button, smoke detector and activity sensor. Fig. 3 shows a bird's-eye view of the u-care system which is actually in use in each municipality in Korea. The house is fully equipped with various sensors and gateways to connect them. The activity sensor is used to analyze the user's activity level, which is monitored in five-second intervals, and the activity data calculated every hour; hence the activity level ranges from 0 to 720. Then the activity data are sent to the remote server once a day through the gateway.

Table 1 shows the demographic distribution of the elderly people being served.

Table 1
Demographics.

Criteria	Value	Frequency	Ratio (%)
Gender	Male	2288	14.5
	Female	13,526	85.5
Ages	40s	15	0.1
	50s	41	0.3
	60s	2282	14.4
	70s	7789	49.3
	80s	3659	23.1
	90s or more	279	1.8

4.3. Data acquisition process

Fig. 4 shows the installed sensor devices, which are classified as detection and notification sensors. The detection sensors monitor for activity, fire and gas leaks. Using an infrared sensor, the activity sensor decides whether the elderly person moves in the five-second cycle time, and transmits the resulting data every hour. Therefore, the maximum possible activity count per hour is 720. In addition, if smoke or a gas leak is detected, the fire sensor or gas sensor sound alarms and notify a fire station through the gateway.

The notification sensor consists of the absence button near the door and the emergency button on the gateway. It is associated with the activity sensing device, and prevents the situation from being considered dangerous when the elderly person is out of the house. When the elderly person goes out, he or she pushes the button to turn the activity sensor off. In the same way, when the patient comes back, the button turns the activity sensor back on. If the elderly person needs care from caregivers, then he or she can push the emergency button. Then a signal is sent directly to the service center, fire station and/or medical center for an ambulance.

Finally, the gateway sends the activity data gathered from the activity sensor to the center through the CDMA network. In addition, it has a phone call function to allow caregivers to re-check the situation in the elderly person's house.

4.4. Implementation

Fig. 5 shows the overall architecture of the u-care system for elderly people. Data are gathered by sensors installed indoors and then sent to the u-care monitoring center. Based on the context information, caregivers may visit the elderly person. If a fire or gas leak is detected or the emergency call button is pushed, the situation is reported automatically and rapidly to the emergency center and fire station. This leads to the dispatching of an ambulance or a fire engine. Finally, a progress report is submitted to the u-care center.

The prototype system was developed using the Java application, compiler version SDK 1.4.x, with 1.5 GB of main memory. The profile and model base were connected with a JDBC connection. To estimate health status, two kinds of data were used: user profile information and activity patterns using model-based reasoning. User profile information consists of gender, location, age, and past history of disease. Three of the following patterns were derived from activity data through model-based reasoning: normality with trend, normality with pattern change, normality with inactivity, and normality with inactive duration. The state of health ranged from 0 (very healthy) to 5 (very sick). The data values obtained for each factor were then transformed into a vector. Next, the optimal rule base finds the rule with a vector exactly matching the first vector. If there is more than one match, then the rule which contains the most frequently appearing vector would be selected. If the frequency is higher than a specific level, τ_1, then the conclusion would be the result of the rule; otherwise, the decision would be pended. If an exactly matched vector does not exist, then the most similar rule would be found. At this point greater weight is placed on agreement with the results yielded from the analyses of normality with trend,

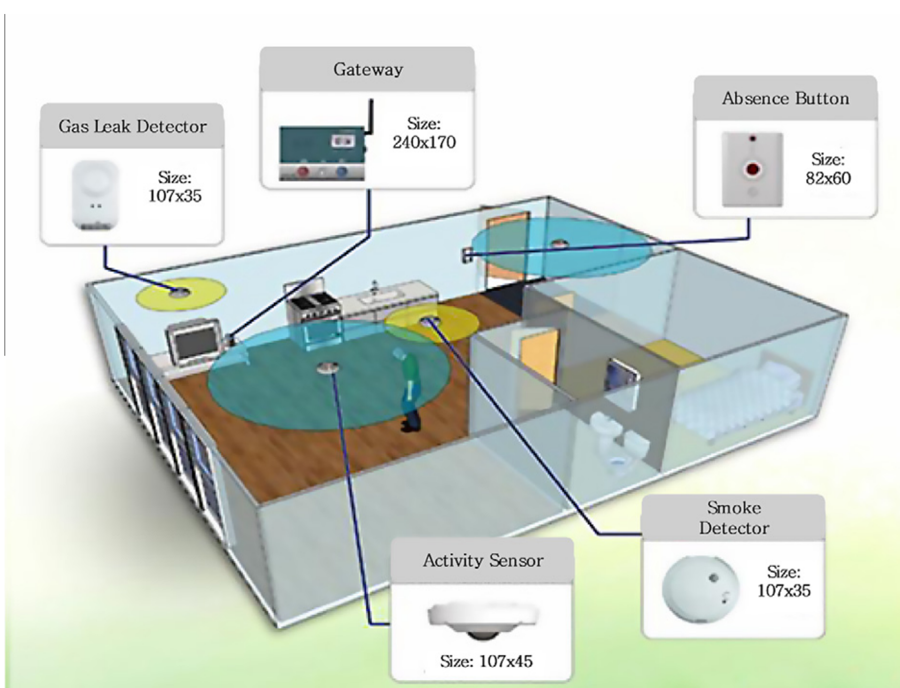

Fig. 3. U-care system.

Fig. 4. Sensors and gateway.

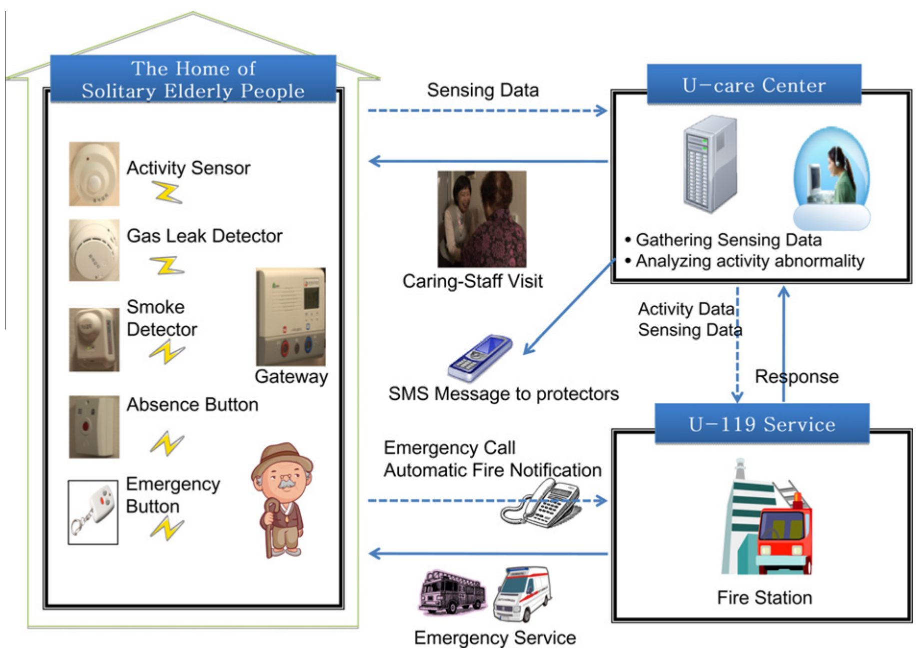

Fig. 5. U-care service architecture for elderly people.

normality with pattern change, normality with inactivity, and normality with inactive duration. When the most similar rules are found, the rule with the highest frequency is selected. If the frequency is higher than $\tau_2(\tau_2 \geqslant \tau_1)$, the result would be predicated by the rule. If less than τ_2, the decision would be pended. In short, the use case of the implemented system is shown in Fig. 6.

Then learning software creates the pattern base by combing a total of eight kinds of abnormality reports, including the profile-based analysis and the result of the real inspection.

The implemented interface of the u-care system is given in Fig. 7. The left screen shows an elderly person's daily activity history. For each date, the activity data is displayed on a graph, as well as in table format for better understanding. Along with the activity data, the interface system can display the user profile, if necessary. A daily activity pattern can be shown by displaying hourly activity data, as shown on the right screen in Fig. 7. The pattern can be interpreted through model-based reasoning to get more abstract information based on available models stored in the model base. Moreover, the state of health is estimated dynamically based on the user profile and model-based reasoning. As shown in Fig. 8, the activity sensor data are categorized in sets as normal, abnormal, inactive, and out-of-home. Moreover, the results of error handling are also reported, i.e. the number of sensors which are not operating properly or are turned off. If necessary, the system reports on people who need to be monitored or treated urgently. Then, based on the reasoning result and user profile, the u-care system recommends that the caregivers contact the elderly people.

5. Experimental results

5.1. Design

To evaluate the performance of this system, an experiment was conducted using data on elderly people who actually receive the u-care service from the Ministry of Health and Welfare in Korea.

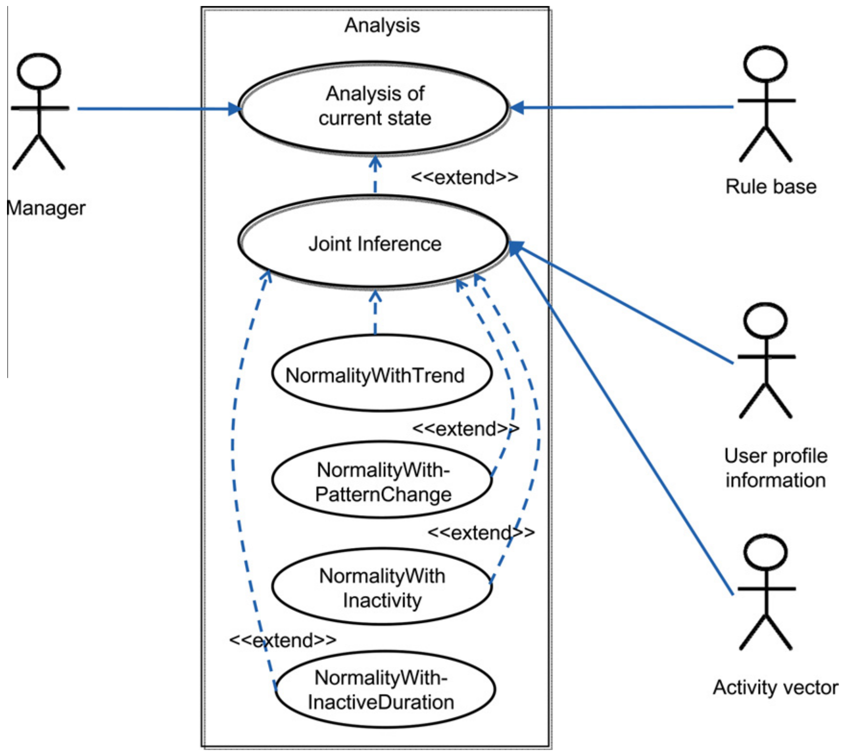

Fig. 6. Use case.

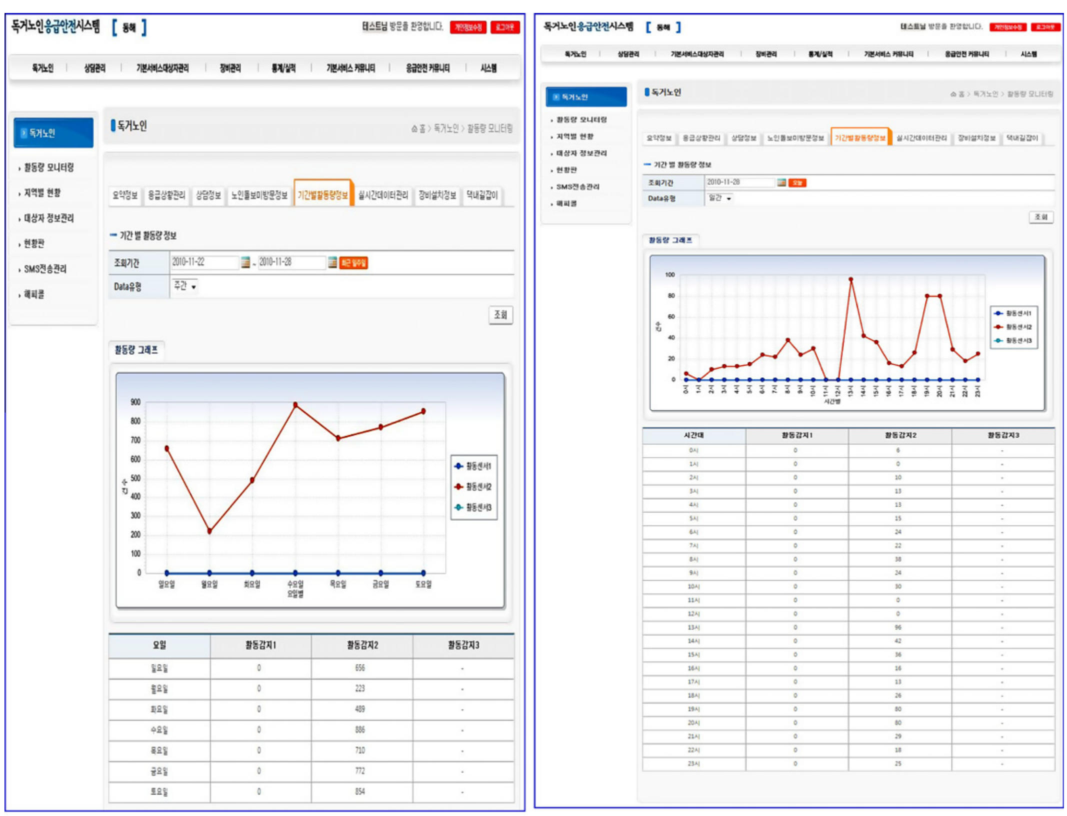

Fig. 7. Screenshot of displayed activity pattern.

First of all, a data table was acquired from an actual health monitoring system. Among the various factors, gender, age, initial health state observed by caregivers, and living location were selected for estimating the current state of health. An actual health monitoring report for each patient was given to conduct the performance evaluation. To test if the model-based reasoning method contributes positively to the quality of estimation, two models were considered: a model of activity pattern change and that of

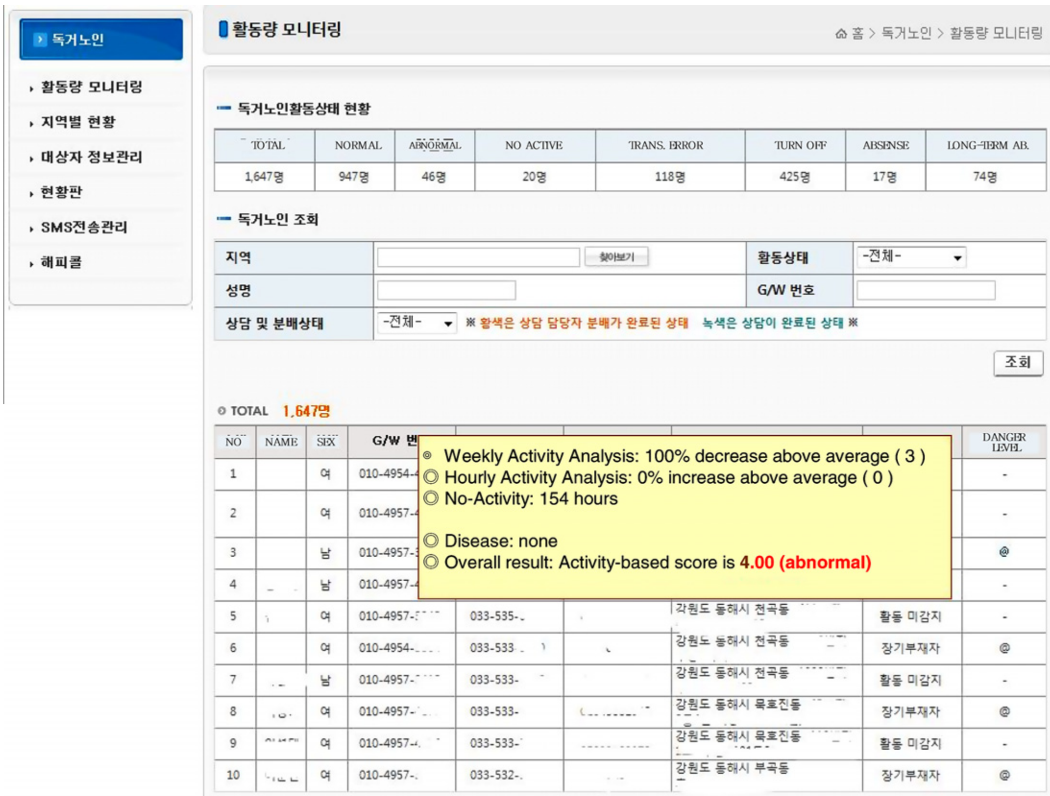

Fig. 8. Screenshot of health monitoring.

inactivity duration. Three categories and belonging attributes with their values are shown in Table 2.

For the test, we collected all data on 150 elderly people during the period from August 2nd, 2010 to August 17th, 2010. The total number of hourly activity records was 1236. To keep the analysis realistic, we did not discard any data which might be erroneous due to improperly operated or turned-off sensors or any incomplete data. The test of the quality of the proposed activity reasoning methods includes to what extent they can deal with noise. The demographic information from the collected records is shown in Table 3.

We tested the proposed model-based reasoning method, combined with a multiple regression algorithm (MLE_MODEL) and a boosting ensemble strategy (BOOST_MODEL), against the random selection (RAND) method and multiple regression method without models (MLE). The experiment was performed 120 times with different random sampling each time. For each experiment, out of 1236 samples, 5% were randomly used for training and the remaining 95% were used to test the methods. In addition, for experimental simulation, a Java application program was developed.

Performance analysis was conducted with four metrics. First was overall precision, the traditional accuracy measurement. In previous research, overall performance has been computed using a global metric, namely Mean Absolute Deviation (MAD) and Root Mean Squared Error (RMSE), which can be computed as in (1) and (2):

$$MAD = \frac{1}{N} \times \sum_{\forall i} |y_i - \hat{y}_i| \quad (1)$$

and

$$RMSE = \sqrt{\sum_{\forall i} (y_i - \hat{y}_i)^2 / N} \quad (2)$$

where N indicates the total number of examples in the test data set (Brennan & Schwartz, 1985).

Table 2
Attributes considered in the performance evaluation.

Category	Attribute	Values
User profile information	Gender	0 male 1 female
	Age	0 under 70 1 70 or more
	Initial health state	0 has disease 1 no disease
	Living location	0 living in urban area 1 living in rural area
Model-based reasoning	Activity pattern change	0 no pattern change 1 moderately changed 2 rapidly changed
	Inactivity duration	0 none 1 moderate 2 long
Result	Current health condition	0 (normal) ~ 5 (abnormal)

Table 3
Demographic information for the sample.

Item	Value	Frequency (%)
Gender	Male	23 (18.1)
	Female	127 (81.9)
Age	Under 70	50 (33.3)
	70 or more	100 (66.7)
Initial health state	Has disease	72 (48.0)
	No disease	78 (52.0)
Living location	Urban area	150 (100)
	Rural area	0 (0)

As the second metric, we used accuracy in predicting a desirable state, that is, estimating that an elderly person is in an abnormal state, when that really is the case.

The random selection method (RAND) randomly selects the degree of current health ranging from 0 to 5. For MLE, we performed regression analysis with four attributes from the user profile to identify the best-fit regression model without the results from model-based reasoning. Then we found that gender (x_1) and initial health state (x_2) were statistically significant variables (t-value = $-2.2117, -1.8159$) for estimating the current health condition (y) as follows (3):

$$y = 2.9340 - 0.1433x_1 - 0.0025x_2 \tag{3}$$

Next, the proposed model-based approach is used in conjunction with multiple regression analysis by including reasoning results from the two activity pattern recognition models, as stated in Section 3.3. We considered eight variables identified from user profile information and model-based reasoning. As a result, initial health state (x_1) and activity pattern change (x_2) were selected as independent variables for the current health condition (y_1), based on the t-values: -2.1176 and 1.8349, respectively. The regression model for MLE_MODEL is identified as follows (4):

$$y = 2.3897 - 0.1172x_1 + 0.1232x_2 \tag{4}$$

Finally, we combined the model-based approach with the boosting strategy. Each of the six variables in the user profile and model-based reasoning categories were identified as classifiers.

The experiment was performed 120 times with different random sampling each time. For each experiment, out of 1236 samples, 5% were randomly used for training and the remaining 95% were used to test the methods. Only 5% of the records were used because we observed no differences in accuracy despite variations in the size of the training set. Hence, we concluded that limiting the size of the training set would improve test efficiency by minimizing the elapsed time required for generating estimation rules. Actually, the average elapsed time to learning was 8.48 seconds (standard error = 6.02). In the worst case among the 120 runs, the elapsed time was 28.70 s. In addition, for experimental simulation, a Java application program was developed. The total number of attributes was seven, including a technology transfer outcome as the dependent variable. Therefore, six classifiers were constructed along with six attributes.

5.2. Results

In the first efficiency test, the overall accuracy of the MLE_MODEL method was 34.63%, which is nearly two times superior to RAND (17.45%), better than MLE (28.50%), and slightly better than the BOOST_MODEL (31.79%; see Table 4).

Secondly, assessment by MAD and RMSA was performed. MAD and RMSE for the MLE_MODEL were 0.8082 and 1.0364, respectively, which were lower values compared to 0.8860 and 1.1210 for MLE, 1.0645 and 1.7945 for RAND, and 0.9367 and 1.2200 for the BOOST_MODEL. Hence, we concluded that the MLE_MODEL method performs best across the board in terms of MAD and RMSA. The comparison is shown in Table 4.

When it comes to accuracy, we adopted two metrics: overall accuracy and hit ratio (HIT). HIT indicates how accurately the method predicts meaningful outliers, the BOOST_MODEL shows 80.07% accuracy, clearly more accurate than any other method: RAND (49.95%), MLE (3.77%), and the MLE_MODEL (8.88%). This happens due to the characteristics of health monitoring in the specific domain – only a few results of the samples fall into the category of 'undesirable state' or 'abnormal state'. In fact, finding abnormality is one of the mission-critical tasks for the u-care system. In real time, caregivers should detect abnormal cases and respond to their needs relevantly and promptly, even though such round-the-clock monitoring is very costly. Therefore, HIT is more useful in this domain from an economic point of view than overall accuracy, MAD or RMSE for system administrators to test their estimation methods.

Table 4
Evaluation results.

Method	RAND	MLE	MLE_MODEL	BOOST_MODEL
MAD	1.0645	0.8860	0.8082	0.9367
	(0.0192)	(0.0954)	(0.0587)	(0.1068)
RMSE	1.7945	1.1210	1.0364	1.2200
	(0.0362)	(0.3594)	(0.0262)	(0.1098)
Overall accuracy	17.45%	28.50%	34.63%	31.79%
	(1.37%)	(0.08%)	(0.03%)	(3.74%)
HIT	49.95%	3.77%	8.88%	80.07%
	(3.07%)	(36.03%)	(19.13%)	(18.43%)

As a result, we conclude that the proposed model-based methods, the MLE_MODEL and BOOST_MODEL, contribute to improve the quality of health monitoring by increasing overall accuracy and finding meaningful outliers.

6. Concluding remarks

Making full use of a set of primitive context data decreases the number of sensors to be installed in a specific zone, making context-aware systems more cost-effective and saving energy. In this paper, we focus on activity-based context-aware services, which are promising value-added services especially for elderly people, as well as location-aware services.

The proposed combined model-based methods for activity interpretation using time series activity data have the advantage that they can utilize any type of rule or model, regarding all of them as reasoning attributes. In particular, model-based interpretation of activity data makes use of implicit information as much as possible, increasing estimation accuracy compared with the use of activity data alone. It obtains the context information derived by each inference method, compares the result with the actual inspected result, and stores the right and wrong patterns separately in the pattern base for later use in making a joint inference.

In this paper, we show that the proposed estimation algorithm and system have been successfully implemented in an actual nation-wide elderly care system. Based on a real data sample, our experimental study was conducted to show the feasibility of the proposed method. The results explicitly show that the performance of the system is better than that of conventional u-care systems, and that the system is more usable with the proposed method, although the sample data were incomplete and somewhat inconsistent due to sensor conditions. If the quality of sensors and sensor network are improved, then the performance in terms of accuracy will be enhanced.

To improve the performance of the proposed method further, considering other relevant models of activity pattern interpretation in addition to the two models proposed in this paper should be useful. Since our method provides an extensible framework, combining model-based reasoning results with statistical or AI-based diagnosis would be one promising possibility.

Acknowledgments

This research is supported by the Ubiquitous Computing and Network (UCN) Project, Knowledge and Economy Frontier R&D Program of the Ministry of Knowledge Economy (MKE) in Korea as a result of UCN's subproject 11C3-T2-10M.

References

Axisa, F., Schmitt, P. M., Gehin, C., Delhomme, G., McAdams, E., & Dittmar, A. (2005). Flexible technologies and smart clothing for citizen medicine, home healthcare, and disease prevention. *IEEE Transactions on Information Technology in Biomedicine, 9*(3), 235–336.

Brennan, M. J., & Schwartz, E. S. (1985). Evaluating natural resources investments. *Journal of Business, 58*, 135–157.

Chan, M., Bocquet, H., Campo, E., Val, T., Estève, D., & Pous, J. (1998). Multisensor system and artificial intelligence in housing for the elderly. *Studies in Health Technology and Informatics, 48*, 145–149.

Chan, M., Campo, E., Laval, E., & Esteve, D. (2002). Validation of a remote monitoring system for the elderly: Application to mobility measurements. *Technology and Health Care, 10*, 391–399.

Finking, G. (2008). The European Ambient Assisted Living Innovation Alliance, Newsletter Preface, 1, Department of Innovation Europe, Berlin.

Ipina, D. L. (2001). An ECA rule-matching service for simpler development of reactive applications. In *Proceedings of the Middleware 2001 at IEEE Distributed Systems* 2(7).

Kang, D. O., Kang, K., Lee, H. J., Ko, E. J., & Lee., J. (2010). A systematic design tool of context aware system for ubiquitous healthcare service in a smart home. In *Proceedings of the 7th IEEE Conference on Consumer Communications and Networking*, Nevada, pp. 476–480.

Kim, J., Choi, H.S., Wang, H., Agoulmine, N., Deen, M. J., & Hong, J. W. (2010). POSTECH's u-health smart home for elderly monitoring and support. In *Second International Workshop on Interdisciplinary Research on E-Health Services and Systems (IREHSS 2010)*, Montreal.

Noury, N. & Rumeau, P. (2006). Ambient multi-perceptive system for residential health monitoring based on electronic mailings. In *Proceedings of the HEALTHCOM 2006*, PP. 95–100.

Shin, H., Chung, G. S., Kim, K. K., Kim, J. S., Hwang, B. S., & Park, K. S. (2007). Ubiquitous house and unconstrained monitoring devices for home healthcare systems. In *Proceedings of the 6th International Special Topic Conference on ITAB*, Tokyo, pp. 201–204.

Si, H., Kawahara, Y., Morikawa, H., & Aoyama, T. (2005). Stochastic approach for creating dynamic context-aware services in smart home environment. In *Proceedings of the Pervasive Conference*, Munich, Germany.

Tapia, E. M. (2004). Activity recognition in the home using simple and ubiquitous sensors. In Proceedings of the Pervasive Conference, pp. 158–175.

UbiSense project (2010). http://www.doc.ic.ac.uk/vip/ubisense/home/home.html.

Yamazaki, T. (2006). Elderly people supporting experiment in a real-life environment. In C. Nugent & J. C. Augosto (Eds.), *Smart Homes and Beyond* (pp. 149–156). IOS Press.

Ferdous, N., Eluru, N., Bhat, C., & Meloni, I. (2010). A multivariate ordered-response model system for adults' weekday activity episode generation by activity purpose and social context. *Transportation Research: Part B, 44*(8/9), 922–943.

McKenzie, T. L., Sallis, J. F., & Nader, P. R. (1991). SOFIT: System for observing fitness instruction time. *Journal of Teaching in Physical Education, 11*, 195–205.

McKenzie, T. L., Cohen, D. A., Sehgal, A., Willianson, S., & Golinelli, D. (2006). System for observation play and recreation in communities (SOPARC): Reliability and feasibility measures. *Journal of Physical Activity and Health, 1*, 203–217.

McCormick, B. P., Frey, G. C., Lee, C. T., Gajic, T., Stamatovic-Gajic, B., & Maksimovic, M. (2009). A pilot examination of social context and everyday physical activity among adults receiving community mental health services. *Acta Psychiatrica Scandinavica, 119*(3), 243–247.

Hattori, S., Tezuka, T., & Tanaka, K. (2006). Activity-based query refinement for context-aware information retrieval. *Lecture Notes in Computer Science, 2680*, 164–177.

Rasku, J. (2009). A method for the classification of corrective activity in context dependent postural controlling tasks. *Computers in Biology and Medicine, 39*(10), 940–945.