A Comparison Study between RCCAR and Conventional Prediction Techniques for Resolving Context Conflicts in Pervasive Context-Aware Systems

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Abstract—*In Pervasive computing environment, context-aware systems face many challenges to keep high quality performance. One-challenge faces context-aware systems is conflicted values come from different sensors because of different reasons. These conflicts affect the quality of context and as a result the quality of service as a whole. This paper is extension to our previous work, which is published in [15]. In our previous work, we presented an approach for resolving context conflicts in context-aware systems. This approach is could RCCAR (Resolving Context Conflicts Using Association Rules). RCCAR is implemented and verified well in [15], this paper conducts further experiments to explore the performance of RCCAR in comparison with the traditional prediction methods. The basic prediction methods that have been tested include simple moving average, weighted moving average, single exponential smoothing, double exponential smoothing, and ARMA. Experiments is conducted using Weka 3.7.7 and Excel; the results show better achievements for RCCAR against the conventional prediction methods. More researches are recommended to eliminate the cost of RCCAR.*

Keywords— *RCCAR, Pervasive Computing, Context–Aware System (CAS); Context Conflicts; Prediction.*

I. INTRODUCTION

Pervasive computing is still away from Mark Weiser vision. Context-aware systems (CASs) which are a vital construct in this environment face many challenges to keep high performance. Context conflicts is one of these challenges. Context conflicts reflect the contradictions within the context [10][13]. This was due to different reasons; it may occur while collecting data from redundant context sources/sensors or while aggregating that data to compose the whole context. These conflicts could affect the produced decisions and consequently lead to undesirable actions. This situation could be serious if the CAS is critical. Resolving context means selecting the valid value between some conflicted ones. Most researches tried to resolve conflicts according to quality of context (QoC) parameters [8][10][12][11][13]. QoC parameters reflect the level of context quality such as correctness, trust-worthiness, resolution, and up-to-dateness [1][2][3][4][5][6][7][9]. This paper is an extension of our previous work presented in [15], which introduced an approach for resolving context conflicts using prediction. This approach called RCCAR (Resolving Context Conflicts Using Association Rules). In this paper, we introduces a further experiments of RCCAR compared with the traditional methods for prediction; namely simple moving average, weighted moving average, single exponential smoothing, double exponential smoothing, and ARMA.

RCCAR resolves context conflicts by exploiting the previous history of context to predict the valid values form different conflicted ones. The technique that is used to predict the valid value is the Association Rules technique. Based on Association Rules basic known measures, RCCAR have developed a mathematical model to calculate the total affirmation, which is coming from different values of context elements for each conflicted value of the investigated context element. Then, simply the value that has the greater affirmation will be selected among the conflicted values [15].

The rest of this paper is layout as follows: Section 2 has been devoted to introduce an overview of RCCAR as this work is updating for it. Section 3 introduces an overview of traditional prediction methods. Experiments and implementation has been described in Section 4. Section 5 is devoted for presenting the results for the different experiments. Finally, Section 6 conducts the conclusions and future work.

II. AN OVERVIEW OF RCCAR

Our approach RCCAR (Resolving Context Conflicts Using Association Rules) is based on exploiting the pervious history of a context for predicting which among the context conflicted values are valid and which is not. The prediction uses Association Rules technique to get all associations that combine context elements together to get the affirmation from each association individually and then get the total affirmation. Association rules is a technique that is commonly used in data mining for discovering patterns in a huge historical database or data warehouse. Association rules discovers what goes together in data based on data occurrences in database. Thus, we found Association rules is an appropriate technique to get associations that affirm the different values of investigated context element and then deciding according to the affirmation values, which is valid from those conflicted values. The following expression clarify the formula of association rule stating that the occurrence of y context element affirms the occurrence of x [14][16].

$$y \Rightarrow x$$

Where y could be one context element and also could be a combination of some context elements, and x is the context element under investigation. Now, how affirmation for each association rule is produced. RCCAR uses the association rules measure, which called "confidence". It is calculated as stated by the following equation:

$$Confidence\,(Y \Rightarrow X) = \frac{last\text{-}occurances\ of\ x,y\ together}{last\text{-}occurances\ of\ y}$$

Confidence reflects the affirmation strength. To compute the $Total-affirmation$ of context element x , the summation of the confidence for all possible associations which affirm the context element under investigation x is calculated by scanning the database of previous history. The following equation is used to calculate $Total-affirmation$ as follows:

$$Total-affirmation(x) = \sum_{i=1}^{m} confidence(yi \Rightarrow x)$$

Where m is the number of available possible associations that could be produced according to the different context elements, and also according to the occurrences in database. To clarify that, we will start by introducing the "itemset" concept. According to association rules analysis, a collection of zero or more elements is referred to by $itemset$. If itemset contains k items, it is called as $k-itemset$. Examples of itemset are shown in Table I.

TABLE I. EXAMPLES OF ITEMSETS

1-itemset			2-itemset			3-itemset		
id	elements	σ	id	elements	σ	id	elements	σ
$y_1(1)$	a	13	$y_1(2)$	a c	8	$y_1(3)$	a c d	4
$y_2(1)$	b	9	$y_2(2)$	a d	7			
$y_3(1)$	c	10	$y_3(2)$	b c	5			
$y_4(1)$	d	15	$y_4(2)$	d c	5			

Where a, b, c, and d are context elements. The frequency (occurrences) of context element individually and all possible combinations of them are calculated by scanning database. By scanning the database, we get all possible associations and its confidence values and then simply sum them. We apply that to all conflicted values and select the context element that has the greater $Total-affirmation$ value. Table II clarifies an example for that. Assume Table I contains the occurrences for some context elements. These values are concluded by scanning the context database. Assume that a and b are two conflicted values for a context element. In addition to a and b, the current situation of context is represented by other context elements c and d. According to occurrences in Table II, the associations illustrated in Table II will be produced.

TABLE II. PRODUCED ASSOCIATIONS

Associations affirm a	Confidence value	Associations affirm b	Confidence value
$c \Rightarrow a$	$\frac{8}{10} = 0.80$	$c \Rightarrow b$	$\frac{5}{10} = 0.50$
$d \Rightarrow a$	$\frac{7}{15} = 0.46$		
$c,d \Rightarrow a$	$\frac{4}{5} = 0.80$		
$Total-affirmation\,(a)$	2.06	$Total-affirmation\,(b)$	0.50

According to Table I, total-affirmation of a is greater than the total affirmation of b. Table I shows that number of associations and the total value of their confidence indicate that a is the recommended value of context element under investigation.

RCCAR then examined according different conditions. Results showed that RCCAR has succeeded against different conditions. Using all possible combinations of context elements in Association rules improve the prediction. Utilizing all context elements recorded in the previous history also improves the result but in varying degrees. More explanations and details could be found in [15].

III. OVERVIEW OF THE EXISTING PREDICTION TECHNIQUES

Prediction is the estimation of the value of a variable (or set of variables) at some future point of time. The basic prediction techniques are almost time series analysis techniques, which are consider a one category of prediction techniques. There are two main categories to classify prediction techniques: qualitative and quantitative methods. Qualitative techniques include a number of prediction approaches; these approaches does not have a formal mathematical model. These approaches are subjective as they depend on estimations by informed experts. In this category, no statistical data is involved. These methods are usually recommended in case that there is no good historical data is available, or we want to find out general insights through the different opinions of experts. In contrast, quantitative techniques include different statistical approaches for prediction depending on the analysis of historical data. The quantitative techniques are divided into two sub-categories: causal techniques, and time series techniques; our investigated traditional techniques belong to this category. Causal techniques depend on regression analysis that studies the relationship between the forecasted variable and other variables. Causal techniques are useful where dependent and independent variables are available [21].

Time series techniques are useful when the historical data exists only for the variable that is needed to be forecasted. Most basic and most common prediction methods are included in time series category such as moving average models, auto-regression models, seasonal regression models, and exponential smoothing models. The accuracy of prediction methods is usually measured by the prediction errors. Several methods are used to measure the prediction accuracy. Mean Absolute Error (MAE) and Mean Squared Error (MSE) are two popular measures for prediction accuracy. MAE is defined as sum of errors divided by number of periods in the forecast and MSE is defined as sum of squared errors divided by number of periods in the forecast [22]. This section provides a brief overview of some basic prediction methods, which are compared to RCCAR. These methods are namely: a) Simple Moving Average, b) Weighted Moving Average, c) Single Exponential Smoothing, d) Double Exponential Smoothing and e) ARMA Models [21][22].

A. Single Moving Average

The simplest known prediction method is the moving average method. To forecast a certain value, this method simply averages the past N observations for the same variable. The N observations will include the most recent observations for the next period. The general expression for the moving average is as follows [21]:

$$yhat_i=[y_t+y_{t-1}+...+y_{t-N+1}]/N$$

Where $yhat_i$ is the forecasted value. Determining the value of N depends on the value of N that provides the best prediction accuracy (i.e. minimizes MAE or MSE).

B. Weighted Moving Average

In the single moving average method, each observation in the average is equally weighted whereas in the weighted moving averages method, the most recent observation has the largest weight in the average. The general expression for weighted moving average is as follows [21]:

$$yhat_i= [\ w_t*y_t + w_{t-1}*y_{t-1}+ ... + w_{t-N+1}* y_{t-N+1}]$$

The total sum of the weights is1.

C. Single Exponential Smoothing

Unlike the single moving average method in which the past observations are weighted equally, recent observations in exponential smoothing are given relatively more weight than the older observations. Single exponential smoothing is an extension of weighted moving averages where the greatest weight is placed on the most recent value and then progressively smaller weights are placed on the older values. The general expression is the following [21]:

$$yhat_{i+1} = \alpha y_i + (1-\alpha)\ yhat_I, \quad \text{Where } 0<=\alpha<=1$$

This means the following:

Forecast for the next period = forecast for current period + smoothing constant * error for current period. The forecast for the current period is a weighted average of all past observations. The weight given to past observations declines exponentially. The larger the α, the larger weight is given to recent observations. Exponential smoothing works better when the time series fluctuates about a constant base level.

D. Double Exponential Smoothing

Double exponential smoothing is defined as exponential smoothing of exponential smoothing. Exponential smoothing does not work well where there is a trend in data. This situation can be improved by applying another equation with another smoothing constant β, which represents the trend component that must be chosen in conjunction with α, which represents the mean component. Double exponential smoothing is defined in the following manner [21]:

$$yhat_{i+1} = E_i + T_i, \quad i=1,2,3...$$

Where:

$$E_i= \alpha y_i+(1-\alpha)(E_{i-1}+T_{i-1})$$

$$T_i=\beta\ (E_i - E_{i-1}) + (1-\beta)\ T_{i-1}$$

Where: $0< \alpha<= 1$ and $0<=\beta<=1$.

This method works better when the time series has a positive or negative trend (i.e. upward or downward). After observing the value of the time series at period i (yi), this method computes an estimation of the base, or the expected level of the time series (Ei) and the expected rate of increase or decrease per period (Ti). It is customary to assume that E1= y1unless told otherwise, and assume T1= 0. To use this method, first calculate the base level Ei for time i. Then compute the expected trend value Ti for time period i. Finally, compute the forecast yhati+1. Once an observation yi is found out, calculate error and continue the same process for the next time period.

E. ARMA Models

ARMA model can be defined as a combination of both autoregressive and moving average models. The autoregressive (AR) model uses past values of dependent variable to explain the current value. Whereas, moving average (MA) model uses lagged values of the error term to explain current value of the explanatory variable [23].In ARMA model, current value of the time series is expressed linearly in terms of its previous values and in terms of current and previous residual series [24]. The time series defined in AR, MA, and ARMA models are considered stationary processes, which means that the mean of series of any of these models and the covariance among its observations do not change with time. For non-stationary time series, transformation of series to a stationary series has to be performed first [24]. Given a time series of data X_t, the ARMA model is a tool for understanding and, perhaps, predicting future values in this series. The model consists of two parts, an autoregressive (AR) part and a moving average (MA) part. The model is usually then referred to as ARMA(p,q) model where p is the order of the autoregressive part and q is the order of the moving average part. The notation AR(p) refers to the autoregressive model of order p. The AR(p) model can be written as follows [18][19][20]:

$$X_t = c + \sum_{i=1}^{p} \varphi_i X_{t-i} + \varepsilon_t.$$

Where $\varphi_1, \ldots, \varphi_p$ are parameters, c is a constant, and the random variable ε_t is white noise.

The notation MA(q) refers to the moving average model of order q:

$$X_t = \mu + \varepsilon_t + \sum_{i=1}^{q} \theta_i \varepsilon_{t-i}$$

Where the θ1, ..., θq are the parameters of the model, μ is the expectation of X_t (often assumed to equal 0), and the ε_t ,ε_{t-i} ,... are again, white noise error terms.

The notation ARMA(p, q) refers to the model with p autoregressive terms and q moving average terms. This model contains AR(p) and MA(q) models.

$$X_t = c + \varepsilon_t + \sum_{i=1}^{p} \varphi_i X_{t-i} + \sum_{i=1}^{q} \theta_i \varepsilon_{t-i}.$$

The general ARMA model was described in the 1951 by the paper of Peter Whittle, who used mathematical analysis and statistical inference. This method was useful for low order polynomials.

IV. EXPERIMENTS AND IMPLEMENTATION

This section describes the implementation of the experiments, the nature of the data, the used techniques, and the basic preprocessing processes. The dataset that are used in this paper is Southampton monthly weather historical data from the year 1855 to 2000 [17]. This data is a historical data for some weather variables. This data is officially collected and recorded by Southampton Weather Station and published by its Website [17]. This data set contains 1744 instances. The collected weather data is recorded as instances, each instance contains values of some weather variables, which are: Year, Month, Temperature Max (Avg), Temperature Min (Avg), Air Frost, Rainfall, Sunshine Hours. Table III shows a snapshot of data.

TABLE III. A SNAPSHOT OF DATA WITHIN SOUTHAMPTON WEATHER HISTORICAL DATASET

YYYY	MM	Tmax	Tmin	AF	Rain	Sun
		degC	degC	days	mm	hours
1989	7	25.2	15.0	0	16.3	289.0
1989	8	23.3	13.2	0	27.5	271.6
1989	9	20.7	12.3	0	26.9	125.1
1989	10	16.6	9.9	0	93.6	93.5
1989	11	11.8	4.6	5	52.1	105.3
1989	12	9.6	4.0	3	159.0	35.9

Southampton weather dataset is used to predict Temperature (max_value) using the previous history. Excel with Solver Data Analysis feature is used to carry out the experiments for traditional methods [21]. Weka Tool has been used to implement RCCAR approach. For associations discovery, Weka uses association rules technique, which has been used in RCCAR. The version used in this paper for our approach RCCAR is WEKA 3.**7.7**.

Unlike RCCAR, all traditional techniques mentioned above are usually used for time series analysis where we have a single variable that changes with time and whose future values are related in some way to its past values. Temperature (max_value) in our experiments was this variable. In the case of RCCAR, all available variables in dataset contributed in the prediction. For RCCAR, we have examined the prediction during a short depth of history and also a long depth of history. On the other hand, for all traditional techniques, the previous instances of temperature had to be ordered according to the timestamp and most current instances should be available. In the case of RCCAR, this is not necessary as it works on studying the occurrences of other variables to derive the current value of the variable under investigating. We examine RCCAR against the traditional methods using 6 months' timescale within the year 1991. For all traditional methods, prediction for each value depends directly on the most current values. It differs a little bit from a method to another but it is still the rule. In contrast, RCCAR did not use the current values that are captured before each predicted value; it depends on the previous history before the year 1991.

Before applying the different prediction techniques, dataset have been subjected to some pre-processing to make them ready for use. The pre-processing actions include missing values processing, and applying some data transformations.

V. RESULTS AND EVALUATION

The actual results are as shown by Figure 1. To compare the results accurately, the absolute error for each predicted value is computed and then the mean absolute error is computed for each method.

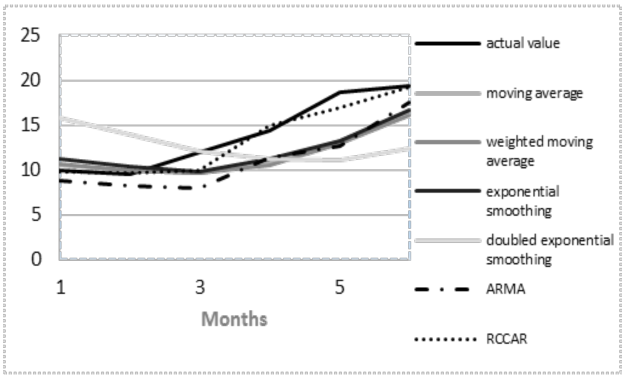

Fig. 1. The Actual Results for RCCAR against Traditional Methods through 6 Months (Jan-Jun 1991)

As shown by Fig. 1, the behavior of RCCAR is similar to ARMA in terms of the curve pattern, with better values according to the curve of actual values. To be more scientific, absolute error and mean absolute error for each method are computed as shown by Table IV and Table V.

TABLE IV. ABSOLUTE ERROR USING RCCAR AND TRADITIONAL METHODS THROUGH 6 MONTHS (JAN-JUN 1991)

Absolute Error

moving average	weighted moving average	exponential smoothing	doubled exponential smoothing	ARMA	**RCCAR**
0.6	0.7	1.324273	5.851867	1.12686	0.1
0.45	0.46	0.886314	4.432455	1.243232	0.2
2.3	2.26	2.174518	0.130979	3.992489	2
3.65	3.9	3.198551	3.218061	3.023364	0.6
5.4	5.64	5.374608	7.504209	5.868951	1.6
2.9	3.32	2.773724	7.082875	1.932623	0.2

TABLE V. MEAN ABSOLUTE ERROR (MAE) USING RCCAR AND TRADITIONAL METHODS THROUGH 6 MONTHS (JAN-JUN 1991)

Mean Absolute Error (MAE)					
moving average	weighted moving average	exponential smoothing	doubled exponential smoothing	ARMA	**RCCAR**
2.55	2.713333	2.621998	4.703408	2.864586	0.783333

As shown by Table V, RCCAR achieved the smallest error rate comparing to the traditional methods. Doubled exponential smoothing is the worst. The rest methods are very close even ARMA. That is maybe because of the period 6 months is very short to examine the behavior.

As a conclusion of this section, RCCAR has been examined against the conventional prediction methods. Results show that RCCAR outperforms all conventional methods in terms of the mean absolute error. RCCAR uses all context attributes to predict the required value whereas traditional methods use only the previous values of the attribute under investigation. On the other hand, RCCAR does not require the current values to find out the predicted value. Instead, it depends on learning from a suitable history period based on the nature of data.

A. *Examining RCCAR with Non-numeric Data*

In addition to above, we examined RCCAR for non-numeric data to show if it can deal with different data types or not. What we have expected initially is that the approach RCCAR can deal with different data types because it depends on data occurrences whatever data type of variable.

The used data is the well-known "Weather Nominal Data". The attributes of this data are outlook, temperature, humidity, and wind. The values of all attributes are nominal as shown by Table VI. Table VII shows a snapshot of dataset. The value of humidity for the last record will be predicted using RCCAR. The correct value of humidity that must be predicted is "High".

TABLE VI. VALUES OF DIFFERENT ATTRIBUTES OF THE WEATHER NOMINAL DATA

Attribute	**Values**
Outlook	{ sunny, overcast, rain }
Temperature	{ hot, mild, cool }
Humidity	{ high, normal }
Wind	{ weak, strong }

TABLE VII. SNAPSHOT OF INSTANCES FOR WEATHER NOMINAL DATASET

Outlook	**Temperature**	**Humidity**	**Wind**
sunny	Cool	normal	weak
rain	Mild	normal	weak
sunny	Mild	normal	strong
overcast	Mild	high	strong
overcast	Hot	normal	weak
Rain	Mild	??????	strong

When applying RCCAR, the affirmation value for all predicted variables are produced. The high limit for the affirmation would be 7 as we have 3 variables beside the variable under investigation. Results of experiments were as shown by Table VIII:

TABLE VIII. RESULTS OF RCCAR FOR NON-NUMERIC VARIABLES

The predicted values	**The affirmation for predicted values using RCCAR**	**The affirmation for predicted values using RCCAR %**
Humidity= High	3.01	43%
Humidity= Normal	1.60	23%

Therefore, RCCAR can predict the correct non-numeric value despite the number of instances involved by the experiment was only 13 (instances). In addition, RCCAR can predict the correct value for non-numeric values as quality as with numerical values. That is because it depends on the previous occurrences of values regardless the type of value. Although the data used in this experiment is slightly small with only a total number of 14 instances, the result was correct; this means that the result would be better with bigger datasets. Generally, in addition to numeric data, RCCAR can deal with any type of data. That is because RCCAR counts the frequencies of each variable value with the variable value under investigation, and then the greatest frequency will be produced for the correct value. This advantage is an added value for RCCAR over the traditional time series prediction methods, which can deal only with numeric data.

VI. CONCLUSIONS AND FUTURE WORK

This paper is extension for our previous work about introducing a novel approach for resolving context conflicts in CASs within pervasive environment. This approach published in [15]; it could RCCAR (Resolving Context Conflicts Using Association Rules). RCCAR uses prediction for resolving context conflicts; this paper introduced a comparison between the conventional prediction methods and RCCAR. The investigated prediction methods include: simple moving average, weighted moving average, single exponential smoothing, double exponential smoothing, and ARMA. Weather dataset is used for experiments as an example of weather forecasting system [17]. Experiments show that RCCAR achieves better results against the conventional prediction methods. In contrast to conventional methods, it is useful for any data type where the other methods work with only numerical data. The remarkable drawback of RCCAR is the cost [15] in comparison with the conventional methods. Our future research will concentrate on elimination the cost of RCCAR.

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