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An Efficient Classifier Decision Tree For Active Context Source Discover On Mobile Pervasive Environment

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ABSTRACT

Mobile pervasive environment interact with several devices at varying service ranges. The technical heterogeneity of pervasive environment is expected to increase the system flexibility and adaptability on modeling with context training phase. While working with context based training phase, time entity measure is considered as the significant issue. The evaluation of the services through numerous devices during training phase does not acquire an effective service monitoring on mobile pervasive environment. Mobile pervasive environment based information extraction fails to modify the patterns as activities change over time. To improve the flexibility of context training phase in mobile pervasive environment, an Active Context Source Discover Training Phase (ACSDTP) with Classifier Decision Tree Support (CDTS) mechanism is proposed in this paper. Our research work is to develop an effective modification (i.e., updation) of the pattern on training phase with real world context as per changes over time. Initially, the ACSDTP set up the available sensors in pervasive environment to work with the ever changing set of context users. The available sensors are maintained using the Active Discover process. Second, the CDTS mechanism is designed using weighted prediction for easy identification of context result on the training phase. Decision tree is operated separately using the learning techniques, where the identification is performed in a significant manner with minimal time factor. The learning process is performed to identify the inferred situations. Finally, the integration process is carried out to work with the complex association between the situations and sensor data in the mobile pervasive environment to achieve flexibility and adaptability factor. Experiment is conducted on factors such as time entity measure rate, precision ratio, and user context result determination level.

Keywords— Classifier Decision Tree, Integration, Learning Process, Mobile Pervasive Environment, Context Training Phase, Flexibility, Adaptability, Active Source Discover

1. INTRODUCTION

The contributions of ACSDTP include the following:

- To improve the flexibility of context training phase in mobile pervasive environment using an Active Context Source Discover Training Phase (ACSDTP) with Classifier Decision Tree Support (CDTS) mechanism
- To develop an effective pattern modification on training phase with real world with respect to changes over time
- To increase the user context result determination level using the Active Discover process by setting up the available sensors in pervasive environment to work with ever changing set of context users
- To increase the precision ratio using the decision tree with the aid of weighted prediction for easy identification of context result on the training phase using the learning techniques, where the learning process is performed to identify the inferred situations.
- To improve the system adaptability efficiency on different devices in a significant manner by integrating the complex association between the situations and sensor data in mobile pervasive environment

2. ACTIVE CONTEXT SOURCE DISCOVER TRAINING PHASE WITH CLASSIFIER DECISION TREE SUPPORT

Active context discovery helps to work with updated context information to produce effective result in a uniform manner for varying applications, and flow devices. The avoidance of redundancy on context discovery phase in ACSDTP benefits the system with manageable network resources. The mobile pervasive environment also manages overload requests effectively in our proposed work.

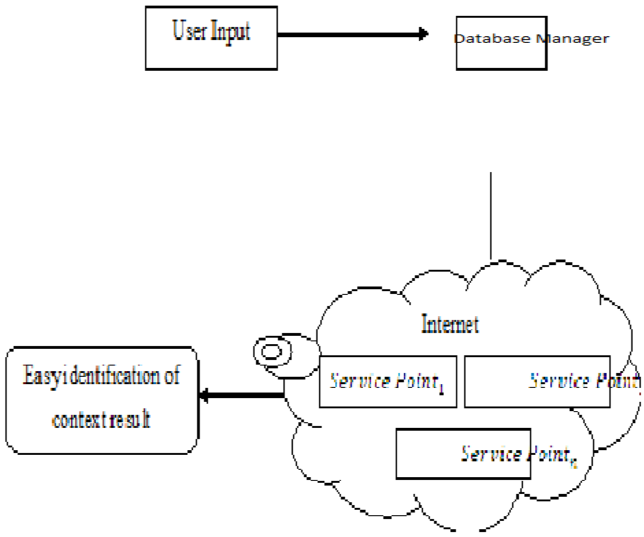

Figure 1 Active context discovery based on user input

Figure 1 shows the design of active context discovery based on the user input. To start with, the user input is obtained and provided to the database manager, where it refers to different service points for easy identification of context result. The user input is fetched to analyze the query with network database information for producing the appropriate results. The internet consists of several context point lists including $Service\ Point_1, Service\ Point_2, \ldots, Service$. This information is used to reduce the complexity rate with distributed system of comparatively high robustness. The architecture diagram of ACSDTP with CDTS mechanism is shown in Figure 2.

In figure 2, the architecture diagram of Active Context Source Discover Training Phase (ACSDTP) with Classifier Decision Tree Support (CDTS) mechanism clearly represents the step by step procedure in diagrammatical form. User information is collected with the help of sensors for easy monitoring of activities. The sensed data are stored in the memory with the perceived experience. The objective of Active Context Source Discover Training Phase is to update the context actively as per the change over time according to the user requests obtained through sensor data.

The updated active context source training phase performs the classifier decision process for obtaining the result through easy steps. The identified result through the decision process works with the weighted prediction model. The weighted predicted model also uses the learning process in ACSDTP with CDTS Mechanism to produce the inferred solutions. These two steps are combined together in the integration process. The integration process widely takes the updated context to perform decision making process to users in mobile pervasive environment.

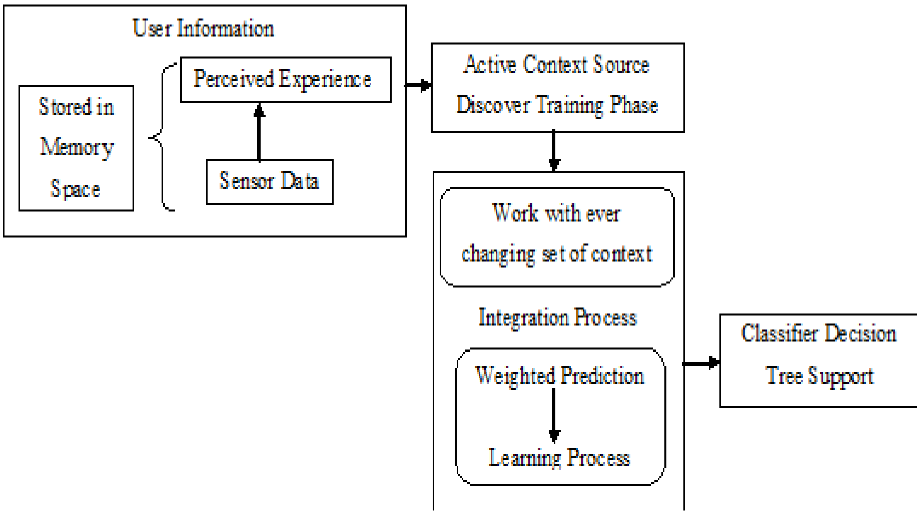

Figure 2 Architecture diagram of ACSDTP with CDTS Mechanism

2.1 Active Context Source Discover Training Phase

In the context training phase, the mechanism is designed to actively collect the updates of the context sources with smart mobile pervasive environmental system. The system adapts to the updated contexts in ACSDTP with request and distributes procedure. The request denotes high user requested accepted with the sensors. The sensor data are worked with the updated context discovery sources to fetch the result through the distributed procedure. The request and distributes procedure helps ideally for mobile device users to fetch the updated information in context training phase.

Multiple users submit the request and service points are accessed to fetch the information with minimal time entity factor. Different prediction using active context source discovery solves possible conflicts in mobile pervasive environment. The ever changing context of users with sensor data is effectively handled in ACSDTP with CDTS Mechanism and it is formularized as,

$$Sensor\ Vector\ Data = (D_1, D_2, D_3 \dots D_n)_t \rightarrow U(D_1, D_2, D_3 \qquad (1)$$

The information to be extracted is performed through the active process domain specific range of mobile pervasive user requests.

2.2 Classifier Decision Tree Support

Classifier provides higher weighted prediction as the best evaluated decision result to mobile pervasive environment users. The relevant use of the classifier for human activities in ACSDTP with CDTS mechanism produces higher precision rate.

The ACSDTP obtains the subjective sensor data and decide the context using the specified condition. The decision tree process is supported in proposed work using the specification procedure. The specification procedure helps to easily determine the user need of interest based on the learning process. The specification process of ACSDTP with CDTS mechanism easily locates the relevant contexts based on the weighted result.

$$DTW = \begin{cases} H(Weight) \rightarrow Accurate\ Decision\ , if \\ \qquad\qquad otherwise\ , if\ CV < 1 \end{cases} \tag{2}$$

2.2.1 Weighted Prediction

Weighted prediction is clearly described with the decision tree process in ACSDTP. The Active Context based decision tree is a predictive model in the proposed work to easily classify the result in the mobile pervasive environment. The decision tree construction using the weighted prediction model is shown in Figure 3.

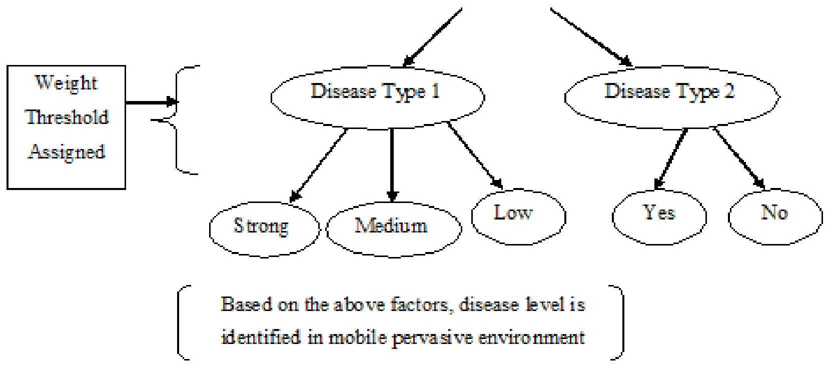

Figure 3 Decision Tree based on Weighted Sum Value

Figure 3 illustrates the decision tree based on weighted sum value where leaf node in the tree represents the result of classification and each node branches represents the unique set of service point features for achieving target classification. The decision tree based classifier in proposed work helps to obtain the desired result with minimal time entity with high built in information entropy. Information entropy is the weighted threshold value assigned to easily identify the level of confidence rate. The construction of decision tree based on weighted sum value selects an initial value in ACSDTP with CDTS mechanism and performs the weight prediction process.

If the condition get fails, then the next value bit is chosen to perform the decision making process using the tree structure. The decision tree easily generates the classifier rules for an effective understanding of the process with higher flexibility ratio. The rules in CDTS mechanism are useful in analyzing the sensor body acceleration data requests through mobile pervasive devices. The efficiency of the decision tree is still improved when it is subjected to the size of the training data in ACSDTP. The proposed decision tree mines even from very large real world data and produce high efficacy result through mobile pervasive environment.

2.2.2 Learning Process

The learning process is carried out in the mobile pervasive environment using pre-classified instances in the active context source discover training phase. The obtained learning process is helped to easily process the system with higher level of confidence.

$$Learning\ Process\ (LP) = \sum_{i=1}^{n} C[\quad (3)$$

2.3 Integration of active context source discover training phase and classifier decision tree

The evaluation of the services through varying devices on training phase acquires an effective service monitoring using the integration process. Mobile pervasive environment based information extraction modify the patterns as activities change over time factor with an integrated approach. The integration algorithm is briefly explained in the section given below.

2.3.1 Integration Algorithmic Step

Input: Set of sensor data 'D' on each activity 'a' set

Output: Minimal Time Entity Predictive result to the users with active context source discovery

//Active Context Source Discover Training Phase

Step 1: Initial process with ever changing set of context

Step 2: Available Sensor data maintained

Step 2.1: Using Active Discover process

//Classifier Decision Tree Support

Step 3: Weighted prediction for easy identification of the context result

Step 4: Learning process is employed

Step 4.1: Pre-classifier learning achieved maximal confidence rate

Step 4.2: Minimal time factor on inferred solutions

Step 5: (1) and (2) step combined with rest of the steps

Step 6: Complex association between the situations and user request information

The above step recognizes to obtain the context based on the updated user mobile pervasive information. The extensive integration algorithm in ACSDTP produces a synchronized context results with balanced classifier prediction. The decision process is widely considered with higher degree of confidence rate. The higher degree of confidence value predicts the result with maximal adaptability range on varying set of sensor data classes.

3. Experimental Evaluation

Active Context Source Discover Training Phase (ACSDTP) with Classifier Decision Tree Support (CDTS) mechanism is implemented in JAVA platform. OPPORTUNITY Activity Recognition Data Set from UCI repository is used in the experimental work. OPPORTUNITY Activity Recognition Data Set results are predicted with sensor and record the user daily activities for computing the proposed work.

OPPORTUNITY Activity Recognition information is used to compare the

ACSDTP proposed work with the existing Context-aware Service Discovery with Integrated Environment (CSD-IE) [1] and Automated Approach for Activity Tracking in Smart Environment (AAAT-SE) [2]. For conducting experiments in ACSDTP, 7 users are taken with the total of 242 attributes to measure the performance rate of different parametric factors. Experiment is conducted on factors such as time entity measure rate, precision ratio, and user context result determination level and system adaptability efficiency on different devices.

4. Results And Discussion

The performance of Active Context Source Discover Training Phase (ACSDTP) with Classifier Decision Tree Support (CDTS) mechanism is compared with the existing Context-aware Service Discovery with Integrated Environment (CSD-IE) [1] and Automated Approach for Activity Tracking in Smart Environment (AAAT-SE) [2].The performance is evaluated according to the following metrics.

4.1 Impact of user context result determination level

It is measured in terms of percentage (%). Higher the user context result determination level, more efficient the method is said to be.

$$UCD = U(D_1, D_2, D_3 \dots \tag{4}$$

Table 1 Tabulation for user context result determination level

No. of users	User context result determination level (%)		
	ACSDTP	**CSD-IE**	**AAAT-SE**
User_1	65.38	60.36	52.33
User_2	69.45	64.43	56.40
User_3	72.98	67.96	59.93
User_4	67.21	62.19	56.16
User_5	74.99	69.97	63.94
User_6	78.56	73.54	67.51
User_7	81.33	76.31	70.28

Table 1 tabulates the user context result determination level obtained using the proposed ACSDTP scheme and compared elaborately with the existing two works CSD-IE [1] and AAAT-SE [2] respectively.

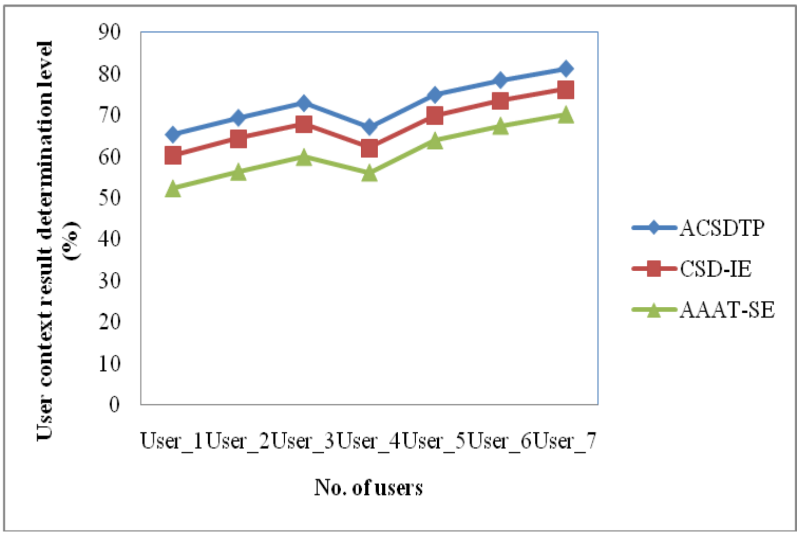

Figure 4 Measure of user context result determination level

Figure 4 shows the result of user context determination level versus varying number of user requests. The results reported above confirm that with the increase in the number of user requests being sent to the database manager, the user context determination level also increases.

As illustrated in Figure 4, the proposed ACSDTP mechanism performs relatively well when compared to two other methods CSD-IE [1] and AAAT-SE [2]. This is because of the application of active context source discover training phase. By applying the active context source discover training phase, the system adapts to the updated context on the basis of request and distributed procedure. Through this, the user context result determination level reaches the zenith using the ACSDTP and improvement observed by 6 – 7 % compared to CSD-IE. Furthermore, the change in context of users are handled in an efficient manner where the sensor points are updated according to the changes over the context via active process domain specific range resulting in the increase of user context result determination level by 13 – 19 % when compared to AAAT-SE.

4.2 Impact of precision ratio

The precision ratio using ACSDTP is the ratio of user desired relevant context obtained to the number requests made by the user. It is measured in terms of percentage (%).

$$P = l \qquad (5)$$

Table 2 Tabulation for precision ratio

Relevant information (KB)	Precision ratio (%)		
	ACSDTP	**CSD-IE**	**AAAT-SE**
15	73.88	62.83	54.74
30	78.45	67.40	59.31
45	81.23	70.18	62.09
60	75.21	64.16	56.07
75	83.89	72.84	64.75
90	85.82	74.75	66.66
105	90.13	79.08	71.09

In the experimental setup, the size of relevant information ranges from 15 KB to 105 KB. The results of 7 sizes of information placed by the mobile pervasive environment are listed in table 2. As listed in table 2, the ACSDTP measures the precision ratio which is measured in terms of percentage (%). The precision ratio obtained using our mechanism ACSDTP offer comparable values than the state-of-the-art methods.

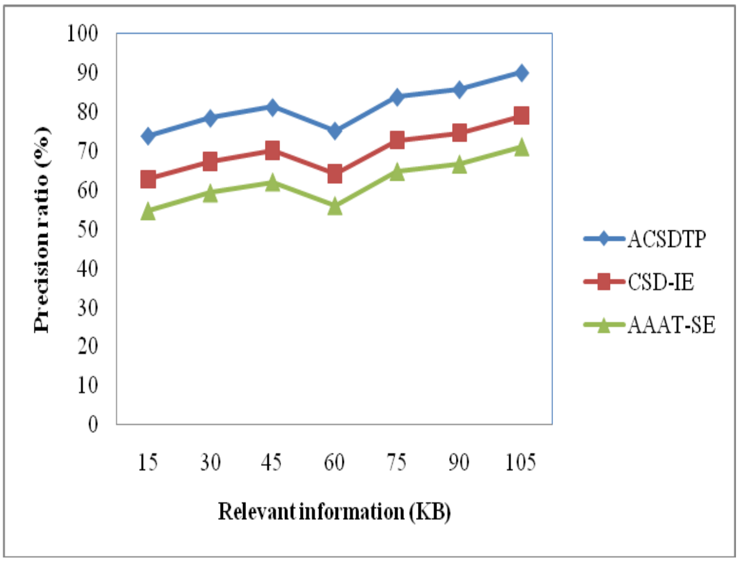

Figure 5 Measure of precision ratio

The targeting results of precision ratio using ACSDTP mechanism is compared with two state-of-the-art methods CSD-IE and AAAT-SE in figure 5 is presented for visual comparison based on the relevant information. Our mechanism ACSDTP differs from the CSD-IE [1] and AAAT-SE [2] in that we have incorporated classifier decision tree.

By applying the classifier decision tree, the classifier produces higher weighted prediction for human activities resulting in the improvement of precision ratio using ACSDTP by 12 – 14 % compared to CSD-IE. In addition, with the application of specification condition and specification procedure, the decision tree process obtains the specific user need of interest according to learning process and locates the relevant context improving the precision ratio in ACSDTP by 21 – 25 % compared to AAAT-SE.

4.3 Impact of time entity measure rate

The time entity measure rate using ACSDTP is the time taken to perform target classification using decision tree. It is measured in terms of milliseconds (ms). The time entity measure rate is the overall time taken to obtain the results of the sensor vector points, D_1, D_2, l.

$$TEMR = Time\ (D_1, D_2, D \qquad (6)$$

Table 3 Tabulation for time entity

No. of users	**Time entity (ms)**		
	ACSDTP	**CSD-IE**	**AAAT-SE**
User_1	0.132	0.144	0.150
User_2	0.140	0.152	0.158
User_3	0.148	0.160	0.166
User_4	0.145	0.157	0.163
User_5	0.152	0.164	0.170
User_6	0.148	0.160	0.166
User_7	0.150	0.162	0.168

In table 3 we further compare the time entity measure rate on inferred solutions of the proposed mechanism using the integration algorithm. The experiments were conducted using the seven users that measure the time entity to obtain the inferred solutions which is measured in terms of milliseconds (ms).

Figure 6 given below shows the time entity measure rate for ACSDTP mechanism, CSD-IE [1] and AAAT-SE [2] versus seven different user requests. The time entity returned over ACSDTP mechanism increases gradually though not linear for differing user requests though lower when compared to the two other methods.

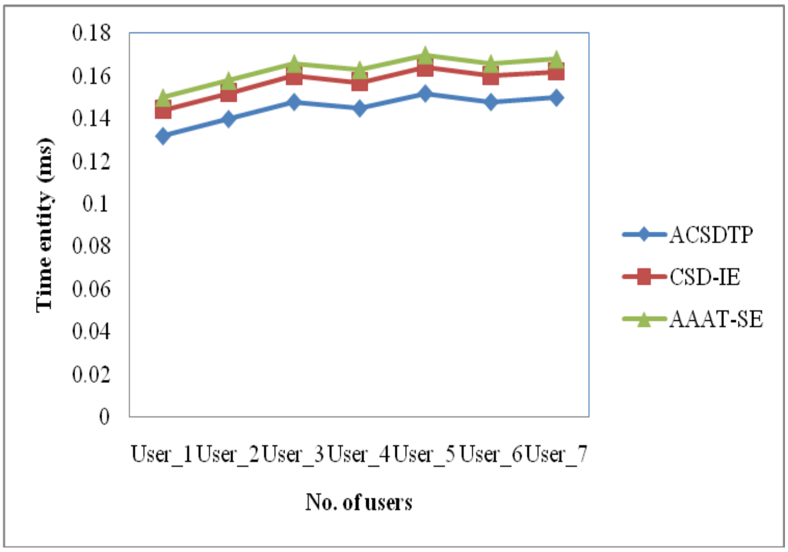

Figure 6 Measure of time entity

From figure 6, it is illustrative that the time entity is reduced using the proposed mechanism ACSDTP. This is because with the application of decision tree based on weighted sum value, the time entity is reduced on inferred solutions. By applying the decision tree based on the values of weighted sum, the proposed work, ACSDTP easily classifies the result in an effective and efficient manner for achieving target classification, resulting in reduced time entity measure rate by 7 – 9 % compared to CSD-IE. At the same time using the information entropy and decision tree based classifier in ACSDTP, the desired result on inferred solution is obtained in a relatively lesser amount of time reducing the time entity by 11 – 13 % compared to AAAT-SE.

4.4 Impact of system adaptability efficiency on different devices

In table 4 we show the analysis of system adaptability with respect to three different methods via mobile pervasive environment measured in terms of percentage (%).

Table 4 Tabulation for System adaptability

Method	**System adaptability (%)**
ACSDTP	83.5
CSD-IE	75.3
AAAT-SE	70.2

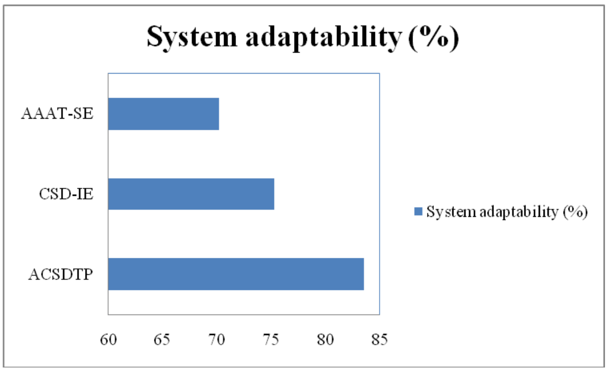

Figure 7 Measure of system adaptability

Table 4 and figure 7 shows the measure of system adaptability using three different methods. From the figure it is evident that the system adaptability rate is improved using the proposed mechanism ACSDTP than when compared to the two state-of-the-art methods. The system adaptability efficiency on different devices is improved by integrating the complex association between the situations and sensor data.

By effective integration of complex association between the situations and sensor data, the extraction of information via mobile pervasive environment modifies the patterns with the activities change over time factor. This in turn improves the system adaptability efficiency on different devices using ACSDTP by 9.82 % and 6.77 % compared to CSD-IE and AAAT-SE respectively.

5. CONCLUSION

The performance of the proposed mechanism is compared with two context aware methods (namely, CSD-IE and AAAT-SE). The proposed mechanism has the following advantages. (i) Works with updated context information, (ii) provides appropriate information to the users, (iii) representation of unique set of service point feature for achieving the target classification. On the other hand, the other context-aware methods do not work with updated context information and does not provide flexibility in context training. Therefore, it is intensely crucial and time consuming to identify the updated context information. In this aspect also, the proposed ACSDTP, mechanism has a convincing improvement over the other context aware counterpart. Active context source discover training phase was applied in ACSDTP to improve the user context result and the introduction of classifier decision tree helped in improving the precision ratio. System adaptability was also improved using ACSDTP mechanism by using an integrated algorithm reducing the time entity in a significant manner. The performance of the proposed integrated algorithm is tested using an OPPORTUNITY Activity Recognition dataset extracted from UCI repository. Results of investigation justify the potentiality of the proposed ACSDTP mechanism using the integrated algorithm in terms of precision ratio, improving user context result, system adaptability consuming moderate time entity. In most of the cases, the improvement in results obtained using the proposed mechanism is found to be statistically compelling compared to its other context aware counterparts.

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