IEEE Access
Multidisciplinary | Rapid Review | Open Access Journal
SPECIAL SECTION ON WIRELESS BODY AREA NETWORKS

Received February 23, 2019, accepted March 6, 2019, date of publication March 11, 2019, date of current version March 29, 2019.

Digital Object Identifier 10.1109/ACCESS.2019.2904122

Context-Enriched Regular Human Behavioral Pattern Detection From Body Sensors Data

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This work was supported by the Deanship of Scientific Research at King Saud University through the Research Group Project under Grant RGP-281.

ABSTRACT Extracting indicative characteristics from the sensor data provide diverse avenues for improving the well-being of the elderly people living alone in their homes through understanding and identifying their behavioral patterns while considering any environmental changes. In this paper, we present a new model to explore the challenges associated with mining patterns from the body sensor data and their potential use in discovering regular human routines through mining periodic patterns from a non-uniform temporal database. The non-uniform nature of the temporal database adds more challenges to the mining of periodic patterns as the items may have different periodicity and frequency occurrences. Another challenge is how to discover the correlation between the discovered patterns. In addition, we examine the context-enriched periodic patterns which provide more insights about residents' health. A new algorithm for the contextualized-correlated periodic pattern mining from a non-uniform temporal database is presented along with an extensive evaluation of its performance using a real-life dataset.

INDEX TERMS Activity monitoring, Apriori, body sensors, FP growth, productive periodic frequent patterns, smart data, temporal database.

I. INTRODUCTION

Wearable body sensors have generally been utilized along with data analytics to monitor and track human behaviors. Wearable health devices such as fitness trackers and smartphones with embedded sensors have been greatly influential and have increased the accuracy of tracking and monitoring one's health conditions. For healthcare domains, sensors data analytics can help caregivers evaluate and provide personalized patient assistance through monitoring of patient body sensor data [1]–[3]. Such application can help prevent negative health outcomes in elderly people who live alone in their homes or detect any abnormal lifestyle-related activities that can be early signs of cognitive diseases [4]–[8]. More specifically, analysis and learning of human behavior must be performed to enable users to retain smart digital assistance related to their personal lifestyle [9]–[12].

Activity tracking applications such as Fitbit and Argus add more insights to improve user well-being and self-knowledge by continuously monitoring the diverse space of users' current actions at any point including sleeping, exercising, diet, or even commuting actions. When people with cognitive impairment fail to complete their activities of daily living (such as 'use-toilet' or 'taking medication' at the right time), caregivers are typically responsible for tracking their behavior and taking the proper action [13]–[17]. For example, when ''diabetic glucose'' measurements increase or decrease from the regular daily values, a prompt is sent to provide assistance. Additionally, if the heartrate (HR) increases sharply multiple times after exercising, there is no need for any abnormality alarm as the context of the patient has been changed by doing exercises.

However, there are some challenges associated with the monitoring of patient performance using body sensor data, which impact behavior learning and tracking. In particular, the captured sensor data contain (1) periodic parameters, (2) interdependency, and (3) time-variance based on context.

The associate editor coordinating the review of this manuscript and approving it for publication was Giancarlo Fortino.

First, people are creatures of habit [15] and exhibit regularity in following their normal lifestyle [9], [10], [16]. For example, *the normal blood sugar (BS) level is less than 100 mg/dL before eating meals for at least* 8 *hours. Within 2 hours after eating, the level should be less than 140 mg/dL. During the day, the normal BS levels tend to be at their lowest values just before meals*. Therefore, normal human behavior often follows a pattern of periodic recurrence in which the same action tends to recur at certain, regular intervals. Second, some of these periodic behaviors are interdependent and co-occur frequently with other actions in the short and long term (e.g., increase in BS after eating, reading before going to bed, or using the toilet after waking up) [18], [19]. It is important to exploring the correlations of actions to provide users with what they need or prompt the right action at the right time without asking them explicitly. For example, *while modeling the user actions in exercising, certain actions will follow such as drinking water or the HR falling off sharply after running*. Third, over time, contextualized and accurate learning of collected user data could further help health providers accurately understand or detect any abnormality in users' health conditions. For example, *the caregivers may need to modify the diagnostic paradigm to suit the evolving characteristics in patient performance*. Thus, a context-aware approach is required [20]–[22].

In light of wearable smart sensors and ambient assisted living, great advances have been made in modeling human behavior patterns, in particular in the space of activity modeling and tracking or recommender systems [23]. These works have focused in modeling human behavior through repeated actions from captured videos, images, or websites [20], [24]–[27]; action prediction [20], [28], [29]; periodic action prediction [16], [25], [26]; or learning context [20]–[22]. These works have not jointly modeled all these key aspects of user actions (periodicity, interdependence, and context variation). However, failing to account for any of the action characteristics results in degradation in prediction performance.

Consider the following scenario, which illustrates how personal actions are periodic and correlated and can change depending on the context. *Sara lives alone in her house. Every morning, Sara goes to the park for a walk and does some exercise. She returns home and takes a shower, then starts eating her lunch. However, on Monday, she has a family visit, and they eat lunch outside her house. Sometimes, when it rains, she doesn't leave the house and watches TV.*

If we want to model a schedule for ''exercise'' activity, we have to model the periodicity of exercising (i.e., every day except in raining weather) and the following activities (''enter home'', ''take a shower'', then'' eat''). The routine will be changed if it is raining.

In our current work, we present a new model for the task of modeling users' actions. First, we handle the temporal features of human activity patterns through mining periodic patterns from a temporal sensor database. A temporal database is a collection of dissimilar patterns (in terms of support count and periodicity) matching usual human behavior ordered by their timestamps. Determining the periodic patterns in a given temporal database has two important sub-tasks: the first task is how to determine the periodic interestingness of patterns and then how to find the periodic patterns using such an interestingness measure. Seminal works have considered pattern-growth and its variation to find the periodic patterns from transnational data or time series data. However, determining the periodic interestingness of the patterns from temporal database is a non-trivial task since there are multiple items with the same inter-arrival time. Moreover, there are usually time gaps between consecutive observations. The current line of periodic pattern mining approaches has made a great achievement in discovering temporal patterns. Unfortunately, such approaches assess the interestingness of a pattern by only taking its support into account. Another major limitation of these studies is that they consider time series as a symbolic sequence of itemsets and ignore the temporal occurrence information about events in a series. This paper addresses these challenges by exploring a new measure(s) to explore the periodic interestingness of the patterns discovered from temporal databases while considering the multiple patterns occurrences timestamps and allow time gabs. Unlike existing periodic-mining algorithms, a new model is presented to discover correlated periodic patterns from non-uniform temporal databases. For each database item, the user has to identify a maximum activity observation time (MAOT) to the database. Thus, different patterns may satisfy different period depending on their items' MAOT values.Additionally, a new periodicity measure (namely, the interested-recurrence period of activity (IRPER)) is used to to extract the elapsed time between pairs of database items. Thus, the non-uniform distribution of items in a database is captured efficiently using user-defined arrival time value and periodicity measures. We also propose a new tree structure and a pattern-growth algorithm that discovers the complete set of periodic patterns. As the dependency between patterns varies across actions, a productivity test is used to find the correlation between various numbers of activity patterns.

Nevertheless, learning context during periodic pattern mining will increase the accuracy and productivity of the mining results. In different applications domains [30]–[32], [32], context encoded as *Features* for the model and the model variables must be represented in a single scale. For example, considering only day as a context variable as opposed to the whole weekend. However, this can be risky in light of the fact that the most reasonable scale depends on the feature selected. Moreover, these models will not scale well with the addition of more context features, and still need still require further research to be applicable to real-world applications. Also, Context are modeled as *rules* in the model analysis which limits the model's flexibility by adding more factors to the context learning process. Finally, some approaches model the context as a *slicing dimension* in the data-preprocessing step by creating a different model for each context variable. This methodology has been proven to be more effective in context learning process. In our current work, we extend the regular pattern mining algorithm by adding the context as a slicing dimension to provide a continued learning process of human behavior patterns without storing the monitored data. A new tree structure is defined to capture the context variation of users. To the best of our knowledge, this is the first study that considers the problem of finding contextualized correlated periodic patterns of temporal databases.

Our proposed model flexibly mine the temporal database with the specified users' constraints for the arrival time interval of each activity with one database scan over the collected data. Additionally, the correlation between the discovered patterns is identified, and any random pattern is discarded. Finally, we manage the different context parameters for exploring the unnoticed interestingness of the discovered periodic patterns.

A. CONTRIBUTIONS

1) We explore the problem of mining and assessing the periodic interestingness of human actions through mining a non-uniform temporal database of human actions using a novel tree-based data structure called a Temporal Correlated-Periodic tree (TECP-tree) with a single database scan. Our algorithm allows database items to have different periodicity values by letting the user specify an inter-arrival time for each item.
2) We then design an efficient FP growth-inspired algorithm TECP-growth to recursively mine the TECP-tree.
3) We model the interdependency between the discovered patterns through a productiveness test to ensure only the correlated users' actions are discovered.
4) To adapt the user context to the mined patterns, we model the context variation of users' actions that may otherwise go unnoticed in the TECP-tree and devise a new-context TECP-tree.
5) We demonstrate the usefulness of the proposed algorithm through mining various users' activities and daily routines and comparing the findings with the current existing algorithms.

II. RELATED WORK

Over the last few decades, body sensor data mining has led to many accomplishments and solutions for understanding human life routines. Furthermore, temporal features discovered from body sensor patterns add more important insights for the purpose of monitoring human daily life and wellness tracking. For instance, these data can help provide a complete view of the patient's situation and determine the regular values of body measurements [33], [34]. In this section, we will review some of the recent work related to learning human behavior patterns. First, we will review some recent human behavior learning and monitoring approaches. Then, we will review some of the work related to human behavior pattern mining from sensor data.

A. LEARNING AND MONITORING HUMAN BEHAVIOR APPROACHES

The scientific research community has effectively addressed the idea of remotely monitoring patients' health status using smart wearable sensors.

With the widespread development of Internet of Things technologies in the context of wellness and healthcare, the remote screening of human daily life has led to improved quality of life by reducing or even preventing critical events (e.g., preventing the most probable death causes like heart attack).[1]

A real-time analysis for processing and extracting knowledge from wearable sensors (such as accelerometers, proximity sensors, HR-monitoring chest straps, and gyroscope data) guided various innovations and improvement in tracking health conditions and diagnostic procedures. Greco *et al.* [1] proposed an Internet of Medical Things architecture for real-time analysis of a stream of data from wearable sensors. The architecture is composed of 4 layers: sensing, pre-processing, cluster processing, and persistence. After collecting and pre-processing the data, the cluster processing layer is used to collect semantic data and detect any abnormality. Finally, any further analysis needed can be done using the collected data stored at the persistence layer. Similarly, Suryadevara and Mukhopadhyay [2] present a monitoring system based on Wireless Sensor Network technology. The system is capable of monitoring home residents' vital signs like HR and motion rate. The system prompts an alert for any connected caregivers if it detects any abnormality event in body measurements due to falls, tachycardia, or bradycardia. Elbayoudi *et al.* [35] introduce a new approach for understanding any progressive changes in human behavior. The proposed approach can find the relationship between the gathered sensory data and interpret them in a meaningful manner using trend analysis techniques when interpreting human behavior. In [36], the Walking and Transition Irregularity Detection using an Artificial Neural Network model is designed to determine abnormalities in walking and transition pattern. The experimental analysis of the proposed model shows that the model can accurately determine the irregularities with 100% accuracy in the postures. Kim and Cho [37] present a new system for web traffic anomaly detection. Web traffic data are the amounts of website data sent and received by online users. The proposed system uses a hybrid of the convolutional neural network and the long short-term memory recurrent neural network known as C-LSTM.

The goal of human tracking is to identify the next event based on occurrences of past events [33], [38], [39]. The Active LeZi (ALZ) algorithm [40] approaches have achieved great success in this area. Without requiring any domain-specific information, the ALZ algorithm provides an online sequential activity prediction framework for tracking human behavior. The developed sequential prediction algorithm was experimentally analyzed on MavHome smart home environ-

[1]World Health Organization Statistics, 2017, http://www.who.int/mediacentre/factsheets/fs310/en/

ment collected data [41]. In [42], the researchers presented LeZi-update, an algorithm for the prediction of a resident's location as application in cellular communication-connected networks. The LeZi-update model uses an unsupervised pattern-matching algorithm to provide an alphabetic symbol representing the sensed smart environments. In this way, the algorithm is a string of symbols capturing the resident's movement history.

Furthermore, Cook *et al.* [41] propose an architecture to detect any abnormal situation in smart environments using a multi-agent architecture. This architecture has a component layer for human activity prediction that works in a similar way as the active LeZi algorithm. Additionally, Tapia *et al.* [43] introduce a prompt system using the activity-prediction component. The system automatically fires a textual or verbal prompt to prevent accidents. Additionally, Mahmoud *et al.* [44] build a prediction model for predicting elder behavior in smart environments. The researchers also employ a different type of artificial neural network to build their model. The experiment analysis claims that the recurrent neural network can achieve seminal results in the discovery of temporal relationships between activity patterns.

To overcome the offline data segmentation limitation of the proposed work, the researchers in [45] discuss an extension of their approach to provide a real-time general activity-prediction model. A sliding-window technique was used to extract activity features over the real-time collected data. Recently, an activity-forecasting algorithm was proposed by Minor and Cook [46] for activity prediction from a smart home. The algorithm can automatically forecast the time of the resident's activities using a regression tree classifier. Additionally, Kurashima *et al.* [9] discuss a model for predicting the higher set of resident actions that will occur such as going for a run or watching a movie.

Despite the great ability of the proposed models to predict activity patterns, many of them are typically designed for constrained situations with pre-segmented data. Moreover, many other works cannot discover the periodic behavior routine and ignore the interestingness of adding context to human behavior while discovering their habits. Moreover, some approaches use Markov models to capture the dependencies between human actions with works such as Unix commands [47], interface adaption [48], clicks on web search [49], user behavior anomalies, and future location-based check-ins [47], [50], [51]. However, Markov models are inefficient in capturing the dependences in huge search-space since the overall state-space will grow exponentially in the number of time steps considered [51].

B. PATTERN-MINING APPROACHES

Another set of approaches for modeling and predicting human situations is based on mining behavioral patterns. An infinite sequence of collected data generated from resident tracking and monitoring wearable devices is defined as a stream. Several researchers have focused on automatic recognition of simple and complex daily life activities from stream data [42], [52], [53], such as walking, cooking, and taking medication.

FP-mining algorithms discover the frequently occurring patterns in a given dataset. An item is considered a frequent pattern by counting repetitions with respect to the given user constraint. Frequent patterns can efficiently model human behavior [54], [55]. In the activity tracking and modeling applications, if a resident's behavior has occurred enough times, it is considered a frequent behavior pattern. Recently, there is an increasing trend of using sequential FP-mining algorithms from smart home data. Moreover, the mining algorithm can be adequately performed on small computing devices such as mobile phones [55]. FP-mining approaches [56] have been applied in smart home stream data to generate sequential patterns through multiple passes. Some of the streaming FP algorithms use a sliding-window technique to keep the most recent frequent pattern. When a new observation is inserted into the database, the older data are discarded, and new data are added. The window size keeps growing to adapt to the incoming data [57], [58]. Despite the seminal work achieved through sequential FP-mining approaches in learning human behavior, some particularities are not handled by these common algorithms like handling the ordering of activities, dependences, and user context.

TiMe [59] is an efficient framework for mining FP from stream smart home data. TiMe is an unsupervised pattern-growth-inspired approach. A prefix-tree is used to summarize the stream data considering both time and context data. A sequential pattern learned through the model can help to schedule the resident's activities efficiently. Additionally, the context variation can be added to accurately model human behavior.

The discovery of temporal relation between human patterns can add more insights into human life; for example, "Dressing" and "Leaving the House" activities often co-occur in the morning. In [60], the researcher presented an algorithm to define the temporal resident activities given a user-defined calendar schema. An association rule mining algorithm is used to define the temporal relation between user patterns during time intervals. Although mining temporal association rules is well defined and researchers have devised a number of algorithms in the literature to efficiently discover temporal activities patterns, some challenges remain.

Nazerfard [33] proposed a Temporal Features and Relations Discovery of Activities (TEREDA) framework for predicting human behavior considering the temporal features of activity pattern. An FP growth-inspired algorithm is used to find association rules of human patterns, and then the Expectation Maximization (EM) clustering method, is used to classify the discovered activities based on the time of their occurrence. The discovered temporal relations can be used to detect any abnormality or prevent any health obstacles. For example, the "Eating" activity has a 50% likelihood of being a successive activity of "Taking Medication". However, while the discovered patterns well addressed the dependencies between human patterns, the number of generated patterns could be cumbersome and confuse the caregivers regarding how to choose or expect the next activity between the discovered patterns. Additionally, the mining time will increase with the number of observed stream data.

In [59], the Extended Episode Discovery algorithm is described to detect regular activity patterns in smart homes. The algorithm first searches sequentially for frequent episodes characterizing human patterns using an FP growth-mining algorithm. Then, a Gaussian Mixture Model searches for the periodic episodes to discover the most interesting ones, which increase the computation and evaluation time of the episode's discovery process.

Similar to our problem, a number of seminal works have considered the task of discovering periodic patterns from a transactional database. The periodic-frequent pattern is defined as an important class of interesting patterns that occur frequently and periodically in time series data. A great deal of attention has been paid to the problem of finding these patterns [62], [64], [65]. All of these studies have considered time series as a symbolic series, and the events' temporal occurrence information has been ignored. Tanbeer *et al.* [62], [65] have devised many algorithms for periodic pattern mining from a transactional database.

A prefix-tree structure is used to compress the given dataset, and then a pattern-growth is used to discover periodic patterns using double scan over the given data. The periodicity measure that was used, *MaxPer*, cannot discover patterns that occur partially in the database and, thus, could lead to missing important patterns. To overcome the mentioned limitations, a number of studies have considered different periodicity measures to characterize the periodic pattern, but still, the non-uniform nature of the temporal database has not been resolved. A temporal database has different observations with the existence of timestamps. Different items may occur with different inter-arrival times to the database and, thus, different periodicity values. Venkatesh *et al.* [63] provide a new algorithm to mine the periodic patterns from a temporal database. A new measure, periodic-ratio, is used to record the different pattern periodicities. The algorithm devises a simplified model to discover interesting periodic patterns, but it does not consider the correlation between the discovered patterns. Moreover, the double passes over database items make it difficult to apply over stream data, as in our case [63], [66], [67].

As certain patterns may have some correlation with some other patterns, another line of work considers the correlation between periodic patterns to eliminate the randomly generated patterns. In [61] and [67]–[69], the body sensor data correlation is examined, and the correlation (high HR, high blood-pressure) can be efficiently discovered and modeled. However, how to discover such information from a temporal database is an open issue that must be resolved. Context-aware batch learning algorithms have also been proposed [21], [22], [70]. To sum up, the discovered challenges are as follows:

- First, the body sensor dataset includes timestamps. The timestamps imply the time of activity occurrence or, specifically, the sensor triggering time. Moreover, each dataset item can have different time gaps and regularity values. Despite the great achievement of the proposed works, this issue is neglected.
- Second, how to discover the temporal dependencies between discovered patterns from a non-uniform temporal database.
- Third, context-aware mining algorithms use batch processing and have not adapted to stream-mining algorithms. Thus, an algorithm to consider stream mining of contextualized behavior patterns is important to provide accurate learning of behavior patterns.

This paper addresses these challenges. Unlike existing periodic-mining algorithms, a new model is presented to discover correlated periodic patterns from non-uniform temporal databases. For each database item, the user has to identify its arrival time to the database, and a new periodicity measure is used to assess the different period of each database item. Thus, the non-uniform distribution of items in a database is captured efficiently using user-defined arrival time value and periodicity measures to extract the elapsed time between pairs of actions. We also propose a new tree structure and a pattern-growth algorithm that discovers the complete set of periodic patterns. As the dependency between patterns varies across actions, a productivity test is used to find the correlation between various numbers of activity patterns. Finally, a new tree structure is defined to capture the context variation of users. To the best of our knowledge, this is the first study that considers the problem of finding contextualized correlated periodic patterns of temporal databases. Table 1 summarizes the major characteristics of the proposed work compared to activity-monitoring and pattern-mining approaches.

III. PROBLEM DEFINITION AND PROPOSED FRAMEWORK

This section presents the definitions used for modeling and factorization of human behavior to retrieve interesting patterns and their occurrences. Let a set of user activity labels $A = \{a_1, a_2, \ldots, a_n\}$ be generated from a set of sensors $S = \{S_1, S_2, \ldots S_n\}$ disseminated in a smart home. A set of activities a_i is called a pattern. A pattern containing k items is called a k-pattern. The length of this pattern is k for an epoch $epch = (epid; ts; Y)$ such that $X \in Y$, the sensors' generated events (epoch) are composed of the triggered sensor' identifier (*epid*), an occurrence' timestamp (ts) and Y is an itemset occurring in an epoch. An activity pattern a_i may have multiple inter-arrival time intervals (MIAT) during the day - for example, a MIAT in the morning or noon. A temporal Sensor database *TSDB* is an ordered set of epochs, i.e. $TSDB = \{epch_1, epch_2.epch_m\}$, where the $m = |TSDB|$; represents the size of *TSDB*. Let the maximum and minimum timestamp in *TSDB* is ts_{max}, and ts_{min} respectively. Let the ordered list of observations' timestamps of activity a_i in

TABLE 1. Summary of the characteristics of activity mining and monitoring approaches.

Approach	Temporal feature discovery	An observation is . . .	Objective for end user	Periodicity	Correlation	Context-awareness
[62]	No (timestamps are not considered)	Transactional DB	Periodic pattern discovery	Yes	Yes	No
[63]	No	Stream transactional DB	Regular pattern discovery	Yes	No	No
[64]	Yes (timestamps are considered)	Non-uniform temporal DB	Periodic pattern discovery	Yes	No	No
[34]	Yes (clustering)	Activity stream	Frequent activity mining and their succession	No	No	No
[60]	Yes (clustering and description with GMM)	Activity stream	Periodic episode discovery and description	Yes	No	No
[22]	Yes (clustering and description with GMM)	Single source sensor data	Contextualized frequent activity occurrences	Yes	No	Yes
Current work	Yes	Non-uniform temporal sensor data	Contextualized periodic human patterns discovery	Yes	Yes	Yes

(activity , Enter_Home, 2017-03-02 6:15:45 , 2017-03-02 6:15:45) ,
(activity , Relaxing, 2017-03-02 6:20:25 , 2017-03-02 6:28:13) ,
(activity , Cooking, 2017-03-02 6:45:15 , 2017-03-02 6:58:33) ,
(activity , Eating, 2017-03-02 7:10:11 , 2017-03-02 7:10:11) ,
(activity , Take Medication, 2017-03-02 7:10:11 , 2017-03-02 7:10:11) ,
(activity , Enter_Home, 2017-03-03 6:10:37 , 2017-03-03 6:10:37) ,
(activity , Eating, 2017-03-03 6:22:25 , 2017-03-03 6:30:34) ,
(activity , Take Medication, 2017-03-03 6:48:15 , 2017-03-03 6:57:56) ,
(activity , Relaxing, 2017-03-03 7:12:03 , 2017-03-03 7:12:03) ,
(activity , Enter_Home, 2017-03-04 7:43:16 , 2017-03-04 7:43:16) ,
(activity , Relaxing, 2017-03-04 8:00:25 , 2017-03-04 8:23:49) ,
(activity , Eating, 2017-03-04 8:20:17 , 2017-03-04 9:35:09) ,
(activity , Enter_Home, 2017-03-05 7:35:41 , 2017-03-05 7:35:41) ,
(activity , Cooking, 2017-03-05 7:40:11 , 2017-03-05 7:55:01) ,
(activity , Eating, 2017-03-05 8:18:46 , 2017-03-05 8:18:46)

FIGURE 1. Toys' story input stream.

TSDB be $COVts_{(X)} = (ts_{Xa}, ts_{Xb}, \ldots, ts_{Xc})$, *abc*. The support count of a_i in *TSDB* is the total coverage of a_i in *TSDB* divided by the database size and is denoted as

$$SuptSDB(a_i) = \frac{COVts(a_i)}{|TSDB|}. \quad (1)$$

Example 1: A toy example dataset with 15 events spanning four days ($d1$; $d2$; $d3$; $d4$) presented in Figure 1. Five activity labels (i.e. "Enter Home", "Cooking", "Eating", "Take Medication", "Relaxing") are used as a running example.

Table 2 is the TSDB extracted from Fig1. In the first sequence of activities, $epch_1 = (S1;1;$ "Enter Home", "Cooking", "Eating", "Take Medication"), $S1$ represents the *epchid*, 1 represents the occurrence' timestamp of this epoch and the remaining labels represents the activities occurring in this transaction. Other epochs in this database follow the same representation. The TSDB database size is m = 12. The minimum timestamp $ts_{min} = 1$, and maximum

TABLE 2. Sequence of epochs generated from Fig. 1.

S1:	(Enter Home, Cooking, Eating, Take Medication, 1)	S8	(Enter Home, Eating, 8)
S2:	(Enter Home, Take Medication , 3)	S9:	(Enter Home, Cooking, Take Medication , 9)
S3:	(Cooking, Take Medication , 3)	S10	(Enter Home, Cooking, Eating, Take Medication,10)
S4:	(Enter Home, Cooking, Eating, 4)	S11	(Eating, Relaxing, Take Medication , 11)
S5:	(Enter Home, Relaxing, Eating, 5)	S12	(Eating, Relaxing, 12)
S6:	(Cooking, Take Medication ,6)		...
S7:	(Enter Home, Take Medication , Relaxing, 7)		...

timestamps $ts_{max} = 12$. Many routine behavior observations can be extracted from the database, such as (Enter Home, Relaxing, or Cooking and Eating). The pattern $P(Ce)$; "Cooking", "Eating" occurs three times in epochs whose timestamps are 1, 4 and 10, respectively, with MIAT occurred in full-day constraints. Therefore, $Ts(Ce) = (1, 4, 10)$. The length of this pattern is 2, and $Sup(Ce) = 3/12$.

Definition 1 (A Frequent Activity Pattern a_i): is an activity a_i that has a total number of observations greater than or equal to the $minsup(ai)$ value given by a user in specific time points in a circular time space, i.e. every day.

To achieve the goal of having lower periods of frequent candidate activities and, at the same time, increasing the period for frequently occurring activities without missing any values, we allow the user to identify his or her preferable maximum activity observation time.

Definition 2 (Period of Activity a_i): Let MAOT be the user-defined maximum activity observation time for an activity a_i. The period of pattern X, denoted as PER(X), represents the maximum occurrence timestamp of all item in X;

$$PER(X) = max(MAOT(Y, Z)), (Y, Z) \in X). \quad (2)$$

Example 2: Let the MAOT values for the activities "Cooking", "Eating" be 5 and 10, respectively. The period of the pattern "Cooking", "Eating", i.e., *PER*(Cooking, Eating) = max (5; 10) = 10.

Definition 3 (The Interested-Recurrence Period of Activity a_i): Let $ts_{(j+1)}(a_i)$ and $ts_(j)(a_i)$; represent the consecutive timestamp occurrence of activity a_i in TSDB. The period of activity a_i denoted as $PR_1(a_i) = ts_{(j+1)}(a_i) - ts_{(j)}(a_i)$, represents the difference between two consecutive occurrences of the activity in a cyclic period. The period of activity of interest a_i, denoted as IRPER(a_i), represents all periodic values PR(a_i) for activity a_i whose value are less than or equal PER(a_i):

$$IRPER(a_i) = (PR_1, PR_2..PR_n), \quad (\forall PR(a_i) \leqslant PER(a_i)). \tag{3}$$

Example 3: From Example 2, the MAOT values for the activities "Cooking", and "Eating" is 4. The occurrence period of the pattern $Ts(Ce)$; (Cooking, Eating) = {1, 4,10} and PER(Cooking, Eating) = {3, 7}. Now the interesting-recurrence period IRPER(Ce) = {3, 7} as their values are less than MAOT(CE) = 10.

Based on the toy dataset, one can observe that, for normal daily behavior, humans follow different routine activities within a day (e.g., Entering Home, Cooking, Eating, Relaxing). Moreover, each activity has a preferential occurrence time (mean), and it can vary (standard deviation) within a day, for example, sleeping in the afternoon (for 1 hour) or sleeping in the night (for 7 hours). To allow such flexibility, we use the following formalism.

Definition 4 (The Occurrence Interval of Activity a_i): Let (IPX∈ Per(X)) be the set of interested periods such that, $\forall p \in IPX, p \leqslant$MOST. Then the periodicity of activity a_i is defined as occurred in time interval $[ts - \sigma, ts + \sigma]$ with average periodicity (ts) with standard deviation σ. where $ts = avg(IPX)$ and $\sigma = \sum_k^n \frac{(IPX - ts(IPX))}{n}^2$

Definition 5 (Problem Definition): Given a temporal sensor database TSDB, a user-defined minimum support threshold $Sup_{TSDB}(a_i)$, maximum period $maxPrd$, minimal-itemset occurrence threshold MOCL, periodicity measure per, a pattern a_i and period of interest IPX. a_i is periodic frequent sensor pattern if:

$$\begin{aligned} &Sup_{TSDB}(a_i) \geqslant \omega, |LIP^{a_i}| \geqslant MOCL, \\ &\quad (per - D) \leq (avgPr(LIP^{a_i}) - std(LIP^{a_i})) \\ &\qquad and(avgPr(LIP^{a_i}) + std(LIP^{a_i})) \leq (per + D). \end{aligned} \tag{4}$$

IV. PROPOSED MODEL

Fig. 2 illustrates the architecture of the Temporal Discovery of Contextualized-Correlated Periodic-Frequent Patterns (TEDCP) model for discovering the key human behavior with all three key properties: (1) periodicity, (2) correlation between actions, and (3) context propensities of actions. The TEDCP model consists of two main components the temporal feature and relation discovery and the adaption component. Each component will be described in more depth in the following sections. The proposed TEDCP model is an unsupervised learning model; it avoids the need for a human activity labeling process. The input is a stream of sensors' epochs collected from various sensors disseminated in smart homes. Each epoch has an optional activity label, sensor identifier, and timestamp. Each iteration of the TEDCP model has three steps:

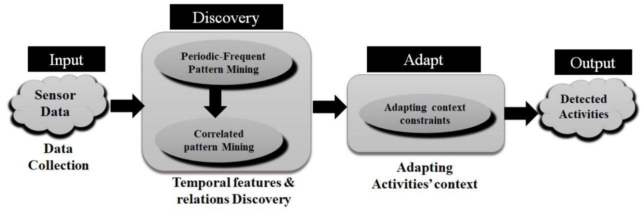


FIGURE 2. The proposed model architecture.

- The discovery of periodic-frequent patterns (Section IV-A),
- The factorization of the most interesting periodic patterns through correlated pattern mining (Section IV-B), and
- Adaption to context constraints via contextualized periodic pattern mining (Section IV-C).

A. THE DISCOVERY OF PERIODIC-FREQUENT PATTERNS

The first component in the TEDCP model is the temporal analysis of user actions for the discovery of his or her daily routine. The input stream presented in Fig. 1 as an example has a set of epochs' observations. Each epoch is represented as $epch = \{Activity_{name}, sensor_{id}, ts_{strart}, ts_{end}\}$. In line 1, the tuple indicates that the activity "Enter Home" starts on March 2 and ends at the same time.

After preprocessing the input stream to match the structure given in Table 2, the algorithm compresses the collected events into a Temporal Correlated-Periodic tree (TECP-tree). The TECP-tree summarizes the database in a way that can be used by an FP-growth-like mining algorithm to find all periodic activities patterns. The pattern-mining phase runs only at the end of each day. In the following subsections, we discuss the details of TECP-tree structure design and construction and then explore the details of mining periodic patterns.

1) TECP-TREE DESIGN AND CONSTRUCTION

Several approaches have been discussed in the literature to address the problem of discover frequent patterns. Aggarwal *et al.* [71] propose the first generate-and test approach to discover frequent patterns with multiple database scan. Several improvement have been made to this approach, to overcome the limitation related to increase in mining time with more items being inserted to the database. Han *et al.* [72] devised a new model to generate the frequent patterns without any candidate test using a divide-and-conquer strategy. Fp-growth works as follows: first it summarize the input transactional database information by creating an FP-tree instance. Subsequently, it uses a recursive process to divide the compressed

Algorithm 1 Periodic Patterns Mining Algorithm

Input : *STDB*: a sensor time series database, X: set of items, *sup*: support counts,*MOTS*: minimum interval time, *Per*: periodic-support

Output: A set of periodic patterns

1 Let $t = tscur\ X$ denote the current transaction timestamp with *tscur* for pattern X ;
2 **foreach** *epoch* $tscur \in STDB$ **do**
3   **if** $ti \neq NULL$ **then**
4   **foreach** *(item* $x \in X$*)* **do**
5   **if** $support(x) == 0$ **then**
6   /
7   **end**
8   * it is first occurrence */ Set $sup(x) = 1$ and $TC = tscur$;
9   **if** $tscur - TC \leq MOTS$ **then**
10   add $tscur - TC$ to $tscur.IRPR$;
11         $Per(x) + +$;
12   **end**
13   Set $+ + sup$ and $lt = tcur$;
14   **end**
15   **end**
16 **end**
17 Insert all calculated values for x into $TECP - HT$;
18 Sort the candidate items in $TECP_H T$ in support descending order of their *MOTS* ;
19 values items with similar *MOTS* values are sorted in support descending order ;
20 Call build-tree($TECP - HT$, Tree);
21 Update $TMCP - HD$ table;
22 Call $TMCP - growth$ ($TMCP - Tree$, null);

database into a set of conditional tree and its pattern base tree to generate the complete set of frequent patterns. Using this strategy, the FP- growth algorithm reduces the number of database scans efficiently and eliminate the requirement of multiple candidate generation. FP-growth algorithm is an efficient and scalable test-only approach (i.e., does not generate candidates, and only tests for frequency). However, the static nature of the FP-tree still limits its application in many real life application that may have huge amount of continues data like the stream data. Moreover, it only handles the frequent items in a database and it is a two-pass solution [73].

A TECP-tree has two components: a TECP-HT header table and a prefix tree. The TECP-HT consists of each database item (*act*) with *MOTS*, support (*sup*), periodicity (*per*), current occurrences' timestamp ($ts - current$), and a pointer to link all item occurrences in the prefix-tree with the first node. The structure of the TECP-tree resembles the prefix-tree in an FP-tree node [72]. However, the nodes in the TECP-tree do not capture the items' frequency; instead, the TECP-tree has an occurrence timestamps list, $ts - list$, to keep the items' arrival times for each epoch in the database. The $ts - list$ is maintained at the last node of every epoch. Now, we will explain the TECP-tree construction process. Algorithm 1 is used to discover the complete set of periodic patterns as follows.

The tree is constructed with one database scan. When a new sensor reading is observed, an activity sequence is created. For example, from the input stream given in Fig. 1, some sequences are obtained as in Table 2. For each new sequence, the $TECP - HT$ is updated with their minimum occurrence timestamp (MOTS), support, and periodicity values (lines 1-16 in Algorithm 1). An ascending order of MOTS is used to resort the header table to resolve memory (line 17). Then, the TECP-tree building procedure is executed (line 18). The root node is created and labeled as "null" (line 1 in Algorithm 2). For each sequence, if the activity is new, then a head-node is created with its label from the empty root. If a node already exists, then we have to check and update the ts-list with the epoch id at the tail node. Otherwise, a head-node is created (lines 2-10 in Algorithm 2).

Algorithm 2 Build-TMCP-Tree (TMCP-List, Tree)

Input : $TMCP - list$ and *Tree*

Output: Updated TECP-Tree, Updated TECP-HD-Table.

1 Create an empty root node ;
2 **foreach** *(sorted epoch l from the given L TMCP-list)* **do**
3   **if** *(l has child N such that* $l.name \neq N.name$*)* **then**
4   Create a new node N and add $N.parent$ to the tree ;
5   **end**
6   Update N-structure by joining its nodes with similar nodes names ;
7   **if** *(l is the final item in the of* $TMCP - list$ *& N is ordinary node)* **then**
8   Assign an epchid-list to N ;
9   update epchid-list ;
10   **end**
11 **end**
12 Call Build-TMCP-tree (L, N) ;

Fig. 3(a) shows both the *TECP-HT* and TECP-tree generated by scanning the first epoch "S1" (line 1 in Algorithm 1), "Enter Home, Cooking, Eating, and Take Medication", which leads to adding a new node to the tree and update its entries in the *TECP-list*. After inserting S5, all *TECP-HT* entries are updated, and no new nodes are created since the node already exists. "Cooking" and "Take Medication" and ts-list are added at the tail-node with $ts = 5$ as shown in Fig. 3b and c. Finally, for each entry in the header table, items with periodicity observations less than PER are eliminated; then, the remaining items in *TECP-HT* are sorted in ascending order of their *MOTS* values (Algorithm 3). To achieve memory efficiency, support-descending order sorting is used for items with similar MOTS values. This sorting is reflected in the TECP-tree as well by using Branching and Sorting method [72]. Fig. 3(d) shows the

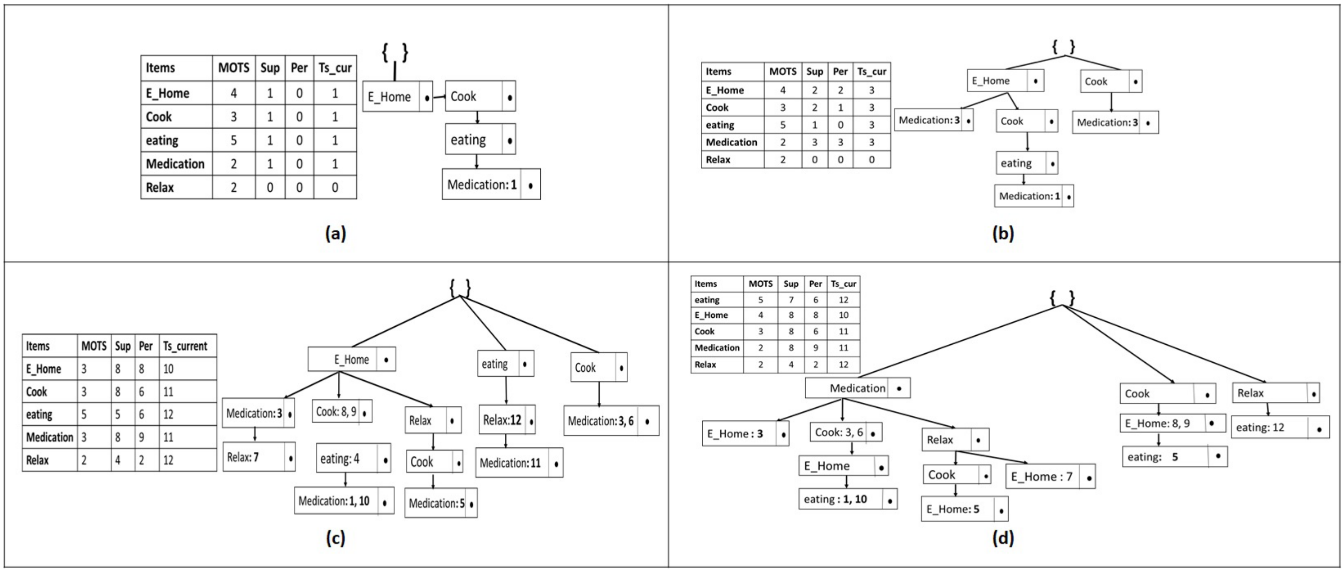


FIGURE 3. The TECP-tree construction process. (a) TECP-tree after inserting the first epoch. (b) TECP-tree after inserting the third epoch "S3." (c) TECP-tree after scanning the entire database. (d) The final sorted TECP-tree.

Algorithm 3 TECP-Growth(*tree*, α)

```
foreach (bottom-most item I in TECP) do
    if (I is periodic-frequent item) then
        Generate pattern β = I ∪ α ;
        Construct the conditional-base for the periodic β
        pattern ;
    end
    Call TECP-growth(S_β-Tree, S_β) ;
    Remove node I from the tree and push the
    epchid − list to its parent nodes ;
end
```

sorted TECP-HT and TECP-tree. The following discussion explains the TECP-growth algorithm that discovers the complete set of periodic patterns from the TECP-tree.

2) THE PATTERN-MINING PHASE

TECP-growth is an unsupervised FP growth-inspired algorithm used to mine the TECP-tree. For each node of the prefix tree starting with an initial length-1 X suffix pattern, we calculate the $Xs-$'$IRCEP$ set of periodicity values. Algorithm 3 describes the procedure for finding periodic patterns in a TECP-tree.

1) If the IRCEP is matched with the user requirement, then consider this pattern a periodic-frequent length-1 pattern.
2) Construct X suffix pattern sub-database with the set of prefix paths in the TECP-tree.
3) Construct X conditional TECP-tree.
4) Recursively mine the pattern TECP-tree.
5) Concatenate the suffix of X-pattern with the periodic patterns generated from the conditional TECP-tree.
6) Finally, prune the X suffix pattern from the original TECP-tree and update the TECP-HT as well.

B. DISCOVERY OF DEPENDENCIES BETWEEN ACTIONS: CORRELATED PATTERN MINING

Discovering temporal relations among human actions can leverage more insights into the daily daily routine. The correlations among the discovered periodic patterns will help in determining the order of activities and randomly eliminate co-occurring activities, i.e., we can explore the more productive probable activities following a specific activity. Through the "temporal relation discovery" component, we explore the possible correlated activities patterns. These patterns of actions can be cyclic in all databases or even occur within a short period. To leverage these correlations among actions and report only the associated behavior patterns, we use the productive-association test as proposed in [74] as follows.

Property 1: An periodic frequent pattern, A in $TSDB$, is a productive pattern if, $\forall$ (A1, A2) such that, (A1 $\subset$ I), (A2 $\subset$ A), (A1 $\cup$ A2 $=$ A), and (A1 $\cap$ A2 $= \emptyset$), then,

$$\left(\frac{|TSDB| - avgPr\,(A)}{avgPr\,(A)\,.\,|TSDB|}\right) > \left(\frac{|TSDB| - avgPer\,(A1)}{avgPer\,(A1)\,.\,|TSDB|} \times \frac{|TSDB| - avgPer\,(A2)}{avgPer\,(A2)\,.\,|TSDB|}\right) \quad (5)$$

Proof: Similar to the productivity test proposed in [74]: For any periodic pattern A_n, $\frac{|TSDB|-avgPr(A_n)}{avgPr(A_n).|TSDB|}$ can be re-written as $\frac{|TSDB|-avgPer(A_n)}{avgPer(A_n)} \times \frac{1}{|TSDB|}$ where $\frac{|TSDB|-avgPr(A_n)}{avgPr(A_n)} = \frac{cov_{TSDB}(A_n)}{|TSDB|} = Sup_{TSDB}\,(A_n)$. Hence the productive test can be utilized as follows:

$$\left(\frac{|TSDB| - avgPr\,(x)}{avgPr\,(A)\,.\,|TSDB|}\right)$$

$$> \left(\frac{|TSDB| - avgPr\,(I1)}{avgPr\,(A1)\,.\,|TSDB|} \times \frac{|TSDB| - avgPr\,(A2)}{avgPr\,(A2)\,.\,|TSDB|} \right)$$
$$= Sup_{TSDB}\,(A) > \ Sup_{TSDB}\,(A_1) \times Sup_{TSDB}\,(A_2) \qquad (6)$$

Based on ***Property 1***, we define a productive pattern as follows.

Definition 6 (Productive Periodic Frequent Pattern Test): A $PPFP, A$ in $TSDB$, is a productive Periodic Frequent Pattern If (∀ A1, A2 such that, A1 subset A, A2 subset A, A1 ∪ A2 = A, and A1 ∩ A2 = ∅, Property 1 is satisfied.

With productive patterns, we can choose which of several periodic co-occurring patterns are correlated. Additionally, we measure the accuracy of each generated pattern (obtained for different period values) with the following formalisms.

Definition 7 (Expected Occurrence of Activity a_i): Expected occurrences of a correlated pattern matching property 1 are said to happen as expected. If several occurrences happen in the same expected interval, the expected one is the one closest to the expected date. The others are extra, non-correlated periodic occurrences.

Definition 8 (Accuracy of Correlated Pattern): The accuracy of a correlated periodic pattern in its validity interval is the number of occurrences happening as expected (Definition 8) divided by the total number of expected occurrences.

To provide a more precise understanding of the temporal correlation discovery component, we consider the following notations. From the set of discovered periodic patterns, A, B, C, D is the set of periodic activities. The temporal correlation "B follows A" or $A \Rightarrow B$ is ultimately obtained.

Once we obtain the set of correlated instances, the accuracy definition is used to ensure the accuracy of the discovered actions routine in a specific time routine.

Example 4: Considering Table 2, we can see the activity "Entering Home" followed by "Eating","Relaxing", or "Taking Medication". The temporal relation {"Enter-Home" ⇒"Taking-Medication"} is the most probable activity discovered based on Property 1

C. DISCOVERY OF CONTEXT-ENRICHED CORRELATED PATTERNS

Human context can affect human behaviors, for example, the time of day or season (e.g., more time spent watching TV on the weekend or eating in the morning and at midday). Thus, a better understanding and handling of context constraints is very helpful and will add insights into ambient assisted living and help to discover unnoticed patterns.

Continue with the example scenario presented in the introduction. Sara's normal lunch and exercises routine can be expressed using the following equations:

1. (Activity: "Excersise", context: "AllDay")

2. (Activity: "Eating out side", context: (dayofweek, "Monday"))

3. (Activity: "No Excersise", context: (Weather, "Raining"))

A flood of alarms on Monday will be sent to her caregivers when she does not have lunch at home. Additionally,

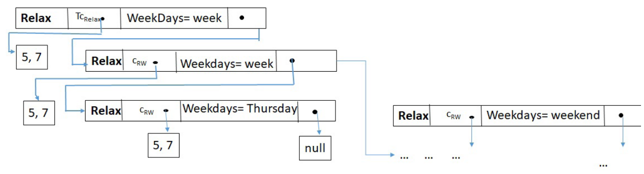


FIGURE 4. The "Relaxing" activity node in the context TECP-tree considering day of week.

the context learning improves the understanding of Sara's exercises routine during rainy days. Therefore, understanding and learning the context during the process of human behavior patterns mining could deepen the knowledge about the user life routines. Therefore, we add the context variations during the process of mining human habits so we can:

1) Interpret normal and abnormal situations accurately. For example; not doing "excises" during "weekends" is a normal behavior under the condition of weekends vacations.
2) Identify a set of patterns that occur exclusively to specific circumstances; for example; personal routines could change depending on the seasons or weather.

To better represent reality, we model the general context data such as weather and temporal precisions like time of day, seasons, or even gusts as follows.

Definition 9 (Context Attribute C): $C = c_1, c_2, \ldots, c_n$. Let a context attribute C be the set of property constraints characterizing human actions, environment, or situations during the time interval ts when it took place. During each time interval ts, the set of most relevant values for each context C is determined using a function.

In TEDCP, we slice data based on each context attribute and consider the subset that matches the context constraint. Therefore, we mine only a subset of the correlated patterns generated from the temporal relation discovery component based on the considered context. To record the context observation for each activity, we add a context identifier to the TECP-tree node. Namely, the node in the contextualized TECP-tree is represented as $|I, Ts(i), cnxt, Pt|(I))$ is the activity name; $Ts(i)$ is a pointer of the occurrence timestamp of each context; $(cnxt)$ is the context name; and (Pt) is a pointer to the complete context domain. Each context attribute has a taxonomy tree represented in the formal model using the is-a relationship among values of the attribute's domain similar to the work presented in [22]. The node in the context TECP-tree(s) is itself a TECP-tree node except that the ts list (i.e. Ts(i)) is stored at the root context node to record all the timestamps of the context occurrences instead of the tail-node list. In the following formalisms, we discuss the construction and mining of the context TECP-tree.

TEDCP is based on the correlated Periodic-Frequent patter mining algorithm. A user defined MAOT measure, determines the regularity of pattern X in a given database. In human behavior analysis, if the human routine has been detected enough time with the specified period, this routine is considered as regular routine. Additionally, if context condition C for specific activity has been seen periodically enough times, then that activity is a pattern for the given condition context C. During the context TECP-tree construction, similar to the TECP-tree when new observations come with specific context attributes, every node that represents the attribute is updated. For example, if the context constraints consider day of the week to be a Friday, all the ts-lists at tail-nodes are updated with the timestamps $ts(C)$ from the root level, at the week node, and at the Friday node. Patterns also are mined as TECP-tree, considering the timestamps *tsx* for each context as the observations in the parent tail-node instead. After the construction of the context TECP-tree, the TMCP-growth is used to mine the set of contextualized correlated patterns, considering the periodicity of the context attribute instead of the activity pattern.

Example 5: Let us consider the activity stream given in Figure 1 after inserting tuple 5 and tuple 7 of the *TSDB* given in Table 2 considering the activity "Relaxing" with "the week" day as a context attribute. Fig. 4 (omitting the remaining tree) shows the context TECP-tree after inserting the observation in the "Relaxing" node. The activity was observed on a weekend, once on Monday, and on weekdays. The days' node is updated with the timestamp representing the observation.

V. EXPERIMENTS DESIGN AND EVALUATION

In this study, we evaluate the algorithm's efficiency in finding user habits considering four datasets (KA,[2] HH120, HH122, and HH123 datasets).

The KA dataset tracks a 26-year-old man living alone. The dataset was recorded between February 25, 2008, and March 21, 2008 in 25 days with 2458 on/off sensors reading. Finally, HH120, HH122, and HH123 datasets contain daily life information spanning 2 months, 1 month, and 1 month, respectively, of people in three different apartments. The sensors used to track the users are implanted between the rooms to detect motions, on the kitchen appliances (like the fridge door, the cupboards, the dish washer, etc.), and on the toilet flusher. A Bluetooth dataset was used with the user to annotate the activities. All sensor activity data are recorded with start and end timestamps.

Fig. 5a- 5d summarize the occurrence count of the activities over different datasets.. We used these datasets because its sensor data matches our target for discovering human normal life routines, nevertheless they are used regularly in the literature.

To show the accuracy of the generated contextualized correlated periodic behavior patterns, we start by comparing the set of TEDCP candidate patterns with that generated from sequential code (Algorithm 4).

Afterwards, we evaluate the efficiency of the proposed model in terms of:

[2]It is available on line at https://sites.google.com/ site/tim0306/datasets, consulted November, 13, 2018.

Algorithm 4 Sequential Algorithm to Discover All Periodic Co-Occurred Patterns

```
Input  : STDB : a sensor time series database,
         INTRVAL : a user-defined maximum
         inter-arrival time for each database items.
Output: candidate CPP (correlated-periodic) patterns
         List;
Let CPP be an empty list to represent occurrences of the
set of co-occurred patterns ;
foreach (epoch epch in STDB) do
    if (epch ≠ NULL) then
        foreach non-empty subset, L in epch do
            Add epch at the end of epchs ;
            Add epch to epchs ;
            Add L at the end of epchs ;
        end
    end
end
foreach p in CPP − list do
    if PINTER − ARRIVALTIMESTAMP ≤ INTRVAL
    and P are correlated according to Property 1 then
        ADD P to CPPE ;
    end
end
Return CPPE ;
```

- Mining Time.
- Number of discovered patterns.
- Missing occurrences error rate.

By comparing the candidate patterns generated from:

1) TECP-growth: our proposed correlated activity mining algorithm. The algorithm mines a temporal sensor database of human activities to find the set of correlated periodic-frequent patterns with a single database scan.
2) Our implementation of TEREDA [33] a temporal relations discovery algorithm for mointoring human activity using frequent patterns.

All our implementation is written in java using components from the SPMF-learn library over machine with a 2.66 GHz CPU with 8 GB memory and running on Windows 10. Subsequently, we compare the performance of the TECP-growth over TEREDA in terms of mining time, number of discovered patterns and finally the error rate of each algorithm. Finally, we explain how the contextualized correlated periodic patterns improve understanding of human habits considering specific context variables.

A. ACCURACY OF TEDCP TECHNIQUE

Since few studies have focused on modeling periodic human behavior. Moreover, no study, to our knowledge, has considered the problem of mining correlated patterns from a temporal database. In the following formalism, in order to justify the accuracy of our TEDCP technique, we compare the Productive periodic frequent patterns generated by the PPFP-growth,

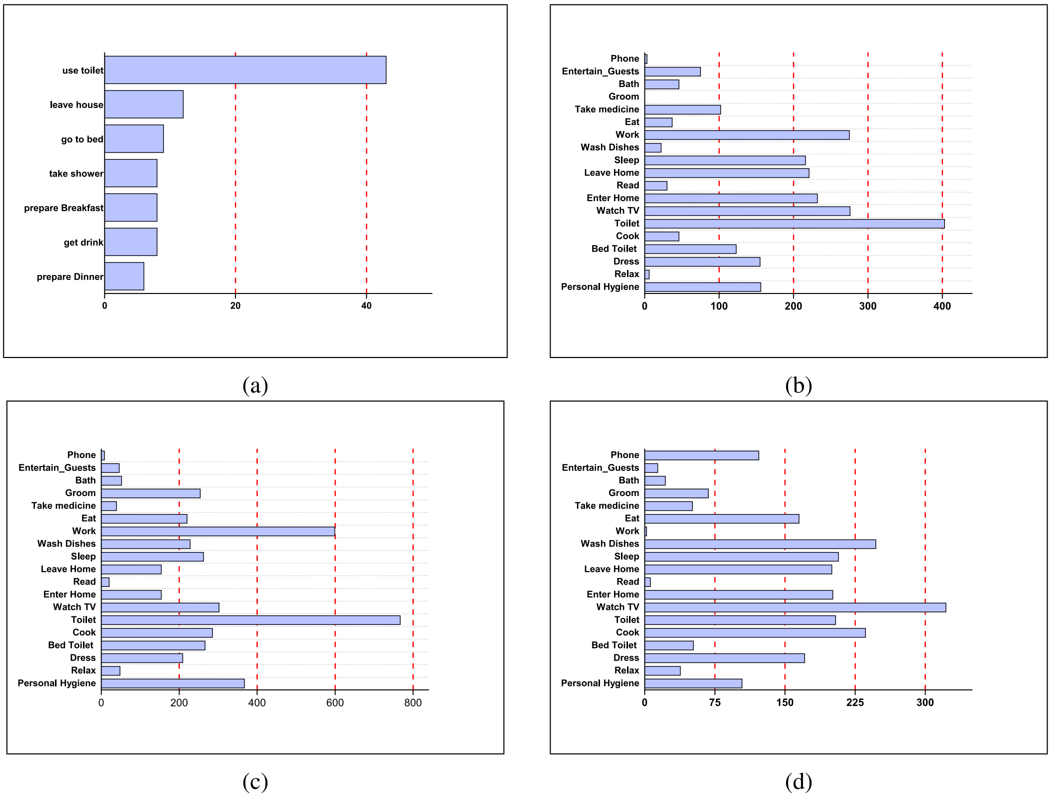


FIGURE 5. Number of occurrences of each activity: (a) KA-dataset. b) HH120 dataset. c) HH123 dataset. d) HH124 dataset.

with the patterns generated directly from sequential code for specific MAOT measures. For this purpose, a sequential algorithm is implemented (Algorithm 4) to find all correlated periodic-frequent patterns sequentially and without using any pattern mining technique.

We process each dataset separately, and set the algorithm parameters with MAOT=30 min and SUP=3 in order to discover the periodic (weekly) frequent (at least once) activities. For each dataset a different set of patterns discovered, but some of the generated patterns appear in all of the datasets, like "eating" or "sleeping" activity patterns.

In order to allow a cross-dataset comparison, the discovered periodic patterns were manually investigated, and classified in five categories: waking up, hygiene-related, bedtime, eating or other.

Over 98% of the set of correlated periodic patterns returned by this sequential mining algorithm for specific MAOT measures on KA-dataset, HH120 dataset, HH123 dataset, and HH124 were discovered the same as the discovered patterns with our algorithm. Runtime comparisons are not considered since the sequential code takes a long time, which is beyond our scope.

With SUP = 3, and MAOT = 30 min, the algorithm generate 56 periodic frequent patterns. Out of the 56 periodic activity, 11 were correlated and satisfy the correlation definition mentioned on Definition# 6.

TABLE 3. discovered correlated periodic activities.

Pattern	Correlated-activity	Periodicity
R1:	(Wake up, Use toilet)	February 26th to March 22nd, (07:58)
R2:	(Take shower start, Leave house start)	February 26th to March 22nd, (08:56)
R3:	(Prepare breakfast start, Use toilet, Take shower, Leave house)	February 26th to March 20th, (17:57)
R4:	(Drink, Prepare breakfast, Use toilet, Leave house)	February 26th to March 20th, (17:57)
R5:	(Use toilet, Leave house	February 26th to March 20th, (17:57)
R6:	(Use toilet start, Prepare Dinner)	March 5th to March 11th, (18:22).
R7:	(Prepare Dinner, Get drink)	February 26th to March 21st, (22:29)
R8:	(Use toilet, Leave house	February 26th to March 20th, (17:57)
R9:	(Sleep, Use toilet, Get drink)	March 5th to March 11th, (18:22)
R10:	(Get drink, Prepare dinner, Use toilet)	March 5th to March 11th, (18:22)
R11:	(Get drink, Prepare dinner, Sleep)	March 5th to March 11th, (18:22)

The use of MAOT values allow the flexibility in mining different activities even the case with short occurring duration, like using the toilet, or preparing breakfast. Table 3 presents the discovered correlated patterns. One can notice that the

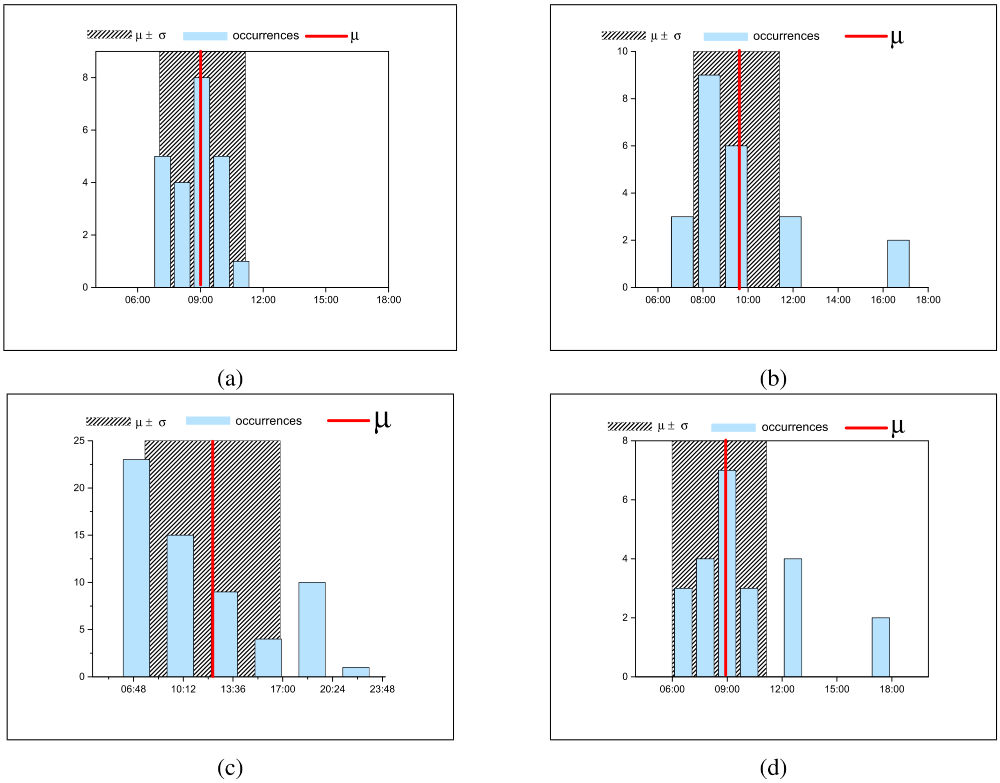


FIGURE 6. Histogram for time occurrence of activities: (a). KA-dataset. B) HH120 dataset. C) HH123 dataset. D) HH124 dataset.

discovered habits represent the periodic patterns that occurred repeatedly; R1 represents the routine of the user in which, when "Waking up", he or she has to "Use toilet", which occurred on nearly all weekdays. Some of the discovered routines are acyclic in the dataset, repeating for a few days like R9, R10, and R11.

Fig. 6a-6d show the histograms for occurrence time of the top-5 correlated patterns discovered by TEDCP, and the middle timeline represents the times at which the activity is expected to happen and the actual discovered activities during the experiment. The parameters $Sup = 3$, and $per =$ 30min are used to enable the discovery of weekly occurring correlated patterns as the KA-dataset has short activities that last less than four weeks. In the histograms, the periodicity description of the top-5 activities is represented by the hashed area. The hashed area is calculated as the time interval $[\mu - \sigma]$ $[\mu + \sigma]$ where μ and σ are the mean and standard deviation of the recurrence period of interest of each activity. Some patterns occurred as expected within the time interval while others did not.

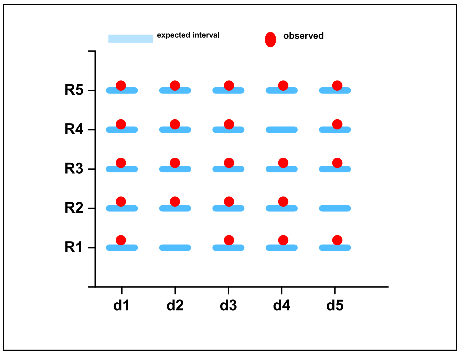
For each day, we compare the discovered and expected activities as shown in Fig. 7 For each mined habit, we highlight the actually observed occurrences (round dot) versus the expected but missing occurrences (no dot); observation occurs in specific MAOT interval.

B. MODEL EFFICIENCY

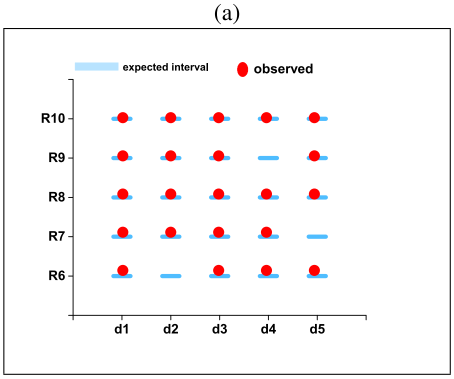
In the following discussion, we compare the efficiency of our model with the work presented in [33]. For this reason, we further add the the Center for Advanced Studies in Adaptive Systems (CASAS) at Washington State University (CASAS) dataset record activity for 220 days collected from 20 participants to enable more variety and increase the dataset instances. The TEREDA algorithm discovers the temporal relations of the activities of daily living based on association rule mining. Moreover, TEREDA uses frequently occurring patterns as the target pattern and then uses a clustering EM approach to identify the temporal relation between the discovered activity patterns. Different number of patterns generated from TEREDA and TEDCP algorithms considering different algorithms parameters values. For TEREDA1 and TECP1, we fixed the support threshold (i.e., $sup = 30\%$ of all dataset epochs) while, for TEREDA2 and TECP2, we fixed the support to cover at least 80% of the epochs. Both algorithms discover interesting temporal patterns, however they are different thanks to the different temporal definition of each algorithm. The following paragraphs discuss the main differences between the results for both algorithms.

Number of generated periodic patterns count:(Fig. 8a) TEREDA algorithm generates more patterns with the increase in the number of considered dataset records. The periodicity threshold values and correlation test reduces the number of candidates slightly.

Mining time(Fig. 8b): the total time for discovering the correlated patterns is represented on the y axes of the graphs for each algorithm. Using only the frequent patterns as a representative pattern for human habits consumes more time

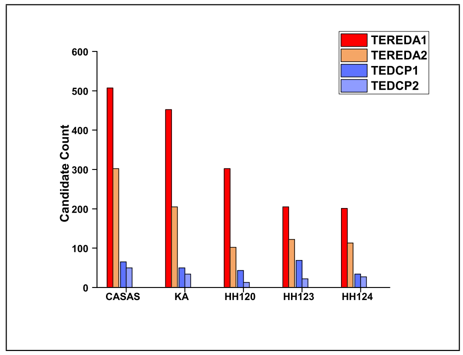


(a)

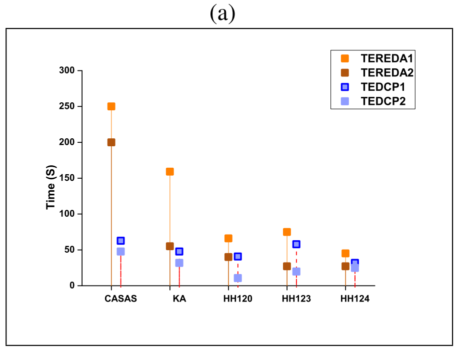


(b)

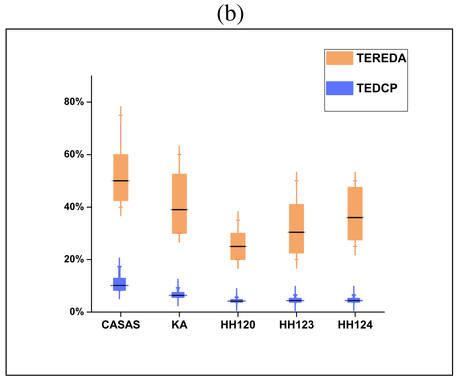
FIGURE 7. Expected vs observed top-10 correlated patterns generated from Table 3.



(a)



(b)



(c)

FIGURE 8. Model efficiency comparison. (a) Number of discovered patterns. (b) Mining time Comparison. (c) Periodic pattern error rates distribution.

compared to the TEDCP model, nearly one minute as a maximum mining time in all cases.

Discovered patterns relevance (Fig. 8c):Despite the difference in the periodicity definition of each algorithm, both discover different patterns of interest matching user requirements with the specific error rates represented in Fig. Fig. 8c. The error rate in the TEDCP model is very low compared to that in TEREDA.

The comparison with TEDERA model highlights the difference between TEDCP and TEDERA in the obtained results. The main difference comes from the way the temporal relation (periodic patterns) are discovered and mining time of both models. Additionally, despite the high variability in human habits monitoring, the correlated periodic pattern discovered with TEDCP model is more informative and is useful to model the human activities correlations.

C. MINING CONTEXTUALIZED BEHAVIORS

To assess how contextualized correlated periodic patterns improve understanding of human habits without any priori knowledge on the subject, we show some of the discovered correlated patterns using day periods of morning, afternoon, and night as context attributes. Tables 4 and table 5 show the discovered patterns from the HH120 dataset using morning and evening contexts, respectively.

For example, "Leave home" after "sleep" in the morning is unusual, although the same sequence in the afternoon is expected. Other patterns such as "Cooking, Eating" were not considered since they are not as periodic in the complete database. Based on Tables 4 and 5, we note that, when context-correlated patterns are mined, some morning patterns emerge. For example, "Reading" activity is unusual in the morning, but, in the other context, it will not exist. Additionally, some expected afternoon patterns are "Entertain Gust" visits, "Take medication". In summary, the contextualized discovery of correlated human actions can add more insights into the relative order of human actions (activities). For example, we can construct a schedule of activities for an upcoming period based on the identified time, interdependency, and context of users. We added the results for the correlated 2-itemsets patterns in Tables 4 and 5; more pattern sizes can be discovered in the same way.

TABLE 4. Discovered correlated activities considering "morning" as context attribute.

Activity	Next-Activity	Context
Toilet	• Dress	Morning Activities
Toilet	• Watch-TV. • Leave home.	
Dress	• Watch-TV	
Watching-TV	• Toilet • Dress • Leave Home	
Work	• Toilet • Entertain Guests • Leave home	
Enter home	• Toilet • work • Leave home	
Personal hygiene	• Dress • Toilet • Watch-TV	
Cook	• Eat • Leave-home	
Eat	• Leave-home	

TABLE 5. Discovered correlated activities considering "afternoon" as context attribute.

Activity	Next-Activity	Context
Toilet	• Dress	Evening Activities
Toilet	• Work • Dress • Sleep	
Toilet	• Watch-TV • Leave home • Work	
Cooking	• Eating • Leave Home • Watch-TV	
Eating	• Leave home • Watch-TV • Wash-dishes	
Enter home	• Work • Take-medicine • Toilet	
Personal hygiene	• Watch-TV • Leave home • Read • Dress • Sleep	
Relaxing	• Personal-hygiene • Toilet	
Taking-Medication	• Work • Watch-TV • Toilet • Leave-home	
DRESS	• Read • Sleep • Personal hygiene	
READ	• Sleep • Personal hygiene	
Work	• Take-medicine • Toilet • Read • Leave home	
Gust	• Leave-home • Watch-TV	

VI. APPLICATION OF TEDCP IN REAL LIFE

Many Real life applications domains [75], [76] can obtain useful knowledge from mining contextualized correlated periodic-frequent patterns. In this section, certain applications are discussed where contextualized and regular correlated patterns need to be discovered.

Traffic jam reduces the quality of life for residents. Thus, economic development experts and planners want to explore more solutions to overcome congestion in specific circumstances. As various events occur regularly, such as special events, festivals, sports, games, or religious services, this can increase congestion during specific long holiday weekends or inclement weather. Experts can use the proposed TEDCP model to effectively analyze such regular traffic patterns while considering the specific context.

Our proposed algorithm is also applicable in the analysis and monitoring of human behavior. Suppose a researcher of human behavior understanding wants to generate knowledge about predicting the next human behavior with respect to specific events or time. TEDCP can help in generating such human behavior while eliminating redundant patterns by finding contextualized correlated regular patterns efficiently.

The proposed algorithm TEDCP can help to find out exact and expected patterns efficiently and effectively. Suppose a travel agency is planning to offer travel and tourism related services packages, such as offers (e.g. vacation packages for busy season times and special packages for less crowded times). In such scenarios, our proposed correlated patterns generated by TEDCP algorithm can greatly assist travel agencies in their efforts to avoid profit losses through extracting valuable knowledge about busy times in tourism in terms of seasons or special events. For example, during specific festivals, many items are sold in huge quantities and the manager wants to accurately identify the most regularly sold items during specific events.

Thus, TEDCP can add more insight in business transactions management systems through helping managers to suggest useful decisions or plans.

VII. CONCLUSION AND FUTURE WORK

Discovering normal human behavior can add insights into the aging population problem and help in understanding personal daily life. In this work, we present a new algorithm to discover the periodic set of normal human patterns. Moreover, the correlation and context variation are considered during the mining process. The experimental evaluation of the proposed tree and algorithm ensures the effectiveness and accuracy of the algorithm to discover interesting patterns related to human daily life. For future use, we look forward to considering different types of ambient assisted life systems' data including video data and images. Moreover, a parallel sensor fusion approach will be devised to handle the various collected sensors' data accurately. Furthermore, emerging work in the Internet-of-Things and advances in smart environment sensors requires more semantically grounded representations of human collected patterns in smart environments. Semantics will add meaningful meanings into the collected sensors data and represent smart environments. Therefore, we plan to integrate ontological models into TEDCP to enhance the meaning and understanding of human collected patterns and context data.

ACKNOWLEDGMENT

The authors are grateful to the Deanship of Scientific Research at King Saud University for funding this work through the Research Group Project RGP-281. The authors also would like to thank the RSSU at King Saud University for their technical support.

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