Event-Based Data Input, Modeling and Analysis for Meditation Tracking using TDR System

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Abstract

In this paper we describe an experimental TDR system with continuous data input from devices such as smart phones and sensors such as brain wave headsets. We developed event-based data input, modeling and analysis techniques in order to analyze input data and track progress of meditation. Initial experimental results indicate that this approach is quite promising.

Keywords

Meditation tracking, event-based data input, modeling and analysis, slow intelligence system, TDR system.

1 Introduction

In our previous work we developed the TDR system, which is a multi-level slow intelligence system with interacting super-components each of which has its own computation cycle [1], as a platform to explore applications in personal health care, emergency management, social networks and so on. In this paper we apply the TDR system to event-based data analysis and visualization for meditation tracking.

Meditation, defined as "the attention inwards towards the subtler levels of a thought until the mind transcends the experience of the subtlest state of the thought and arrives at the source of the thought", has been proven to have positive effects on social skills, feeling of compassion, self-management, somatic awareness and mental flexibility. It has also been used in treatment of anxiety disorders, stress reduction, chronic pain, persistent pain, depression, autism spectrum disorders, traumatic experiences, acquired brain injury, and even eating disorder, psoriasis and substance abuse.

Nowadays many people are learning meditation. However there are still no adequate meditation monitoring systems to take continuous measurements from various sensors when a person is in meditation and to track its progress. In this paper we describe an experimental TDR system with continuous data input from devices such as smart phones and sensors such as brain wave headsets. We developed event-based data input, modeling and analysis techniques in order to analyze input data and track progress of meditation. Initial experimental results demonstrate that this approach is quite promising.

The paper is organized as follows. In Section 2 we describe the system architecture. The interface to support event-based data input is presented in Section 3. Event-based data modeling is described in Section 4, followed by a detailed example of data analysis presented in Section 5. Section 6 presents user scenarios for the experimental system. Discussion and conclusion are presented in Section 7.

2 System Architecture

Figure 1 illustrates the experimental TDR system consisting of interacting super-components and the chronobot database. Each super-component has its own computational cycles. The super-components interact with one another through the SIS server. Based on requests from the administrator, the super-components process input data and upload them to

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the Chronobot database. In the TDR system there are at least three super-components: Tien (Heaven), Di (Earth) and Ren (Human). The Tien super-component handles sensors for the atmosphere, the Di super-component deals with sensors for the lithosphere and the Ren super-component manages sensors for the human body.

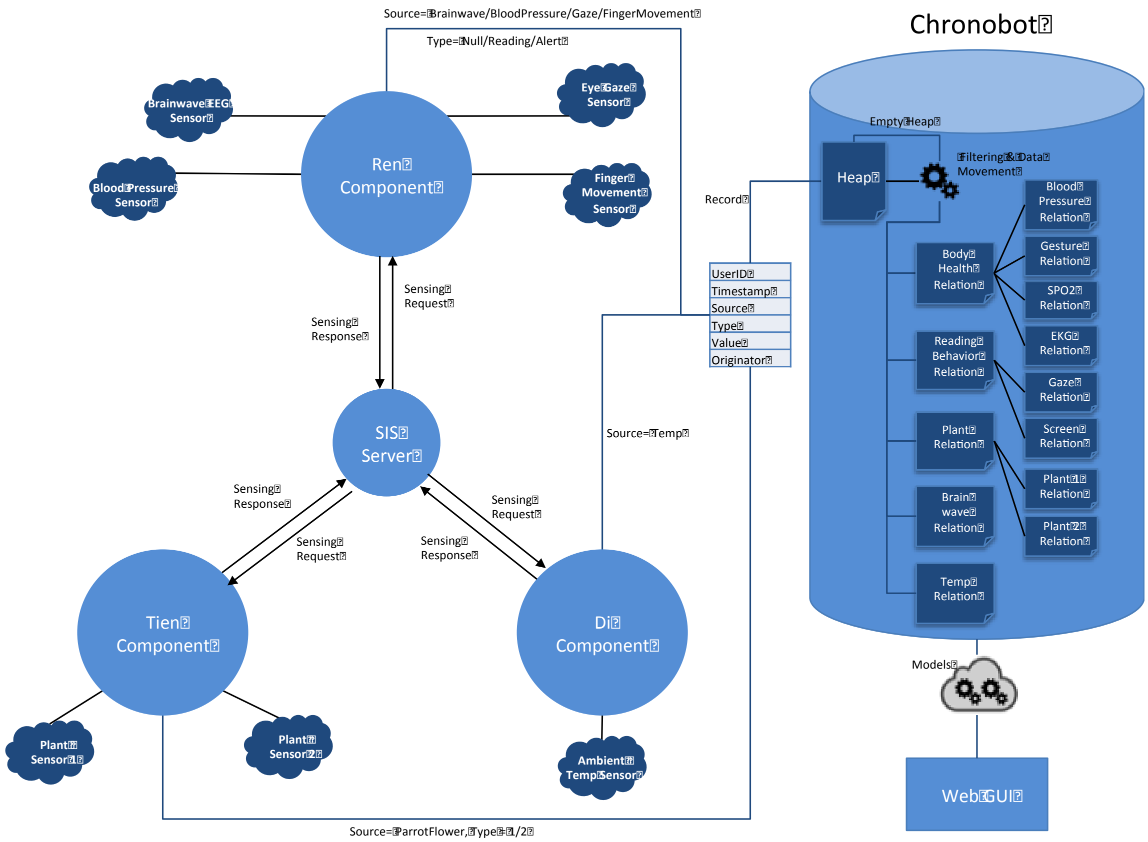


Figure 1. TDR System with super-components and Chronobot database.

In order to track meditation we proposed to use brain wave headset as well as eye gaze tracking by smart phone during meditation [2]. Data from brain wave sensor and eye gaze tracker are collected by their respective input processors in Ren super-component and uploaded to the Heap relation in the Chronobot database. The Heap is a collection of records each with a variable number of attributes for different types of sensor data, which are filtered and moved into different relations such as Gazing Behavior Relation, Brain Wave Relation and so on, by the request of the administrator through the Web GUI.

A more detailed view is shown in Figure 2. Records in the Heap are first filtered and then moved to the corresponding relations. In the filtering of data, the resultant data must conform to the model for the corresponding relation. We will first explain the conceptual framework. The detailed formal model will be presented in Section 4.

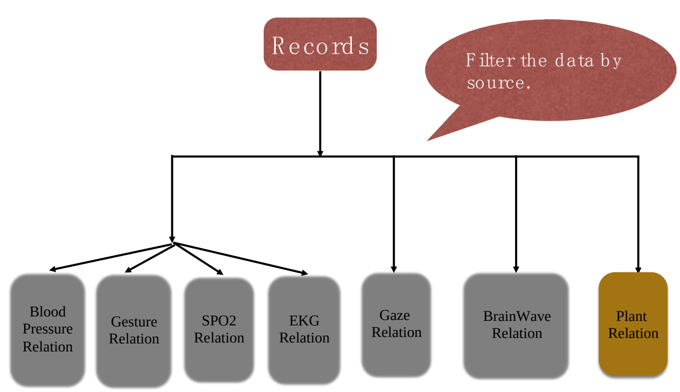


Figure 2. Records are filtered and moved to the corresponding relations.

3. Event-Based Data Input

The database for the TDR system is a time varying database. To make sense of the time varying database, we need to monitor the data streams and detect significant changes. For the best of our knowledge, there's few researches on designing user interface for time varying database. User interface design requires a good understanding of user needs [3], in our approach we need to be able to specify what is normal and what is not normal. In fact, a database is governed by a data model specifying what is the normal pattern. The computation cycles specify the collection, filtering and storage of data that conform to the normal pattern, so the end result is a **normal event**. The cycle then repeats itself. When the data deviates from the normal pattern, it is an **abnormal event** to take notice of. Our approach to user interface design is therefore based upon this concept of normal and abnormal events.

In recent years, visualization has become an important tool to support exploration and analysis of large volumes of data. Therefore, to shift the needs of users into the focus, we should pursue an event-based approach to visualization. This approach allows users to specify their interests as event types. The **normal event** is the data model. The **abnormal event** is what deviates from the data model.

During a computation cycle, the normal event is usually the end result, i.e. the processing and storage of data that conforms to the specified data model. When instances of the specified abnormal event types are detected, the user interface automatically adjusts visual representations according to the detected event instances. This approach results in visualizations that are adapted to the needs and interests of the users. Hence, users are supported in achieving their task at hand.

In terms of event-based visualization, the basic idea is to let users specify their interest by means of event types, to detect instances of these events in the data, and to create representations that can be automatically adjusted with respect to the detected event instances. Accordingly, three main aspects are investigated:.

1. Event specification,
2. Event detection,
3. Event representation.

To bridge the gap between informal user interests and the digital language of computers, a formalism for the event specification must be developed. Here, the difficulty is to build a formal basis that provides a suitable expressiveness while still allowing users to specify their interests as easily as possible. Especially when facing users who are not familiar with event-based visualization, it is essential to provide methods and tools that allow an intuitive specification of event types.

The task of the event specification is to compile event types that are or might be of interest to visualization users. The event specification necessitates a formal foundation to allow a later detection of event instances.

In our approach, we have two types of events: normal events that represent the data model, and abnormal events that represent deviation from the data model. Events are always specified for a certain relation. Before moving data from heap to relation, we first check if the tuple satisfies a certain event type.

(1) **Normal Event:** As an example, if every tuple has an error rate less than the threshold ε (for example ε = 0.1), then it is a normal event. This event can be described as:

$$\Psi(\Delta T(\eta), X(v_I), Y(v_I)) \leq \varepsilon , \qquad \text{..........................} (1)$$

Once a normal event is specified, we can create a computation cycle to get the TDR system started. For formal definition, see Section 4.

(2) **Abnormal Event 1:** As an example, for three consecutive tuples, if each tuple's error rate exceeds the threshold ε, then it is an abnormal event. This event can be described as:

$$\Psi(\Delta T(\eta), X(v_I), Y(v_I)) > \varepsilon ,$$
$$\Psi(\Delta T(\eta), X(v_{I+1}), Y(v_{I+1})) > \varepsilon , \quad \text{......... ....} (2)$$
$$\Psi(\Delta T(\eta), X(v_{I+2}), Y(v_{I+2})) > \varepsilon ,$$

For formal definition, see section 4. If condition (2) is met, user then can use the following steps to specify this event.:

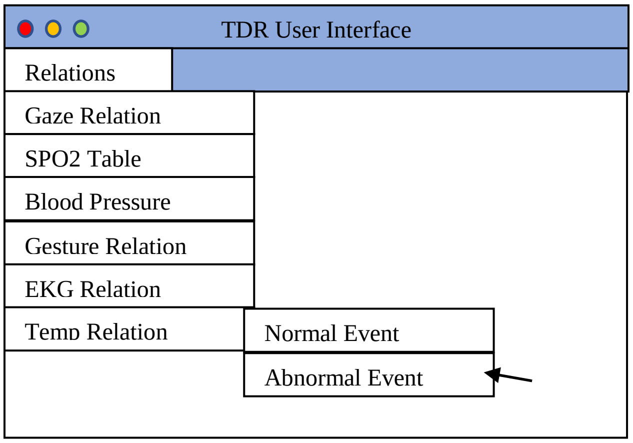


Figure 3. Choose Event Type for a certain relation.

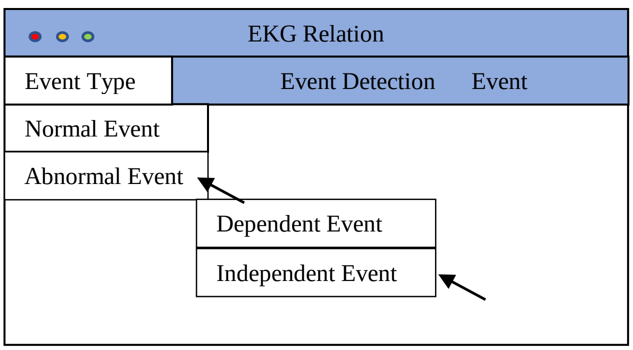


Figure 4. Click on Abnormal Event and then Independent Event.

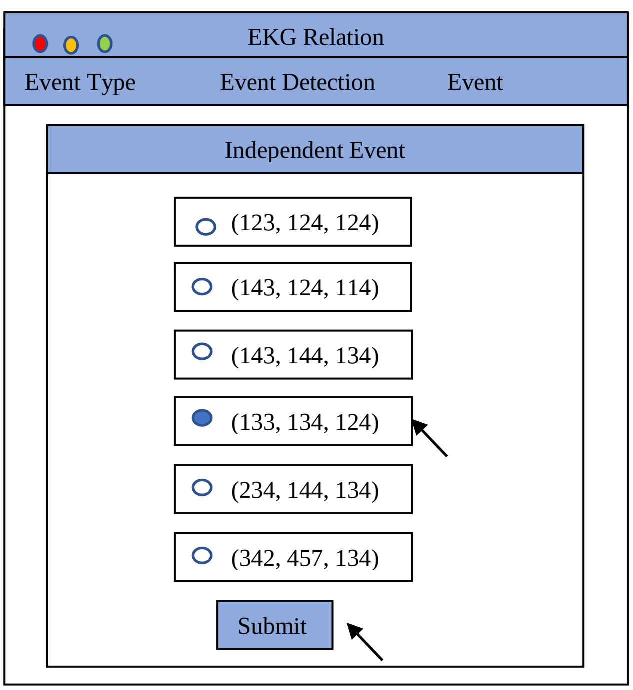


Figure 5. Choose tuple and submit event.

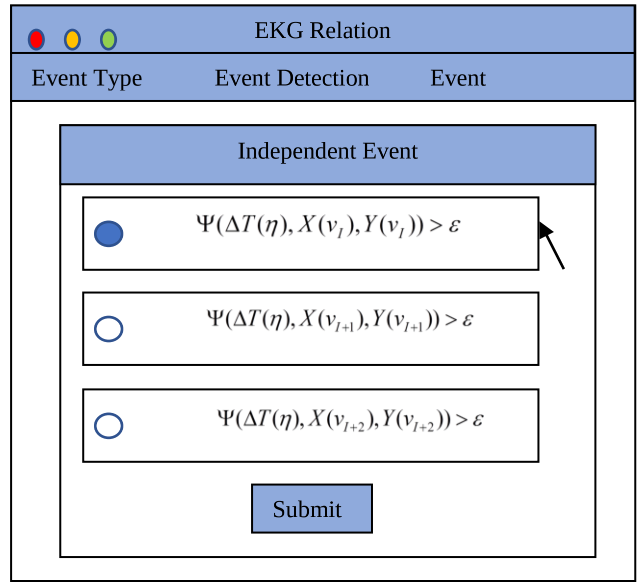


Figure 6. Choose event type.

(3) **Abnormal Event 2:** For three consecutive tuples, if each tuple's error rate is twice as much as the previous tuple, then it is an event. This event can be described as:

$$\Psi(\Delta T(\eta), X(v_I), Y(v_I)) > \varepsilon \qquad \text{(3)}$$

$$\Psi(\Delta T(\eta), X(v_{I+1}), Y(v_{I+1})) > 2 \cdot \Psi(\Delta T(\eta), X(v_I), Y(v_I))$$

$$\Psi(\Delta T(\eta), X(v_{I+2}), Y(v_{I+2})) > 2 \cdot \Psi(\Delta T(\eta), X(v_{I+1}), Y(v_{I+1}))$$

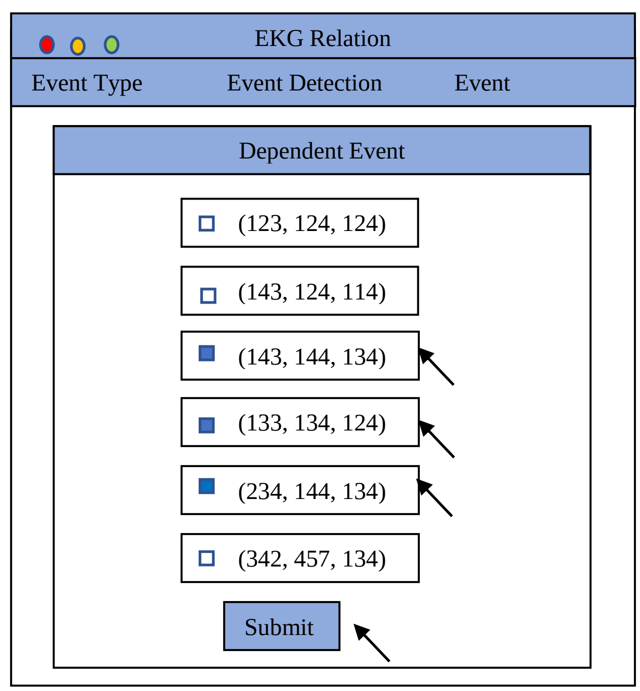
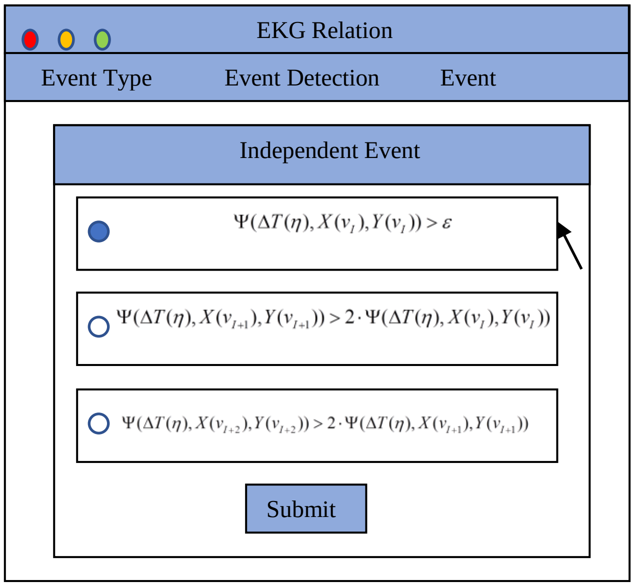


Figure 7. Choose 3 tuples and submit.

The user can click on Abnormal Event and then Dependent Event, similar to Figure 4. For formal definition, see section 4. If condition (3) is met, user then can use the steps in Figure 7 and Figure 8



to

Figure 8. Choose event type.

specify this event.

4. Event-Based Data Modeling

Inspired by [4] and [5], we consider a multimedia database with time-varying $R(T, A_1, \cdots, A_n)$, where T denotes time, $A_1, \cdots, A_n$ are other attributes, v_i is the tuple corresponding to the moment t_i, U is a set of the attributes $A_1, \cdots, A_n$, and $dom(A_k)$ is the domain of each A_k, $v_i[A_k]$ denotes the value of the tuple v_i in the attribute A_k. Thus for any two moments t_i and t_j of T in R, there are always a pair of corresponding tuples $v_i = (t_i, v_i[A_1], \cdots, v_i[A_n])$, $v_j = (t_j, v_j[A_1], \cdots, v_j[A_n])$.

The similarity between any two attribute values $v_i[A_k]$ and $v_j[A_k]$ of A_k is based on a distance function of type $d: dom(A_k)^2 \rightarrow [0,1]$ [4]. For simplicity, we denote with $D(A_k)$ the set of the distance functions defined on A_k.

According to the distance function of type $d: dom(A_k)^2 \rightarrow [0,1]$, definition 1 is given as follows, then from which we get definition 2.

Definition 1 Given a relation $R(T, A_1, \cdots, A_n)$, for a pair of tuples v_i and v_j corresponding to any two moments t_i and t_j of T, we say that v_i is **similar** within τ to v_j with respect to d at the moments t_i and t_j, denoted with $\boldsymbol{v_i[A_k] \cong_{(d,\tau,t_i,t_j)} v_j[A_k]}$, iff $\boldsymbol{d(v_i[A_k], v_j[A_k]) \leq \tau}$, where τ is a threshold.

Definition 2 Given a relation $R(T, A_1, \cdots, A_n)$ and $X, Y \subseteq U$, we say the **type-M function dependency** during the time of $\boldsymbol{T}$ **(T-MFD)**: $\boldsymbol{X_{(d_1,\tau')} \xrightarrow{T} Y_{(d_2,\tau'')}}$ holds, if and only if for a pair of tuples v_i and v_j corresponding to any two moments t_i and t_j of T, whenever $v_i[X] \cong_{(d_1,\tau',t_i,t_j)} v_j[X]$, then $v_i[Y] \cong_{(d_2,\tau'',t_i,t_j)} v_j[Y]$, where $d_1 \in D[X]$, $d_2 \in D[Y]$, $\tau', \tau'' \in [0,1]$ are thresholds.

Obviously, given a relation $R(T, A_1, \cdots, A_n)$ and $X, Y \subseteq U$, sometimes there are a pair of tuples v_I and v_J corresponding to some two moments t_I and t_J of T such that $v_I[X] \cong_{(d_1,\tau',t_I,t_J)} v_J[X]$ holds, whereas $v_I[Y] \cong_{(d_2,\tau'',t_I,t_J)} v_J[Y]$ doesn't hold. Then the following definition is necessary.

Definition 3 Given a relation $R(T, A_1, \cdots, A_n)$ and $X, Y \subseteq U$, if $v_I[X] \cong_{(d_1,\tau',t_I,t_J)} v_J[X]$ holds, whereas $v_I[Y] \cong_{(d_2,\tau'',t_I,t_J)} v_J[Y]$ doesn't hold, we say v_I, v_J at the moments t_I and t_J with respect to X, Y constitute a **dependency violation event (DVE)** of $\boldsymbol{T}$, denote by **T-DVE** $\boldsymbol{-v_I, v_J[X, Y]}$. The DVEs of all tuples during the time of T with respect to X, Y are denoted as **T-DVEs** $\boldsymbol{-X, Y}$.

Thus the occurrence rate of T-DVEs $-X, Y$ with respect to any two attributes X, Y is a very important problem that one concerns, which can be calculated by the following definition.

Definition 4 Given a relation $R(T, A_1, \cdots, A_n)$ and $X, Y \subseteq U$, we define the **dependency violation**

rate (**DVR**) of X,Y during the time of $\boldsymbol{T}$ (**T-DVR -*X,Y***) as follows:

$$\Psi(T,X,Y)=\frac{r_1}{r_T},$$

where r_T, $r_1 \subseteq r_T$ denote the combinatorial number of any pair of attributes in X or Y during the time of T, the number of the T-DVEs -X,Y, respectively.

We know if there are T-DVEs -X,Y, and the T-DVR -X,Y is very small, even very close to zero, then $X_{(d_1,\tau')} \xrightarrow{T} Y_{(d_2,\tau'')}$ almost holds, from which the following generalized T-MFD definition is yielded.

Definition 5 Given a relation $R(T, A_1,\cdots,A_n)$ and $X,Y \subseteq U$, we say the **relaxed type-M function dependency** during the time of $\boldsymbol{T}$ (**T-RMFD**): $\boldsymbol{X}_{(d_1,\tau')} \xrightarrow{\Psi(T,X,Y)\le\varepsilon} \boldsymbol{Y}_{(d_2,\tau'')}$ holds, if and only if for a pair of tuples v_i and v_j corresponding to any two moments t_i and t_j of T, whenever $v_i[X] \cong_{(d_1,\tau',t_i,t_j)} v_j[X]$, then almost $v_i[Y] \cong_{(d_2,\tau'',t_i,t_j)} v_j[Y]$ holds, and $\Psi(T,X,Y)\le\varepsilon$, where $\Psi(T,X,Y)$ is the T-DVR -X,Y, $d_1 \in D[X]$, $d_2 \in D[Y]$, and $\tau',\tau'',\varepsilon \in [0,1]$ are thresholds.

Remark 1: It is depended on the value of ε to a great degree whether $X_{(d_1,\tau')} \xrightarrow{\Psi(T,X,Y)\le\varepsilon} Y_{(d_2,\tau'')}$ holds.

For a relation $R(T, A_1,\cdots,A_n)$ and $X,Y \subseteq U$, when T is too long and there are too many data during the whole time T, we can consider to investigate fewer data during a part time. If we use the symbol $\boldsymbol{\eta}$ to denote the duration of the part time, and get the following definition.

Definition 6 Given a relation $R(T, A_1,\cdots,A_n)$ and $X,Y \subseteq U$, we say the **relaxed type-M function dependency** during ***ΔT(η)*** (***ΔT(η)*** **-RMFD**) :

$$\boldsymbol{X}_{(d_1,\tau')} \xrightarrow{\Psi(\Delta T(\eta),X,Y)\le\varepsilon} \boldsymbol{Y}_{(d_2,\tau'')}$$

holds, if and only if for a pair of tuples v_i and v_j corresponding to any two moments t_i and t_j during $\Delta T(\eta)$ (i.e., $\Delta T=\max_{M_1\le i,j\le M_2, i\ne j} |t_i-t_j|\le\eta$, $M_1, M_2 \in \{1,2,\cdots,m\}$), whenever $v_i[X] \cong_{(d_1,\tau',t_i,t_j)} v_j[X]$ holds, there is almost $v_i[Y] \cong_{(d_2,\tau'',t_i,t_j)} v_j[Y]$ holds, and

$$\Psi(\Delta T(\eta),X,Y)=\frac{r_2}{r_{\Delta T(\eta)}}\le\varepsilon,$$

where $r_{\Delta T(\eta)}$ is the combinatorial number of any pair of attributes in X or Y during $\Delta T(\eta)$, $r_2 \subseteq r_{\Delta T(\eta)}$ is the number of the DVEs $-X,Y$ during $\Delta T(\eta)$ (***ΔT(η)*** **- DVEs -*X,Y***), m is the number of the tuples during the whole time T, $d_1 \in D[X]$, $d_2 \in D[Y]$, and $\tau',\tau'',\varepsilon \in [0,1]$ are thresholds.

Remark 2: Similar to definition 4, we can say $\Psi(\Delta T(\eta),X,Y)$ in definition 6 is the dependency violation rate of X,Y during $\Delta T(\eta)$ (***ΔT(η)*** **- DVR -*X,Y***).

For a relation $R(T, A_1,\cdots,A_n)$ and $X,Y \subseteq U$, if we investigate the data during some part time of T and can get the relation between X and Y during the whole time T, then we only need to consider the relation $R(T, A_1,\cdots,A_n)$ during this part time. The following definition describes this case.

Definition 7 Given a relation $R(T, A_1,\cdots,A_n)$ and $X,Y \subseteq U$, if

$$T=\Delta T_1(\eta)\cup\cdots\cup\Delta T_L(\eta),\quad \Delta T_i(\eta)\cap\Delta T_j(\eta)=\Phi$$
$$(i,j=1,2,\cdots,L,\ \ i\ne j),$$

where $\Delta T_i(\eta)$ denotes $\max_{j\ne k}|t_j-t_k|\le\eta$ ($j,k\in\{1,2,\cdots,L\}$), and $\Psi(\Delta T_i(\eta),X,Y)\le\varepsilon$ $(i=1,2,\cdots,L)$ holds, we use $\boldsymbol{\Psi(\Delta T_I(\eta),X,Y)}$ to denote $\min_{1\le i\le L}\{\Psi(\Delta T_i(\eta),X,Y)\}$. Thus the **RMFD** of X, Y during $\boldsymbol{\Delta T_I(\eta)}$ can be expressed as

$$\boldsymbol{X}_{(d_1,\tau')} \xrightarrow{\Psi(\Delta T_I(\eta),X,Y)\le\varepsilon} \boldsymbol{Y}_{(d_2,\tau'')}.$$

Remark 3: Under the conditions of definition 7, we can get $X_{(d_1,\tau')} \xrightarrow{\Psi(T,X,Y)\le\varepsilon} Y_{(d_2,\tau'')}$ by $X_{(d_1,\tau')} \xrightarrow{\Psi(\Delta T_I(\eta),X,Y)\le\varepsilon} Y_{(d_2,\tau'')}$.

Based on definition 3 and definition 6, it is easy to know there are two classes of dependency violation events during $\Delta T(\eta)$, so we summarize as follows.

Definition 8 Given a relation $R(T, A_1, \cdots, A_n)$ and $X, Y \subseteq U$, for a pair of tuples v_I and v_J corresponding to some two moments t_I and t_J during $\Delta T(\eta)$, if there is one of the following cases happening, we say v_I, v_J at the moments t_I and t_J with respect to X, Y constitute a **dependency violation event** during $\boldsymbol{\Delta T(\eta)}$ ($\boldsymbol{\Delta T(\eta)}$**-DVE**):

(1) $|t_I - t_J| > \eta$;

(2) $v_I[X] \cong_{(d_1, \tau', t_i, t_j)} v_J[X]$ holds, whereas $v_I[Y] \cong_{(d_2, \tau'', t_i, t_j)} v_J[Y]$ doesn't hold.

For simplicity, Case (1) is denoted as $\boldsymbol{\Delta T(\eta)}$**-DVE-**$\boldsymbol{t_I, t_J}$, Case (2) is denoted as $\boldsymbol{\Delta T(\eta)}$**-DVE-**$\boldsymbol{v_I, v_J}$**[X, Y]**.

For a tuple v_I corresponding to some moment t_I during $\Delta T(\eta)$, sometimes we need to know the **DVR** of v_I. To this end we need to introduce the definition of **DVE** of v_I. According to definition 3, we present the following definition.

Definition 9 Given a relation $R(T, A_1, \cdots, A_n)$ and $X, Y \subseteq U$, for some tuple v_I corresponding to some moment t_I and a series of tuples v_j corresponding to some moments t_j during $\Delta T(\eta)$, if $v_I[X] \cong_{(d_1, \tau', t_I, t_j)} v_j[X]$ holds, whereas $v_I[Y] \cong_{(d_2, \tau'', t_I, t_j)} v_j[Y]$ doesn't hold $(1 \le I, j \le m_1,\ I \ne j)$, where m_1 is the number of the tuples during $\Delta T(\eta)$, we say v_I, v_j at the moments t_I and t_j with respect to *X,Y* constitute a **dependency violation event** during $\boldsymbol{\Delta T(\eta)}$, denote by $\boldsymbol{\Delta T(\eta)}$**-DVE-**$\boldsymbol{v_I, v_j}$**[X, Y]**. All of the DVEs of v_I with respect to *X,Y* during $\Delta T(\eta)$ are denoted as $\boldsymbol{\Delta T(\eta)}$**-DVEs-**$\boldsymbol{v_I}$**[X, Y]**.

Based on definition 9, we can get definition 10.

Definition 10 Given a relation $R(T, A_1, \cdots, A_n)$ and $X, Y \subseteq U$, for the tuple v_I corresponding to some moment t_I during $\Delta T(\eta)$, we define the **dependency violation rate** of $\boldsymbol{v_I}$ during $\boldsymbol{\Delta T(\eta)}$ ($\boldsymbol{\Delta T(\eta)}$**-** ***DVR*****-**$\boldsymbol{v_I}$**[X, Y]**) as follows:

$$\Psi(\Delta T(\eta), X(v_I), Y(v_I)) = \frac{r_{v_I}}{m_1 - 1},$$

where $r_{v_I} \subseteq r_{\Delta T(\eta)}$ is the number of $\Delta T(\eta)$-DVEs-v_I[X, Y], m_1 is the number of the tuples during $\Delta T(\eta)$.

For a tuple v_I during $\Delta T(\eta)$ and a given ε, if $\Psi(\Delta T(\eta), X(v_I), Y(v_I)) \le \varepsilon$, then we say v_I constitutes a **normal event** (**NE**) (see section 3). Otherwise we say it is an **abnormal event** (**ANE**). In particular, we study the following cases.

Definition 11 Given a relation $R(T, A_1, \cdots, A_n)$ and $X, Y \subseteq U$, for the three consecutive tuples v_I, v_{I+1}, v_{I+2} corresponding to some moments t_I, t_{I+1}, t_{I+2} during $\Delta T(\eta)$, if

$$\Psi(\Delta T(\eta), X(v_I), Y(v_I)) > \varepsilon,$$

$$\Psi(\Delta T(\eta), X(v_{I+1}), Y(v_{I+1})) > \varepsilon,$$

$$\Psi(\Delta T(\eta), X(v_{I+2}), Y(v_{I+2})) > \varepsilon,$$

we say the tuples v_I, v_{I+1}, v_{I+2} constitute an **abnormal event 1** during $\boldsymbol{\Delta T(\eta)}$ ($\boldsymbol{\Delta T(\eta)}$**-ANE-1)** (see section 3) .

Definition 12 Given a relation $R(T, A_1, \cdots, A_n)$ and $X, Y \subseteq U$, for the three consecutive tuples v_I, v_{I+1}, v_{I+2} corresponding to some moments t_I, t_{I+1}, t_{I+2} during $\Delta T(\eta)$, if

$$\Psi(\Delta T(\eta), X(v_I), Y(v_I)) > \varepsilon,$$

$$\Psi(\Delta T(\eta), X(v_{I+1}), Y(v_{I+1})) > 2 \cdot \Psi(\Delta T(\eta), X(v_I), Y(v_I)),$$

$$\Psi(\Delta T(\eta), X(v_{I+2}), Y(v_{I+2})) > 2 \cdot \Psi(\Delta T(\eta), X(v_{I+1}), Y(v_{I+1})),$$

we say the tuples v_I, v_{I+1}, v_{I+2} constitute an **abnormal event 2** during $\boldsymbol{\Delta T(\eta)}$ ($\boldsymbol{\Delta T(\eta)}$**-ANE-2)** (see section 3) .

More generally, we have the following case.

Definition 13 Given a relation $R(T, A_1, \cdots, A_n)$ and $X, Y \subseteq U$, for the three consecutive tuples v_I, v_{I+1}, v_{I+2} corresponding to some moments t_I, t_{I+1}, t_{I+2} during $\Delta T(\eta)$, if

$$\Psi(\Delta T(\eta), X(v_I), Y(v_I)) > \varepsilon,$$

$$\Psi(\Delta T(\eta), X(v_{I+1}), Y(v_{I+1})) > n \cdot \Psi(\Delta T(\eta), X(v_I), Y(v_I)),$$

$$\Psi(\Delta T(\eta), X(v_{I+2}), Y(v_{I+2})) > n \cdot \Psi(\Delta T(\eta), X(v_{I+1}), Y(v_{I+1})),$$

where $n > 2$, we say the tuples v_I, v_{I+1}, v_{I+2} constitute an **abnormal event N** during ***ΔT(η)*** **(** ***ΔT(η)*** **- ANE-N)**.

Sometimes X and Y don't satisfy definition 6 during $\Delta T(\eta)$ because there are abnormal events. However, the subsets X_I , Y_I of X and Y getting by deleting the abnormal events, maybe satisfy definition 6. The following definition describes this case.

Definition 14 Given a relation $R(T, A_1, \cdots, A_n)$ and

$$X = \left(v_1[X], \cdots, v_n[X]\right) \subseteq U ,$$
$$Y = \left(v_1[Y], \cdots, v_n[Y]\right) \subseteq U ,$$

if there is v_k corresponding to some moment t_k during $\Delta T(\eta)$ such that

$$\Psi(\Delta T(\eta), X(v_k), Y(v_k)) > \varepsilon$$
$$(k = K_1, K_2, \cdots, K_M \in \{1, 2, \cdots, m_1\}) ,$$

whereas for

$$X_I = X - \{v_k[X] \mid k \in \{K_1, K_2, \cdots, K_M\}\} ,$$
$$Y_I = Y - \{v_k[Y] \mid k \in \{K_1, K_2, \cdots, K_M\}\} ,$$

and any $v_i[X],\ v_j[X] \in X_I$, $v_i[Y],\ v_j[Y] \in Y_I$, whenever $v_i[X] \cong_{(d_1, \tau', t_i, t_j)} v_j[X]$ holds, there is almost $v_i[Y] \cong_{(d_2, \tau'', t_i, t_j)} v_j[Y]$ holds, and

$$\Psi(\Delta T(\eta), X_I, Y_I) = \frac{r_3}{r_{I_{\Delta T(\eta)}}} \le \varepsilon ,$$

then the **relaxed type-M function dependency** during ***ΔT(η)***:

$$\boldsymbol{X}_{\boldsymbol{I}(d_1,\tau')} \xrightarrow{\Psi(\Delta T(\eta), X_I, Y_I) \le \varepsilon} \boldsymbol{Y}_{\boldsymbol{I}(d_2,\tau'')}$$

holds, where $\Psi(\Delta T(\eta), X_I(v_k), Y_I(v_k))$ is ***ΔT(η)*** **-** ***DVR-v*** $\boldsymbol{_k[X_I, Y_I]}$, $r_{I_{\Delta T(\eta)}}$ is the combinatorial number of any pair of attributes in X_I or Y_I during $\Delta T(\eta)$, $r_3 \subseteq r_{I_{\Delta T(\eta)}}$ is the number of the DVEs$-X_I, Y_I$ during $\Delta T(\eta)$, m_1 is the number of the tuples during $\Delta T(\eta)$, $d_1 \in D[X]$, $d_2 \in D[Y]$, and $\tau', \tau'', \varepsilon \in [0,1]$ are thresholds.

Remark 4: If $X_{(d_1,\tau')} \xrightarrow{\Psi(\Delta T(\eta), X, Y) \le \varepsilon} Y_{(d_2,\tau'')}$ doesn't hold, and there are ANEs in X and Y , we can delete some $v_I[X]$ s and $v_I[Y]$ s corresponding to them from X and Y , then we get X_I and Y_I , and we have $X_{I(d_1,\tau')} \xrightarrow{\Psi(\Delta T(\eta), X_I, Y_I) \le \varepsilon} Y_{I(d_2,\tau'')}$ holds. This means the case of definition 14 is happening.

5. Event-Based Data Analysis Example

The following records represent a person's meditation input data including EEG from brainwave headset and GazeX and GazeY from the smart phone:

Time		EEG	GazeX	GazeY
2018-2-20	16:57:00	53	0.02884405	0.36825011
2018-2-20	16:57:01	57	-0.0057313	0.39013446
2018-2-20	16:57:02	74	0.00372011	0.33091585
2018-2-20	16:57:03	84	0.07300814	0.36468598
2018-2-20	16:57:04	90	0.06822054	0.39343803
2018-2-20	16:57:05	84	0.01829791	0.35769521
2018-2-20	16:57:06	74	0.07686714	0.4012554
2018-2-20	16:57:07	43	0.05864623	0.40079645
2018-2-20	16: 57:08	27	0.08833459	0.41172976
2018-2-20	16: 57:09	43	0.02981886	0.40139946
2018-2-20	16: 57:10	43	0.08068578	0.3896068
2018-2-20	16: 57:11	67	0.07305756	0.37007838
2018-2-20	16: 57:12	77	0.05570461	0.44665981
2018-2-20	16: 57:13	70	0.05092989	0.44977627
2018-2-20	16: 57:14	67	0.03441077	0.41223145
2018-2-20	16: 57:15	69	0.03749303	0.49343493
2018-2-20	16: 57:16	67	0.03365155	0.42283732
2018-2-20	16: 57:17	61	0.0471089	0.47274698
2018-2-20	16: 57:18	54	0.04033958	0.48874432
2018-2-20	16: 57:19	56	0.04615196	0.45340732
2018-2-20	16: 57:20	60	0.08277113	0.43117775
2018-2-20	16: 57:21	75	0.12389434	0.4264601
2018-2-20	16: 57:22	90	0.02021705	0.47553028
2018-2-20	16: 57:23	90	0.04613996	0.37573326

Firstly we define: for any attribute X ,

$$d_{\max\_X_{ij}} = \max_{1 \le i, j \le m} |v_i[X] - v_j[X]|$$

denotes the maximum of the distance between the values of any two tuples v_i, v_j in the attribute X , where m is the number of the tuples during the whole time T , and

$$d\left(v_i[X], v_j[X]\right) = \frac{|v_i[X] - v_j[X]|}{d_{\max\_X_{ij}}}$$

is the distance function.

Then according to the above distance function, for the attribute EEG, for simplicity we denote it as E , we have

$$d\left(v_i[E],v_j[E]\right)=\frac{|v_i[E]-v_j[E]|}{d_{\max\_E_{ij}}},$$

$$d_{\max\_E_{ij}}=\max_{1\le i,j\le m}|v_i[E]-v_j[E]|.$$

It is easy to see from the table that $d_{\max\_E_{ij}}=90-43=47$.

Assuming we can choose the time from 16:57:00 to 16:57:07 on February 20th, 2018. For any pair of tuples during this time, we calculate their distance functions as follows:

$$d\left(v_1[E],v_2[E]\right)=\frac{|53-57|}{47}=\frac{4}{47}\approx 0.0851.$$

Similarly, we can get

$d\left(v_2[E],v_5[E]\right)\approx 0.7021$, $d\left(v_3[E],v_6[E]\right)\approx 0.2128$,

$d\left(v_4[E],v_7[E]\right)\approx 0.2128$, $d\left(v_5[E],v_8[E]\right)=1$,

$$\vdots$$

Obviously, if $\tau'=0.7$, then except that

$$d\left(v_1[E],v_5[E]\right)\approx 0.7872>\tau',$$
$$d\left(v_2[E],v_5[E]\right)\approx 0.7021>\tau',$$
$$d\left(v_4[E],v_8[E]\right)\approx 0.8723>\tau',$$
$$d\left(v_5[E],v_8[E]\right)=1>\tau',$$
$$d\left(v_6[E],v_8[E]\right)\approx 0.8723>\tau',$$

for the other pair of tuples, $d\left(v_i[E],v_j[E]\right)\le\tau'$ $(i,j=1,2,\cdots,8,\quad i\ne j)$ always holds.

And for the attribute GazeY, for simplicity we denote it as GY, then

$$d\left(v_i[GY],v_j[GY]\right)=\frac{|v_i[GY]-v_j[GY]|}{d_{\max\_GY_{ij}}},$$

$$d_{\max\_GY_{ij}}=\max_{1\le i,j\le m}|v_i[GY]-v_j[GY]|,$$

and

$$d_{\max\_GY_{ij}}=0.4012554-0.33091585=0.07033955.$$

Thus we can similarly get their distance functions:

$$d\left(v_1[GY],v_2[GY]\right)=\frac{|0.36825011-0.39013446|}{0.07033955}\approx 0.3111,$$

and

$$d\left(v_2[GY],v_3[GY]\right)\approx 0.8419,$$
$$d\left(v_3[GY],v_5[GY]\right)\approx 0.9017,$$
$$d\left(v_4[GY],v_6[GY]\right)\approx 0.0994,$$
$$d\left(v_5[GY],v_8[GY]\right)\approx 0.0918,$$
$$\vdots$$

If $\tau''=0.6$, then except that

$$d\left(v_2[GY],v_3[GY]\right)\approx 0.8419>\tau'',$$
$$d\left(v_3[GY],v_5[GY]\right)\approx 0.9017>\tau'',$$
$$d\left(v_3[GY],v_7[GY]\right)=1>\tau'',$$
$$d\left(v_3[GY],v_8[GY]\right)\approx 0.9935>\tau'',$$
$$d\left(v_6[GY],v_7[GY]\right)\approx 0.6193>\tau'',$$
$$d\left(v_6[GY],v_8[GY]\right)\approx 0.6128>\tau'',$$

for the other pair of tuples, $d\left(v_i[GY],v_j[GY]\right)\le\tau''$ ($i,j=1,2,\cdots,8,\quad i\ne j$) always holds.

It is clear that $v_2[E]\cong_{(d_1,\tau',t_i,t_j)}v_3[E]$ holds, whereas $v_2[GY]\cong_{(d_2,\tau'',t_i,t_j)}v_3[GY]$ doesn't holds. By the definition 3, this is a dependency violation event (DVE). In fact, $\Delta T(\eta)$- DVEs -[E, GY] are as follows:

$$\Delta T(\eta)\text{ - DVEs -}v_2,v_3[\mathrm{E},\mathrm{GY}],$$
$$\Delta T(\eta)\text{ - DVEs -}v_3,v_5[\mathrm{E},\mathrm{GY}],$$
$$\Delta T(\eta)\text{ - DVEs -}v_3,v_7[\mathrm{E},\mathrm{GY}],$$
$$\Delta T(\eta)\text{ - DVEs -}v_3,v_8[\mathrm{E},\mathrm{GY}],$$
$$\Delta T(\eta)\text{ - DVEs -}v_6,v_7[\mathrm{E},\mathrm{GY}].$$

Therefore

$$\Psi(\Delta T(\eta),E,GY)=\frac{5}{28}\approx 0.1786.$$

If $\varepsilon=0.18$, then

$$\Psi(\Delta T(\eta),E,GY)\le\varepsilon.$$

And according to the definition 6, as long as $v_i[E]\cong_{(d_1,\tau',t_i,t_j)}v_j[E]$ holds, there is almost $v_i[GY]\cong_{(d_2,\tau'',t_i,t_j)}v_j[GY]$ holds. So

$$E_{(d_1,\tau')}\xrightarrow{\Psi(\Delta T(\eta),E,GY)\le\varepsilon}GY_{(d_2,\tau'')}$$

holds.

We note that for the tuple v_3, according to definition 10, we have

$$\Psi(\Delta T(\eta),E(v_3),GY(v_3))=\frac{4}{7}\approx 0.5714>\varepsilon,$$

i.e., v_3 constitutes an abnormal event (ANE).

At the same time, we can get

$$\Psi(\Delta T(\eta),E(v_1),GY(v_1))=\frac{0}{7}=0\le\varepsilon,$$

$$\Psi(\Delta T(\eta),E(v_2),GY(v_2))=\frac{1}{7}\approx 0.1429\le\varepsilon,$$

$$\Psi(\Delta T(\eta), E(v_4), GY(v_4)) = \frac{0}{7} = 0 \leq \varepsilon,$$

$$\Psi(\Delta T(\eta), E(v_5), GY(v_5)) = \frac{1}{7} \approx 0.1429 \leq \varepsilon,$$

$$\Psi(\Delta T(\eta), E(v_6), GY(v_6)) = \frac{1}{7} \approx 0.1429 \leq \varepsilon,$$

$$\Psi(\Delta T(\eta), E(v_7), GY(v_7)) = \frac{2}{7} \approx 0.2857 > \varepsilon,$$

$$\Psi(\Delta T(\eta), E(v_8), GY(v_8)) = \frac{1}{7} \approx 0.1429 \leq \varepsilon.$$

Therefore there is no ANE-1 happening during the time from 16:57:00 to 16:57:07 on February 20th, 2018. Obviously, there is also ANE-2 appearing.

It is clear during the time from 16:57:00 to 16:57:07 on February 20th that $E = (v_1[E], \cdots, v_8[E])$, $GY = (v_1[GY], \cdots, v_8[GY])$. According to the above calculation process, we know if $\varepsilon = 0.05$, then

$$E_{(d_1,\tau')} \xrightarrow{\Psi(\Delta T(\eta),E,GY)\leq\varepsilon} GY_{(d_2,\tau'')}$$

doesn't hold. However, for

$E_1 = (v_1[E], v_2[E], v_4[E], v_5[E], v_6[E], v_7[E], v_8[E]) \subseteq E$,

$GY_1 = (v_1[GY], v_2[GY], v_4[GY], v_5[GY], v_6[GY], v_7[GY], v_8[GY])$

$\subseteq GY$,

there is only one dependency violation event (DVE): $\Delta T(\eta)$ - DVEs -$v_2, v_3[\mathrm{E}, \mathrm{GY}]$.

Then we can get

$$\Psi(\Delta T(\eta), E_1, GY_1) = \frac{1}{21} \approx 0.0476 < \varepsilon.$$

So $E_{1(d_1,\tau')} \xrightarrow{\Psi(\Delta T(\eta),E_1,GY_1)\leq\varepsilon} GY_{1(d_2,\tau'')}$. This is the case of Definition 14.

6. User Scenarios

In TDR system, sensor data from different devices, devices like temperature, humid, gaze, and etc, will be stored in a heap. In order for the administrator to better organize those data into separate relations, we have developed some tools to facilitate the process. The following are the steps how an admin can manage the system.

6.1. Scenario One: Organize Records

Upon login as an admin, you can see the following:

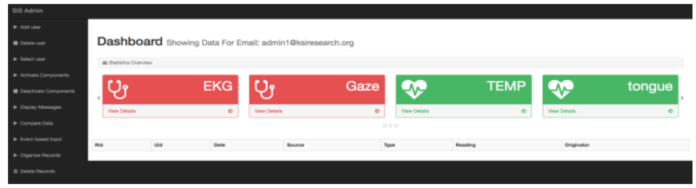


Figure 9. The Dashboard.

To write data into different relations, click organize records, then you can choose which relation you wish to write the data to.

Figure 10. Choose relations.

Upon selecting which relation the admin prefer to write data to, the system will show how many records are available in heap. The admin may type in the number of records he/she wants to write into the specific relation, but the number has to be no greater than maximum records in heap, after click on submit, the system will remind the admin whether his/her action was preformed successfully.

6.2. Scenario Two: Event-based Input

From the main page, if admin wish to move data to relations subject to certain restrict,ion he/she may choose to use event-based input tool.

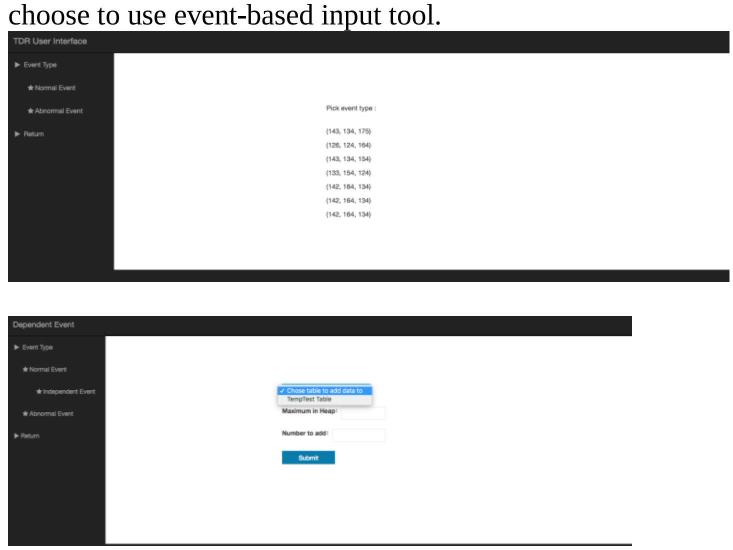


Figure 11. Normal event.

After admin has chosen normal event, admin can then pick which relation he/she wish to choose. If a tuple is a normal event for the relation, then the tool can add the tuple into the relation. Similarly, after chose abnormal event, the tool will prompt admin to pick which event (aka: dependent event or independent event) he/she want to add records to.

We will give an example upon picking dependent event, but the flow will be the same if admin chose independent event.

Figure 12. Independent event.

After chose which relation data admin wish to apply algorithm on, the tool will select data records and apply (2) on it, if data records satisfy (2), then move it to the correspond relation.

7. Discussion

In this paper we describe an experimental TDR system with the following features: 1) the experimental system can run on a smart phone and therefore portable; 2) a meditation validation channel to check the consistency between the predictions via gaze features vs. features to increase the accuracy of meditation prediction; 3) through event-based data input, modeling and analysis, a user can access the brainwave from a one-channel NeuroSky Mindwave headset and gaze data from a Samsung phone and the consistency check graph via a web GUI; 4) QA and rating, where a user can provide feedback right after his/her meditation process, master/teacher will rating the meditation quality based on such feedback and previous measurement data. We can also track user's typing movements when providing feedback to measure the users' muscle change during and after meditation.

An initial experiment was designed and conducted to test the ability of monitoring meditation state via brainwave and gaze tracking techniques, as well as observe the relationship between the two sources of signals. Preliminary results indicated a trend of positive relationship (correlation coefficient = 0.982) between gaze y-axis signals and brainwave signals (Figure 13), which indicates the validity of our approach in meditation detection as well as inspired us to further investigate their degrees of correlations.

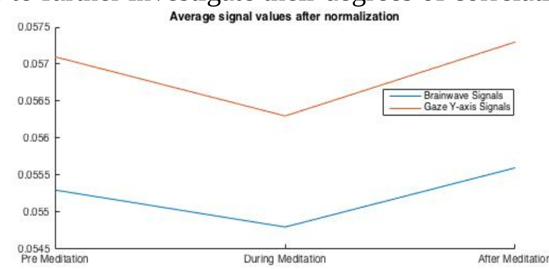


Figure 13. Preliminary results on meditation states tracking via brainwave signals and gaze signals.

The current system has certain limitations: 1) headset requires a precise wearing process to extract sensor data, otherwise a portion of the data may be missing. Users who are not professional enough or without external support, will only have partial data, which is less accurate; 2) Gaze tracking via front facing camera of smart phone is portable and maneuverable, but lack of accuracy due to the noisy luminance effect in real environment as well as the user's meditating habit.

For future work, we need to develop techniques to overcome the above mentioned limitations, as well as to design approaches to help people better understand their meditation state without too much manual intervention. More experiments need to be designed and carried out to validate the proposed approach.

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