Fuzzy Concept Lattice Based Event Composition Model

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Abstract. Because of the existence of uncertainty in physical word, the classical theory-based event model cannot express the change of state accurately. This paper builds a fuzzy concept lattice-based temporal-spatial event composition model to describe events correctly and combine events efficiently. We define fuzzy event concept and formal representation of event instance, and prove the theorems of event type and attribute composition on basis of fuzzy concept lattice. Moreover, we analyze event composition rules from three aspects which are temporal, spatial and internal attributes. Finally, by applying the fuzzy event composition model to smart space and comparing it with Tan's model, the proposed event model in this paper is characterized with variable membership threshold, attributed temporal-spatial relationship, and supporting component coordination.

Introduction

Event-driven mechanism with its loosely coupled and distributed characteristics, and meeting the need of instantaneity in complex environment, is widely used in large complex systems such as CPS, and the interaction between the cyber world and the physical world is realized by defining events [1]. The key problem of event-driven mechanism is to combine some simple events and extract the complex events [2]. Based on the logical and temporal relation between atomic events, five kinds of operations are defined in paper [3]. Gao Jing [4] analyzes the composition events from three kinds of data, which are time, space and data. Tan [5, 6] proposes a uniform event representation which is based on temporal-spatial characteristics. She has defined CPS concept lattice from the perspective of formal concept, and constructed CPS event composition model. By extending the definition of formal concept analysis, the constraint is not only limited to a single attribute or multiple attributes, but also the relationship between them. This model greatly reduces the amount of code and improves efficiency.

In real life, events are often difficult to be quantified with precise semantics, and fuzzy semantics can realize more accurate expression of events. Especially to the systems such as CPS which has high requirements for the instantaneity and accuracy, if fixed critical values corresponding to the attributes are used to judge whether the event occurs, error and low accuracy will be generated. Fuzzy logic and probability theory can be used to describe the state of the system more clearly. In 1990s, the concept of active fuzzy database was proposed [7], which was concerned with the degree of change of state. Wei Yan [8] divides the basic fuzzy events into four categories, which are types of time, operation, transaction and externality. According to the uncertainty of temporal relationships among events, the Paper [9] constructs Markov Chain-based probability event model. As is different from the fuzzy logic-based complex event model, the model emphasized the unknown nature of the event. Based on the fuzzy ECA rules, the Paper [10] proposes the access control strategy, which defines the fuzzy events, fuzzy rules and fuzzy actions respectively.

In this paper, fuzzy logic theory is combined with CPS concept lattice theory. We defines fuzzy event lattice and show the formal expression of event instances. The rules of event composition are analyzed from temporal composition, spatial composition and internal attributes composition. The membership threshold of attributes can be adjusted according to event type. Component-based event
The Definition of Fuzzy Event Lattice and Fuzzy Event

The event-oriented fuzzy concept lattice is different from the traditional fuzzy concept lattice theory [11,12]. On the one hand, the contributions of different fuzzy attributes to the same event are different. Meanwhile, due to the correlation between the attributes of event, the same fuzzy attribute contributes differently in different events. Therefore, the membership threshold of fuzzy attribute should not be fixed. On the other hand, the events are often non-discrete and random, which means the event set is uncertain. Therefore, fuzzy concept cannot be generated by analyzing the attribute value of events. By combining CPS concept lattice proposed by Tan[5] with fuzzy logic theory, we transform the attribute constraints into fuzzy attribute items. Moreover, the formal representation of fuzzy event is defined, and a fuzzy concept lattice-based event composition model is established.

Definition 1 Formal context. The formal context is represented by a triple \((T,C,I)\). \(T\) denotes the event type set. \(C\) denotes the extended fuzzy attribute set [5]. \(I\) denotes the relationship between event type set \(T\) and the extended fuzzy attribute set \(C\), which is represented by membership threshold function \(I(\Gamma,c): R(\Gamma,c) \geq \varphi_{\Gamma,c}\), where \(\Gamma \in T\), \(c \in C\), \(\varphi_{\Gamma,c}\) denotes the membership threshold of attribute \(c\) in the event type \(\Gamma\).

Definition 2 Fuzzy event concept. Formal context \((T,C,I)\) is given, and let \(T_1' = \{c \in C \mid \forall \Gamma \in T_1', (\Gamma,c) \in I\}, C_1' = \{\Gamma \in T \mid \forall c \in C_1', (\Gamma,c) \in I\}\). If \(T_1' = C_1\) and \(C_1' = T_1, T_j\) and \(C_j\) constitute a fuzzy event concept, which is represented by \(E_i = (T_i, C_i)\), where \(T_j \in 2^T, C_j \in 2^C\).

Theorem 1. Let the triple \((T,C,I)\) be formal context. \(T_i, T_j \in 2^T, C_i, C_j \in 2^C\), then

1. \((T_i \cup T_j) = (T_i) \cup (T_j); (C_i \cup C_j)' = (C_i) \cup (C_j)\)
2. \((T_i \cup T_j) \supseteq (T_i) \cup (T_j); (C_i \cup C_j)' \supseteq (C_i) \cup (C_j)\)

Proof. (1) \(\forall c \in (T_i \cup T_j)'\), it holds that \(\forall \Gamma \in (T_i \cup T_j), (\Gamma,c) \in I\). \(\forall \Gamma' \in (T_i, (\Gamma',c) \in I\). As \(\Gamma'\) is arbitrary, \(c \in T_i\). Similarly, \(c \in T_j\). \(\forall c \in (T_i \cap T_j)'\). As \(c\) is arbitrary, \((T_i \cap T_j) \subseteq (T_i \cup T_j)\).

Oppositely, \(\forall c \in (T_i \cap T_j)', \text{ it holds that } c \in T_i\) and \(c \in T_j\). \(\forall \Gamma \in T_i, (\Gamma,c) \in I\). \(\forall \Gamma' \in T_j, (\Gamma',c) \in I\). \(T_i \cap T_j)' \subseteq (T_i \cup T_j)\).

Similarly, we can also demonstrate that \((C_i \cup C_j)' \supseteq (C_i) \cup (C_j)\).

(2) \(\forall c \in (T_i \cup T_j)', c \in T_i\) or \(c \in T_j\). Suppose \(c \in T_i\), then \(\forall \Gamma \in T_i, (\Gamma,c) \in I\). \(\forall \Gamma' \in T_j, (\Gamma',c) \in I\). \(\forall \Gamma \in (T_i \cap T_j)', \text{ we have that } \forall \Gamma \in (T_i \cap T_j), (\Gamma,c) \in I\). \((T_i \cap T_j)' \subseteq (T_i \cup T_j)\).

Similarly, \((C_i \cap C_j)' \supseteq (C_i) \cup (C_j)\).

Theorem 2. Let \((T,C,I)\) be the formal context. \(T_i \in 2^T, C_i \in 2^C\), then \(T_i \subseteq T_i', C_i \subseteq C_i\). The proof is like theorem 1.

Definition 3 Partial order \(\prec\). Let \((T,C,I)\) be the formal context, \(E_1 = (T_1, C_1), E_2 = (T_2, C_2)\) are two fuzzy event concept, respectively. If \(T_1 \subseteq T_2\) or \(C_1 \supseteq C_2, E_1 \prec E_2\).

Definition 4 Fuzzy event lattice. Let \((T,C,I)\) be the formal context. All the fuzzy event concepts and the partial order relation between them build fuzzy event lattice based on \((T,C,I)\).

Definition 5 Formal representation of fuzzy event concept.

\(e = \{\text{SubSys}_d, \text{Obs}_d, \text{Comp}_d(\text{EnvId}), \text{Attr}(\text{Rela}), T^*, L^*, T^*, L^*\}\)

- \(\Gamma\) represents the type of fuzzy event, for example, the type "middle age".
- \(\text{SubSys}_d\) represents subsystem (or component) ID. Component-based architecture design is widely applied to heterogeneous distributed systems [13].
- \(\text{Obs}_d\) represents the observer ID, which can be a sensor, a control node, an actuator or other devices. The format of observer ID is "observer type-observer ID".
- \(\text{Comp}_d(\text{EnvId})\) represents the observed object ID, which can be a single observed or multiple observed objects.
- \(\text{Attr}(\text{Rela})\) represents fuzzy attribute values or fuzzy attribute relations (including fuzzy temporal-spatial attribute relations).
**Temporal-Spatial Attributes**

The temporal-spatial attributes are used to represent the time interval (or time point) and spatial region (or location point). \( T^g, L^g, T^o, L^o \) represent the time and location when and where event \( e \) is generated, and \( T^T, L^T \) are the time and location when and where event \( e \) occurs which is observed by the observer \( O_{bs, id} \).

### Fuzzy Event Composition

Fuzzy event composition not only combines fuzzy attributes of multiple events, but also extends attributes by the relations between the attributes.

**Definition 6.** Let \((T, C, I)\) be the formal context, and \(E_i = (T_i, C_i)\) be a fuzzy event concept. The intersection and union operations on fuzzy event concepts are defined as:

\[
\bigwedge_{i \in J} E_i = \bigwedge_{i \in J} (T_i, C_i) = (\bigcap_{i \in J} T_i, (\bigcup_{i \in J} C_i)^*)
\]

\[
\bigvee_{i \in J} E_i = \bigvee_{i \in J} (T_i, C_i) = ((\bigcup_{i \in J} T_i)^*, \bigcap_{i \in J} C_i)
\]

(J denotes the subset of index set).

The composition of event instances can be analyzed from three types of data: temporal composition, spatial composition, and internal attributes composition. Let \((T, C, I)\) be the formal context, \(e_i\) be the instance of event concept \(E_i = (T_i, C_i)\), and \(e_j\) be the instance of event concept \(E_j = (T_j, C_j)\). The combination of events \(e_i\) and \(e_j\) have two forms: One is to reflect all the characteristics of both events \(e_i\) and \(e_j\), which is realized by operation "and" (\(\cdot\)); The other one is to reflect the common characteristics of both events \(e_i\) and \(e_j\), which is realized by operation "or" (\(+\)).

\[ e_{ij} = e_i \cdot e_j = \Gamma_{ij}(O_{bs, id}, A_{\text{SubSysID}}, SubSysID, ComplID(EnviID), ComplID(EnviID), Attr(Rela)_i, Attr(Rela)_j, T_i, T_j, L_i, L_j, T^T, L^T, T^o, L^o) \]

\[ e_{ij} = e_i + e_j = \Gamma_{ij}(\text{SubSysID}_i \cap \text{SubSysID}_j, O_{bs, id}, \text{ComplID}(\text{EnviID}_i) \cap \text{ComplID}(\text{EnviID}_j), \text{Attr}(\text{Rela})_i \cap \text{Attr}(\text{Rela})_j, T^T, L^T, T^o, L^o) \]

\( O_{bs, id} \) represents the sink node that combines event \(e_i\) with \(e_j\). \( A_{\text{Sub}} \) represents composition rules of internal fuzzy attributes, temporal attributes and spatial attributes. \( T^o, L^o \) represents the time and location when and where the sink node generates the composite event \(e_{ij}\). \( T^T, L^T \) represents the time and location of the occurrence of composite events which are obtained by combining temporal-spatial infos of \(e_i\) and \(e_j\).

### Temporal Attribute Composition

Tan [5] puts forward the rule of interval-based temporal composition that if the time of occurrence of event \(e_i\) and \(e_j\) are \(T_i = [t_{i1}, t_{i2}]\) and \(T_j = [t_{j1}, t_{j2}]\) respectively, the time of occurrence of composite event is \(T = [\min\{t_{i1}, t_{j1}\}, \max\{t_{i2}, t_{j2}\}]\). The temporal attributes determine the sequence of occurrence, and affect the result of composition. Here the start time point and end time point of the interval are discussed to determine the temporal relation.

To simplify time interval relation representation, seven relations as Fig. 1 are defined on base of Paper [14]. The temporal relation "equal" can be represented by \(\text{StartEqual}(x,y) \&\& \text{EndEqual}(x,y)\), where \(x\) and \(y\) represent time of occurrence or generation of the event instance.

| Time interval relation | x.end<y.start and x.start=y.start | x.start=y.start and x.end>y.end | x.start>y.start and x.end<y.end | ignorable relation |
|------------------------|---------------------------------|---------------------------------|---------------------------------|------------------|
| Represen-tation        | Before(x,y)                     | Meet(x,y)                       | Overlap(x,y)                    | StartEqual(x,y)  |
|                        |                                  |                                 |                                 | EndEqual(x,y)    |
|                        |                                  |                                 |                                 | During(x,y)      |
|                        |                                  |                                 |                                 | Any(x,y)         |

Figure 1. Simplified temporal relation representation.
Suppose that the instance of event type "PersonIn" is $\varepsilon_1 = PERSONIN \{ v_{\text{personin}}, T^o_{\text{personin}} \}$, and the instance of event type "Hot" is $\varepsilon_2 = HOT \{ v_{\text{hot}}, T^o_{\text{hot}} \}$. We can combine $\varepsilon_1$ with $\varepsilon_2$ as follows:

$\varepsilon_1 = \varepsilon_1 \land \varepsilon_2 = PERSONIN\text{NOT} \{ \varepsilon_1, v_{\text{personin}}, \varepsilon_2, v_{\text{hot}}, \text{before}(\varepsilon_2, T^o_{\text{hot}}, \varepsilon_1, T^o_{\text{personin}}) \}$

$\varepsilon_1 = \varepsilon_1 \land \varepsilon_2 = PERSONIN\text{THEN} \{ \varepsilon_1, v_{\text{personin}}, \varepsilon_2, v_{\text{hot}}, \text{before}(\varepsilon_2, T^o_{\text{personin}}, \varepsilon_1, T^o_{\text{hot}}) \}$.

Based on one reference and two references respectively, the composition operation "intersection" on temporal relations is shown as Fig.2. "–" represents an uncertain composition relationship. $R_1$ represents the temporal relation between $x$ and $y$, and the membership degree is $v_{R_1}$. $R_2$ represents the temporal relation between $y$ and $z$, and the membership degree is $v_{R_2}$. The membership degree of temporal relation $R_3$ is $v_{R_3} = \min\{v_{R_1}, v_{R_2}\}$.

Figure 2. Temporal relation composition.

Spatial Attribute Composition

The spatial attributes determine the topological relations, orientation relations and metric spatial relations between several events [7]. Tan [5] proposes that the representation of three-dimensional spatial information is $((x, y, z), r)$, where $(x, y, z)$ denotes the geographical coordinates relative to the observer. Let $((x_i, y_i, z_i), r_i)$ and $((x_j, y_j, z_j), r_j)$ be the locations where event $\varepsilon_i$ and $\varepsilon_j$ occur respectively. The location of occurrence of composite event $\varepsilon_i \cdot \varepsilon_j$ is the smallest circle region which contains $((x_i, y_i, z_i), r_i)$ and $((x_j, y_j, z_j), r_j)$, and there is no "hole" in the composite region. It greatly simplifies the spatial attribute composition.

Figure 3. Spatial relation composition.
On the basis of Tan’s spatial composition, five spatial topological relations are proposed, which are split(L_i, L_j), overlap(L_i, L_j), contain(L_i, L_j), equal(L_i, L_j), and any(L_i, L_j) respectively, where L_i and L_j denote the locations of occurrence or generation of events e_i and e_j. In addition to the relation contain(L_i, L_j), the other four relations are symmetric. Here the spatial relation composition based on one reference and two reference are shown as Fig.3, where "-" represents an uncertain composite relationship. R1 represents the topological relationship between the location x and y, and the membership degree is \(\nu_{R1}\), R2 represents the topological relationship between the location y and z, and the membership degree is \(\nu_{R2}\). The membership degree of spatial topological relation R3 is \(\nu_{R3} = \min\{\nu_{R1}, \nu_{R2}\}\).

**Internal Attribute Composition**

The internal attributes include the subsystem ID, the observed object ID, and the fuzzy internal attribute (or the fuzzy attribute relation).

If the fuzzy attribute set of event concept \(E_i = (T_i, C_i)\) is \(C_i = \{c_{i1}, c_{i2}, \ldots, c_{im}\}\), and the fuzzy attribute set of event concept \(E_j = (T_j, C_j)\) is \(C_j = \{c_{j1}, c_{j2}, \ldots, c_{jn}\}\), according to definition 6, \(E_{ij} = (T_{ij}, C_{ij})\) is \(E_i \land E_j \lor (0 \lor E_i \lor E_j) = (T_i, C_i) \land (T_j, C_j) (0 \lor (T_i, C_i) \lor (T_j, C_j))\), and \(C_{ij} = C_i \cap C_j = \{c_{i1}, c_{i2}, \ldots, c_{im}\} \cap \{c_{j1}, c_{j2}, \ldots, c_{jn}\} = \{c_{g1}, c_{g2}, \ldots, c_{gl}\}\), \(\overline{C}_{ij} = C_i \cup C_j = \{c_{i1}, c_{i2}, \ldots, c_{im}\} \cup \{c_{j1}, c_{j2}, \ldots, c_{jn}\} = \{\overline{c}_{g1}, \overline{c}_{g2}, \ldots, \overline{c}_{g(m+n)}\} \subseteq (C_i \cup C_j)^*\).

Let event \(e_i\) and \(e_j\) be the instances of event concept \(E_i = (T_i, C_i)\) and \(E_j = (T_j, C_j)\) respectively. The memberships of attribute sets \(C_i\) and \(C_j\) corresponding to event \(e_i\) and \(e_j\) are \(\{v_{i1}, v_{i2}, \ldots, v_{im}\}\) and \(\{v_{j1}, v_{j2}, \ldots, v_{jn}\}\) respectively. Relative to \(e_i \cdot e_j\), the membership degree of attribute set \(C_{ij} = C_i \cap C_j\) is \(\{\min(v_{i1}, v_{j1}), \min(v_{i1}, v_{j2}), \ldots, \min(v_{im}, v_{jn})\}\). Relative to \(e_i + e_j\), the membership degree of attribute set \(C_{ij} = C_i \cup C_j\) is \(\{\max(v_{i1}, v_{j1}), \max(v_{i1}, v_{j2}), \ldots, \max(v_{im}, v_{jn})\}\), where \(v_{kj}(k = 1, 2, \ldots, I)\) denotes the membership of attribute \(c_{ik}\) relative to event \(e_k\) of \(e_k\). If there holds partial order \(c_{im} < c_{jn}\) between attribute item \(c_{im}\) of \(e_i\) and attribute item \(c_{jn}\) of \(e_j\), retain \(c_{jn}\) and discard \(c_{im}\) when intersection is operated, retain \(c_{im}\) and discard \(c_{jn}\) when union is operated.

**Smart Space Instance**

Based on Tan’s experiment, we apply the fuzzy event lattice to simulate the smart space. CLS sensor is used to monitor location information, and LS light sensor is used to monitor light intensity. When CLS detects that someone enters the room and stay long, and the light is dark, the system automatically turn on the light. The fuzzy attribute set is as follows:

\[\text{Attr} = \{\text{Range}, \text{Listr}, \text{SeqNum}, \text{Loc}, \text{InRoom}, \text{RoomDim}, \text{InRoomLong}, \text{Before}(T^a_{\text{InRoomLong}}, T_{\text{RoomDim}})\}\]

The metric values of attributes Range, Listr, SeqNum, Loc are obtained by sensors. The membership degrees of attributes InRoom, RoomDim, InRoomLong, Before are calculated according to the attribute membership functions respectively, where Before denotes that the instance of event type \(\Gamma_{\text{InRoomLong}}\) occurs before the instance of event type \(\Gamma_{\text{RoomDim}}\).

The fuzzy event lattice-based event composition model is as Fig. 4.
Suppose that the corresponding membership thresholds are as Table 1. At one timeslot, the membership degrees of fuzzy attributes are measured as follows:

\[
\begin{align*}
    v_{\text{InRoom}} &= 0.95 > \Gamma_{\text{LightOn}, \varphi_{\text{InRoom}}}, \\
    v_{\text{InRoomLong}} &= 0.9 > \Gamma_{\text{LightOn}, \varphi_{\text{InRoomLong}}} \\
    v_{\text{RoomDim}} &= 0.99 > \Gamma_{\text{LightOn}, \varphi_{\text{RoomDim}}} \\
    v_{\text{before}((\text{Subsys}_{id}, \text{CLS}_{id}, \{\text{Person}_{id}, \text{Room}_{id}\}), \text{InRoomLong}, \text{RoomDim}, \text{before}(\text{InRoomLong}, T^g, T^o, T^s, T^e))} &= 1 > \Gamma_{\text{LightOn}, \varphi_{\text{before}((\text{Subsys}_{id}, \text{CLS}_{id}, \{\text{Person}_{id}, \text{Room}_{id}\}), \text{InRoomLong}, \text{RoomDim}, \text{before}(\text{InRoomLong}, T^g, T^o, T^s, T^e))}}
\end{align*}
\]

Composite events are as follows:

\[
\begin{align*}
    \mathcal{E}_{\text{LightOn}} &= \mathcal{E}_{\text{InRoomLong}, \mathcal{E}_{\text{RoomDim}}} = \Gamma_{\text{LightOn} << \text{Subsys}_{id}, \text{CLS}_{id}, \{\text{Person}_{id}, \text{Room}_{id}\}}, v_{\text{InRoom}} = 0.95. \\
    v_{\text{InRoomLong}} &= 0.9, v_{\text{RoomDim}} = 0.99, v_{\text{before}((\text{Subsys}_{id}, \text{CLS}_{id}, \{\text{Person}_{id}, \text{Room}_{id}\}), \text{InRoomLong}, \text{RoomDim}, \text{before}(\text{InRoomLong}, T^g, T^o, T^s, T^e))} = 1 > T^g, T^s, T^o, T^e
\end{align*}
\]

Then the light turns on.

Table 1. Attribute membership threshold of event concept.

| Event type     | The membership threshold of event type |
|----------------|----------------------------------------|
| InRoom         | \(\varphi_{\text{InRoom}} = 0.9\)     |
| InRoomLong     | \(\varphi_{\text{InRoom}} = 0.93; \varphi_{\text{InRoomLong}} = 0.9\) |
| RoomDim        | \(\varphi_{\text{RoomDim}} = 0.95\)   |
| LightOn        | \(\varphi_{\text{RoomDim}} = 0.95; \varphi_{\text{before}((\text{Subsys}_{id}, \text{CLS}_{id}, \{\text{Person}_{id}, \text{Room}_{id}\}), \text{InRoomLong}, \text{RoomDim}, \text{before}(\text{InRoomLong}, T^g, T^o, T^s, T^e))} = 1\) |

The Table 2 shows the characteristics of Tan’s event model and fuzzy concept lattice-based event model.
Table 2. Compare Tan’s spatial-temporal event model with fuzzy concept lattice-based event model.

| Characteristics                  | Tan’s spatial-temporal event model | Fuzzy concept lattice-based event model |
|----------------------------------|------------------------------------|----------------------------------------|
| Component-based event definition | nonsupport                         | Support                                 |
| Variability of attribute membership threshold | nonsupport                         | Support                                 |
| Temporal relation                | nonsupport                         | Support                                 |
| Spatial relationship             | nonsupport                         | Support                                 |
| Runtime cost                     | low                                | higher                                  |

By contrast, Tan's temporal-spatial event model only supports event composition in global system or the specific subsystem, and fuzzy event concept-based event model defines component-based event representation which is in favor of component coordination. The attributes are constrained with constant critical values in Tan's model, and our model can adjust attribute membership thresholds according to event types. Tan's model hasn’t analyzed temporal-spatial relationships between events. Meanwhile, our model has higher runtime cost than Tan's because of the variability of membership thresholds.

Summary

Based on fuzzy concept lattice, this paper proposes a fuzzy event composition model. In view of the different contributions of attributes in different event types, a variable membership threshold is considered to define fuzzy event. According to temporal-spatial characteristics of events, the temporal-spatial relations between events are analyzed in detail, which are viewed as fuzzy attribute terms of the composite events. In the formal expression of the event, the component or subsystem ID term is defined, which is helpful to build the interactions between components or subsystems. In the future, we will make use of the form of event algebra to represent the logical relationship among events, and realize the coordination between components by event interaction.

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