# A Novel Event-based Method for Abducting Evolutional Motivation of Empirical Engineering Knowledge

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***Abstract*—In the engineering field, empirical engineering knowledge (EEK) accumulated from long-term engineering activities is the knowledge source for engineers to solve the innovative design and decision-making problems. Cognition and utilization of the mechanism and rules of EEK evolution over time are the real and urgent problems in knowledge management and seem to lack attention from researches. To deal with these problems, this paper proposes a novel method that abducts the motives of EEK evolution with the events related to the evolution of EEK field, completely and clearly finding the factors that influence the EEK evolution. An experiment in computer-aided design (CAD) is executed to verify the feasibility of the proposed method, and the result shows that the proposed method can effectively acquire the motives of EEK evolution and also be beneficial for engineers to deeply cognize the EEK evolution.**

**Keywords-***knowledge evolution; empirical engineering knowledge; evolutional motive; evolutional event; abductive reasoning.*

## I. INTRODUCTION

Driven by the rapidly emerging concepts, techniques, methodologies, experiences and activities, knowledge is fast maturing and mutating in this era of knowledge-driven economy. The effective management of such evolving knowledge is the key to maintain the competitiveness preponderance of the organizations and enterprises in creativity and adaptability [1]. Especially in the engineering field, empirical engineering knowledge (EEK), which is concluded and accumulated from engineering activities over years, is the knowledge source for engineers to solve the innovative design and decision-making problems [2]. Observing the evolutional process and then acquiring the rules and factors that motivate the process is an urgent problem that needs an answer in knowledge management. A proper knowledge management mechanism founded on the answer to this question will help the intellectual workers and practitioners obtain a deep cognition of the developments of the engineering field in a long period of time. They could also agilely adapt themselves to the changes of demands in the engineering activities, and more precisely forecast the future trends in the engineering field.

Therefore, the investigation on the motivation of EEK evolution is a task with high necessity, yet lacking attention from researches. To rectify this, based on the representation of network structure of EEK field, this paper proposes a novel event-based method for abducting the motives of the evolution of EEK. The evolutional patterns in the EEK evolution process are recognized and extracted in the first step, and then abductive reasoning is used for finding the factor events that influence the process of EEK evolution based on the construction of the archive of collected evolutional events. Because of the complete search for the possible explanation of evolutional patterns and because it offers the evolutional events in readable texts, the proposed method will help the engineers in cognizing the EEK evolution in depth.

The remainder of this paper is organized as follows. Section 2 introduces some related works of the proposed method. The general framework of the proposed method is designed in Section 3. Section 4 details the implementation of the proposed method by illustrating the evolutional patterns recognition and event-based abductive reasoning. The example of using the proposed method to acquire the motive events in the evolution of EEKs originated from computer-aided design (CAD) missions is presented in Section 5 and verifies the feasibility of the proposed method. The last section concludes the paper with some possible improvements.

## II. RELATED WORKS

The theory of evolution was initially designed for understanding and explaining the development of complex biological systems by Charles Darwin in 1842. In knowledge evolution, the fundamental hypothesis of a generalized evolution theory is that the mutating internal concepts of knowledge are chosen or eliminated in order to cope with the rapidly changing external environments, such as the demands or costs of engineering projects [10]. Although the practitioners in the domain could perceive the evolution process with the experience concluded and accumulated from engineering activities over a very long time, they have little understanding of the motives that may influence or even determine the development of the domain, as well as the degrees of impact brought by such motives. Taking accomplishing CAD missions as an example, the evolution of EEKs in CAD field and its benefits can be felt by the engineers through the increase of work efficiency in handling such missions. However, they know little about exactly what kind of new process or new approach that leads to such evolution, if without the complex experiments, measurements and analysis conducted by professional research institutions (see Figure 1).

There are few studies that focus on acquiring the motives of knowledge evolution. Existing related works can be categorized into three kinds: concluding empirical laws

 

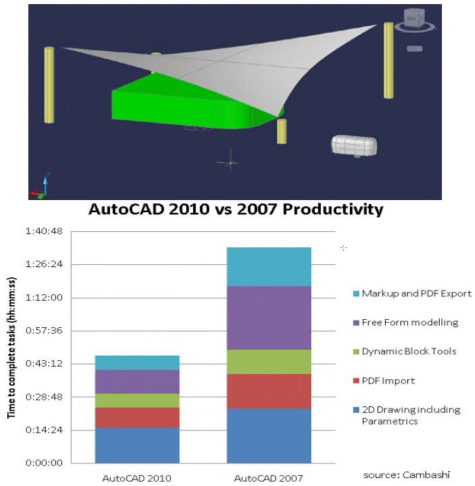


Figure 1. Work efficiency measurement: to find out the new features in AutoCAD 2010 that lead to a significant save of time in accomplishing a design task [11]

[7][8], using statistical analysis [4]-[6] and using complex networks analysis [3][9].

According to the observed relationships between the phenomena of knowledge evolution and related modifications in the field, some researches empirically proposed some reasonable explanations and hence summarize some laws of motivation of the evolution. Grebel [8] used four generic rules as behavioral assumptions and constructed a percolation model to empirically explain the motivations of the structural evolution of the network of research topics in basic science researches. Gross et al. [7] investigated the motivation of biology ontology evolution by detecting the changes in the results of statistical applications and analyzing corresponding modifications in the categories of ontology caused by new knowledge accumulation. Using such qualitative explanations and empirical laws that measure the effect of factors on the knowledge evolution, practitioners could obtain a global comprehension of the motivation of the evolution and easily forecast the future trend of the field, but the specific properties of the motivation (for example, involved concepts and occurrence time) may not be clearly elicited. The intellectual workers are still unaware of the motives of the special breaking points of the evolution process.

Some scholars also analyzed the statistics collected from the working process and environment to propose the factors that influence the knowledge evolution and their degree of impact. Erdil et al. [6] examined 14 statistics about employee interaction, information systems and organizational structure in the enterprises to measure the process of technological knowledge evolution. Johnson et al. [4] and De Noni et al. [5] investigated the factors in social nature of online communities and open source software communities separately to discuss some mechanisms that interact with the generation of new knowledge. Generally, motives tested and obtained from the statistical methods have rather high significance and strong persuasiveness, but they are often the external factors that have weak relations with the knowledge and the engineering fields, and therefore unable to reveal the internal factors of the motivation of the knowledge evolution.

With the proposal and implementation of the theories and tools of complex network analysis (CNA), measurements obtained from the knowledge networks were used to investigate the motives of the knowledge evolution. Modeling the existing knowledge as nodes with potentials in the network, Schumann et al. [9] concluded the motivation of evolution of the domain network with the interactions of the knowledge nodes, including splitting of high concentrated knowledge nodes and fusion of individual ones. Also modeling the knowledge sharing and diffusion with networks, Jiang et al. [3] utilized Exponential Random Graph Models (ERGMs) to examine the interactions and evaluate their impacts of network structure on a longitudinal data set that covered 1991-2010. However, in their works, knowledge is quantified to a node that contains little semantic information, leading to the imperfect integrity of their conclusions.

## III. PROPOSED METHOD

Oriented to acquire the motives of the EEK evolution, this paper proposed a novel event-based abducting method, based on the network-based representation of the structure of EEK field. Figure 2 presents the framework of this two-step method.

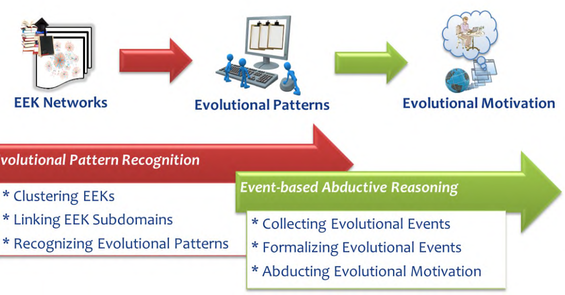


Figure 2. Framework of the proposed abducting method

**Evolutional pattern recognition:** Utilizing the EEK networks in continuous time intervals, the sorts and scales of the subdomains of the field of EEK are firstly acquired through clustering approaches; then the subdomains in neighboring time intervals are numerically and semantically compared to recognize two kinds of evolutional patterns; the patterns are formalized with the vectors in semantic space model for the convenience of subsequent calculations.

**Event-based abductive reasoning:** An archive of events is constructed with the events that are possibly related to the EEK evolution, and key information of each event is also refined; then the relationships of evolutional events and patterns are determined with cosine similarities of semantic vectors and occurrence time; using abducting algorithm, some events that obey the rules are chosen to form the motives chains, and finally used to explain the motivation of EEK evolution.

## IV. IMPLEMENTATION OF PROPOSED METHOD

### A. Evolutional pattern recognition

#### 1) Representing EEK subdomain with EEK clusters

New ideas and concepts are often the consequences of the original ones [12]. In engineering field, such relationships are also helpful for generating the links among EEKs and establishing the EEK networks. Li et al. [13] proposed a corresponding modeling method. They firstly formalized EEK with seven kinds of attributes: *Engineering Problem*, *Problem Context*, *Problem Solution*, *Feature Association*, *Effectiveness*, *Contributor* and *Time*, and then determined the strength of relevance relationships of EEK pairs using the supervised fuzzy neutral networks, and finally used the pairs with high relationships to construct the EEK networks.

Although the networks established by Li et al. could fully consider the properties of EEK and precisely portray the structure of the EEK field, the networks are static and unable to reveal the evolution of EEK directly. To improve this, this paper firstly arrays the EEK with their time attribute, and categorizes EEKs with several continuous time intervals. Relevance relationship networks of each time intervals are separately established and the dynamic change of these networks are utilized for portraying the phenomena of EEK evolution.

Different from the approaches based on complex network analysis (CNA), when analyzing the phenomena of EEK evolution using the proposed method in this paper, EEK groups containing a bunch of strongly inter-related EEKs are focused, rather than some key nodes in the networks. This paper assumes that these groups could represent a category of EEKs that are accumulated from the engineering activities over a long time and verified by a large number of practitioners, dividing the engineering field into several subdomains. The variation of the sorts and scales of such subdomains could quantitatively illustrate the evolution of EEK. So, how to get the EEK groups in the networks is the initial problem for investigating the motives of the evolution. To solve this problem, the commonly used K-means clustering method is adopted to cluster the EEK nodes in the networks.

In order to guarantee that the representative EEK groups can be found and noise EEK nodes are filtered out, minimal number of members in the cluster $|C|_{threshold}$ is set to reserve the EEK clusters with certain scale. A reserved cluster in time interval $T_n$ is denoted as $C_{n,i}$. Only the dynamic variations of these reserved clusters are analyzed in the following process of the proposed method.

#### 2) Linking corresponding EEK subdomains

The sorts and scales of the subdomains in each time interval can be acquired directly from the clustered EEK network. However, the corresponding relations of subdomains in neighboring time intervals are unknown, and the development sequences of correspondingly same or similar subdomains are unavailable to extract.

This paper handles this unavailability with the calculation of semantic relations between clusters. Specifically, we firstly calculate the Term Frequency-Inversed Document Frequency (TF-IDF) weights of all the concepts contained in cluster $C_{n,i}$ of time interval $T_n$, and extract the key concepts with the highest weights. For a concept *NP*, its weight in $C_{n,i}$ is calculated as follows:

$$TFIDF(w) = \frac{Count(w)}{\sum_{w_k \in C_{n,i}} Count(w_k)} \times \log \frac{|C_{n,i}|}{|\{EEK \mid EEK \in C_{n,i}, w \in EEK\}|} \quad (1)$$

$$W(NP) = \frac{1}{|NP|} \sum_{w \in NP} TFIDF(w) \quad (2)$$

where *w* is a word, *Count(w)* is the count of occurrence of *w* in $C_{n,i}$, the sum of $Count(w_k)$ is the total count of words in $C_{n,i}$. $|C_{n,i}|$ is the count of containing EEKs, which is divided by the count of EEKs that contains *w*. $|NP|$ is the length of noun phrase of concept *NP*.

Key concepts and their weights are used to express the $C_{n,i}$ with a vector in semantic space model constructed by the concepts in the corpus, namely $\{W^{n,i}(NP_1), W^{n,i}(NP_2),\ldots, W^{n,i}(NP_k)\}$. $k$ is the number of all noun phrases in the vocabulary of corpus. For two clusters $C_{n,i} =\{W^{n,i}(NP_1), W^{n,i}(NP_2),\ldots, W^{n,i}(NP_k)\}$ and $C_{n+1,j}=\{W^{n+1,j}(NP_1), W^{n+1,j}(NP_2),\ldots, W^{n+1,j}(NP_k)\}$ in neighboring time intervals $T_n$ and $T_{n+1}$, semantic similarity is computed with the cosine similarity of their semantic vectors:

$$\cos Sim(C_{n,i}, C_{n+1,j}) = \frac{\sum_{p=1}^{k} W^{n,i}(t_p) W^{n+1,j}(t_p)}{\sqrt{\sum_{p=1}^{k} (W^{n,i}(t_p))^2} \sqrt{\sum_{p=1}^{k} (W^{n+1,j}(t_p))^2}} \quad (3)$$

If the value of cosSim($C_{n,i}$,$C_{n+1,j}$) exceeds a pre-set threshold $CosSim_{threshold}$, which means the key concepts contained in $C_{n,i}$ and $C_{n+1,j}$ overlap to a certain degree, then two clusters are semantically similar, hence representing the same or similar EEK subdomains in neighboring time intervals.

#### 3) Recognizing evolutional patterns

After the linking of corresponding EEK subdomains in all time intervals, the phenomena of EEK evolution can be quantitatively represented with the variation of scales. Three evolutional patterns can also be concluded: expansion, contraction and staying.

The knowledge expansion pattern is defined as the rapid raise of EEK numbers contained in EEK clusters, while the key concepts of the corresponding subdomain are not changed too much. The backgrounds of expansion patterns are often the emergence of some new concepts and approaches, or the sudden concentration on the existing original ones in the corresponding subdomains, which leads to the burst in adoption in related engineering missions and activities and abundant accumulation of empirical knowledge in the subdomains. The knowledge contraction pattern is a reversed pattern of knowledge expansion pattern. With the updating of the engineering field, obsolete experience and methods are gradually eliminated by the engineers, and the corresponding subdomains will also be marginalized or even disappeared. Both kinds of patterns will reflect the distinct changes in the evolution of the EEK field, while the other patterns not belonging to one of these two kinds are not considered in this paper.

According to the representations of the clusters extracted before, this paper formally defined two kinds of patterns as follows, and recognized them with (4) - (5).

**Knowledge Expansion Pattern:** if in neighboring time intervals $T_n$ and $T_{n+1}$, two clusters $C_{n,i}$ and $C_{n+1,j}$ are semantically related, and the size of $C_{n+1,j}$ are larger than $C_{n,i}$, namely:

$$\begin{cases} \cos Sim\left(C_{n,i},C_{n+1,j}\right) \geq CosSim_{threshold} & \text{(a)} \\ \dfrac{\left|C_{n+1,j}\right|}{\left|C_{n,i}\right|} \geq Scale_{threshold} & \text{(b)} \end{cases} \tag{4}$$

then an expansion pattern $P: C_{n,i} \xrightarrow{\text{KEP}} C_{n+1,j}$ is recognized.

**Knowledge Contraction Pattern:** if in neighboring time intervals $T_n$ and $T_{n+1}$, two clusters $C_{n,i}$ and $C_{n+1,j}$ are semantically related, and the size of $C_{n+1,j}$ are smaller than $C_{n,i}$, namely:

$$\begin{cases} \cos Sim\left(C_{n,i},C_{n+1,j}\right) \geq CosSim_{threshold} & \text{(a)} \\ \dfrac{\left|C_{n,i}\right|}{\left|C_{n+1,j}\right|} \geq Scale_{threshold} & \text{(b)} \end{cases} \tag{5}$$

then a contraction pattern $P: C_{n,i} \xrightarrow{\text{KCP}} C_{n+1,j}$ is recognized.

The degrees of scale variations of subdomains are judged by $Scale_{threshold}$, which is a positive number larger than 1. The sensitivity of recognizing evolutional patterns from linked clusters is affected by the setting of this threshold. The larger of $Scale_{threshold}$, the larger degree of changes are revealed in the evolutional patterns, yet the fewer sorts of subdomains are considered. For a recognized evolutional pattern $P: C_{n,i} \rightarrow C_{n+1,j}$, it can also be represented with the semantic vectors in semantic space model as $P=\{W^P(NP_1), W^P(NP_2),\ldots, W^P(NP_k)\}$, and $W^P(NP_q)$ in it is computed as:

$$W^{p}\left(NP_q\right) = \frac{\left|C_{n+1,j}\right| W^{n+1,j}\left(NP_q\right) - \left|C_{n,i}\right| W^{n,i}\left(NP_q\right)}{\left|C_{n+1,j}\right| - \left|C_{n,i}\right|} \tag{6}$$

Besides that, the time of duration of the evolutional pattern is also considered with the involving clusters and valued with $T_n \cup T_{n+1}$.

### B. Event-based abductive reasoning

#### 1) Collecting and formalizing evolutional events

Although the recognized patterns could infer some information about the evolution process of EEK over a long period of time, it is difficult for engineers to understand the meanings since these patterns are expressed with concepts and weights, lacking readable explanation texts.

Therefore, this paper uses texts of events described with natural language to infer and explain the patterns and their motives. Such events are evolutional events, which are the facts that already happened at a certain time, strongly related to the knowledge evolution or directly lead to the evolution. They are derived from the news of tools updating, the investigations of authorized institutions, the summaries from experienced long-term practitioners, or other records of domain-related comments. Table I shows an illustrative record of an evolutional event, describing the event of adding parametric design tools in AutoCAD 2010. This event aroused strong repercussions of the users and finally result the evolution in EEKs in CAD field.

TABLE I. AN ILLUSTRATIVE RECORD OF EVOLUTIONAL EVENT

| |
|---|
| **Time:** 2009.329 |
| **Content:** The geometry in AutoCAD has always driven the dimensions. We draw a line the correct length and then dimension the line. What if you could drive the geometry from the dimensions? You change the value of the dimension and the geometry automatically updates! That is exactly what we now have in AutoCAD 2010. |

For these natural-language-described texts, Song et al. [14] proposed a processing method by selecting some key phrases from the texts to represent the events. They used Stanford Parser to find the noun phrases and chose those with large IDF weights in order to filter out the common words and reflect the characteristics of the texts.

This paper also maps the events to vectors in semantic space model, namely $E=\{W^E(NP_1), W^E(NP_2),\ldots, W^E(NP_k)\}$. $W^E(NP_r)$ is the IDF weights of $NP_r$, which is calculated with all the documents of evolutional events. Semantic similarities between events and patterns, and among events, can also be computed with (3). The occurrence of events can be acquired directly from the source of texts and denoted with $t_E$.

#### 2) Abducting evolutional motives

Abductive reasoning is a kind of logical inference which goes from an observation to a theory which accounts for the observation, seeking the possible explanations for the happened phenomena[15]. Abductive reasoning, accompanied by deductive reasoning and inductive reasoning, is an indispensable part of human cognitive activities[16]. We use the EEK of new features listed in Figure 1 as an example to illustrate the process of abductive reasoning. We observe the significant decrease of the cost of time when accomplishing the CAD missions, which response to the evolution of CAD field in shaping and modeling. And according to the work efficiency measurement, the EEK of new features will lead to such decrease. Therefore we construct the probable causal association that the EEK of new features is the motive of the evolution of CAD field if there are no other conflicting rules. Even though the modification of the measurement reports or the proposal of more persuasive surveys will vary the belief of this causal association, or even disconfirm the association, some interesting explanations may still be found and useful conclusions will be probably refined.

In abducting the motives of the evolution, the set of evolutional patterns $\{P\}$, the set of evolutional events $\{E\}$, and the set of rules $\{R\}$ are the inputs of the reasoning process. If an event $E$ is the motive of a pattern $P$ according to $\{R\}$ and denoted as $\mathrm{M}(E \rightarrow P)$, it should satisfy two conditions:

- $P$ follows from $E$ according to $\{R\}$;
- $E$ is consistent with $\{R\}$.

Three reasoning rules are put into $\{R\}$. These rules constrain the explaining of unrelated or contradictory events for the motives of the evolutional patterns:

**Rule 1**: Evolutional event $E_i$ is a possible cause of event $E_j$, if $E_i$ and $E_j$ are semantically related and $E_i$ is happened earlier than $E_j$;

**Rule 2**: Evolutional pattern $P$ is a possible consequence of event $E$, if $P$ and $E$ are semantically related and $E$ is happened earlier than the end of $P$;

**Rule 3**: A motive chain M($E_i \rightarrow E_j \rightarrow P$) is constructed, if event $E_i$ is the possible cause of event $E_j$ and pattern $P$ is the possible consequence of event $E_i$ and $E_j$ simultaneously.

The process of abducting algorithm is listed as follows:

**Input:** evolutional pattern set $\{P\}$, evolutional event set $\{E\}$ and rule set $\{R\}$;

**Output:** the set of possible motives $\{M\}$;

**Process:**

(1) Create an empty motive set $\{M\}$;

(2) Choose an earliest begun and undiagnosed evolutional pattern $P$ from $\{P\}$;

(3) Choose a latest happened and unchecked evolutional event $E$ from $\{E\}$; find all possible causes of $E$ according to Rule 1, then construct *List*<*E*>;

(4) Choose a latest happened and unchecked $E_i$ in *List*<*E*>, add a motive chain M($E_i \rightarrow P$) into $\{M\}$ if $P$ and $E_i$ satisfy Rule 2;

(5) Repeat step 4, until all the events in *List*<*E*> are checked; merge the motive chains with Rule 3;

(6) Repeat step 3-5, until all the events in $\{E\}$ are checked; save $\{M\}$ for $P$; set all the events in $\{E\}$ unchecked;

(7) Repeat step 2-6, until all the patterns in $\{P\}$ are diagnosed; output $\{M\}$.

With the readable appendix texts of the evolutional events, it will be easier for engineers to understand the evolution process of EEKs with the clear and specific motives, hence is helpful for them to obtain a deep cognition of the knowledge evolution. Meanwhile, the output motive chains can also be further verified and evaluated by domain experts, escalating the relationship between evolutional events and evolutional patterns from the statistical correlation to more cogent logical correlation.

## V. CASE STUDY

From three professional virtual communities forums *autodesk.com*, *www.cadtutor.net* and *www.cadforum.cz*, 3276 EEKs of accomplishing computer-aided engineering design missions using AutoCAD software were elicited and formalized, ranging from February 2001 to September 2015. The evolutional patterns were recognized from the networks constructed by these EEKs. For the evolutional events related to the evolution of CAD field, *ReadMe* documents of each update and all software versions ranging from AutoCAD version 14.0 (AutoCAD R14, published in 1997, February) to version 20.1 (AutoCAD 2016, published in 2015, March) were downloaded from the official website *www.autodesk.com*, in which detailed the emergence of new tools and the modifications in original functions in AutoCAD software. Proposed by an authorized institution *HyperPics Consult Company*, open accessed documents of news of the software *AutoCAD What's New* were also collected. We also collected the long-term experienced user's summary *AutoCAD Tips & Tricks Booklets* written by Lynn Allen, who has used AutoCAD for over 25 years and served as Autodesk University emcee for over 10 years. 1080 records of evolutional events, as shown in table 1, were finally extracted.

The whole time span was divided into five time intervals: 2001-2003, 2004-2006, 2007-2009, 2010-2012, and 2013-2015. The EEKs were clustered in each EEK network, and Figure 3 shows the clusters in EEK network of time interval 2001-2003. The number of initial clusters $k$ in K-means was set to 30, and minimal number of cluster member $|C|_{threshold}$ was set to 4. Similar EEK subdomains in the five networks were linked with $CosSim_{threshold}$=0.5. 28 evolutional patterns were recognized when $Scale_{threshold}$=2, containing 17 knowledge expansion patterns and 11 knowledge contraction patterns. Using abducting algorithm, evolutional patterns were explained with the acquired motive chains. An evolutional pattern and its abducted motives chains are shown in Table II.

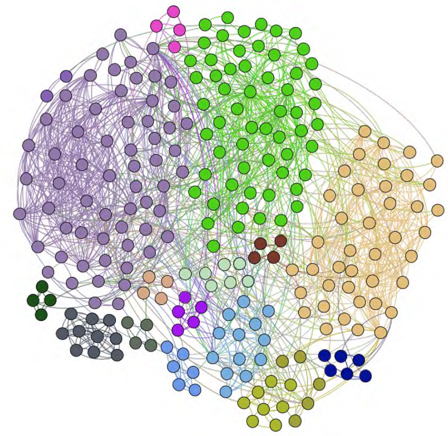

Figure 3. Clusters in CAD EEK network of time interval 2001-2003

TABLE II. AN ILLUSTRATIVE RECORD OF EVOLUTIONAL EVENT

| **Pattern:** $C_{3,11}$ $\underline{\text{KEP}}$ $C_{4,2}$ | | | | **Motive Chains** |
|---|---|---|---|---|
| $C_{3,11}$ (Size: 25 Time: 2007-2009) | | $C_{4,2}$ (Size: 66 Time: 2010-2012) | | |
| **Concepts** | **Weights** | **Concepts** | **Weights** | |
| object | 0.2078 | object | 0.2056 | |
| cursor | 0.1391 | angle | 0.1345 | **Chain 1:** Adding Constraints → Inferring Geometric Constraint → P |
| angle | 0.0927 | constraint | 0.0824 | |
| parameter manager | 0.0637 | parameter manager | 0.0736 | |
| drawing | 0.0545 | drawing | 0.0563 | |
| dimension | 0.0499 | cursor | 0.0486 | |
| length | 0.0477 | distance | 0.0425 | |
| distance | 0.0383 | dimconstraint | 0.0424 | |
| vertex | 0.0315 | block | 0.0422 | |
| acad line | 0.0297 | plane | 0.0386 | **Chain 2:** Changing to Annotational Dimensions → P |
| perpendicular | 0.0273 | direction | 0.0292 | |
| geometry | 0.0269 | polyline | 0.0260 | |
| object snap | 0.0260 | degree | 0.0252 | |
| degree | 0.0260 | object snap | 0.0239 | |
| intersection | 0.0259 | intersection | 0.0230 | |
| plane | 0.0249 | selection | 0.0225 | **Chain 3:** Dynamic Block → P |
| polyline | 0.0238 | geomconstraint | 0.0222 | |
| grid | 0.0222 | vertex | 0.0217 | |
| polar point | 0.0216 | dynconstraint | 0.0211 | |
| selection | 0.0206 | polar point | 0.0184 | |

Parametric design is a milestone in the development process of CAD field. The fundamental principle of parametric design is using the geometric constrains and variable parameters to conveniently manipulate and rapidly modify the drawings, which significantly accelerate the speed in plotting and promotes the transition from design intent to design response [17]. The tools of parametric design were firstly added into AutoCAD 2010 in 2009, triggering a positive response from the majority of CAD engineers. They frequently applied dynamic blocks with geometric constraints and dimensional constraints to accomplish the engineering projects and accumulated abundant related experiences. According to the aforementioned report [11], it is the emergence of these parametric design tools that consequently motivated to the evolution of EEKs in subdomain of modeling and shaping in CAD field. The abducted motives chains in Table II are also consistent with the motivation concluded from this professional report.

These motive chains were also verified by the domain experts in order to prove their validities. Some motives chains in abducted results were deleted according to their evaluation. Finally motivations of 25 evolutional patterns in all 28 were firmly explained with these evolutional events, while the other 3 patterns did not obtain persuasive motivations.

## VI. DISCUSSION AND CONCLUDING REMARKS

Explaining the evolutional patterns with the evolutional events, this paper proposed a novel method for investigating the motivation of EEK evolution. Based on the networks representing the structure of the field of EEKs, clustering algorithm is adopted to divide the subdomains of the networks in each time intervals. EEK evolutional patterns are recognized with the scales and semantic informations of the linked subdomains in neighboring time intervals. Evolutional events related to EEK evolution are collected and used to abduct the motive chains, explaining the motivation of the evolution in depth. Evolution of EEKs in CAD is investigated and evaluated with the experts and practitioners, proving the feasibility and effectiveness of the proposed event-based abducting method in acquiring the clear and specific motivation of the EEK evolution.

The advantages of the proposed method are in three aspects. Firstly, semantic meanings of the EEKs are fully considered in the method. Therefore, our method can provide a more integrated motivation of the EEK evolution than most of traditional works. Secondly, our method uses the domain-related events to investigate the factors that impact the evolutional process, making our motivation more facilitated to those intellectual workers in the domain. At last, the utilizing of abductive reasoning is consistent with human cognitive activities. It will mine all possible motives according to the input event archives, which significantly promotes the discovery of new interesting explanations.

There are several possible improvements for our methods. First, according to the flowchart in Figure 3, the maximum computational complexity of the algorithm is $O(1/2|P||E|^2)$. In order to shorten the operation time when $|E|$ is larger, more compatible filtering rules should be added into rule set $\{R\}$. Second, although the motive chains are acquired in this paper, the quantitative degree of their impact on the semantic meaning and scales of the subdomains is less considered and will be paid attention in the future research.

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