An analytical approach for situational behavioral pattern in MSN

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Abstract: The past decade has witnessed the emergence and progress of multimedia social networks (MSNs), which have explosively and tremendously increased to penetrate every corner of our lives, leisure and work. Moreover, mobile Internet and mobile terminals enable users to access to MSNs at anytime, anywhere, on behalf of any identity, including role and group. Therefore, the interaction behaviors between users and MSNs are becoming more comprehensive and omplicated. This paper primarily extended and enriched the situation analytics framework for the specific social domain, named as *SocialSitu*, and further proposed a novel algorithm for users' intention serialization analysis based on classic Generalized Sequential Pattern (GSP). We leveraged the huge volume of user behaviors records to explore the frequent sequence mode that is necessary to predict user intention. Our experiment selected two general kinds of intentions: playing and sharing of multimedia, which are the most common in MSNs, based on the intention serialization algorithm under different minimum support threshold (*Min_Support*).
By using the users' microscopic behaviors analysis on intentions, we found that the optimal behavior patterns of each user under the *Min_Support*, and a user's behavior patterns are different due to his/her identity variations in a large volume of sessions data.

Keywords: *multimedia social networks, situation analytics, intention prediction, behavior pattern, big data.*

I. INTRODUCTION

The rapid development of Multimedia Social Networks (MSNs) causes the tremendous growth of users and digital contents. It's also convenient for users to access digital contents in MSNs with a large-scale video dataset [1]. Meanwhile, the interaction between user and user, user and system increases. Therefore, providing users with timely and rapidly personalized services considering the complex interaction [2] is now a challenge in the study of multimedia social networks. Generally speaking, multimedia computing can be decomposed into three different stages, from data centric multimedia compression, content-centric Multi media communication and content analysis, to user-centric social media analysis till today, including user trust modeling [3, 4], propagation paths mining [5, 6] and digital right sharing [7], and digital forensics[8-10].
However, understanding and predicting what multimedia content users' real needs in different situations and contexts have not been well studied [11]. Context-Aware (CA) [12-15] was first proposed by Schilit et al in 1994. They defined context as the set of location, people nearby, objects, and the changes of the objects. Prof. Carl K. Chang [16] proposed the Situ theory by combining the service environment with situation awareness to handle the dynamic update or development of service at run time. Therefore the service can meet the changing needs of users and provide users with personalized service. In order to adapt to the dynamic service environment and make a timely respond to the feedback of service environment, social media services increasingly require situation awareness. In social media networks, the human being is a complex and open system. The individual's intention can change at any time, which also causes a change in the user's needs. Moreover, the user's context and behavior are dynamic. Some studies show that the characteristics of the dynamic change will have different effects in a user's potential needs [17, 18]. A user's intention can be reflected through the acquiring attributes of the user's situation awareness and feedback on resources. The system can formulate a timely personalized service for the user based on user's intention, which will increase the user's service experience.

II. RELATED WORKS

Chang studied the significance and influence of the situation analysis theory and Situ framework on software engineering, as well as introduced the Situ framework in detail, which could provide users with personalized service by identifying the new intention of the user and the real-time update of service [19]. Ming et al raised a spatial scenario analysis based on the Situ theory and the proposed (MR)2 paradigm promoted comprehensive decision-making which is conducive to the transformation of data, information, knowledge, and wisdom (DIKW) [20]. Rahman et al stated that, in a given environment, the user could share data with friends in the social circle through the part of the social service which they are involved in. So they put forward a SenseFacen framework to recommend services for users by using perceptual data from the user sensor network and multimedia information [21]. Shen et al put forward an algorithm which considers the surrounding environment and social network relationship. This algorithm could make use of user's recognized situation, preference, and social network relationship to acquire user's nearest neighbours through the calculation of the user's comprehensive situation similarity, and predict the potential situation user preference to make a recommendation [18]. Tong et al combined with the characteristics of Internet of things, to discuss information acquisition, modelling and intelligent processing etc by taking the situation awareness process as the main line [22]. Hence, it becomes more and more important to employ a novel situational awareness for computing services to provide users with more personalized functions, including multimedia recommendation service [23, 24], customized security and privacy one, and so forth.

III. EXTENSION OF THE SITU FRAMEWORK IN MSNS

In MSNs environment, a large number of users may be in different groups with different roles. The roles of users in groups may cause them to generate different desires. Therefore, this paper extends and enriches Situ framework in social media, as defined below：

Definition 1 [16] (*Situation(t)*): It represents the situation at *t*, which consists of a three-tuple, *Situation(t) = {d, A, E}*. Where *d* refers to the desire of user at *t*; *A* refers to the action of the user which achieves the *d*; *E* refers to environmental context at *t*.

Definition 2 (*SocialSitu(t)*): It refers to the situation at *t* which is the extensional *Situation(t)* for the social domain. *SocialSitu(t)* is a four-tuple *SocialSitu(t) = {ID ,d, A, E}*. Here, *ID* refers to user's identity information; *d* refers to user's desire at *t*; *A* refers to user's behavior corresponding to *d* at the moment; *E* refers to environment information, including the terminal information which the user utilized.

Definition 3 (*ID*): *ID* refers to the user's identity information; it is a two-tuple *ID= {Group, Role}*. In MSNs, there is a corresponding relationship between the user's role and group. When a user's role is changed, the user's behavior may also change.

Definition 4 (*Group*): It refers to a small group formed in social media network because of a particular reason. It's a part of the whole social media network.

Definition 5 (*Role, R*): a user's role in MSNs. The role is a set *R={r1, r2, ..., rn}*, referring to RBAC96.

Definition 6 (*Desire, D*): It refers to what users want to achieve when using a social media service, namely, the user's purpose. It consists of a series of atom-desire (*d*), namely *{d1, d2,..., dn}*, d_i ($1 \le i \le n$) refers to user's desire at *i*.

Definition 7 (*Goal, G*): the user's general target *G={g1, g2, ... , gn}* for MSNs.

Definition 8 [16] (*Intention, I*): It refers to the *SocialSitu(t)* sequence of user from starting point to target achievement, namely *I={SocialSitu(1), SocialSitu(2), ..., SocialSitu(n)}*， $n \in N$， *SocialSitu(1)* refers to the starting point; *SocialSitu(n)* refers to the ending point when the target is achieved. Here, *SocialSitu(t)* sequence is directly correlated to the target achievement. Through the intention sequence, the user achieves the target, as shown in Fig.1.

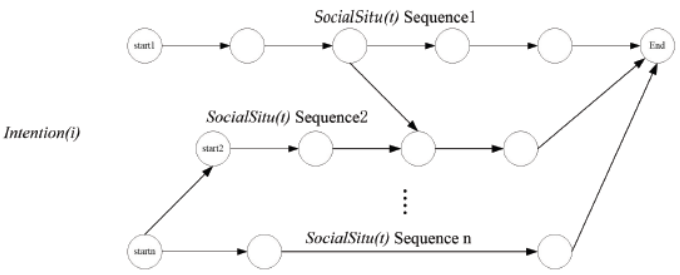

Fig.1. Intention sequence

In the figure, each point refers to *SocialSitu(t)* at a certain moment. The point *startj* ($1 \le j \le n$, $j \in N$) refers to the starting point of *Intention(i)*. These starting points can be the same or different. *End* refers to the ending point of *Intention(i)*. Each stripe of *SocialSitu(t)* sequence refers to the sequence composed by different *SocialSitu(t)* that the user passed from starting point to ending point. Except for the ending point, the same nodes may exist in each sequence of *Intention(i)*. In the MSNs, there is at least one sequence which corresponds to the user's intention, namely $i \in N, i \ge 1$.

IV. INTENTION SERIALIZATION ALGORITHM OF USER

All frequent *SocialSitu(t)* related to a certain goal achievement in a user's historical access record consist of an intention sequence. The user has at least one goal in MSNs, and this corresponds to at least one intention sequence. The user's intention sequence with a specific goal is saved to the database. The current sequence of a user is compared with intention sequences of the user in the database to predict the current intention of the user to make a rapid and timely response to the user's request and provide a personalized service, intention prediction flowchart is shown in Fig.2. A key problem in this paper is how to find out the user's Intention sequence.

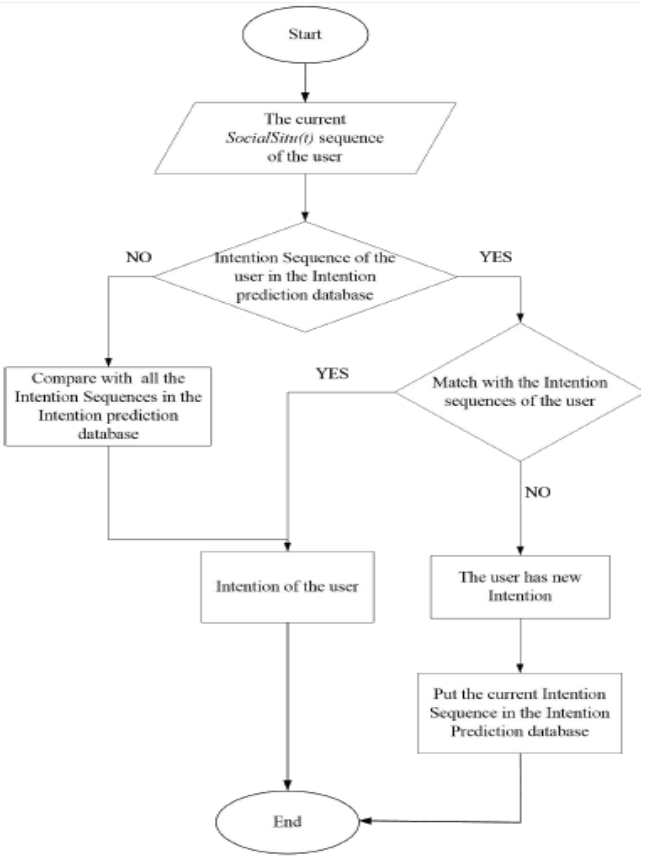

Fig.2. Intention prediction flowchart of the user

The association rule which was proposed by Agrawal et al in 1993 is used to find out the relationship among various items in a large quantity of data. *DS* is a set which represents the entire transaction set where each attribute is called as an *item*. The set including all items in a *DS* is named as the data item set, *I= {i1, i2, ..., im}*, |*I*|=m, m refers to the number of items in *DS*.

The association rule contains the following logic implication form: $A \Rightarrow B$, wherein, $A \subseteq I$, $B \subseteq I$ and $A \cap B = \Phi$; item set A is the antecedent of the association rule; item set B is the result of the association rule; $A \Rightarrow B$ is the item set which corresponds to this rule.

- **Support**: the number of item set R contained in the DS called as the supporting number of R, recorded as R .Support. The number of support for rule $R=>S$ refers to number that the item sets R and S coexisting in DS. Therefore, the support for rule $R=>S$ is Support ($R=>S$) = P ($R \cup S$).
- **Confidence**: Confidence of rule $R=>S$ refers to the probability that entire data set DS that contains A includes B meanwhile, recorded as Confidence($R=>S$)=P(R|S).

The item set satisfying the *Min_Support* is called the frequent item set. The rule satisfying the *Min_Support* and the minimum confidence threshold (*Min_Conf*) is the strong association rule. Therefore, *Intention(i)* serialization in this paper adopts the method based on he association rule to find out each sequence corresponding to the intention. The ending point of each *Intention(i) sequence* is used as the result of association rule, and association rule is used to obtain the antecedent of association rule.

Flowchart of intention serialization algorithm is shown in Fig.2. The steps of serialization algorithm based on association rule are as follows:

1. The web log database is scanned after data Processing, the goal in definition 7 was identified in the database as the ending point of user in *Intention(i)*, recorded as $G=\{g1, g2 ,\dots , gm\}$, $1 \leq m \leq n$, $G \subset G$.
2. g_i obtained from Step (1) is used as a result of association rule. Each *SocialSitu(t)* is used as the antecedent of the association rule to calculate the Support of each rule, and find out the rule satisfying the *Min_Support*.
3. The antecedents of the rule obtained from Step (2) are used to build a set *L1*, for set *Lk* in the length of k, where the link operation and pruning operation are used to generate a candidate sequence *Ck+1* in the length of k+1. Then, scan data set *DS*, calculate the Support of each candidate sequence as the antecedent and $g_i$as the result of the association rule to generate sequence *Lk+1* in the length of k+1, and *Lk+1* is used as the seed set of the antecedent of new association rule.
4. Step (3) is repeated until the new candidate sequence can no longer be generated, and all *SocialSitu(t)* sequences related the target *g'i* of *Intention(i)* is obtained.
5. All *SocialSitu(t)* sequences corresponded to target g_{i+1} are acquired and recorded as *Intention(i+1)*. Then, Steps (2), (3), and (4) are repeated.
6. Until there is no longer a new goal.

- Link operation: if the sequence obtained after removing the first item of sequence pattern s1 is the same as the sequence obtained after removing the last item of sequence pattern s2, then s1 should be connected with s2.
  That is, the last item of s2 should be added into s1.
- Pruning operation: if a certain sub-sequence of a candidate sequence pattern is not a sequence pattern, this candidate sequence pattern is unlikely to be a sequence pattern; therefore, it is deleted from the candidate sequence pattern.

V.CONCLUSIONS

The existing MSNs environment increasingly requires situation awareness. Users' environment and behavior are dynamic, and an individual's intention is also to change. In order to adapt to the dynamic changes of user identities in the social domain, this paper extends and enriches the Situ theory, and builds a *SocialSitu* framework for the social media networks. We design and achieve the intention serialization algorithm in multimedia social networks. The user's frequent intention sequence mode is obtained through the intention serialization algorithm. When the user's identify changes, we conclude his behavior pattern with different ID, and prove that different *SocislSitu(t)* sequences are acquired in the same *Min_Support* with the same intention when his role and group change. In the future works, the existing intention sequence patterns of the user could be adopted to predict the user's more and deeper intentions. Besides, we will employ the *SocialSitu* and the proposed algorithm to improve multimedia recommendation system and some killer applications in MSNs

VI.REFERENCES

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