Detecting Abnormal Attention in Online Social Networks from Local Views

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***Abstract*—With the development of the Internet, more and more people actively interact with others via online social networks. Potentially, people can hide themselves in the dark and continually gather information from other users from the Internet. To assist individual users to protect their privacy and security, in this paper a computational approach for abnormal attention detection is presented. The proposed approach can detect abnormal attention from the local view of a user, without invading other people's privacy.**

***Keywords*—Online social networks, abnormal attention detection, cyber security**

I. Introduction

Online social networks (OSNs) have become extremely popular in our daily life. Through OSNs, users can easily establish new friendships, share their stories and opinions. With the convenience and fast development of online communication, there is also danger lurking in the dark. People post a vast amount of personal information in the OSNs, which if abused for purpose reasons, could lead to tragic outcomes.

Nowadays, many OSNs have tens of millions of registered users. With the increasing usage of OSNs, many users have unknowingly exposed their privacy to threats. Phishing attacks and spammers threats not only attack themselves but also their friends [1]. Many people use OSNs for uploading photos of themselves and their friends [2]. Such information can be used to create a biometric database, which can be used to identify OSNs users without their consent. People stand naked in front of the OSNs, their personal private information expose to the public. Moreover, people has to face to the fake profiles threats, identity clone attacks threats, inference attacks threats and information or location leakage threats.

Online safety and privacy protection is an important research field in computer science [1]. When a person posts a message in OSNs, the readers of the message stay anonymous. Moreover, the person even may not be aware of who has read the message or not. It is hard for a user to detect potential risks without the knowledge of the entire OSN, e.g., the network topology, other users' activities, etc. In addition, messages posted by users are related to their personal privacy and cyber security. It is impossible for a normal user to gain the information about other users' behaviours from a global view, which may also cause invasion of other users' privacy. Hence, a major challenging issue is how a user can know who has paid how much attention to him/her from a local view.

Abnormal attention is regarded as a user pays excessive attention to another, which is far beyond the level of their real relationship. In this paper, we propose a computational model to facilitate a user to analyse received attention and detect potential abnormal attention in OSNs from his/her local view only. We only take users' local views into consideration to protect other users' privacy in the OSNs. Meanwhile, in most OSNs applications, it is impossible to have a global view for an individual user.

The rest of the paper is organised as follows. Section II presents an overview of related works in the related fields. We formally describe the focused problems and important definitions in Section III. In Section IV, we use fuzzy logic to establish model to detect abnormal attention. Then, we discuss simulation and experiments conducted in this research in Section V. Finally, we conclude and mention the future directions in Section VI.

II. Related work

Our work is related to several distinct research fields in the social network analysis and computer science. Firstly, Backstrom et al. propose a measure that an individual divides his or her attention across contacts for analysing personal networks that addresses a dimension distinct from network size and composition [3]. Some people focus most of their attention to a small circle of close friends, while others disperse their attention more broadly over a large set. They capture users' behaviours as the different modalities of attention. They define the Messages, Comments, Wall Posts, Profile Views and Photo Views to measure how users allocate attention across friends. Jiang et al. propose the "plus-one" mechanism to identify optimal allocations of limited frequency among neighbours for each user in the network. They assume that each user has a limited budget of attention [4]. They take the approach of conceiving a general model for studying the balance of attention and an analysis for several network topologies.

Secondly, there are also some researches are related to cyberbullying detection. Nahar et al. find predators and victims by determining the most active users in the form of the most active users [5]. They propose a novel statistical detection approach, which is based on the weighted TFIDF scheme on bullying-like features. Research on cyberbullying detection associate the theory of communication and text mining methods to differentiate between predator and victim conversations, as applied to one-to-one communication like in a chat-log dataset [6].

In [7], we present a network-based framework for describing online user interactions. Attention has been measured using the amount of messages which posted and retrieved by users from the global view. This work assumes that all users' behaviours in the social network can be recorded and accessed.

Most existing works assume the availability of a global view for analysis. However, such information is related to personal privacy, and is hard to collect for normal users. In this paper, we focus on the detection of abnormal attention, and attempt to propose a solution based on individual users' local views only. Attention analysis is a more generic problem for most OSN applications, and the proposed solution is more practical for the real-world.

III. Problem Description and Definitions

In this research, an online social network is considered as a Multi-agent System (MAS), which consists of a number of agents. Human users are represented as agents, which can take different types of actions, including posting articles, leaving comments to other people's posts, or reading posts. These actions result different types of mutual relationships among users (agents). Some of these relationships are not formed through interactions, or with the awareness of the users. For example, a post on Weibo[1] can be viewed by any registered users regardless of whether the viewer has followed the owner of the post or not. Similarly, the cyberspace supports communications between two users regardless whether they know each other or not. With this view in mind, in the proposed approach, various interactions and relationships are considered.

A. Modelling of User Interactions in OSNs

We introduce the following formal model to describe an OSN. The user interactions model consists of a directed graph where nodes represent agents (i.e., users). Directed links represent established connection between two users; a mutual relationship can be represented by a pair of directed links. Each agent in this network has the ability to carry out three actions: *posting* messages, *interaction* with other users like clicking *like* button or leaving comments and *reading* messages which friends posted. Once a message is posted, it can be read or interacted by others in the cyberspace. We assume that there is a universal set of messages that could be posted, read and interacted with users over the network.

[1]www.weibo.com

Definition 1. *A* social network *is defined as a directed graph $G = (V, E)$, where V is a set of* nodes *(i.e.,* agents*) and E is a set of* directed edges *denoting relationships among agents. $E = E^P \cup E^I \cup E^R$, where E^P is a set of Physical Links, E^I is a set of Interactive Links and E^R is a set of Reading Links.*

In Definition 1, a Physical Link e^P_{ij} ($e^P_{ij} \in E^P$) denotes a physical connection (e.g., Twitter "follow") between Agents v_i and v_j in G. An Interactive Link e^I_{ij} ($e^I_{ij} \in E^I$) denotes an interactive behaviour between Agents v_i and v_j. A Reading Link e^R_{ij} ($e^R_{ij} \in E^R$) denotes that v_i once read an article or post published by v_j.

Agent behaviours: Let M be a set of *messages* propagated in the network G. In the proposed model, an Agent v_i has three types of social behaviours associated with a message m ($m \in M$). $m \in \mathsf{post}(v_i)$ denotes that m is posted by v_i. $m \in \mathsf{read}(v_i)$ denotes that m is read by v_i. $m \in \mathsf{interact}(v_i)$ indicates that v_i has interactions with other agents with m, e.g., commenting or liking m.

Agent local view: As mentioned earlier, it is hard for an individual user to possess a global view in an OSN. Hence, in the proposed approach, each agent analyses received attention from others based on its local view. The local view of Agent v_i contains the information about the actions taken by other agents which are only associated with itself. Namely, v_i is aware of who once interacted with it, and who once read or commented on its posts. However, v_i is not aware of other agents' actions which are not associated with itself or its posts.

B. Attention Model

Attention is a core concept in this research. It refers to an invested interest from one person to another. An acceptable amount of attention has generally a positive effect to the target person; as it could be viewed as the result of increased personal influence which leads to new personal ties or opportunities. However, excessive attention may lead to negative effects and potential risks. An extremely high level of attention often means one user pays an abnormal attention to another user and privacy invasion.

Definition 2. *Individual Physical Distance (PD_{ij}) between Agents v_i and v_j is defined as the number of agents (nodes) that the shortest path between v_i and v_j travels through.*

We suppose that the weight of each Physical Link equals to 1, and use the Floyd-Warshall's shortest path algorithm [8] to calculate the Physical Distance (PD_{ij}) between two agents. If PD_{ij} equals to 1, it shows that Agents v_i and v_j are the closest friends, e.g., v_i follows v_j directly. When the value of the distance becomes larger, it means that the relationship between v_i and v_j is further. For example, in Fig. 1, $PD_{12} = 1$, $PD_{13} = 1$, $PD_{23} = 1$, $PD_{34} = 1$ and $PD_{14} = 2$.

Definition 3. *Social Interaction Distance (ID_{ij}) is the measure of the interaction frequency between Agents v_i and v_j.*

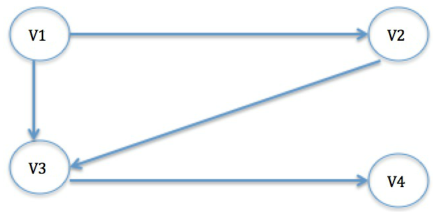

Fig. 1. The Example of PD_{ij} in 4 nodes Graph

ID_{ij} can be calculated by using Equation 1.

$$ID_{ij} = \frac{I_{ij}}{I_j} \tag{1}$$

In Equation 1, I_{ij} is the amount of interactions from v_i to v_j. I_j is the total amount of interactions from all agents to v_j. The Social Interaction Distance between v_i and v_j (ID_{ij}) is the ratio of I_{ij} against I_j.

Definition 4. *The Message Reading Ratio RM_{ij} is the ratio of messages that Agent v_i read out of the total posted messages of v_j. RM_{ij} can be calculated by using Equation 2.*

$$RM_{ij} = \frac{|R_{ij}|}{|P_j|} \tag{2}$$

In Equation 2, P_j represents the set of messages which Agent v_j posted. R_{ij} represents the set of messages posted by Agent v_j which were read by v_i. RM_{ij} is between 0 and 1. When RM_{ij} equals to 0, it means v_i has not read any messages that v_j posted. When RM_{ij} equals to 1, it means v_i reads all messages that v_j posted. If v_i reads most messages v_j posted (i.e., $RM_{ij} \approx 1$), it indicates that v_i pays much attention to v_j. However, in such situation, we still cannot make the conclusion that v_i pays abnormal attention to v_j. We have to consider their Physical Distance and Interaction Distance, as v_i and v_j can be close friends or always frequently interact with each other. Therefore, PD_{ij}, ID_{ij} and RM_{ij} are all affecting the detection result of abnormal attention.

IV. Fuzzy-based Abnormal Attention Detection

As discussed in the previous section, PD_{ij}, ID_{ij} and RM_{ij} all need to be considered for abnormal attention detection. In this research, we adopt fuzzy logic [9] [10], and aim to establish a computational model to capture the linguistic states of these three factors.

In the proposed fuzzy-based approach, PD_{ij}, ID_{ij} and RM_{ij} are input parameters. The output from the fuzzy approach is Excessive Attention Index (EA^t_{ij}), which indicates the excessive attention v_i pays to v_j at time stamp t.

A. Fuzzy Membership Functions

1) Input Parameters: We regard Physical Distance (PD_{ij}), Interaction Distance (ID_{ij}) and Message Reading Ratio (RM_{ij}) as three input parameters in the fuzzy approach.

In terms of PD_{ij}, we define three fuzzy sets, i.e., "Close", "Medium" and "Far", to capture the linguistic meanings of the Physical Distance. The membership functions are shown from Equations 3 to 5.

$$F_{PDClose}(x) = \begin{cases} 1, & x \in [0,1] \\ -x+2, & x \in [1,2] \end{cases} \tag{3}$$

$$F_{PDMedium}(x) = \begin{cases} x-1, & x \in [1,2] \\ 1, & x \in [2,4] \\ -x+5, & x \in [4,5] \end{cases} \tag{4}$$

$$F_{PDFar}(x) = \begin{cases} x-4, & x \in [4,5] \\ 1, & x \in [5,\infty) \end{cases} \tag{5}$$

ID_{ij} is fuzzified it based on the following three fuzzy sets: "Frequent", "Moderate" and "Seldom". The membership functions for the fuzzy sets are shown from Equations 6 to 8, respectively.

$$F_{IDSeldom}(x) = \begin{cases} 1, & x \in [0,0.1] \\ -10x+2, & x \in [0.1,0.2] \end{cases} \tag{6}$$

$$F_{IDModerate}(x) = \begin{cases} 10x - \frac{3}{2}, & x \in [0.15,0.25] \\ 1, & x \in [0.25,0.4] \\ -5x+3, & x \in [0.4,0.6] \end{cases} \tag{7}$$

$$F_{IDFrequent}(x) = \begin{cases} 10x-5, & x \in [0.5,0.6] \\ 1, & x \in [0.6,1.0) \end{cases} \tag{8}$$

Apart from that, for RM_{ij}, linguistic meanings are defined as "High", "Medium" and "Low". The membership functions for these three fuzzy sets are defined from Equations 9 to 11.

$$F_{RMLow}(x) = \begin{cases} 1, & x \in [0,0.2] \\ -10x+3, & x \in [0.2,0.3] \end{cases} \tag{9}$$

$$F_{RMMiddle}(x) = \begin{cases} 10x - \frac{5}{2}, & x \in [0.25,0.35] \\ 1, & x \in [0.35,0.55] \\ -10x - \frac{13}{2}, & x \in [0.55,0.65] \end{cases} \tag{10}$$

$$F_{RMHigh}(x) = \begin{cases} 10x-6, & x \in [0.6,0.7] \\ 1, & x \in [0.7,1.0] \end{cases} \tag{11}$$

2) Output Parameter: Excessive Attention Index (EA^t_{ij}) is the output parameter in the fuzzy approach. We fuzzify it based on the five fuzzy sets, i.e., "low", "more or less low", "medium", "high", "very high", and their degrees of memberships are calculated from Equations 12 to 16.

$$F_{AILow}(x) = \begin{cases} 1, & x \in [0,0.08] \\ -\frac{100}{7}x + \frac{15}{7}, & x \in [0.08,0.15] \end{cases} \tag{12}$$

$$F_{AILessLow}(x) = \begin{cases} \frac{25}{3}x - \frac{2}{3}, & x \in [0.08,0.2] \\ 1, & x \in [0.2,0.3] \\ -20x+7, & x \in [0.3,0.35] \end{cases} \tag{13}$$

$$F_{AIMedium}(x) = \begin{cases} 10x - 3, & x \in[0.3,0.4] \\ 1, & x \in[0.4,0.55] \\ -10x + \dfrac{13}{2}, & x \in[0.55,0.65] \end{cases} \tag{14}$$

$$F_{AIHigh}(x) = \begin{cases} 10x - 6, & x \in[0.6,0.7] \\ 1, & x \in[0.7,0.8] \\ -20x + 17, & x \in[0.8,0.85] \end{cases} \tag{15}$$

$$F_{AIVeryHigh}(x) = \begin{cases} \dfrac{20}{3}x - 5, & x \in[0.75,0.9] \\ 1, & x \in[0.9,1.0] \end{cases} \tag{16}$$

B. Fuzzy Inference

We perform the fuzzy reasoning to evaluate the Excessive Attention Index between two agents based on the three fuzzy inputs. The fuzzy rules are represented by a three dimensional matrix, and shown from Tables I to III (each table is for PD_{ij} with a particular value).

TABLE I
FUZZY RULE BASE MATRIX WHEN PD_{ij} IS "CLOSE"

ID_{ij} \ RM_{ij}	High	Middle	Low
Frequent	Low	Low	Low
Moderate	More or less low	Low	Low
Seldom	More or less low	Low	Low

TABLE II
FUZZY RULE BASE MATRIX WHEN PD_{ij} IS "MEDIUM"

ID_{ij} \ RM_{ij}	High	Middle	Low
Frequent	Medium	More or less low	More or less low
Moderate	High	Medium	More or less low
Seldom	High	Medium	Medium

TABLE III
FUZZY RULE BASE MATRIX WHEN PD_{ij} IS "FAR"

ID_{ij} \ RM_{ij}	High	Middle	Low
Frequent	High	Medium	More or less low
Moderate	Very High	High	Medium
Seldom	Very High	Very High	High

Based on Tables I to III, we can find the fuzzy rules to infer the attention index as "low", "more or less low", "medium", "high" and "very high".

We adopt one of the most commonly used compositional operation Max-min operation [11], to calculate EA_{ij}^t values. The output membership degree $\mu(EA_{ij}^t)$ can be calculated from Equations 17 to 18.

$$\begin{aligned} Min_\delta =&(\mu_\alpha(PD_{ij}), \mu_\beta(ID_{ij}), \\ &\mu_\gamma(RM_{ij})) \end{aligned} \tag{17}$$

$$\mu(EA_{ij}^t) = Max(Min_\delta) \tag{18}$$

C. Defuzzification

In the previous subsection, we define the linguistic states mapped to the fuzzy sets and fuzzy rules. We also need to obtain an real value for each time stamp. Here, we adopt Center of Area (COA) defuzzification method [12] to calculate the value. The defuzzification equation is shown in Equation19.

$$EA_{ij}^t = \frac{\sum_{i=1}^{N} y_i \times \mu_{EA_{ij}^t}(y_i)}{\sum_{i=1}^{N} \mu_{EA_{ij}^t}(y_i)} \tag{19}$$

, where y_i is the output from the output membership functions (refer to Equations 12 to 16); $\mu_{EA_{ij}}$ is the membership degree (refer to Equation 18). The real value of EA_{ij}^t can be calculated. N is the total number of fuzzy rules y_i satisfied.

Furthermore, the Average Excessive Attention Index v_j received from all other agents in the t^{th} time stamp $\overline{EA_j^t}$ can be calculated by using Equation 20.

$$\overline{EA_j^t} = \frac{\sum_{i=i}^{N} EA_{ij}^t - Max_{EA_{ij}^t} - Min_{EA_{ij}^t}}{N-2} \tag{20}$$

, where $Max_{EA_{ij}^t}$ is the maximum value of EA_{ij}^t from the all agents to v_j in the t^{th} time stamp. $Min_{EA_{ij}^t}$ is the minimum value of EA_{ij}^t from all agents to v_j.

Definition 5. *The Difference Excessive Attention Index DEA_{ij}^t is the difference of EA_{ij}^t and $\overline{EA_j^t}$ at the t^{th} time stamp. DEA_{ij}^t can be calculated by using Equation 21.*

$$DEA_{ij}^t = \begin{cases} \dfrac{EA_{ij}^t - \overline{EA_j^t}}{\overline{EA_j^t}} & EA_{ij}^t > \overline{EA_j^t} \\ 0 & EA_{ij}^t \leq \overline{EA_j^t} \end{cases} \tag{21}$$

We consider that DEA_{ij}^t indicates the degree of abnormal attention v_i pays to v_j at time stamp t. From Equation 21, it can be seen that EA_{ij}^t contributes to DEA_{ij}^t when it is greater than $\overline{EA_j^t}$. Namely, DEA_{ij}^t is 0 when the attention paid by v_i to v_j is less than average.

Definition 6. *The Accumulated Difference Excessive Attention Index ($ADEA_{ij}^t$) from v_i to v_j at time stamp $t = n$ ($n \geq 0$) is the accumulated value of DEA_{ij}^t. It indicates the accumulated abnormal attention v_i pays to v_j in the period from $t = 0$ to $t = n$. It can be calculated by using Equation 22.*

$$ADEA_{ij}^t = \sum_{t=0}^{n} e^{-\frac{\Delta t}{\lambda}} DEA_{ij}^t \tag{22}$$

, where Δt is the time difference between the t^{th} time stamp and the beginning. We also introduce a diminishing factor, i.e., $e^{-\frac{\Delta t}{\lambda}}$, to gradually decrease the impact of abnormal attention over time. We adopt weighted moving average method [13], in order to strength the influence of data which is close to the current time stamp and eliminate the effect of out of date data.

$ADEA_{ij}^t$ indicates the accumulated abnormal attention from v_i to v_j, when $ADEA_{ij}^t$ becomes larger and quickly increased, it means v_i pays abnormal attention to v_j continually in the period of Δt.

V. Experiments and Analysis

We perform experiments on synthetic data generated based on a real-world network topology. In the experiments, we consider two types of users, i.e., ordinary users and star users. Ordinary users follow others and at the same time are followed by other people. Ordinary users' indegrees are no larger than their outdegrees. Star users want their fans to pay high attention to them, and their indegrees are much larger than their outdegrees. Ordinary users and star users represent two typical types of users in the OSNs according to the number of users they followed or followed by others. We aim to indicate our model can fit different types of users in different situations.

In the experiments, the network topology is extracted from the Blogs network graph from the Konect dataset [14]. This directed network contains front-page hyperlinks between blogs in the 2004 US election. It contains 1224 vertices and 19025 edges.

Users can have normal behaviours and abnormal behaviours in the network. For normal behaviours, users randomly post messages, read messages and interact with others. For abnormal behaviours, users still randomly post messages, but purposely read messages and interact with some particular users. For example, we assume v_i pays abnormal attention to v_j. v_i reads most messages posted by v_j and his closest friends. At the same time, v_i seldom has interactions with v_j. Namely, v_i hides himself in the social network but continually and incredibly reads the messages from v_j.

A. *Experiment 1: Ordinary and Star Users under the Normal Attention*

Experiment 1 aims to indicate our model fits users in the different social statuses. We generate normal behaviours for all agents. They all randomly post messages, read messages and interact with others. Then we selected a star user v_s and a ordinary user v_o, and analyse their received attention from one particular user v_i.

In Fig.2, we plot the Excessive Attention Index (EA^t_{ij}) from the local view of a star user and an ordinary user. The horizontal axis represents the time stamps while the vertical axis indicates the ranges of Excessive Attention Index EA^t_{ij} which users received from other users. The plot clearly demonstrates that the star user received much higher attention than the ordinary user. The value of EA^t_{is} is from 35 to 40, while the value of $EA^t io$ is from 0 to 5. The value of EA^t_{is} is nearly 9 times higher than the value of EA^t_{io} in each time stamp. This is because that, when a user is a star user in the network, it means that the user has high in-degree and more users will pay higher attention to him.

In Fig. 3, we plot the Difference Excessive Attention Index DEA^t_{ij}, which calculates the differential ratio of EA^t_{ij} and $\overline{EA^t_j}$. Though the curve of ordinary user has sharply increased and decreased, the value of DEA^t_{ij} always stays in a low level which is less than 0.8. For the star user, the DEA^t_{ij} values are also in a low level, even when the EA^t_{ij} values are high (refer to Fig. 2).

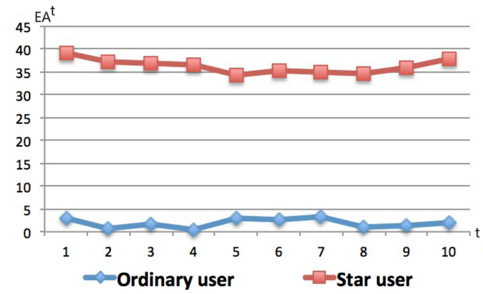

Fig. 2. The Excessive Attention Index star user and ordinary user received from normal behaviours

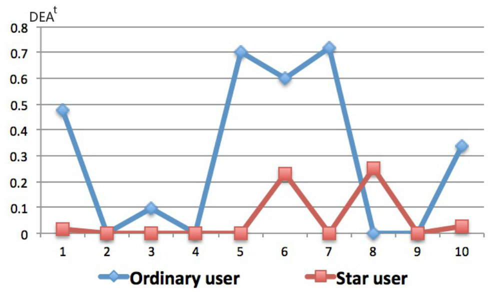

Fig. 3. The Difference Excessive Attention star user and ordinary user received from normal behaviours

Fig.4 plots the Accumulated Difference Excessive Attention Index ($ADEA^t_{ij}$) that star user and ordinary user received from one agent. The curves are corresponding to the tendency of star user and ordinary user respectively. For star user, the values are between 0 to 0.5. For the ordinary user, through the $ADEA^t_{ij}$ value is higher than the star user, it is below 2 and fluctuates which is in the normal range.

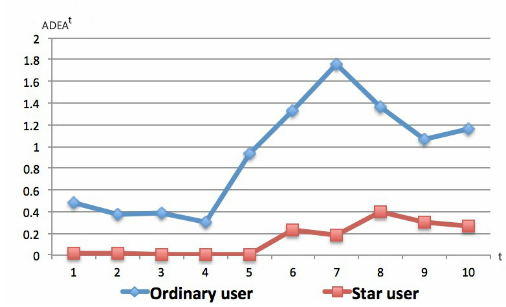

Fig. 4. The Accumulated Difference Excessive Attention star user and ordinary user received from normal behavrious

B. *Experiment 2: Detect Abnormal Attention*

In Experiment 2, we focus on how to detect abnormal attention. We set one user v_a pays abnormal attention to another user v_b while all other agents (e.g., v_c) have normal behaviours in the network.

Fig.5 shows the values of Excessive Attention Index of users under normal attention (EA^t_{ac}) and abnormal attention (EA^t_{ab}). We compare the value of top line which indicates the agent received attention from abnormal behaviours with the value of bottom line which from normal behaviours. The line corresponding to the agent who has abnormal behaviours on another agent always has higher EA_{ab}^{t} value than the one has normal behaviours in each time stamp.

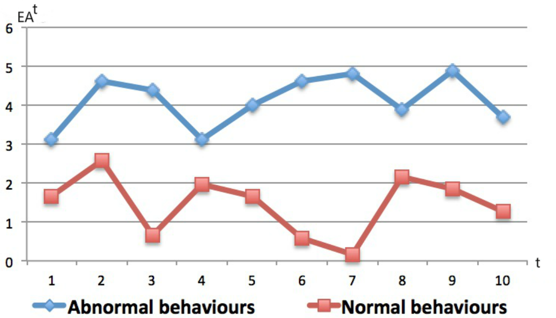

Fig. 5. The Excessive Attention Index from abnormal behaviours and normal behaviours

Fig.6 shows the Difference Excessive Attention Index. If user has abnormal behaviours, he might pays higher attention to his target. The value of DEA_{ab}^{t} of abnormal behaviours are all positive, it means the user always pays higher attention to the target and higher than the target's social status. The value of DEA_{ac}^{t} of normal behaviours are located around 0 in the 6 time stamps during the 10 time stamps, which indicates the user pays normal attention to the target.

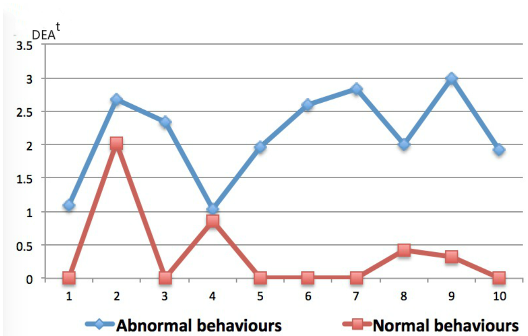

Fig. 6. The Difference Excessive Attention Index from abnormal behaviours and normal behaviours

In Fig.7, we plot the Accumulated Difference Excessive Attention Index versus time. With the time goes by, both two curves show the different tendency. Since the beginning, two curves start from low value which represent that the agent received nearly similar Excessive Attention Index from abnormal behaviours and normal behaviours. The value of top line about abnormal behaviours dramatically increases in a continuous style, which represents v_i continuously pays higher attention to the target. The value of bottom line about normal behaviours has fluctuated which is slowly increased and slightly decreased, also it stays between 0 and 1.5. Hence our model clearly detect the abnormal attention in the network.

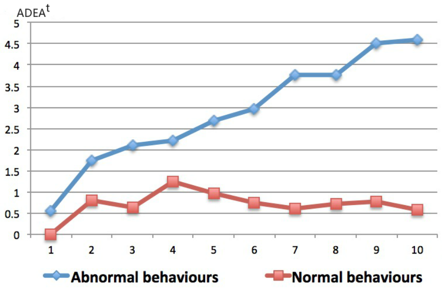

Fig. 7. The Accumulated Difference Excessive Attention Index from abnormal behaviours and normal behaviours

VI. Conclusion

In this paper, we proposed a fuzzy logic-based approach for detecting abnormal attention in OSNs. Experimental results demonstrated that the proposed approach can effectively detect abnormal attention in different situations with local information of individual users. Namely, it can achieve abnormal attention detection without a global view or the invasion of other users' privacy. We claim that the proposed approach is more suitable for real-world OSN applications.

In the future, we will take message content into consideration for abnormal attention detection, and verify the proposed approach in real-world data.

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