# Catching Instant Messaging Worms with Change-Point Detection Techniques

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## Abstract

Instant messaging (IM) systems have gained a lot of popularity in recent years. The increasing number of IM users has lured malware authors to develop more worms and viruses that spread in IM networks. In response to such growing security threat to IM systems, it is imperative to develop a fast and responsive IM worm detection system. In this paper, we apply change-point detection techniques to catch two families of IM worms, one aimed at infecting all vulnerable machines as quickly as possible and the other aimed at spreading slowly in a stealthy fashion to evade detection. Experimental results demonstrate that the proposed solutions are very effective in detecting both families of IM worms.

## 1 Introduction

Instant messaging (IM) systems have grown tremendously in the past few years. It is estimated that the total number of active IM accounts will increase from 867 million by the end of 2005 to 1.2 billion by 2009 [5] and the number of enterprise IM users will increase from 67 million in 2007 to 127 million in 2011 [6]. Accompanied with such increasing popularity of IM systems is the growing security threat that IM malware poses to both residential and enterprise IM users. For instance, from January 1, 2005 through September 2005, more than 360 new IM worms have surfaced [8]. According to a report from Akonix Systems Inc., there have been 346 IM attacks in 2007 [4]. In 2005, Reuters was even forced to shut down its instant messaging service temporarily due to the Kelvir IM worm [16].

IM worms have posed significant challenges to security protection for enterprise-like networks. IM worms can be leveraged to implant rootkits or bots onto victim machines inside an enterprise network after traditional perimeter protections such as firewalls have been bypassed. The two major propagation vectors of IM worms are *file transfers* and *URL-embedded chat messages*. An IM worm using the first approach (e.g., Sumom.a [19]) requests transferring a file, which contains the worm code, to an online buddy; in the second approach, an IM worm (e.g., Kelvir.k [7]) sends a hyperlink, which is embedded in a text chat message, to an online buddy. If the receiver accepts the file transfer request or clicks the embedded URL, a malicious file will be downloaded onto her machine and its execution creates a new infection.

Outbreaks of traditional Internet worms such as Code Red tell us that any effective defense scheme against an epidemic spreading requires a fast and responsive alert system [18]. Motivated by this, we propose to apply change-point detection techniques to detect two families of IM worms quickly. The first family of IM worms aim to infect all vulnerable machines as quickly as possible by aggressively hunting for new victims. We detect this type of IM worms by monitoring abrupt increase of file transfer requests or URL-embedded chat messages in the IM system. The second family of IM worms allow only a limited number of infection attempts within a certain period of time. Although spreading more slowly, this type of IM worms do not trigger a large number of file transfer requests or URL-embedded chat messages. Our detection scheme relies on the observation that different degrees of social online intimacy among IM buddies lead to uneven communication messages exchanged among them. An IM worm that randomly chooses online buddies as infection victims can, very likely, generate file transfer requests or URL-embedded chat messages between IM buddies that barely chat in the past. To detect this type of IM worms, we measure the average log-likelihood of file transfer requests or URL-embedded chat messages in the IM system; its abrupt decrease is a good indication of stealthy IM worm propagation. We evaluate our detection schemes with an IM dataset collected from a large enterprise network and experimental

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results show that they are very effective in detecting both families of IM worms.

The remainder of this paper is organized as follows. Section 2 presents some background knowledge about IM architecture and IM worms. Section 3 discusses IM worms that aggressively scan for new victims and their detection. Section 4 discusses how an intelligent IM worm evades the detection scheme described in Section 3. In this section, we also provide an algorithm that detects this type of IM worms. In Section 5, we evaluate the effectiveness of the proposed solutions with an IM dataset collected from a large corporate network. We present some related work in Section 6 and conclude this paper in Section 7.

## 2 IM Architectures and IM Worms

**IM architectures.** Popular IM systems include MSN messenger, AIM, Yahoo Messenger, IRC, ICQ, and Google Talk. Although these systems are built on different protocols, they bear little difference in their basic client-server structures. The general framework of an IM system in an enterprise-like network is depicted in Fig. 1. IM servers form the backbone of an IM system and their typical functionalities include account management, user authentication, presence notification, text-based chat message relaying, file transfer establishment, and group chatting. Albeit major IM systems provide similar functionalities, their server architectures may differ from each other. For instance, a text-based chat message in the AIM system has to go through two BOS (Basic Oscar Services) servers before it is delivered to the receiver, but a similar message in the MSN system traverses only one SB (switchboard) server [23].

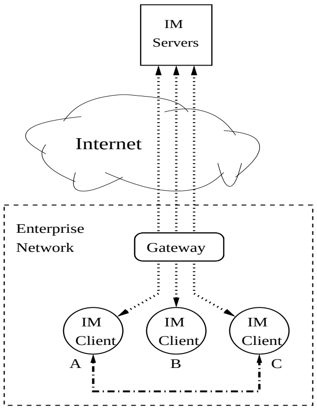


Figure 1: Architecture of a typical IM system

In our work, we focus on schemes that detect IM worm propagation in a centralized fashion. More specifically, we consider approaches that can be directly deployed at the IM servers, or at the enterprise gateway if the goal is to protect an enterprise network. The feasibility of such a solution requires further explanation. Encryption is rarely used in existing major IM systems, suggesting IM servers or enterprise gateways can see most text-based chat messages delivered through them. Hence, if an IM worm uses the URL-embedded chat messages to spread itself, the IM servers or the enterprise gateway can parse unencrypted chat messages and derive the URL information. However, the IM servers or the enterprise gateway can not capture the file being transferred between two IM clients, unless the sender and receiver are both protected by a firewall or NAT router [23]. Hence, if an IM worm propagates through file transfers, we may not be able to detect IM worm propagation through binary malware code analysis at the enterprise gateway or the IM servers. Nevertheless, any file transfer between two IM clients must involve some IM servers to set up their initial connection, so we can still infer that a file transfer is going to take place between two IM clients by analyzing IM command traffic at the enterprise gateway or the IM servers.

**IM worms.** An infection attempt through an IM network consists of two processes: *handshaking* and *downloading*. In the handshaking step, an infected machine with IM account $u$ requests a file transfer or sends a URL-embedded chat message to $u$'s online buddy $v$. When IM user $v$ receives the file transfer request or the URL-embedded chat message, she decides whether to accept the request or click on the URL. Only if she does so will the next step take place: the recipient machine downloads the worm code body from the machine that $u$ is using if the file transfer scheme is used, or from the host specified by the URL if the worm spreads by URL-embedded chat messages. Once the second step finishes, the recipient machine gets infected if it is vulnerable to the worm infection; otherwise, the infection attempt fails.

We use $T_h$ and $T_d$ to denote the durations of the handshaking step and the downloading step, respectively. We also use $T_e$ to denote the time needed to execute the worm code on a victim machine, e.g., modifying the registry on a Windows machine. Let $P_d$ be the probability that a node accepts a file transfer request or clicks on the embedded URL. $P_d$ essentially reflects the probability that the worm spreading attempt succeeds in each hop. We also use $P_v$ to denote the probability that a node is vulnerable to the worm infection after the worm code body is downloaded.

## 3 Fast Scanning IM Worms

Many existing IM worms adopt the fast scanning strategy, that is, they, after infecting a new host, immediately iterate the online buddy list and attempt to infect each contact on it either by requesting a file transfer or sending out a URL-embedded chat message. Such IM worms include Bropia and Kelvir that have been observed spreading on the MSN IM network. The common objective of fast scanning IM worms is to infect all vulnerable machines as quickly as possible. Experiences with traditional Internet worms such as Code Red and Slammer suggest that an effective defense scheme against a fast scanning worm must detect it at its early propagation stage [18].

**Algorithm description.** The aggressive spreading strategy used by fast scanning IM worms, although accelerating their propagation, inevitably increases the number of file transfer requests or URL-embedded chat messages in the IM systems, depending on their infection vectors. Moreover, these file transfer requests or URL-embedded text messages introduced by fast scanning IM worms bear different source-destination pairs. Such a distinguishing feature of fast scanning IM worms motivates us to apply sequential change detection theory for their detection. The key idea of sequential change detection theory is to locate the point of change, if it occurs, within an observed time series by checking whether it is statistically homogeneous in an online fashion. Further explanation requires more notations. We discretize time into measurement windows of equal length $\delta_1$, denoted by $\{\Delta_n^{(1)}\}_{|n\in\mathbb{N}}$. We use random sequence $C^{(f)} = \{C_n^{(f)}\}_{|n\in\mathbb{N}}$ and $C^{(u)} = \{C_n^{(u)}\}_{|n\in\mathbb{N}}$ to denote the total number of file transfer requests and URL-embedded chat messages with different source-destination pairs that have been observed within the $n$-th measurement window, respectively.

To detect fast scanning IM worms, we use the CUSUM algorithm [14], which is a standard tool in statistical process control. Particularly, we apply its non-parametric version [1] as it does not demand any *a priori* information on distributions of the random sequence before and/or after the change point. Let $X = \{X_n\}_{|n\in\mathbb{N}}$ be a random sequence with mean $\alpha(X)$ under normal operation. Our goal is to detect whether there is an abrupt change of mean in $\{X_n\}$. As the non-parametric CUSUM algorithm only works on random sequences with negative means before the change point and positive means after the change point, we transform $\{X_n\}_{|n\in\mathbb{N}}$ into a new random sequence $\{Z(X_n)\}_{|n\in\mathbb{N}}$, where $Z(X_n) = X_n - \beta(X)$, $\beta(X)$ is a constant depending on random process $X$, and $\alpha(X) < \beta(X)$.

The non-parametric CUSUM algorithm works as follows. First we define sequence $\{y_n\}_{|n\in\mathbb{N}^+}$:

$$y_n(X) = S_n(X) - \min_{0\le k\le n} S_k(X), \tag{1}$$

where $S_k(X) = \sum_{i=1}^{k} Z(X_i)$ and $S_0(X) = 0$. We can calculate $\{y_n\}$ more efficiently in a recursive manner:

$$\left\{ \begin{array}{lcl} y_n(X) & = & \max\{0, y_{n-1}(X) + Z(X_n)\}, \\ y_0(X) & = & 0, \end{array} \right. \tag{2}$$

In this way, $y_n(X)$ can be immediately computed based on $y_{n-1}(X)$ once measurement $X_n$ is available. Thereafter, we decide whether there is an abrupt change at time $n$ by comparing $y_n(X)$ against a predefined threshold $\theta(X)$: if $y_n(X) \le \theta(X)$, there is no abrupt change of mean in random sequence $X$; otherwise, there is.

One might suggest that we apply the CUSUM algorithm directly on random sequence $\{C_n^{(f)}\}$ or $\{C_n^{(u)}\}$ to detect fast scanning IM worms spreading by file transfers or URL-embedded chat messages. A basic assumption of the CUSUM algorithm, however, is that the process before the change point should be stationary. It is easy to see that both random sequences $\{C_n^{(f)}\}$ are $\{C_n^{(u)}\}$ vary with the number of online users, which typically changes over the time in a day. For instance, measurements of IM traffic in a large corporate network reveal that the peak times of user login and user logout are around 9AM and 5PM, respectively, which are strongly correlated with employees' working hours [23]. If we attempt to detect a fast scanning IM worm quickly by selecting a measurement window $\delta_1$ much smaller than a day, applying the CUSUM algorithm directly on random sequence $\{C_n^{(f)}\}$ or $\{C_n^{(u)}\}$ may lead to high false alarm rates.

To circumvent this problem, we measure another random process $M = \{M_n\}$, in which $M_n$ is the number of online IM users within the $n$-th measurement window $\Delta_n^{(1)}$. Instead of detecting abrupt changes on $\{C_n^{(f)}\}$ or $\{C_n^{(u)}\}$ directly, we normalize them by $M_n$ first before applying the CUSUM algorithm. Algorithm 1 provides a brief overview of our solution to detecting fast scanning IM worms:

**Algorithm 1** Detect fast scanning IM worms within the $n$-th measurement window $\Delta_n^{(1)}$

```
Collect $M_n$, $C_n^{(f)}$, and $C_n^{(u)}$
if $M_n$ is 0 then
    Ignore this measurement window
end if
Update $y_n(\frac{C^{(f)}}{M})$ and $y_n(\frac{C^{(u)}}{M})$ according to Eq. (2)
if $y_n(\frac{C^{(f)}}{M}) > \theta(\frac{C^{(f)}}{M})$ then
    Alert that a fast scanning IM worm is propagating by file transfers
end if
if $y_n(\frac{C^{(u)}}{M}) > \theta(\frac{C^{(u)}}{M})$ then
    Alert that a fast scanning IM worm is propagating by URL-embedded chat messages
end if
```

When implementing Algorithm 1, if there are no online IM users (i.e., $M_n = 0$), we ignore this measurement window, which means that the next measurement window is still the $n$-th measurement window.

**Parameter configuration.** We set the model parameters in a similar way as in [21]. First, $\alpha(\frac{C^{(f)}}{M})$ and $\alpha(\frac{C^{(u)}}{M})$ can be estimated from training data. Define:

$$\gamma(X) = \inf\{n : y_n(X) > \theta(X)\} \tag{3}$$

$$\rho(X) = \frac{\max\{0, \gamma(X) - m\}}{\theta(X)} \tag{4}$$

where $m$ is the time when the worm starts to propagate, $X$ is either $\frac{C^{(f)}}{M}$ or $\frac{C^{(u)}}{M}$, $\gamma(X)$ denotes the time of the change point, and $\rho(X)$ is the normalized detection time after the change point. Let $h(X)$ be the increase of mean after the IM worm starts to propagate. We then have:

$$\rho(X) \rightarrow \frac{1}{h(X) - |\alpha(X) - \beta(X)|}. \tag{5}$$

By choosing $h'(X)$, which is a lower bound of $h(X)$, to replace $h(X)$, we can set $\theta(X)$ as follows:

$$\theta(X) = \max\{0, \gamma(X) - m\} \cdot (h'(X) - |\alpha(X) - \beta(X)|). \tag{6}$$

Similar to [21], we let $h'(X)$ be $2|\alpha(X) - \beta(X)|$. Recall that $\beta(X)$ is an upper bound of $\alpha(X)$; hence, we can choose $\beta(X)$ to be $(1+\epsilon)\alpha(X)$, where $\epsilon$ is a positive number. We also specify $\max\{0, \gamma(X) - m\}$ as the target detection delay $d$. We thus have:

$$\theta(X) = d\epsilon\alpha(X). \tag{7}$$

**Algorithm analysis.** We now analyze how effective the CUSUM algorithm is in detecting fast scanning IM worms. We assume that a machine attempts to spread the worm onto its online IM buddies immediately after it gets infected. For simplicity, we also assume that at the initial propagation stage, the number of buddies that have already been infected can be ignored. Let $l$ be the average number of online users and $m$ be the average number of online buddies of each online user in the IM network when the IM worm is spreading. When an infected machine attempts to spread the worm onto $m$ online buddies, $m \cdot P_d$ of them actually download the worm code. We assume that the worm downloading time is $T_d$[1]. Hence, if an infected machine initiates a successful infection attempt to an online buddy at time $t$, the victim machine is infected at time $t + T_h + T_d + T_e$. Among the $m$ online buddies, an infected machine can only infect $mP_dP_v$ of them successfully. Let $\kappa$ be the number of worm generations before the worm is detected by the CUSUM algorithm. The number of infected machines in the $i$-th worm generation, where $1 \le i \le \kappa$, is $(mP_dP_v)^{i-1}$. Suppose that the IM worm starts to spread at the beginning of measurement window $\Delta_a^{(1)}$ and the IM worm is detected at the end of measurement window $\Delta_b^{(1)}$. We then have:

$$(\kappa - 1)(T_h + T_d + T_e) \le (b - a + 1)\delta_1 < \kappa(T_h + T_d + T_e). \tag{8}$$

Therefore, $\kappa$ can be represented as:

$$\kappa = \lfloor \frac{(b-a+1)\delta_1}{T_h + T_d + T_e} + 1 \rfloor. \tag{9}$$

Moreover, $y_b(X)$, where $X$ is $\frac{C^{(f)}}{M}$ or $\frac{C^{(u)}}{M}$, can be approximated as follows:

$$\begin{aligned} y_b(X) &\approx (b-a+1)(\alpha(X) - \beta(X)) + \\ &\quad \frac{m(1 + (mP_dP_v)^1 + ... + (mP_dP_v)^{\kappa-1})}{l} \\ &= (b-a+1)(\alpha(X) - \beta(X)) + \\ &\quad \frac{m((mP_dP_v)^{\kappa} - 1)}{l(mP_dP_v - 1)} \end{aligned}$$

As we have $y_b(X) > \theta(X)$ and $y_{b-1}(X) \le \theta(X)$, we can estimate $b - a + 1$, which is the number of measurement windows required to detect the fast scanning IM worm. First, suppose that $y_{b-1}(X) \approx \theta(X)$ and $\kappa \approx \frac{(b-a+1)\delta_1}{T_h + T_d + T_e} + 0.5$. Let $x$ be $b - a$, $g$ be $mP_dP_v$, and $r$ be $\frac{\delta_1}{T_h + T_d + T_e}$. We then have:

$$x(\alpha(X) - \beta(X)) + \frac{m(g^{rx+0.5} - 1)}{l(g-1)} \approx \theta(X) \tag{10}$$

As it is difficult to solve the above equation analytically, we use Taylor approximation for $g^{rx}$. Although it is possible to use Taylor series of orders higher than one, the solution becomes lengthy. Hence, we use the first-order Taylor series at point 0, i.e., $1 + r\ln(g) \cdot x$, to approximate it. Finally, we have:

$$x \approx \frac{l(g-1)\theta(X) + m(1 - \sqrt{g})}{l(g-1)(\alpha(X) - \beta(X)) + mr\ln(g)\sqrt{g}}. \tag{11}$$

We can thus establish the following theorem:

**Theorem 1** *Given the assumptions we have made, Algo. 1 needs approximately $[x] + 1$ measurement windows to detect the fast scanning IM worm, where $x$ is given in Eq. (11).*

From Eq. (11), we observe that if $\theta(X)$ is high, or $\beta(X)$ is chosen much larger than $\alpha(X)$, it takes a longer

[1] Here, we ignore the network-level interaction among multiple sessions that download worm code from the same infected host. This is because typical IM worms have small sizes, especially after packing themselves when spreading. For instance, the code size of Kelvir IM worm is about 24KB, if unpacked, or 9KB if packed [20]. Hence, using TCP, typical IM worm code can be downloaded within only a few round trip times and thus less than one second. Moreover, receivers of file transfer requests think for different time before they decide to download the worm code. Such stochasticity also reduces the synchrony among worm code downloading processes that are initiated by the same worm instance.

time to detect the fast scanning IM worm, which is consistent with our intuition.

**Implementation.** If Algorithm 1 is implemented by the IM servers, it needs to know the online status of each IM user. Such information is already available because the IM servers need to notify an IM user of each buddy's presence status when she just logs into the IM system. If Algorithm 1 is implemented at the enterprise gateway, there are two ways of keeping the online status of each internal IM user. One is to intercept every IM command that carries the presence information of an IM user. The second approach is to monitor the persistent TCP connections between the IM user and some IM servers, such as the BOS server in the AIM system and the notification server in the MSN system [23]: if such TCP connections are still alive, the corresponding IM user is online.

## 4 Self-Restraining IM Worms

Security by obscurity is never a good practice. If an adversary knows that Algorithm 1 has been deployed to detect IM worms, can he design an intelligent IM worm that spreads without being caught? We demonstrate its possibility in the following discussion. Note that the CUSUM algorithm triggers an alarm only when the cumulative sum reaches threshold $\theta(X)$; this allows an IM worm to ramp up its infection coverage using the fast scanning strategy to a certain point without being detected. After that, the difference between $\alpha(X)$ and $\beta(X)$ allows the IM worm to spread at a constant speed without increasing $y_n(X)$. Following the scenario analyzed in Section 3, an adversary estimates $x$ according to Eq. (11) and predicts that a fast scanning IM is detected after $[x]+1$ measurement windows. To avoid detection, the IM worm is designed to stop propagating in a fast scanning mode after $\kappa'$ generations, where:

$$\kappa' = \lfloor \frac{(x'+1)\delta_1}{T_h + T_d + T_e} + 1 \rfloor \tag{12}$$

and $x' < x$.

Since $(x'+1)$-th measurement window, the worm spreads in a self-restraining manner. If the number of file transfer requests or URL-embedded chat messages per measurement window generated by the worm does not exceed $l(\beta(X) - \alpha(X))$, it is highly likely that the worm propagates without triggering an alarm. We now show how an intelligent IM worm can achieve this using a token-based approach. Note that the number of infected machines in the $\kappa'$-th generation is $g^{\kappa'-1}$, where we recall $g = mP_dP_v$. Let $\Upsilon$ be $l(\beta(X) - \alpha(X))$. After a $\kappa'$-th worm instance is created, $\frac{\Upsilon}{g^{\kappa'-1}}$ tokens are generated for it[2].

The color of a token can be *green* or *red*. Initially, we set the colors of all tokens to green. The protocol works as follows: **(1)** If the color of a token changes to green, the holding worm instance randomly chooses a new victim that it has never tried to infect from the online IM buddy list and then attempts to infect it. If the holding worm instance cannot find an online buddy contact that has never been tried, it passes the green token to a random online buddy that it knows has already been infected, or to the machine from which it gets infected[3]; otherwise, it changes the color of the token to *red*, inscribes the current time onto the token, and schedules an *activation timer* which fires after $\delta_1$ time units since the timestamp on the token. **(2)** When an activation timer fires, the associated token changes to green and the holding worm instance proceeds as in (1). **(3)** If a worm instance successfully infects a new machine, it cancels any of its red tokens, if it has such one, and passes it to the new machine without altering its inscribed timestamp. **(4)** When a worm instance receives a red token with time stamp $t_0$, it schedules an activation timer after time $\delta_1 - (t - t_0)$, where $t$ is the current time. **(5)** When a worm instance receives a green token, it proceeds in the same way as in (1). We can easily establish the following property of the token-based protocol (proof omitted due to space limitation):

**Theorem 2** *The token-based protocol guarantees that within any time interval of length $\delta_1$ since the last $\kappa'$-th generation worm instance has been installed, the total number of file transfer requests or URL-embedded chat messages generated by the worm is at most $\Upsilon$.*

**Algorithm description.** We call intelligent IM worms that use rate limiting methods such as the token-based protocol *self-restraining IM worms*. To detect such type of IM worms, monitoring surges of file transfer requests or URL-embedded chat messages in the IM system is not sufficient. Instead, we measure likelihoods of file transfers or URL-embedded chat messages between IM clients and use them to decide whether a self-restraining IM worm is spreading. This idea is based on the measurements on IM messages in a large corporate network: on average, an AIM user chats with only 1.9 buddies, about 7% on her buddy list, and an MSN user chats with 5.5 buddies, 25% on her buddy list, in a month [23]. Such an observation suggests that an IM user tends

[2] In one implementation, $\lfloor \frac{\Upsilon}{g^{\kappa'-1}} \rfloor$ tokens are created deterministically and another one is created with probability $\frac{\Upsilon}{g^{\kappa'-1}} - \lfloor \frac{\Upsilon}{g^{\kappa'-1}} \rfloor$. If the protocol is implemented as such, the following Theorem 2 may not strictly follow due to randomness.

[3] We suppose that once a new machine is infected, it reports to the machine that infects it. If the worm spreads by file transfers, the sender and the receiver know each other's IP address. But if the worm spreads by URL-embedded chat messages, the sender and the receiver may not know each other's IP address. But such information can be relayed by the remote server where the worm code resides.

to chat more often with a small set of her online buddies, which reflects her online social intimacy. However, self-restraining IM worms as described do not have that knowledge about social relationships between IM users. Hence, when an IM worm instance chooses a victim from the online buddy list, it randomly picks one from those that have not been attempted before. As such randomness may not reflect real-world online social intimacy, it offers a weakness for their detection.

Similar to Algorithm 1, we discretize time into measurement windows of equal length $\delta_2$, denoted by $\{\Delta_n^{(2)}\}_{|n\in\mathbb{N}}$. $\delta_2$ is not necessarily equal to $\delta_1$. Let $W_n^{(f)}$ and $W_n^{(u)}$ denote the set of IM user pairs $\langle a, b\rangle$, where IM user $a$ sends at least one file transfer request and at least one URL-embedded chat message to IM user $b$ within measurement window $\Delta_n^{(2)}$, respectively. We also use $\pi(a, b)$ to denote the metric that reflects how close IM user $b$ is to IM user $a$ in the IM world. Essentially, $\pi(a, b)$ is the probability that IM user $a$ sends a chat message or a file transfer request to $b$ in the history. Let $Q$ be the whole set of IM users. We have:

$$\sum_{\forall b\in Q} \pi(a, b) = 1, \quad \text{for any } a \in Q \tag{13}$$

We use the EWMA (exponentially weighted moving average) approach to update $\pi(a, b)$. First, we discretize time into intervals of the same length. A time interval here can represent, for instance, a week. Let $\pi_i(a, b)$ denote the $\pi(a, b)$ value estimated after the $i$-th time interval and $\tilde{\pi}_i(a, b)$ denote the fraction of chat messages or file transfer requests that are sent from $a$ to $b$ during the $i$-th time interval. We then update $\pi_i(a, b)$ as follows:

$$\pi_i(a, b) = \varphi\tilde{\pi}_i(a, b) + (1 - \varphi)\pi_{i-1}(a, b), \tag{14}$$

where $\varphi \in [0, 1]$ is the weighting factor. It is trivial to verify that Eq. (13) must be true for any $a \in Q$ and $i > 1$ if initially $\sum_{\forall b\in Q} \pi_0(a, b)$ is equal to 1.

We define sequences $J^{(f)} = \{J_n^{(f)}\}_{|n\in\mathbb{N}}$ and $J^{(u)} = \{J_n^{(u)}\}_{|n\in\mathbb{N}}$ as follows:

$$\begin{cases} J_n^{(f)} = \frac{-\sum_{\langle a,b\rangle\in W_n^{(f)}} \ln\max\{\hat{\pi},\pi(a,b)\}}{|W_n^{(f)}|} \\ J_n^{(u)} = \frac{-\sum_{\langle a,b\rangle\in W_n^{(u)}} \ln\max\{\hat{\pi},\pi(a,b)\}}{|W_n^{(u)}|} \end{cases} \tag{15}$$

where $\hat{\pi} \in (0, 1)$. $-J_n^{(f)}$ and $-J_n^{(u)}$ give the average log-likelihood of file transfer requests and URL-embedded chat messages within measurement window $\Delta_n^{(2)}$, respectively. In Eq. (15), we use the minimum of $\hat{\pi}$ and $\pi(a, b)$ in case that the latter is 0.

We then monitor abrupt change of $J_n^{(f)}$ and $J_n^{(u)}$ to detect self-restraining IM worms:

**Algorithm 2** Detect self-restraining IM worms within the $n$-th measurement window $\Delta_n^{(2)}$

```
Collect $J_n^{(f)}$ and $J_n^{(u)}$
Update $y_n(J_n^{(f)})$ and $y_n(J_n^{(u)})$ according to Eq. (2)
if $y_n(J_n^{(f)}) > \theta(J_n^{(f)})$ then
    Alert that a self-restraining IM worm using file transfer method is propagating
end if
if $y_n(J_n^{(u)}) > \theta(J_n^{(u)})$ then
    Alert that a self-restraining IM worm using URL-embedding method is propagating
end if
```

Parameters in Algorithm 2 are specified in a similar manner as in Algorithm 1. For brevity, we do not replicate it here.

**Algorithm analysis.** We consider the self-restraining IM worm that uses the token-based scheme to control its propagation speed. The total number of tokens is $\Upsilon$. We assume that at the initial stage of worm propagation, each worm instance has received at most one token[4]. Also let the number of online buddies per user be $m$. To ease analysis, we further assume that under normal conditions, the nominators and denominators in Eq. (15) are constant. That is,

$$\begin{cases} J_n^{(f)} = \frac{B(J^{(f)})}{A(J^{(f)})} \\ J_n^{(u)} = \frac{B(J^{(u)})}{A(J^{(u)})} \end{cases} \tag{16}$$

where $A(J^{(f)})$, $B(J^{(f)})$, $A(J^{(u)})$, and $B(J^{(u)})$ are constants. Suppose that the self-restraining IM worm starts propagating at the beginning of the $i$-th measurement window and Algorithm 2 detects it after $z$ measurement windows. We ignore the cases in which the worm sends a file transfer request or a URL-embedded chat message from $u$ to $v$ but there is also a normal file transfer request or URL-embedded chat message from $u$ and $v$. This is a reasonable assumption because the infection attempts by a self-restraining IM worm are usually small (otherwise, Algorithm 1 can detect it). Suppose that we choose a small $\hat{\pi}$ such that it is smaller than $1/m$. We then have:

$$z \cdot \frac{-\frac{\delta_2\Upsilon}{T_h+T_d+T_e}\ln(\frac{1}{m}) + B(X)}{\frac{\delta_2\Upsilon}{T_h+T_d+T_e} + A(X)} - z \cdot \beta(X) > \theta(X), \tag{17}$$

where $X$ is $J^{(f)}$ or $J^{(u)}$, depending on the spreading vector of the IM worm. Hence, the CUSUM algorithm is

[4] If a worm instance has received more than one token, the worm instance will not attempt to infect the buddies that it has already tried. This may not hold for the $\kappa'$-th generation worm instances if $\frac{\Upsilon}{g^{\kappa'-1}} > 1$, but after that, it is very likely that tokens are passed onto different IM users.

able to detect the self-restraining IM worm after $z$ measurement windows, where

$$z = \lceil \frac{\theta(X)}{\frac{-\frac{\delta_2 \Upsilon}{T_h+T_d+T_e} \ln(\frac{1}{m})+B(X)}{\frac{\delta_2 \Upsilon}{T_h+T_d+T_e}+A(X)} - \beta(X)} \rceil. \tag{18}$$

We can thus establish the following theorem:

**Theorem 3** *Given the assumptions we have made, Algorithm 2 needs approximately $z$ measurement windows to detect the self-restraining IM worm, where $z$ is given in Eq. (18).*

From Eq. (18), it is clear that a too large $\theta(X)$ or $\beta(X)$ extends the detection period. But in reality, $A(X)$ and $B(X)$ change over time. Hence, making $\theta(X)$ or $\beta(X)$ too small can introduce high false alarm rates.

**Implementation.** One implementation issue with the aforementioned algorithm is the complexity of collecting $J_n^{(f)}$ and $J_n^{(u)}$. The algorithm requires knowledge of buddy relationships in the IM system. If the algorithm is implemented at the IM servers, such knowledge is already available, as the IM servers need it to notify an IM client of the presence statuses of her buddies if they change. For instance, in the AIM system, when an IM user logs in, the client software sends a list of her IM buddies in screen names to the message server; these names will be monitored for login/logout events. If the detection algorithm is implemented at the enterprise gateway, we need to parse IM command messages to derive buddy relationships. For instance, the detection algorithm designed for the AIM system can capture the "oncoming buddy" commands at the enterprise gateway that appear in the following three cases: first, the AIM messenger server notifies each user of the statuses of her buddies when she is logging into the system; second, whenever one of the buddies comes online after a user logged in, she gets a notification from the servers; third, the IM servers regularly use these commands to update the buddy list of each user [13].

Algorithm 2 also requires knowledge of $\pi(a, b)$ from each online IM user $a$ to each of her buddies $b$. As text-based chat messages and file transfer requests go through IM servers, we can calculate $\pi(a, b)$ by parsing IM chat messages or IM command messages for setting up file transfers at the IM servers or the enterprise gateway.

## 5 Experimental Evaluation

We use a realistic MSN IM messaging dataset to evaluate the effectiveness of our algorithms in detecting IM worms. This dataset, collected from a large corporate network, records chat messages of internal IM users and their online durations within a year. Our experiments are based on part of this dataset that has ten weeks' records. This subset has 193 internal IM users; on average, each of them has 22 IM buddies. In total, 3851 external IM contacts appear on the buddy lists of these 193 internal IM users. Unfortunately, we cannot get the buddy lists of these external IM users. As observed in [12, 17], IM networks tend to have power-law structures. We use the Power-Law Out-Degree Algorithm [15] to generate power-law graphs with 3581 nodes, whose average out-degree is 22. The power law exponent is set to be 1.7, based on measurement results from [12, 17]. For simplicity, we let the buddy relationships in the external graph be symmetric. Furthermore, if an external user is on the buddy list of an internal user, she also has that internal user on her own buddy list.

In our experiments, we consider only IM worms that are based on file transfers. Due to some technical problems, we are not able to obtain sufficient data on normal file transfers between internal IM users or between internal IM users and external IM users as of writing. We thus use measurement results from [10]: on average an online IM user sends out 1.84 file transfer requests per 24 hours. Similarly, we assume that the average number of file transfer requires an IM user receives is also 1.84. For each file transfer request, the probability that it falls into a time interval is proportional to the number of online internal IM users; once the time interval is chosen, its exact appearance time at the enterprise gateway is uniformly distributed within that time interval.

Now we introduce how to generate the sender and receiver of a file transfer request if it is issued by an internal IM user. For each of the 193 internal IM users, we build a buddy relationship table, an entry in which indicates the probability that a chat message is sent from her to the corresponding contact on her buddy list within the current week (i.e., not history based). These probabilities are empirically measured from the IM dataset. Let $\tilde{\pi}(u, v)$ denote the probability that a chat message goes from internal IM user $u$ to another IM user $v$. Also, we measure the probability that an outbound chat message (i.e., it is generated from an internal IM user) comes from a specific internal IM user $u$, denoted by $\omega(u)$. Then, when a file transfer request sent by an internal IM user is generated within a time interval, we first collect the entire set of IM user pairs $(u, v)$, where $u$ is an internal IM user and both IM users $u$ and $v$ are online during that time interval. Let $\Phi$ be this set. Then, IM user pair $(u, v)$ is chosen with probability $p(u, v)$:

$$p(u, v) = \frac{\omega(u) \cdot \tilde{\pi}(u, v)}{\sum_{(a,b)\in\Phi} \omega(u) \cdot \tilde{\pi}(a, b)} \tag{19}$$

In the experiments, we assume that the delay in seconds from one IM user to another obeys normal distribution $\mathcal{N}(0.1, 0.01)$ in seconds. The time that a recipient of a file transfer request spends on deciding whether to accept the request is exponentially distributed with mean 5 seconds. The downloading time is generated from normal distribution $\mathcal{N}(2,1)$. We ignore the execution time of downloaded malware in our experiments. We vary the acceptance ratio of a file transfer request (i.e., $P_d$) among 0.25, 0.5, 0.75, and 1.0. We also vary the vulnerable probability of a machine (i.e., $P_v$) among 0.25, 0.5, 0.75, and 1.0.

For each simulation scenario, we randomly pick an IM node, either internal or external, as the initial infection. The first infection takes place at simulation time 42000 seconds[5]. For each simulation scenario, we run it 10 times with different random number generation seeds. In our experiments, IM worm detection is performed at the enterprise gateway.

## 5.1 Fast Scanning IM Worms

In Fig. 2, we present the growth curves of internal infections (i.e., infected machines that are behind the enterprise gateway) when the IM worm uses the fast scanning spreading strategy. Obviously, when the acceptance ratio (i.e., $P_d$) is fixed, a higher percentage of vulnerable IM contacts leads to faster IM worm spreading; similarly, when a fixed portion of IM contacts is vulnerable, a higher acceptance ratio also accelerates IM worm propagation. Both observations agree with our intuition. Moreover, the maximum number of infected internal IM contacts is bounded by the number of internal vulnerable machines. This is confirmed in the right graph: the number of internal infections is always less than 97 (recall that there are 193 internal IM users in our dataset). However, this is not true when the acceptance ratio is fixed at 50% and the vulnerable probability is 100%. It is because an IM user can receive multiple file transfer requests from different buddies and accepting any one of them leads to a new infection.

We now investigate how effective Algorithm 1 is in detecting these fast scanning IM worms. We let the measurement window size be 300 seconds. The threshold parameter is computed based on Eq. (7), in which we let $\epsilon$ be 3 and $d$ be 3. Here, we choose a relatively large $\epsilon$ so that effects of white noise (e.g., bursts of normal file transfer requests) can be offset. We first test the algorithm when there is no IM worm spreading. No false positives have been observed. We then test 160 sample runs with 16 different combinations of vulnerable probabilities and acceptance ratios. We find that there are eight false negatives. A closer examination at the eight false negatives reveals that in all of them either one (the initial infection point) or two have been infected before simulation time 250,000 seconds. Due to no widespread worm propagation, Algorithm 1 cannot detect it based on the number of file transfer requests observed.

Fig. 3 depicts the detection delay in terms of measurement windows. For most of the scenarios, it takes between one and three measurement windows to detect the IM worm propagation. We, however, observe that when both the acceptance ratio and vulnerable probability are low, it takes a significant number of measurement windows to detect the IM worm. This is because in these cases the IM worm propagates very slowly and thus does not generate a large number of file transfer requests within a single measurement window. This is further confirmed in Fig. 4, which demonstrates the fraction of internal IM contacts that are infected among all internal vulnerable machines when the IM worm is detected. It is observed that for those cases with large detection delays, the fraction of internal infections is below 10%. On the other hand, when the vulnerable probability is 1.0, the fraction of internal infections reaches between 15% and 20% when the IM worm is detected, even though it takes only one measurement window. In these cases, we can accelerate IM worm detection by decreasing the measurement window size.

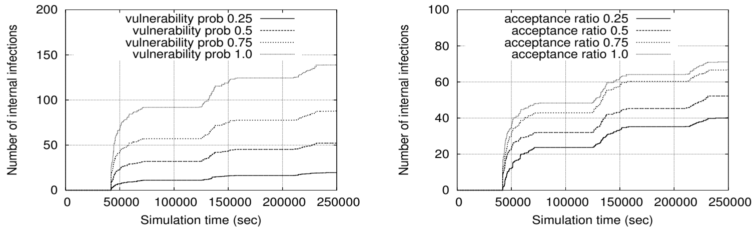
## 5.2 Self-Restraining IM Worms

We now consider a self-restraining IM worm that limits its spreading speed to evade detection by Algorithm 1. This worm allows only three infection attempts (i.e., file transfer requests in our experiments) every 300 seconds. It uses the token-based protocol, as described in Section 4, to control its propagation speed. Fig. 5 depicts the number of internal infections at simulation time 250,000 seconds as a function of acceptance ratio and vulnerable probability. Compared against the fast scanning IM worm, the self-restraining IM worm propagates much more slowly. For instance, when the acceptance ratio is 50% and the vulnerable probability is 75%, the number of internal infections is only 9 after simulation time 250,000 seconds, as opposed to 88 internal infections with the fast scanning spreading strategy.

Fig. 6 presents the successful detection ratio of the self-restraining IM worm by Algorithm 1. Among 160 sample runs, Algorithm 1 can only catch 11 of them before simulation time 250,000 seconds. This leads to a poor average detection ratio of 7%. The result is not surprising because Algorithm 1 relies on the abrupt increase of file transfer requests for detection but the self-restraining IM worm generates only a limited number of file transfer requests per measurement window.

We now evaluate the effectiveness of Algorithm 2 in detecting self-restraining IM worms. The measurement window $\delta_2$ used in this algorithm is also set to be 300 seconds. We let the weighting factor $\varphi$ be 0.25 in Eq. (14) and parameter $\hat{\pi}$ be $10^{-9}$ in Eq. (15). The $\pi_i$ pa-

[5] This initial infection time is carefully chosen so that there are a significant number of online IM users at that point.



(1) Acceptance ratio = 0.5

(2) Vulnerable prob = 0.5

Figure 2: Growth curves of internal infections when the IM worm uses the fast scanning spreading strategy

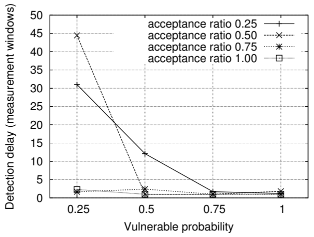


Figure 3: Detection delay in measurement windows for fast scanning IM worms

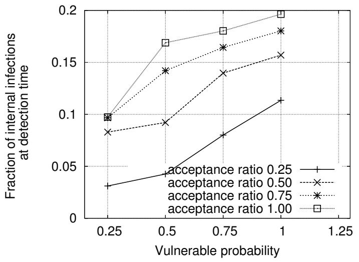


Figure 4: Fraction of internal infections at detection time for fast scanning IM worms

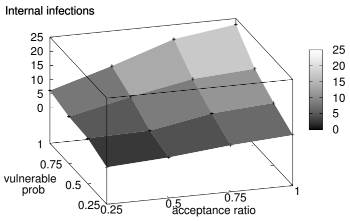


Figure 5: Number of internal infections with the self-restraining spreading strategy

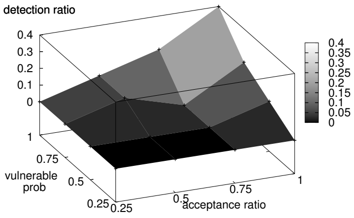


Figure 6: Detection ratio of self-restraining IM worms with Algorithm 1

rameter in Eq. (14) is updated every week. Similar to the experiments in Section 5.1, we let both $\epsilon$ and $d$ be 3.

The experimental results show that Algorithm 2 is able to detect the propagation of the self-restraining IM worm in all the 160 sample runs. Fig. 7 depicts the number of measurement windows that are needed to detect the IM worm under different combinations of acceptance ratios and vulnerable probabilities. The average detection delay is 16 measurement windows, which is equivalent to one hour and 20 minutes. Fig. 8 gives the fraction of internal infections among all internal vulnerable machines when the IM worm is detected. Obviously, only a small fraction of internal IM contacts has been infected before the IM worm is detected, suggesting that Algorithm 2 is effective in detecting self-restraining IM worms at their early stages.

## 6 Related Work

IM malware has posed significant security threats to both residential and enterprise IM users. Mannan et al. presented a survey on secure public instant messaging in [9]. They later proposed to use limited throttling and CAPTCHA-based challenge-response schemes to defend against IM worms [10]; they also developed a cryptographic protocol to further enhance authentication and secure communications in public IM systems [11]. Smith analyzed a French language IM system and after observing the IM network is scale-free, he suggested that IM worms can be effectively mitigated by disabling the top few most connected IM accounts [17]. In [22], Williamson et al. demonstrated the effectiveness of a virus throttling algorithm against IM worm propagation. Xie et al. proposed a framework called HoneyIM that uses decoy IM accounts in normal users' buddy lists to detect IM propagation in enterprise-like networks [24]. Compared with previous solutions, our work focuses on a centralized approach that leverages statistical metrics collected from IM systems. As our solution does not require involvement of IM clients, it can be more easily deployed than those distributed detection schemes such as HoneyIM.

Applying change-point detection techniques to detect network attacks is not a new idea. Wang et al. applied the non-parametric CUSUM algorithm to detect TCP SYN flooding attacks [21]. The CUSUM algorithm has also been used to detect Internet worms in [2, 3]. IM worms differ from traditional Internet worms such as Code Red II and Slammer because they propagate in social IM networks. In our work, we demonstrate that the change-point detection techniques are effective in catching IM worms with different spreading strategies.

## 7 Conclusions And Future Work

In this paper, we have proposed to apply change-point detection techniques to detect both fast scanning and self-restraining IM worms. We monitor abrupt increase

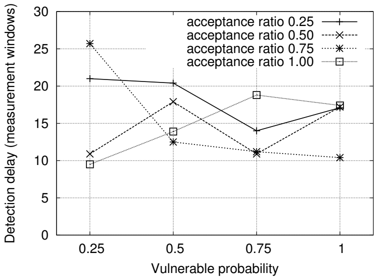


Figure 7: Detection delay of self-restraining IM worms with Algorithm 2

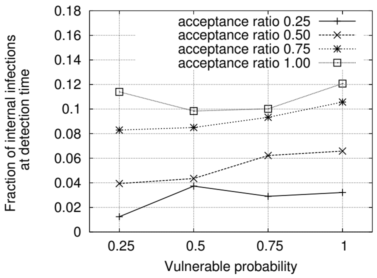


Figure 8: Fraction of internal infections at detection time with Algorithm 2

of file transfer requests or URL-embedded chat messages to detect fast scanning IM worms; we leverage social intimacy of IM users to detect stealthy IM worms that spread slowly. Experimental results show that the proposed solutions are effective in detecting both families of IM worms. We are currently developing algorithms for detecting another type of stealthy IM worms, which spread themselves between two online users only after they observe some ongoing conversations between them. In the future, we plan to evaluate the detection schemes proposed in this paper against more realistic IM datasets.

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