MINC and Misbehavior

Vijay Arya, Thierry Turletti

INRIA

INSTITUT NATIONAL DE RECHERCHE EN INFORMATIQUE ET EN AUTOMATIQUE

MINC and Misbehavior

Vijay Arya — Thierry Turletti

N° 5203

May 2004

Thème COM

Rapport de recherche

ISSN 0249-6399   ISRN INRIA/RR--5203--FR+ENG

MINC and Misbehavior

Vijay Arya , Thierry Turletti

Thème COM — Systèmes communicants
Projet Planete

Rapport de recherche n° 5203 — May 2004 — 17 pages

Abstract: Network tomography tools such as MINC can be used to infer important internal properties of a network underlying a multicast tree. This inference is made by analyzing receiver feedbacks to the measurement probes sent from the source and can be utilized to make significant decisions concerning the network. However, certain misbehaving receivers can return incorrect feedback and mislead the MINC inference resulting in an erroneous decision. Hence it is required to verify if the feedbacks collected from the receivers can be utilized to make a trustworthy MINC inference. In this report, the MINC inference procedure which computes the loss probabilities of various paths in the multicast tree is investigated. Firstly, it is shown how the loss probabilities computed by MINC change when receivers alter their feedback. Then, a statistical detection procedure is presented, which searches for loss probability inconsistencies in the feedback data. Some preliminary results based on old mbone loss traces are presented.

Key-words: MINC, Misbehavior, Network Tomography, Statistics, Multicast

Unité de recherche INRIA Sophia Antipolis
2004, route des Lucioles, BP 93, 06902 Sophia Antipolis Cedex (France)
Téléphone : +33 4 92 38 77 77 — Télécopie : +33 4 92 38 77 65

MINC et Fraude

Résumé : Les outils de tomographie de type MINC sont utiles pour inférer les caractéristiques du réseau sous-jacent correspondant à un arbre de transmission multipoint. Ces mécanismes d'inférence se font en analysant les rapports de réception de paquets de contrôle (appelés sondes) envoyés par la source; ils peuvent être utilisés pour prendre des mesures importantes concernant le réseau ou pour modifier la politique de transmission. Cependant, la mauvaise conduite (ou fraude) de certains récepteurs en renvoyant des rapports incorrects peut induire de mauvaises décisions. Il est donc important de pouvoir vérifier la validité des différents rapports de réception. Dans ce rapport de recherche, on étudie le mécanisme d'inférence de MINC qui calcule les probabilités de perte de paquets sur les différentes branches de l'arbre de transmission multipoint. On montre de quelle manière la probabilité de perte de paquets calculée par MINC est modifiée lorsque les récepteurs trichent. On décrit un mécanisme de détection statistique qui recherche les inconsistences de probabilité de perte de paquets au sein de l'ensemble des rapports de réception. Des résultats préliminaires effectués sur des traces de perte de paquets sur MBone sont présentés

Mots-clés : Fraudes, tomographie de réseau, MBone, MINC, Multicast, Statistique

1 Introduction

Network tomography infers the internal characteristics of a network based on end-to-end measurements. *Multicast-based Inference of Network internal Characteristics* (MINC) [1] is a tomography tool that infers the internal characteristics of a network which lies under a multicast tree. For MINC inference, the source injects probe packets into the multicast tree and each receiver reports whether it received the probe packet (1) or not (0). Based on these binary traces collected from receivers, the loss rates of paths in the multicast tree are inferred. The RTP [2] packets used to transfer data on the multicast tree can also replace the probe packets [3]. These loss rates inferred by MINC essentially provide a "congestion tomography" of the multicast tree and can be used either in real-time by congestion control protocols or by network operators to improve their network. But before the inference is used to make any important decision, it is essential to verify if the inference is trustworthy since the inference relies solely on receiver feedbacks.

The following general model of misbehavior can be utilized by the receivers in a multicast tree. When probing is performed each receiver answers probes correctly and the MINC inference is made. This inference is used to make a decision, but some of the receivers may not be satisfied with this decision. As a result, when probing is done again, some receivers misbehave by giving out wrong answers. Now the MINC inference is misguided and a different decision is taken. Some of the misbehaving receivers may now be satisfied with this decision but some of the honest receivers and other network flows may now suffer. In this manner, receivers can alter probes and misguide the MINC inference, resulting in an erroneous decision. Hence it is required to verify if the feedback data collected from receivers can be utilized to make a trustworthy MINC inference.

Examples of Misbehavior

(i) In multicast congestion control, a receiver can report wrong feedback to mislead the congestion control protocol to increase its sending rate harming other well behaved flows in the network [4]. Loss rate snapshots inferred by MINC can be used to find out if there is persistent congestion in the multicast tree when the sending rate increases. However, misbehaving receivers can also provide wrong feedback to MINC to hide their congestion related misbehavior.

(ii) A receiver can provide incorrect feedbacks due to the presence of bugs in the networking software/hardware or in the receiver software which reports answers to probes.

In this report, the main principle used in MINC itself is utilized to check the feedback data. In the balance of the report, section 2 presents how loss probabilities are inferred in MINC. Section 3 presents an analysis which shows how the loss probabilities of various paths in the multicast tree are affected if each receiver alters its feedback with a certain probability. Section 4 presents a statistical detection procedure which can detect loss probability inconsistencies in the feedback data. The detection procedure requires as input only the binary feedback data collected from the receivers and does not require the multicast tree topology.

This section concludes with some preliminary results based on mbone loss traces which test the core idea of the detection procedure. Section 5 concludes the report.

2 MINC

In this section, the principle used by MINC to infer the loss rates or the passage rates of links is described. A good starting point for MINC is [1]. MINC infers the internal characteristics

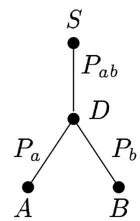

Figure 1: Multicast tree with two receivers

of a network underlying a multicast tree by exploiting the inherent correlation in multicast traffic. Consider the multicast tree shown in figure 1 with source S, two receivers A, B and the branching node D. Suppose that the source sends a stream of probe packets and each receiver observes whether it received the probe (1) or not (0). Suppose that it is required to estimate the passage probability of the path DB. For this, consider those packets which were received by A. Since A received them, these multicast packets must have definitely crossed the branching node D and were replicated on path DB. *Among them*, some may have crossed the path DB and some lost on this path. Thus, the ratio of the number of packets which both A and B received to the total number of packets which A received estimates the passage probability of the path DB.

More formally, suppose that the sender injects n probe packets into the multicast tree. Let (i, j), $i, j \in \{0, 1\}$ denote the probe for which A reported i and B reported j. Let n_{ij} denote the total number of probes of type (i, j). For example, n_{10} denotes the total number of probes for which A reported 1 and B 0. We extend this notation slightly by allowing $i, j \in \{0, 1, *\}$, where "$*$" means a *dont care* (either a 0 or 1). For example, n_{1*} denotes the total number of probes for which A reported 1 (B reported either a 0 or 1, $n_{1*} = n_{10} + n_{11}$). Now, the passage probability of the path DB, denoted by P_b and the passage probability of path DA, denoted by P_a are given by

$$P_b = \frac{n_{11}}{n_{1*}}, \quad \bar{P}_b = \frac{n_{10}}{n_{1*}}, \quad P_a = \frac{n_{11}}{n_{*1}}, \quad \bar{P}_a = \frac{n_{01}}{n_{*1}} \tag{1}$$

Having done this, the passage probability of path SD (*common passage probability*), denoted by P_{ab} can be estimated as follows :

$$P_{ab} = \frac{n_{11}/n}{P_a \cdot P_b} = \frac{n_{*1} n_{1*}}{n \cdot n_{11}} \tag{2}$$

This principle is extended in MINC to calculate the passage probability of all the paths in the multicast tree. These passage probabilities can also help in inferring the topology of the multicast tree [5],[1]. (Note that, in MINC the losses are considered to be bernoulli losses).

2.1 Simple Observations I

An observation which aids the subsequent analysis is now made. Consider the (00) probe. This probe may have *(i)* got lost on the path SD (*common loss*) or *(ii)* crossed SD and got lost simultaneously on both paths DA and DB (*independent loss*). We split the (00) probes into these two respective categories. Let n_{00}^c denote the total number of probes lost on path SD. Let n_{00}^i denote the total number of probes which crossed SD and were lost simultaneously on DA and DB. Now, it is noted that $n_{00}^i + n_{01}$ are the total number of probes which crossed the path SD and were lost on DA. *Among them*, n_{01} crossed DB and n_{00}^i were lost on DB. Thus, the passage probability P_b can also be written as

$$P_b = \frac{n_{01}}{n_{00}^i + n_{01}} = \frac{n_{11}}{n_{1*}} \tag{3}$$

3 Misbehavior and its impact on passage probabilities

A misbehaving receiver can misbehave by either altering a feedback from 0 to 1 ($0 \rightsquigarrow 1$) *i.e,* it reports it received the probe packet when it actually did not, or altering a feedback from 1 to 0 ($1 \rightsquigarrow 0$) *i.e,* it reports it did not receive the probe packet when it actually did. If a receiver reports a wrong feedback, the passage probabilities inferred by MINC in the multicast tree are altered. Figure 2(a) shows one possible impact of misbehavior on the passage probabilities, when the receiver A tries to misbehave by altering feedbacks from $0 \rightsquigarrow 1$. The passage probability of the path from A to the source increases and the passage probability of any path from any other receiver to A's ancestor decreases. Thus passage probabilities in a large region of the multicast tree are altered. Figure 2(b) shows a possible impact of misbehavior when the receiver A tries to misbehave by altering feedbacks from $1 \rightsquigarrow 0$. In this case only the passage probability of the path from A to A's father changes to be congruous with data reported by A. The passage probabilities in the rest of the multicast tree remain unchanged.

To explain the above changes in probabilities, the misbehavior mechanism of a user is modeled as follows. It is assumed that a receiver j misbehaves with probability α_j. If the receiver j misbehaves from $0 \rightsquigarrow 1$, it changes its 0 feedback to 1 with probability α_j and vice versa.

Consider again the two receiver system shown in figure 1 with receivers A, B and sender S. The *expected* passage or loss probabilities after misbehavior are now calculated. Firstly, the misbehavior from $0 \rightsquigarrow 1$ is considered.

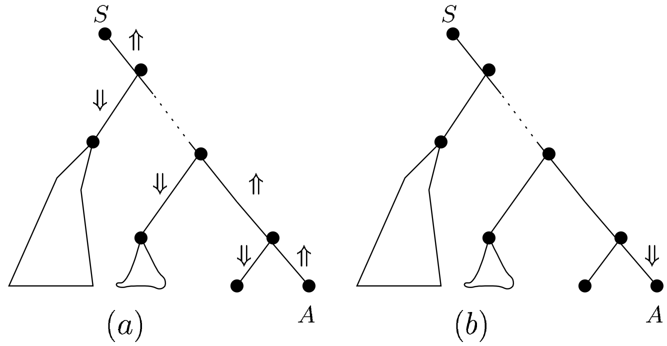

Figure 2: Effects of misbehavior on passage probabilities. (a) Receiver A always says Yes, (b) Receiver A always says No

3.1 Receiver A misbehaves from $0 \rightsquigarrow 1$

After A misbehaves, let $\mathbb{P}_a$, $\mathbb{P}_b$ and $\mathbb{P}_{ab}$ denote the respective altered passage probabilities.

Lemma 1 *If A misbehaves from $0 \rightsquigarrow 1$ with probability α_a, (i) $E[\mathbb{P}_b] \le P_b$, (ii) $E[\mathbb{P}_a] \ge P_a$, (iii) $E[\mathbb{P}_{ab}] \ge P_{ab}$*

Proof When A misbehaves from $0 \rightsquigarrow 1$, it causes two types of probe transformations: $x : (00) \Rightarrow (10)$ and $y : (01) \Rightarrow (11)$. The following table shows the *expected* probe system after these transformations.

n_{00}		$n_{00}(1-\alpha_a)$
n_{01}	$\Rightarrow$	$n_{01}(1-\alpha_a)$
n_{10}		$n_{10}+\alpha_a \cdot n_{00}$
n_{11}		$n_{11}+\alpha_a \cdot n_{01}$

The altered passage probability of path DB denoted by $\mathbb{P}_b$ will be,

$$E[\mathbb{P}_b] = \frac{n_{11}+\alpha_a \cdot n_{01}}{n_{1*}+\alpha_a \cdot n_{00}+\alpha_a \cdot n_{01}} = \frac{n_{11}+\alpha_a \cdot n_{01}}{n_{1*}+\alpha_a(n_{00}^i+n_{01})+\alpha_a \cdot n_{00}^c} \quad (4)$$

We know that $a/b = c/d \Rightarrow (a+c)/(b+d) = a/b = c/d$. Applying this to equation (3), we get

$$P_b = \frac{n_{11}+\alpha_a \cdot n_{01}}{n_{1*}+\alpha_a(n_{00}^i+n_{01})} \quad (5)$$

Subtracting (4) from (5) gives,

$$E[\mathbb{P}_b] = P_b\left\{1 - \frac{n_{00}^c \cdot \alpha_a}{n_{1*}+n_{0*} \cdot \alpha_a}\right\} \qquad \Downarrow \quad (6)$$

Now,

$$E[\bar{\mathbb{P}}_a] = \frac{n_{01}(1-\alpha_a)}{n_{*1}} = \bar{P}_a(1-\alpha_a) \qquad \Downarrow \tag{7}$$

Proof for *(iii)* is similar to that of *(i)*.

From (6), we have the following two observations.

Corollary 1 (i) *The higher the probability of misbehavior α_a, the larger the decrease in $E[\mathbb{P}_b]$.* (ii) *The higher the the number of losses on path DA, the larger the decrease in $E[\mathbb{P}_b]$.*

In general, suppose that A misbehaves by causing n_x transformations of type x and n_y transformations of type y. The following corollary gives the general conditions for observing the expected changes in probabilities after misbehavior.

Corollary 2 *If receiver A misbehaves from $0 \rightsquigarrow 1$ resulting in n_x and n_y transformations, then $\mathbb{P}_b < P_b$, $\mathbb{P}_{ab} > P_{ab}$ if $n_x/n_y > n_{10}/n_{11}$.*

Proof After misbehavior we have,

$$\mathbb{P}_b = \frac{n_{11}+n_y}{n_{1*}+n_x+n_y}$$

$$\mathbb{P}_b < P_b \quad \text{iff} \quad \frac{n_{11}+n_y}{n_{1*}+n_x+n_y} < \frac{n_{11}}{n_{1*}}$$

$$ie., \quad \text{iff} \quad (n_{1*}-n_{11})n_y < n_{11}n_x$$

$$ie., \quad \text{iff} \quad \frac{n_x}{n_y} > \frac{n_{10}}{n_{11}} = \frac{\bar{P}_a}{P_a}$$

Similarly for P_{ab}.

Corollary 3 *If both receivers A and B misbehave from $0 \rightsquigarrow 1$ with the same probability, the receiver which suffers more losses before misbehavior causes a greater decrease in the passage probability of the other receiver.*

Proof After A and B misbehave from $0 \rightsquigarrow 1$ with probabilities α_a and α_b, the expected probe system is shown below.

n_{00}		$n_{00}(1-\alpha_a)(1-\alpha_b)$
n_{01}	$\Rightarrow$	$n_{01}(1-\alpha_a)+\alpha_b(1-\alpha_a)n_{00}$
n_{10}		$(n_{10}+\alpha_a \cdot n_{00})(1-\alpha_b)$
n_{11}		$n_{11}+\alpha_a \cdot n_{01}+\alpha_b(n_{10}+\alpha_a \cdot n_{00})$

Working out $E[\bar{\mathbb{P}}_a]$ and $E[\bar{\mathbb{P}}_b]$ as before, we have

$$E[\bar{\mathbb{P}}_a] = (1-\alpha_a)\left\{\frac{n_{01}+\alpha_b\cdot n_{00}}{n_{*1}+\alpha_b\cdot n_{*0}}\right\} \tag{8}$$

$$E[\bar{\mathbb{P}}_b] = (1-\alpha_b)\left\{\frac{n_{10}+\alpha_a\cdot n_{00}}{n_{1*}+\alpha_a\cdot n_{0*}}\right\} \tag{9}$$

If $\alpha_a = \alpha_b$, the increase in each of the above depends on either the ratio $n_{00}/(n_{00}+n_{10})$ or $n_{00}/(n_{00}+n_{01})$.

3.2 Receiver A misbehaves from $1 \rightsquigarrow 0$

After A misbehaves, let $\mathbb{P}_a$, $\mathbb{P}_b$ and $\mathbb{P}_{ab}$ denote the respective altered passage probabilities.

Lemma 2 *If A misbehaves from $1 \rightsquigarrow 0$ with probability α_a, (i) $E[\mathbb{P}_b] = P_b$, (ii) $E[\mathbb{P}_a] \le P_a$, (iii) $E[\mathbb{P}_{ab}] = P_{ab}$*

Proof If a receiver misbehaves from $1 \rightsquigarrow 0$, it causes two types of probe transformations: $\bar{x}$: (10) $\Rightarrow$ (00) and $\bar{y}$: (11) $\Rightarrow$ (01). Writing down the expected probe system after transformations as before, we will have

n_{00}		$n_{00}+\alpha_a\cdot n_{10}$
n_{01}		$n_{01}+\alpha_a\cdot n_{11}$
n_{10}	$\Rightarrow$	$n_{10}(1-\alpha_a)$
n_{11}		$n_{11}(1-\alpha_a)$

$$\begin{aligned} E[\mathbb{P}_b] &= \frac{n_{11}(1-\alpha_a)}{n_{1*}(1-\alpha_a)} = P_b \\ E[\mathbb{P}_a] &= \frac{n_{11}(1-\alpha_a)}{n_{*1}} = P_a(1-\alpha_a) \qquad \Downarrow \end{aligned}$$

Proof for *(iii)* is same as that for *(i)*

In general, suppose that A misbehaves by causing $n_{\bar{x}}$ and $n_{\bar{y}}$ transformations. The following corollary gives the general conditions for observing the expected changes in probabilities after misbehavior.

Corollary 4 *If A misbehaves from $1 \rightsquigarrow 0$ resulting in $n_{\bar{x}}$ and $n_{\bar{y}}$ transformations, then $\mathbb{P}_b = P_b$, $\mathbb{P}_{ab} = P_{ab}$ if $n_{\bar{x}}/n_{\bar{y}} = n_{10}/n_{11}$.*

Proof After misbehavior we have,

$$\mathbb{P}_b = \frac{n_{11} - n_{\bar{y}}}{n_{1*} - n_{\bar{x}} - n_{\bar{y}}}$$

$$\mathbb{P}_b = P_b \text{ iff } \frac{n_{11} - n_{\bar{y}}}{n_{1*} - n_{\bar{x}} - n_{\bar{y}}} = \frac{n_{11}}{n_{1*}}$$

$$ie., \text{ iff } (n_{1*} - n_{11})n_{\bar{y}} = n_{11}n_{\bar{x}}$$

$$ie., \text{ iff } \frac{n_{\bar{x}}}{n_{\bar{y}}} = \frac{n_{10}}{n_{11}} = \frac{\bar{P}_a}{P_a}$$

Similarly for $\mathbb{P}_{ab}$.

In the rest of the report, only $0 \rightsquigarrow 1$ misbehavior is discussed, since $1 \rightsquigarrow 0$ misbehavior has almost no impact.

4 Statistical tests

Consider the three receiver topology shown in figure 3(a) with receivers A, B, C and sender S. With usual notation, let n_{ijk} denote the number of probes for which A reports i, B reports j and C reports k. Let P_c, P_a and P_b denote the passage probabilities of paths DC, EA and EB respectively.

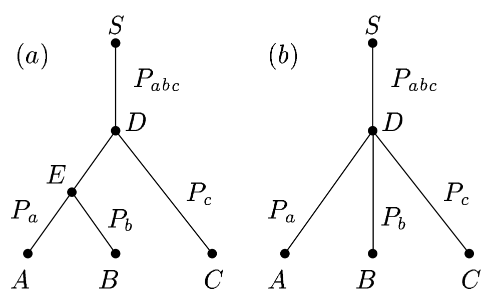

Figure 3: Multicast trees with three receivers

4.1 Simple Observations II

Consider the problem of estimating the passage probability of path DC. $(n_{10*} + n_{01*} + n_{11*})$ probes crossed SD and were replicated on DC (we know that since either A or B has received them). *Among them*, $(n_{100} + n_{010} + n_{110})$ were lost on DC and $(n_{101} + n_{011} + n_{111})$ crossed DC. Thus P_c is estimated in MINC as

$$P_c = \frac{n_{101} + n_{011} + n_{111}}{n_{10*} + n_{01*} + n_{11*}}$$

It is now noted that P_c can also be estimated as

$$P_c = \frac{n_{011}}{n_{01*}} = \frac{n_{101}}{n_{10*}} = \frac{n_{111}}{n_{11*}}$$

An observation similar to the one in section 2.1 is made. The n_{000} probes are split into two groups - n^c_{000} and n^i_{000}. Now, n^c_{000} are the number of probes lost on the path SD. n^i_{000} are those which crossed SD and were lost in the *left subtree* rooted at D. Now it is observed that $(n^i_{000} + n_{001})$ crossed SD and were lost in the left subtree. Among them, n^i_{000} were lost on DC and n_{001} crossed DC. Thus we have,

$$\frac{n^i_{000}}{n_{001}} = \frac{n_{100}}{n_{101}} = \frac{n_{010}}{n_{011}} = \frac{\bar{P}_c}{P_c} \tag{10}$$

4.2 A and B misbehave from $0 \rightsquigarrow 1$

Lemma 3 *After A and B misbehave from from $0 \rightsquigarrow 1$ with probabilities α_a and α_b, in the expected new system*

$$\frac{\mathbb{n}_{100}}{\mathbb{n}_{101}} \neq \frac{\mathbb{n}_{010}}{\mathbb{n}_{011}}$$

except when either of these conditions hold

(i) $P_{abc} = 1$

(ii) $\alpha_a/\alpha_b = n_{101}/n_{011}$

Proof After A and B misbehave, the relevant part of the expected new system is shown ($\mathbb{n}_{ijk}$ denotes n_{ijk} in the expected system):

$$\begin{aligned}
\mathbb{n}_{010} &= (n_{010} + \alpha_b \cdot n_{000})(1-\alpha_a)\\
\mathbb{n}_{011} &= (n_{011} + \alpha_b \cdot n_{001})(1-\alpha_a)\\
\mathbb{n}_{100} &= (n_{100} + \alpha_a \cdot n_{000})(1-\alpha_b)\\
\mathbb{n}_{101} &= (n_{101} + \alpha_a \cdot n_{001})(1-\alpha_b)
\end{aligned}$$

Thus,

$$\begin{aligned}
\frac{\mathbb{n}_{100}}{\mathbb{n}_{101}} &= \frac{n_{100} + \alpha_a \cdot n_{000}}{n_{101} + \alpha_a \cdot n_{001}}\\
&= \frac{n_{100} + \alpha_a \cdot n^i_{000}}{n_{101} + \alpha_a \cdot n_{001}} + \frac{\alpha_a \cdot n^c_{000}}{n_{101} + \alpha_a \cdot n_{001}}
\end{aligned} \tag{11}$$

$$\begin{aligned}
\frac{\mathbb{n}_{010}}{\mathbb{n}_{011}} &= \frac{n_{010} + \alpha_b \cdot n_{000}}{n_{011} + \alpha_b \cdot n_{001}}\\
&= \frac{n_{010} + \alpha_b \cdot n^i_{000}}{n_{011} + \alpha_b \cdot n_{001}} + \frac{\alpha_b \cdot n^c_{000}}{n_{011} + \alpha_b \cdot n_{001}}
\end{aligned} \tag{12}$$

From equation (10) we have,

$$\frac{n_{100} + \alpha_a \cdot n^i_{000}}{n_{101} + \alpha_a \cdot n_{001}} = \frac{n_{010} + \alpha_b \cdot n^i_{000}}{n_{011} + \alpha_b \cdot n_{001}}$$

Thus, $\mathbb{n}_{100}/\mathbb{n}_{101} = \mathbb{n}_{010}/\mathbb{n}_{011}$ if

$$\frac{\alpha_a \cdot n^c_{000}}{n_{101} + \alpha_a \cdot n_{001}} = \frac{\alpha_b \cdot n^c_{000}}{n_{011} + \alpha_b \cdot n_{001}} \tag{13}$$

i.e, if

(i) $n^c_{000} = 0 \Rightarrow P_{abc} = 1$ or

(ii) $\alpha_a/\alpha_b = n_{101}/n_{011}$

The second condition above essentially implies that

$$\frac{\alpha_a}{\alpha_b} = \frac{P_a(1 - P_b)}{P_b(1 - P_a)} \tag{14}$$

It is noted that, if A and B misbehave with the same probability the above condition *does not* hold *unless* P_a is also equal to P_b.

Lemma 4 *If C misbehaves, in the expected new system, all estimates of C remain equal.*

Proof After misbehavior,

$$\begin{aligned} E[\bar{\mathbb{P}}_c] &= \frac{(n_{100} + n_{010} + n_{110})(1 - \alpha_c))}{n_{10*} + n_{01*} + n_{11*}} \\ &= \frac{n_{010}(1 - \alpha_c)}{n_{01*}} = \frac{n_{100}(1 - \alpha_c)}{n_{10*}} \\ &= \frac{n_{110}(1 - \alpha_c)}{n_{11*}} = \frac{n^i_{000}(1 - \alpha_c)}{(n^i_{000} + n_{001})} \end{aligned}$$

As a result of lemma 4, we have that lemma 3 holds irrespective of whether C misbehaves or not. (It is now noted that all the above results hold for the other 3 receiver topology 3(b))

4.3 Misbehavior Detection

Figure 4 shows the algorithm for misbehavior detection. Essentially, $MisDetect$ chooses random groups of three receivers and applies the test of lemma 3(in $HTest$) to detect inconsistencies. As a result, for a particular receiver group (A, B, C), the algorithm does not check if C misbehaves. However, since the algorithm repeatedly applies the test for different receiver groups, a receiver x which appears "as C" in one group may appear "as A

Procedure $MisDetect(F, k, \delta)$
$F[N \times r]$: Binary feedback matrix
$k \leq \binom{N}{3}$: Times to repeat
δ : confidence level

$inconsistent \leftarrow 0$
while $k > 0$ **do**
  $(i, j, k) = Random(N)$ //same set not repeated
  $(A, B, C) = LabelTree(F, i, j, k)$
  $failed \leftarrow HTest(F[A], F[B], F[C], \delta)$
  if $failed$ **then**
    $inconsistent \leftarrow inconsistent + 1$
  end if
end while
print $inconsistent$

Procedure $LabelTree(F, x, y, z)$

Compute P_{xy}, P_{yz}, P_{zx}
$temp \leftarrow min(P_{xy}, P_{yz}, P_{zx})$
if $temp = P_{xy}$ **then**
  return(x, y, z)
else if $temp = P_{yz}$ **then**
  return(y, z, x)
else
  return(z, x, y)
end if

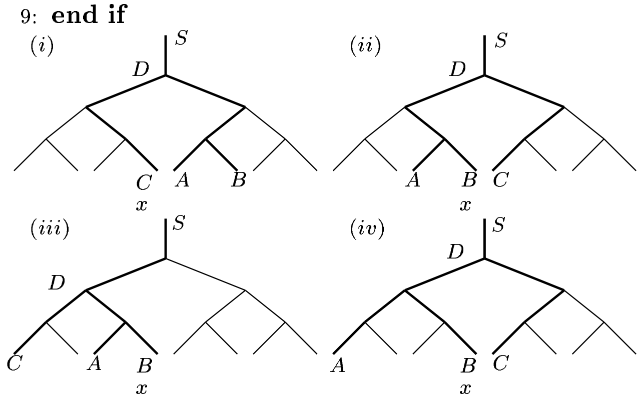

Figure 4: Algorithm for detection and its functioning

or B" in another group, depending on how it is connected in the multicast tree. A simple example of how the algorithm functions is shown below in Figure 4. The figure shows four random cases when a potentially misbehaving receiver x is chosen, each time considering a different three receiver tree from the original multicast tree. In 4(i), x appears as C and in the rest as B. The algorithm also tries to overcome the other two restrictions of lemma 3 by exploring different receiver groups. For example, in 4(ii), the algorithm may have been unlucky as the path SD may have no losses, yielding $P_{abc} = 1$. This may have been overcome in 4(iii). Suppose on the other hand, if in 4(ii), $P_a = P_b$ and $\alpha_a = \alpha_b$, this may have been overcome in 4(iv). As the number of receivers increase and the tree grows larger, the variety of paths available to the algorithm increase and aid in detection. The $LabelTree$ procedure labels a group of three receivers (x, y, z), to (A, B, C). It labels the receiver that attaches itself closest to the source as receiver C and arbitrarily labels the other two receivers as A, B. The procedure utilizes the principle that was introduced in [5],[1]. It computes the common passage probabilities P_{xy}, P_{yz}, P_{zx} and labels the two receivers corresponding to the $min(P_{xy}, P_{yz}, P_{zx})$, as (A, B) and the other as C. It is now noted that, the $LabelTree$ procedure works on feedback data potentially containing misbehavior. When a receiver misbehaves, it tends to increase its common passage probability with other receivers (It is recalled for instance from lemma 1 that when A misbehaves, P_{ab} increases). Thus there is a chance that in the presence of misbehavior, either of A or B can end up as C after labeling. In this case, two completely unrelated ratios will be compared by the algorithm. If A is swapped with C then the pair $(n_{010}/n_{110}, n_{001}/n_{101})$ is compared and if B is swapped C then the pair $(n_{100}/n_{110}, n_{001}/n_{011})$ is compared. These unrelated ratios continue to remain different after A and B misbehave (there is almost no chance that the labeling procedure yields a topology which does not match its data if there is no inconsistency).

4.4 HTest

$HTest$ is a standard hypothesis test from statistics to test the difference between two proportions. Given a set of three receivers A, B, C, the following contingency table is constructed.

	Lost	*Crossed*	*Total*
Sample 1	n_{100}	n_{101}	n_{10*}
Sample 2	n_{010}	n_{011}	n_{01*}
Total	$n_{100} + n_{010}$	$n_{101} + n_{011}$	$n_{10*} + n_{01*}$

A two-tailed test is performed with *null hypothesis* H_0 and *alternative hypothesis* H_1 as,

$$H_0 : \frac{n_{100}}{n_{101}} = \frac{n_{010}}{n_{011}} \qquad H_1 : \frac{n_{100}}{n_{101}} \neq \frac{n_{010}}{n_{011}}$$

$HTest$ tests whether the difference between the two proportions is "normal" given the current sample size of $(n_{10*} + n_{01*})$ and given that the two samples come from the same population (bernoulli losses conducted by link DC). As the sample sizes grow, if A and B have misbehaved, the difference between the two proportions will converge to the expected difference $i.e$, the difference between equations (11) and (12). On the other hand, if there

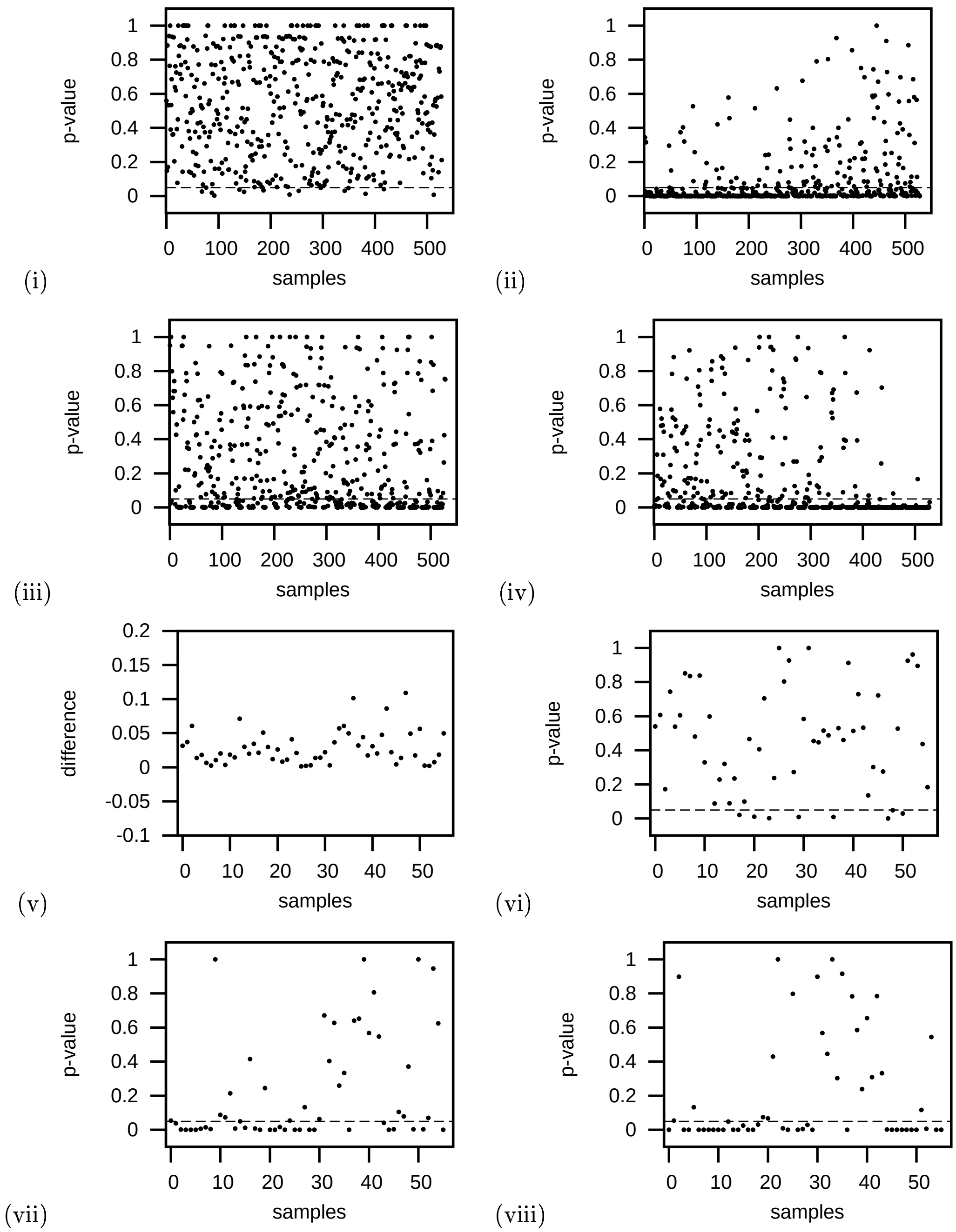

Figure 5: HTest for Model based((i)-(iv)) and mbone traces((v)-(viii))

is no misbehavior, the difference between the two proportions will converge to 0. Thus, it is noted that in the presence of misbehavior, although a certain sample size may not be sufficient to reject H_0 with a given confidence level, there will exist a larger sample size which can eventually do so.
We used *Fisher's exact test* as a representative HTest in our experiments. Fisher's exact test is based on hypergeometric distribution and gives a *p-value* between 0 and 1. If the p-value is less than 0.05, null hypothesis H_0 can be rejected with 95% confidence. We simulated the topology of figure 3(a) with 5000 probes and bernoulli losses on each link. The passage probabilities were $P_{abc} = 0.9$, $P_{ED} = 0.9$, $P_c = 0.85$. P_a and P_b were varied from 0.75 to 0.97 in steps of 0.01. Each time, the check $n_{100}/n_{101} = n_{010}/n_{011}$? was made by Fisher's test. Figure 5((i)-(iv)) plot the p-value for the cases when (i) there is no misbehavior (ii) when A alone misbehaves with probability 0.1, (iii) A and B misbehave with same probability 0.1 and (iv) A and B misbehave with probabilities 0.1 and 0.3 respectively.
We applied HTest on mbone loss traces collected by [6] and available at "ftp://gaia.cs.umass.edu/pub/yajnik/". These traces are available in three sets corresponding to multicast audio sessions of World Radio Network, UCB seminar and Radio Free Vat (documents available at the website). Each dataset is about a one hour trace in which receivers in the multicast group recorded the sequence number of audio packets they received. We analyzed 12 traces WRNSep19, WRNDec11, WRNNov28, WRNNov1, WRNOCT30, WRNNov13, WRNNov14, WRNNov13, UCBSep20, UCB96Apr24, RFV96Apr16 and RFV96May8 (all of which have topologies documented). For each dataset, 3 receivers which experienced sufficient losses were chosen and correctly labeled A, B and C. The traces were made binary based on whether the packet was received or not and divided into batches of size $10,000$ each (total of 56 batches, 3 batches were removed for very little loss and one for too much loss). For each batch, the values $n_{100}, n_{101}, n_{010}, n_{011}$ were calculated. Figure 5((v)-(viii)) document the results. The plot (v) shows the absolute difference $|(n_{100}/n_{101}) - (n_{010}/n_{011})|$ for each batch. As expected, there is very little difference between the two ratios. Plot(vi) shows the p-value when the $(n_{100}, n_{101}, n_{010}, n_{011})$ values of each sample were given to Fisher's test. 8 out of the total 56 samples were falsely put below 0.05 by Fisher's test (in spite of the fact that the difference between ratios is small). Then, in each batch we introduced misbehavior. Plot (vii) shows the p-value after A misbehaved with probability of 0.1 (28 out of 56 are above 0.05). Plot (viii) shows the p-value when A and B misbehaved with probabilities 0.1 and 0.3 respectively (23 out of 56 are above 0.05). In (vii) and (viii) plots, among the samples above 0.05, there are 12 and 13 samples respectively are from RFV96May8 (in all 14 samples were taken from RFV96May8). In most of these samples, P_{abc} was high resulting in low impact after misbehavior.

5 Conclusions and Discussion

In this report, we proposed the test $n_{100}/n_{101} = n_{010}/n_{011}$? to detect inconsistencies in the feedback data collected for MINC inference. We analyzed the changes which occur in these ratios when feedbacks are altered and showed that this test can be applied even if feedbacks are altered with the same probability. Using our preliminary experiments, we showed how the test works in practice. We developed *MisDetect* to show how the test can be applied for the entire multicast tree. In future we would like to check the test more rigorously and analyze the impact of excessive spatial correlations on the test as to whether they appear as inconsistency to the test. We would also like to investigate if this test can help to predict lost MINC feedbacks in cases when there is no misbehavior.

References

[1] A. Adams, T. Bu, T. Caceres, N.G.Duffield, T. Friedman, J.Horowitz, F.Lo Presti, S.B. Moon, V. Paxson, and D. Towsley, "The use of end-to-end multicast measurements for characterising internal network behavior," *IEEE Communications Magazine*, May 2000.

[2] H. Schulzrinne, S. Casner, R. Frederick, and V. Jacobson, "RTP: A transport protocol for real-time applications," *RFC 1889*, 1996.

[3] R. Caceres, N.G. Duffield, and T. Friedman, "Impromptu measurement infrastructures using RTP," *IEEE Infocom 2002*, June 2002.

[4] Sergey Gorinsky, Sugat Jain, and Harrick Vin, "Multicast congestion control with distrusted receivers," *NGC*, 2002.

[5] Sylvia Ratnasamy and Steven McCanne, "Inference of multicast routing trees and bottleneck bandwidths using end-to-end measurements," *IEEE INFOCOM*, 1999.

[6] M. Yajnik, J. Kurose, and D. Towsley, "Packet loss correlation in the mbone multicast network," *Global Internet Conference*, Nov 1996.

Contents

Unité de recherche INRIA Sophia Antipolis
2004, route des Lucioles - BP 93 - 06902 Sophia Antipolis Cedex (France)

Unité de recherche INRIA Futurs : Parc Club Orsay Université - ZAC des Vignes
4, rue Jacques Monod - 91893 ORSAY Cedex (France)
Unité de recherche INRIA Lorraine : LORIA, Technopôle de Nancy-Brabois - Campus scientifique
615, rue du Jardin Botanique - BP 101 - 54602 Villers-lès-Nancy Cedex (France)
Unité de recherche INRIA Rennes : IRISA, Campus universitaire de Beaulieu - 35042 Rennes Cedex (France)
Unité de recherche INRIA Rhône-Alpes : 655, avenue de l'Europe - 38334 Montbonnot Saint-Ismier (France)
Unité de recherche INRIA Rocquencourt : Domaine de Voluceau - Rocquencourt - BP 105 - 78153 Le Chesnay Cedex (France)

Éditeur
INRIA - Domaine de Voluceau - Rocquencourt, BP 105 - 78153 Le Chesnay Cedex (France)
http://www.inria.fr
ISSN 0249-6399