Towards Trouble-Free Networks for End Users

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ABSTRACT

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Network applications and Internet services fail all too frequently. However, end users cannot effectively identify the root cause using traditional troubleshooting techniques due to the limited capability to distinguish failures caused by local network elements from failures caused by elements located outside the local area network.

To overcome these limitations, we propose a new approach, one that leverages collaboration of user machines to assist end users in diagnosing various failures related to Internet connectivity and poor network performance.

First, we present DYSWIS ("Do You See What I See?"), an automatic network fault detection and diagnosis system for end users. DYSWIS identifies the root cause(s) of network faults using diagnostic rules that consider diverse information from multiple nodes. In addition, the DYSWIS rule system is specially designed to support crowdsourced and distributed probes. We also describe the architecture of DYSWIS and compare its performance with other tools. Finally, we demonstrate that the system successfully detects and diagnoses network failures which are difficult to diagnose using a single-user probe.

Failures in lower layers of the protocol stack also have the potential to disrupt Internet access; for example, slow Internet connectivity is often caused by poor Wi-Fi performance. Channel contention and non-Wi-Fi interference are the primary reasons for this performance degradation. We investigate the characteristics of non-Wi-Fi interference that can severely degrade Wi-Fi performance and present WiSlow ("Why is my Wi-Fi slow?"), a software tool that diagnoses the root causes of poor Wi-Fi performance. WiSlow employs user-level network probes and leverages peer collaboration to identify the physical location of these causes. The software includes two principal methods: packet loss analysis and 802.11 ACK number analysis. When the issue is located near Wi-Fi devices, the accuracy of WiSlow exceeds 90%.

Finally, we expand our collaborative approach to the Internet of Things (IoT) and propose a platform for network-troubleshooting on home devices. This platform takes advantage of built-in technology common to modern devices — multiple communication interfaces. For example, when a home device has a problem with an interface it sends a probe request to other devices using an alternative interface. The system then exploits cooperation of both internal devices and remote machines. We show that this approach is useful in home networks by demonstrating an application that contains actual diagnostic algorithms.

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Introduction

While operating systems and computing devices have generally become more user-friendly and reliable, Internet usage can still be frustrating — applications fail silently, exhibit inconsistent performance, and failures are often transient. Compared to the past, consumer Internet usage has changed in at least three aspects: 1) Users now expect to connect to a wide variety of networks, from home and office networks to Wi-Fi hotspots in hotels, planes, and coffee shops. 2) Applications have become more demanding in terms of Internet connectivity and network bandwidth because nearly every application, from calendars to games, relies on remote "cloud" storage and servers. In addition, applications that enable communications based on real-time voice and video are used frequently. Moreover, drastically growing usage of video streaming services now dominates Internet traffic, which requires consistent performance of both provider and consumer networks. 3) These applications frequently rely on the proper functioning of up to half a dozen parties, from the local wireless network to DNS servers, content delivery networks (CDNs), and various middleboxes such as network address translation (NAT) devices and firewalls. Yet, for all of these components, professional assistance is either unavailable or expensive, and therefore, most users need to become unwilling network administrators (or rely on their technically-savvy children or friends for assistance).

The goal of this thesis is to explore improved and alternative ways to assist diagnosis of network issues using automated software tools. We observe that traditional troubleshooting tools for computer networks, running on a local computer, had limited capability to diagnose network failures because they are designed to observe and probe the failures on a single machine only. In contrast to the approach, this thesis presents three studies that focus on the possibility of collaboration using multiple machines instead of just one. First, we describe DYSWIS ("Do You See What I See?") [33], a framework for network troubleshooting applications that leverages cooperation of users and their machines. The framework is designed to support crowdsourced rules and collaborative probes. Second, on top of the framework, we have developed two applications: WiSlow ("Why is my Wi-Fi slow?") [32], a Wi-Fi performance troubleshooting application and MoT ("Medic of Things") [34], a network diagnosis platform for mobile devices and the Internet of Things (IoT). The main features and contributions of the framework and applications are summarized below.

DYSWIS: Troubleshooting network failures

The key contribution of the DYSWIS framework is supporting collaboration of peers. First, DYSWIS uses passively collected data from multiple users such as failure statistics and normal patterns of network packets. The data is used to automatically detect abnormal network packets and problematic behavior of an end user's application. Second, for the actual diagnosis, DYSWIS triggers active probes on multiple end-user machines located in different networks. Then, receiving the results of those probes, DYSWIS collects various perspectives on the problems observed by other users. Since this information captures multiple views from different networks and locations, the probability of identifying the root causes is much higher than the case that the data is collected only from a local machine.

In addition, reflecting the proliferation of services, both standardized and proprietary, new probes and rule sets are designed to be extensible by users and third parties, including the vendors of the applications. For this purpose, DYSWIS adopts a crowdsourcing approach to create extensible sets of rules and probes. The rule system is designed to systemically support a crowdsourcing process and take advantage of collected rules and probes. To achieve this, we use sets of tiny independent rules instead of a single verbose rule to diagnose a problem. Finally, the architecture includes practical cooperative mechanisms such as parallel distribution of the probe requests and a scoring system that achieves fast and error-tolerant diagnosis.

Using the framework, various diagnostic rules and probes can be developed. First, we focus on failures on the higher layers of the protocol stack, including the network, transport, and application layers rather than the link or physical layers. For example, DYSWIS attempts to diagnose Internet connectivity issues, DNS failures, NAT problems, and TCP errors. To verify the feasibility of our approach, we artificially inject several network-related failures addressed by other research studies into our testbed, and then compare the diagnostic results of DYSWIS with four other software applications. By taking advantage of the assistance of other nodes, DYSWIS successfully identifies the root cause in seven out of eleven scenarios.

WiSlow: Diagnosing failures in wireless networks

Networks failures are not always caused by upper-layer protocols. Problems caused by the lower layers such as 802.11 wireless networks also cause significant connectivity and performance issues. Although poor Wi-Fi performance often causes an unsatisfactory user experience, isolating the root causes is nontrivial, even for a network expert because there are no effective software tools for investigating the lower layers. Additionally, these problems often show very similar symptoms at the user level, requiring special devices to investigate them. This motivated WiSlow, which is designed to diagnose the root causes of poor Wi-Fi performance with user-level network probes and leverages peer collaboration to identify the physical locations of these causes. WiSlow first distinguishes channel contention from non-Wi-Fi interference, then infers the product type of the interfering device (e.g., a microwave oven, cordless phone, or baby monitor) by analyzing the network packets. Finally, WiSlow points out the approximate location of the source of interference by exploiting user collaboration. We evaluate WiSlow with various interference sources and it demonstrates high diagnostic accuracy.

MoT: Diagnosing failures in wireless networks

Finally, we present a network problem diagnosis platform for the IoT environment. In this environment, devices are required to connect to Internet to perform their functions correctly. However, when they have a network problem, small devices that have less computing power are often not capable of troubleshooting the issues. Therefore, we propose a platform in which not only computers, but also smart objects such as smart TVs or network-connected door locks interact with each other to contribute to identifying the causes of network failures. In this model, it is possible that small devices offload the troubleshooting task to other devices that have more capabilities (e.g., network accessibility or computing power). We present the architecture and mechanism that support the collaboration of home devices and end-user devices such as laptop computers and smartphones. We also demonstrate the feasibility of this approach by describing an Android application that contains an algorithm that diagnoses failure scenarios.

Overview of the Thesis

This thesis is composed of three chapters. Chapter 1 discusses DYSWIS in detail with architecture and mechanisms of DYSWIS presented in Section 1.2 to Section 1.4. We evaluate the collaborative approach in Section 1.6 and discuss additional issues, including security concerns, on DYSWIS in Section 1.8.

Chapter 2 presents WiSlow. In Section 2.2, common sources of Wi-Fi performance degradation are described. In Section 2.3, restrictions of an end user's environment are discussed as well as how WiSlow attempts to overcome them. Section 2.4 to Section 2.8 explain the detailed methods employed by WiSlow and Section 2.9 evaluates our approach.

Chapter 3 describes MoT. In Section 3.2, we introduce the architecture of MoT, and in Section 3.3, we discuss several practical scenarios of problem diagnosis. Then, we present the details of MoT implementation in Section 3.4 and demonstrate the feasibility of this approach in Section 3.5. Finally, we state our conclusions in the last chapter.

Chapter 1

DYSWIS: a network troubleshooting framework

1.1 Introduction

When applications fail due to network problems, most of them provide minimal support, at best, to help identify potential sources of trouble. If Web access is slow, for example, the cause could be high packet loss on the local wireless network due to interference, an overloaded residential Internet connection, wide-area network problems, a misconfiguration in the NAT box, or a remote server problem. The appropriate action varies in each case, ranging from using a third-party DNS server to simply waiting and hoping that the server recovers.

The diagnostic mechanism of DYSWIS differs from other conventional methods in relying on the assistance of other network users, modeling the common pattern where one person asks someone close by, "Hey, is your Internet working?" In other words, DYSWIS focuses on collaborative diagnosis and parallel probing. Reflecting the proliferation of services, both standardized and proprietary, DYSWIS is designed to be extensible by users and third parties such as vendors of applications. In addition, we present a crowdsourcing approach that enables end users, developers, and network administrators to contribute new rules and diagnostic modules to expand DYSWIS functionality.

To summarize, DYSWIS is a complete system that automatically diagnoses common network problems for end users using peer assistance in addition to an extensible probing and a rule framework. The main contributions of the DYSWIS architecture are as follows:

Detecting problems autonomously

DYSWIS uses a statistical mechanism to determine whether particular network packets observed in a user machine are indicators of significant network failures, which should be further diagnosed, or if they are part of a normal behavior which can be ignored.

Optimized design for crowdsourced rules

To support crowdsourcing of network experts effectively, we build a rule system that is composed of small independent rules. DYSWIS also provides a simple application interface that enables multiple groups of developers, network administrators, and application vendors to participate in writing new probe modules and diagnostic rules.

Designed for distributed networks

DYSWIS is specially designed to support decentralized networks such as distributed hash tables (DHTs) which enables nodes to collaborate without an infrastructure and achieve Internet scale. As each node's information is published as key-value pairs into a DHT, other nodes can discover appropriate nodes effectively. In this thesis, we use 'node' and 'peer' interchangeably to indicate a user machine that participates in probing network failures in the DYSWIS system.

Practical design for distributed probes

A node categorizes other nodes by their properties. The categories are useful for helping a problematic node find appropriate peers that are able to help the node. Once a peer is found, a node distributes probing requests to multiple peers simultaneously to obtain probing results from different networks. Using the results, it infers the status of the network infrastructure, which is normally invisible to end-users, without any help from network core devices.

1.2 DYSWIS network

The key feature of DYSWIS is the collaboration of end users. Therefore, a node first needs to discover other users who are willing to assist in the problem diagnosis. A centralized server is one of the possible options to maintain a list of available peers; an alternative method is to build a distributed hash table (DHT) composed of end users. Although centralized-server approach is straightforward and easier to implement, it does not function perfectly in this case since we assume this system will run in problematic situations in most cases, which means it is highly probable that the end-user system is not able to connect to the centralized server. Therefore, our current implementation adopts the distributed-network approach, which is more scalable and also tolerant to the single-point-of-failure problem [42].

Figure 1.1 shows the DYSWIS network that uses DHT to connect to other collaborative nodes. Since we are focusing more on partial network faults, we assume that a node is able to connect to a few other nodes, or at least have a list of network addresses of other

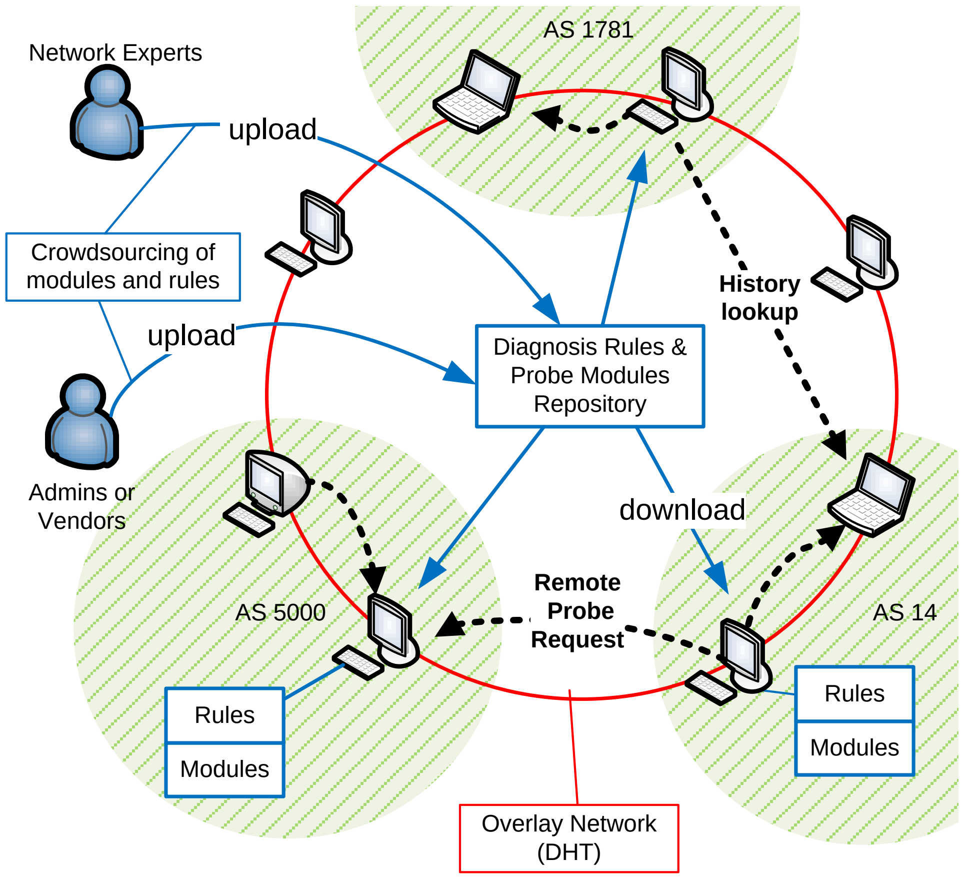


Figure 1.1: DYSWIS Architecture

nodes cached from when the network was available. Service discovery technologies such as Bonjour [8] can also be used when a DYSWIS node cannot join the DYSWIS network while the local area network is available.

Peer classification and discovery

To register for the DYSWIS network, each node must publish its network-related information first. Since DHT systems only support exact-match lookups, a DYSWIS node publishes the information with multiple key-value pairs. For example, a single node can be represented by multiple keys such as an Autonomous System Number (ASN), a subnet,

Table 1.1: Examples of node information

Node type	Format of key	Example of key
Sister	NAT@[IP address]	"NAT@128.59.21.16"
Near	public@[subnet]	"public@128.59.16.0/24"
Internet	public	"public"
Far	public@[subnet]	"public@AS22"

an IP address, or whether it uses a NAT. Table 1.1 describes several examples of the keys. The value mapped to the key contains the node's IP address, port number, and properties such as type of operating system (OS), network connection (e.g., Ethernet or wireless), or whether it uses a firewall.

These key-value pairs are stored in the DYSWIS network and enable other users to discover appropriate nodes easily. Once appropriate nodes are found, a node sends remote-probing requests to other nodes and receive the result from them.

When a DYSWIS node selects the collaborating nodes, it relies on their relative locations. To make diagnostic rules systemically, we categorize other collaborating nodes into five groups according to where they are located:

- ***Local node***: A node currently diagnosing a failure.
- ***Sister node***: A node behind the same NAT device.
- ***Near node***: A node within the same subnet.
- ***Internet node***: A node located in any other subnets.
- ***Far node***: A node located in the service provider network of a remote server (e.g., a web server).

To discover a specific type of collaborating nodes, a *local node* queries the DYSWIS network with a corresponding key. For example, to obtain a *near node*, the key must include the subnet information or address of the first-hop router of the *local node*. If the *local node* is behind a NAT, we often need to discover a *sister node* to obtain the view from the same environment. In this case, the key includes the public IP address of the NAT device. To seek an *Internet node*, we simply query with a key, "public", that returns a list of random nodes from other networks. Then, we can filter out *near nodes* from the list to obtain only *Internet nodes*. In addition, we can discover a *far node* located at a specific subnet. This *far node* is useful when we need to probe the subnet at which a problematic remote server is located.

1.3 Detecting faults

DYSWIS has two methods for detecting a network problem automatically: packet monitoring and application plugins. Although packet capturing causes additional CPU and memory overhead, it provides rich information about current network status and enables to monitor network packets of every application. In contrast, application plugins are able to obtain information about current problems from applications directly without packet capturing. Although this approach does not cause heavy overhead on a user machine, it requires additional implementation effort for each application. We describe these two methods in detail in the following sections.

Monitoring packets

DYSWIS monitors raw network packets and checks various failure conditions such as application layer errors, TCP flag bits indicating failures, TCP timeout situations, and the number of TCP retransmissions and duplicated ACKs. First, we check whether the response packets contain error indicators such as “name not found” in DNS, “404 not found” in HTTP, or an RST flag in TCP packets. We also look for the no-response situations — we check if there are responses to outgoing requests such as TCP SYN packets, DNS queries, or HTTP GET messages. If there is no response to these packets, DYSWIS reports it as a problem. Finally, we track the number of TCP retransmissions and duplicated ACKs to examine the status of the current network performance.

This monitoring approach enables us to detect a number of hidden failure symptoms without the assistance of other applications. However, we discovered that many of these failure indicators occur as part of normal application-specific mechanisms, which should not be detected as failures. In this thesis, we define a *false positive failure* as a problem detected by the packet-level monitoring but not an actual failure when application-specific behaviors are considered. We describe several examples and present an automatic filtering mechanism in the following paragraphs.

Filtering false positive failures

Monitoring packets on real end-user machines, we periodically observe a number of multicast DNS (mDNS) packets that contain a “no such name” error. Although this is a failure message of a DNS query, it is expected if the OS uses the DNS Service Discovery (DNS-

SD) protocol to discover services. This happens when a machine sends a service query message, but the service does not exist in the network. In this case, there is no point in reporting these errors to end users. Another example is HTTP long polling [14]. Long polling is one of the push technologies, which is used by many applications and web sites to communicate interactively with clients without disconnecting a TCP connection. With long polling, a web server does not respond immediately after receiving an HTTP GET request but rather responds after a period of time (e.g., one minute) to maintain the connection. Although this delay is intended, its pattern is identical to the case of a slow response due to poor network performance or a problematic web server. Therefore, even though it is not an actual failure, long polling will be considered as a failure (i.e., high latency) in the packet monitoring system.

Other examples include TCP-related failures such as TCP retransmission and TCP RST packets. Although TCP RST packets usually imply that a session is unexpectedly terminated, they are normal in some applications. For example, it is known that YouTube may cause a number of TCP RST packets when a client changes video resolution while watching a video [37].

Another example is TCP retransmission. Although the occurrence of a large number of TCP retransmissions indicates significant performance degradation, it is normal to have a small number of retransmissions caused by temporary network congestion. Thus, a fault detection system needs to set off an alarm only when an unusual number of TCP retransmissions have been detected. In addition, some TCP RST packets can also be misidentified as failures.

Table 1.2 summarizes the examples of false positive failures and applications that cause

Table 1.2: Examples of *false positive failures*

False positive failures	Applications
mDNS packets	Bonjour
HTTP long polling	Facebook, Dropbox, Gtalk
TCP Retransmission	Video streaming, file download
TCP RST packets	Video streaming (YouTube)

them. It is also possible that other scenarios that we are not aware exist.

However, it is impractical to configure every false positive failure scenario beforehand because not all of them are known. For example, it is impossible to know a list of web sites that are using long polling. In addition, it is difficult to set up a threshold of TCP retransmission or TCP RST counts because this depends on applications, protocols, and websites.

In DYSWIS, instead of configuring all the exceptional cases and threshold parameters manually for each application and website, we filter out the false positive and less important failures using an automatic judging system that uses other peers' failure ratios. We define the failure ratio as the number of detected failures per packet in a session. For example, if one TCP retransmission has occurred within five TCP packets, then the failure ratio of TCP retransmission is 20%.

DYSWIS periodically publishes these values to the DHT and other peers use them to estimate the significance level of their own failures. In other words, the peers in the DYSWIS network collect failure ratio samples from multiple peers and compare them with their local failure ratio to determine whether the failures are actual problems or not. We define the *global failure ratio* as the collected ratios from other nodes.

Figure 1.2 and Figure 1.3 illustrates the filtering mechanism. We group the failures into

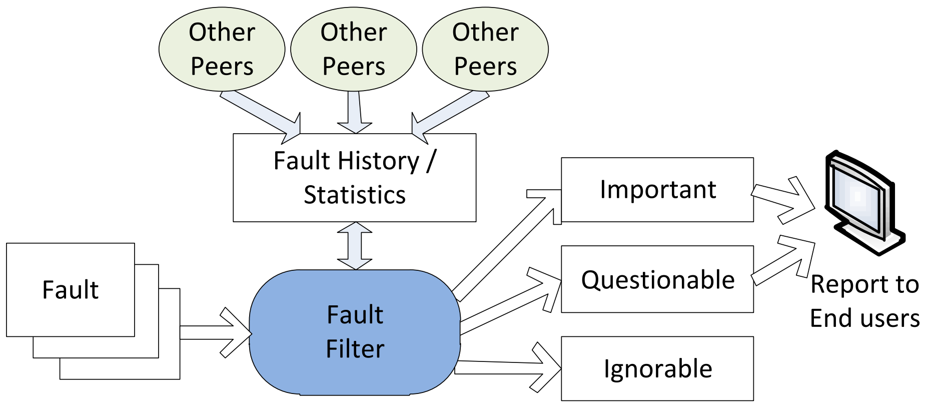


Figure 1.2: Fault filtering mechanism

three levels: *important*, *questionable*, and *ignorable*. When a failure is detected, DYSWIS sends a query to the DHT to obtain the samples of global failure ratio. This step can be also optimized using a local cache. After that, we calculate the average and standard deviation of the failure ratio using the collected samples. If the local ratio is higher than the average of the global failure ratio samples, then we consider this failure as *important* or *questionable*, depending on the degree. The notable situation is when the failure ratio is similar to or less than the average of the global samples. This means that many other peers have observed the same types of failures as frequently as the local machine has. In this case, it is possible that either the failure is not significant or that other peers have been suffering from the same problem. We can distinguish these situations by observing the timestamps of the failures reported by other nodes. If the failures have been observed frequently by others over time (e.g., if every node constantly observes failures on a particular application that uses the long polling technique), then we consider the problem on the application as *ignorable*. On the contrary, if the failures were all observed very recently, then we consider this failure as *questionable* because it is reasonable to infer that

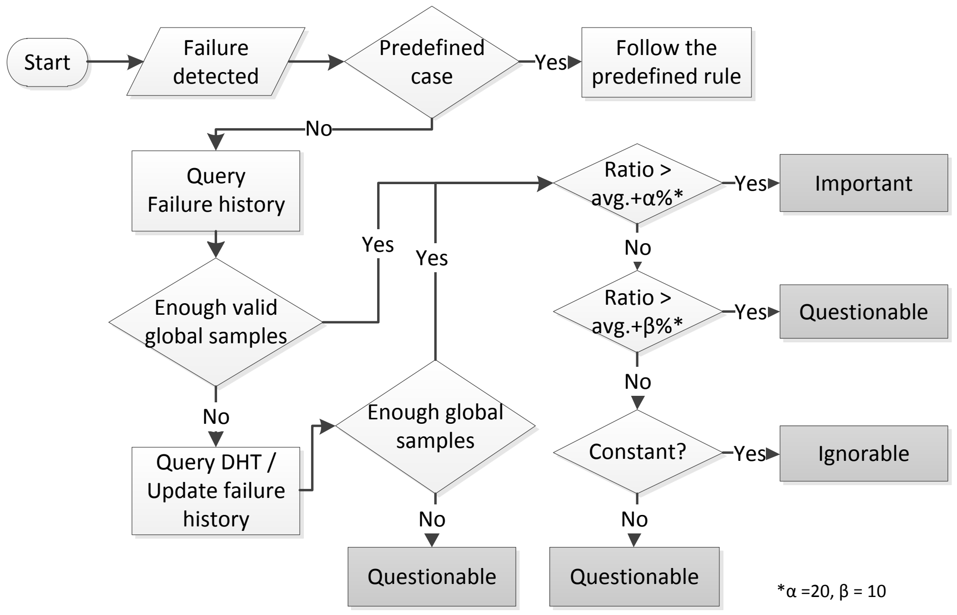
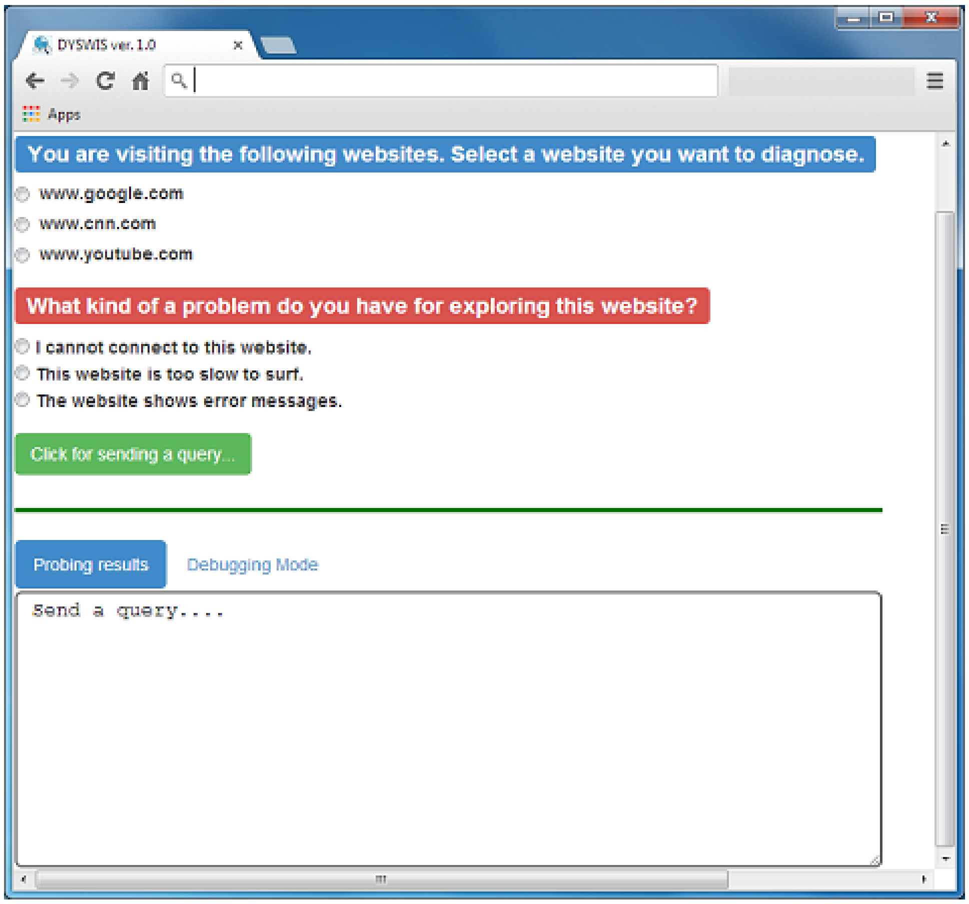


Figure 1.3: Flow chart of fault filtering

the problem has actually occurred and it can be significant.

If no global failure ratio of a particular failure exists, it implies that nobody has reported this failure before. It is possible that the application (or website) that caused the failure is not popular enough for anyone to have used it. We do not have sufficient clues to judge this case; therefore, we mark this failure as important and report it to the user. This case shows that a lack of event history is one of the limitations of passive probing approaches. This is why we use the passive probing only for detecting failures. Instead, we use active probing for the diagnostic process, which investigates a problem dynamically, as described in Section 1.4.



You are visiting the following websites. Select a website you want to diagnose.

- www.google.com
- www.cnn.com
- www.youtube.com

What kind of a problem do you have for exploring this website?

- I cannot connect to this website.
- This website is too slow to surf.
- The website shows error messages.

Click for sending a query...

```
Send a query....
```

Figure 1.4: DYSWIS plugin for Google Chrome web browser

Application plugins

The second method to detect network failures uses failure reports from applications. Since applications can observe their failures directly, if they report descriptions of failures to DYSWIS, we do not need to parse captured packets to obtain problem information. For example, if a web browser fails to connect to a DNS server or a particular web server, it reports the problematic server address and failure symptoms to DYSWIS and request a problem diagnosis. Then, the browser can receive back the diagnostic result from DYSWIS and show it to the user. If an application supports plugin development, this approach can be implemented as plugins without modifying the application itself. To prove the feasibility of this concept, we implemented a Google Chrome plugin that interacts with DYSWIS to report network failures that occur while surfing the Internet.

1.4 Diagnostics

We have described how to detect and filter network failures in the previous sections. The next step is to diagnose the detected network faults. In this phase, we actively diagnose faults in real time to avoid relying on stale information. The history of faults obtained from other nodes is helpful for filtering the faults, but it is often useless in identifying the root cause. For example, a result of probing that was performed an hour ago has no significance if a failure occurred five minutes ago. In addition, if nobody has tried to connect to a problematic server during that period, it is difficult to collect proper data to diagnose the fault. In the following sections, we elaborate the probing process and introduce our crowdsourcing-based rule and probing system.

Probing modules

Probing modules in the DYSWIS system are small programs that investigate various networking conditions. Each DYSWIS node has a set of probing modules, which can be updated via the module repository.

A probing request contains a name of a probing module to be invoked and fault information to be used as parameters. The response can be either a return value generated by the probing module or 'no response,' which means that the node does not answer. Sometimes, 'no response' also provides an important clue for diagnosing the fault. For example, if a node is able to contact some *near nodes* while failing to contact every *far node*, we can infer that there is a network connection issue from the local subnet to the outside network.

Crowdsourced rules

The diagnostic rules specify which probing modules need to be invoked in which order and where (local or remote). Their roles also include analyzing the feedback from other nodes and providing final diagnostic results to users. A decision tree is a straightforward way to formulate diagnostic rules. Such a tree indicates which probing module should be invoked, and its result decides the next step of probing. This is repeated until a leaf of a tree is reached, which is either a conclusion or the execution of another rule. We use our own Python-like syntax to represent the decision trees.

However, although decision trees show the diagnostic flow clearly, they do not fit a crowdsourcing approach. For example, our prior work [7] diagnoses VoIP failures using decision-tree-based rules that are designed carefully by VoIP experts. Ironically, however, these complete and large-size rules are not easily upgraded or expanded by others because the rules are too intricate to be completely understood. It is very common that a decision tree does not work as originally intended when a single part of the decision tree is modified. Furthermore, more importantly, a decision tree-based-rule can mislead if one of the probes in the middle of the decision tree returns incorrect information. In addition, it often takes a long time to complete the entire decision process since a next step will be chosen only after the current probe is completed and the result is returned.

If a collaborative node does not answer quickly due to the probing process itself or to network latency, the steps are entirely suspended. For these reasons, we suggest a rule system that is tailored to crowdsourcing of rules and parallel remote probes.

In DYSWIS framework, there are two groups who participate to build new diagnosis strategy: Probing module programmers and network experts (e.g., network administrators, application vendors). Programmers create new probing modules for new protocols that they want to diagnose, or they can also modify basic probing modules which we provide. Network experts write rules to determine the sequence of executing probing modules. When they build new diagnosis strategy, they simply list up necessary probing modules and construct new rules with them.

Voting-based rules

Searching for "network problems" on Google returns millions of web pages. Many of these are linked to Q&A boards where people discuss their symptoms and others suggest possible causes. However, it is very inefficient to visit every website and read every answer to determine a correct solution for a specific situation. The DYSWIS rule repository is intended to provide a unified platform for collecting such knowledge in a single place. Questions and answers on the Internet are equivalent to the diagnostic rules in DYSWIS. To support crowdsourcing efficiently, we design the rules to be simple and independent. Each rule contains the name of a probing module, a type of node, a probe result, *likely causes*, and *unlikely causes*. *Likely causes* are the causes that the author of the rule believes to be the probable causes when the particular type of node runs the probing module and returns the specified result. On the contrary, *unlikely causes* are the causes that are believed to be irrelevant to the returned result.

When a user creates or updates a rule on the DYSWIS rule website, other experts can judge the new rule and vote; plus one if they think it is true and useful (up-vote), and minus one if it is incorrect (down-vote). The effectiveness of this type of voting has been proven through many crowdsourced social websites such as *Reddit* and *Stackoverflow*. Similar to these websites, the useful rules acquire greater points and more attention. The total voting points for an incorrect or unhelpful rule will be low or even negative. Ignoring the rules that have negative voting scores, DYSWIS can filter out inappropriate rules.

Parallel remote probing

To diagnose faults, DYSWIS first selects an appropriate set of rules based on the detected symptoms of failures and automatically excludes the rules that have negative or low voting points. Then, it sends probe requests to particular types of remote users according to the rules. Remote users respond with their probing results asynchronously, and whenever a result arrives, the possibility scores of potential causes are updated.

When a probe result arrives, the diagnosis module in DYSWIS finds a rule matched to the received result. It then increases the possibility score of each cause in the *likely causes* list and decreases the score of the causes in the *unlikely causes* list. For example, in our example described in Table 1.3, if a sister node is asked to run the `TCPConnection` module, it will verify whether a TCP connection to the remote server is successful. If it succeeds, it will respond ‘Yes’, and we increase the *possibility score* of problem C1 in Table 1.3a and

Table 1.3: An example of DYSWIS's diagnostic rules

Problem ID	Description
C1	Misconfiguration on the user's computer
C2	A problem on the link to a router
C3	Misbehavior of the local router
C4	ISP outage
C5	Link between the ISP and the Internet
C6	Remote service provider network outage
C7	Remote server down
C8	The service provider blocks your ISP
C9	The server blocks your ISP
C10	The service provider blocks your IP address
C11	The server blocks your IP address

(a) Possible causes of connectivity errors

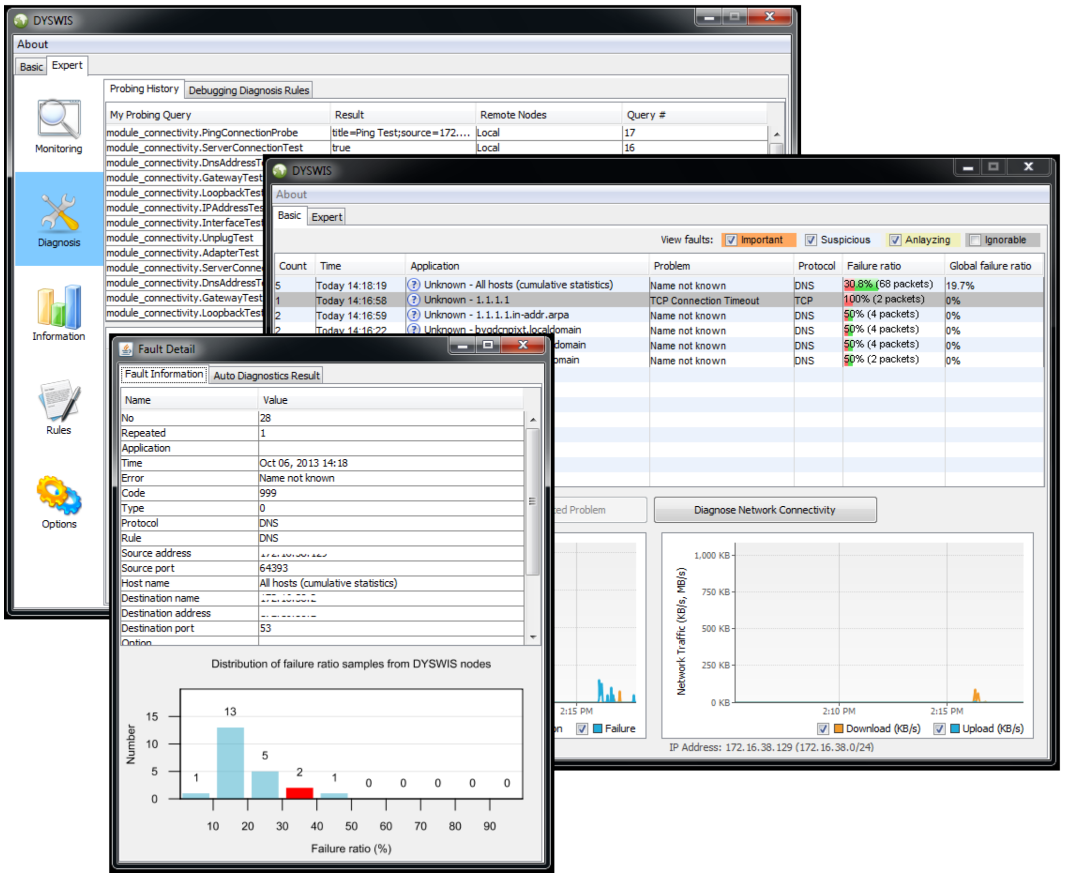
Rule ID	Requesting probing to:	Probing module	If response is:	Likely cause	Unlikely cause
R1.1	Sister node	TCP connection	Yes	C1	C2–C11
R1.2	Sister node	TCP connection	No	C3–C11	C1, C2
R1.3	Sister node	TCP connection	No response	C2	-
R1.4	Near node	TCP connection	Yes	C10, C11	C1–C9
R1.5	Near node	TCP connection	No	C5, C7–C9	C1–C3
R1.6	Near node	TCP connection	No response	C2–C4	-
R1.7	Internet node	TCP connection	Yes	C8–C11	C1–C7
R1.8	Internet node	TCP connection	No	C6, C7	C1–C5
R1.9	Internet node	TCP connection	No response	C1–C5	-
R1.10	Far node	TCP connection	Yes	C11	C1–C8, C10
R1.11	Far node	TCP connection	No	C7	C1–C6, C8–C11

(b) Examples of probing and diagnostic rules decrease all the other *possibility scores* according to rule R1.1, as shown in Table 1.3b. The results from other collaborative nodes also update the scores, and finally, the cause with the highest score is considered the most probable root cause. After informing the users of the diagnostic results, we can also collect useful feedback information by asking them whether the diagnostic result was correct. The statistics obtained from this survey can be used to improve the rules and estimate the occurrence frequencies of the actual causes. In the case where our diagnostic results fail to pinpoint a specific cause, this occurrence frequency will be helpful for users to know which cause is the most common one.

Our architecture makes crowdsourcing approach feasible in developing diagnostic rules — the independence of rules enables multiple participants to create their rules easily without disturbing other rules. The voting feature enables DYSWIS to exclude useless or incorrect rules, and distinguish more commonly occurring causes. In addition, the separation of rules makes parallel remote probing possible. Since the diagnostic process is not affected by the order of received probe results, a node can distribute probe requests to multiple nodes and process returned results asynchronously, which is faster than sequential probes. Furthermore, this approach can avoid the situation that the entire diagnostic process is misdirected by a few incorrect probes from malicious nodes.

1.5 Implementation

We implemented DYSWIS as a framework that provides multiple APIs that hide the detail of underneath operations (e.g., capturing packets, searching nodes, and executing diagnosis rules).



My Probing Query	Result	Remote Nodes	Query #
module_connectivity.PingConnectionProbe	title=Ping Test;source=172....	Local	17
module_connectivity.ServerConnectionTest	true	Local	16
module_connectivity.DnsAddressT			
module_connectivity.GatewayTest			
module_connectivity.LoopbackTest			
module_connectivity.IPAddressTes			
module_connectivity.InterfaceTest			
module_connectivity.UnplugTest			
module_connectivity.AdapterTest			
module_connectivity.ServerConne			
module_connectivity.DnsAddressT			
module_connectivity.GatewayTest			
module_connectivity.LoopbackTest			

Count	Time	Application	Problem	Protocol	Failure ratio	Global failure ratio
5	Today 14:18:19	Unknown - All hosts (cumulative statistics)	Name not known	DNS	30.8% (68 packets)	19.7%
1	Today 14:16:58	Unknown - 1.1.1.1	TCP Connection Timeout	TCP	100% (2 packets)	0%
2	Today 14:16:59	Unknown - 1.1.1.1.in-addr.arpa	Name not known	DNS	50% (4 packets)	0%
2	Today 14:16:22	Unknown - bygdcnpixt.localdomain	Name not known	DNS	50% (4 packets)	0%
		domain	Name not known	DNS	50% (4 packets)	0%
		omain	Name not known	DNS	50% (2 packets)	0%

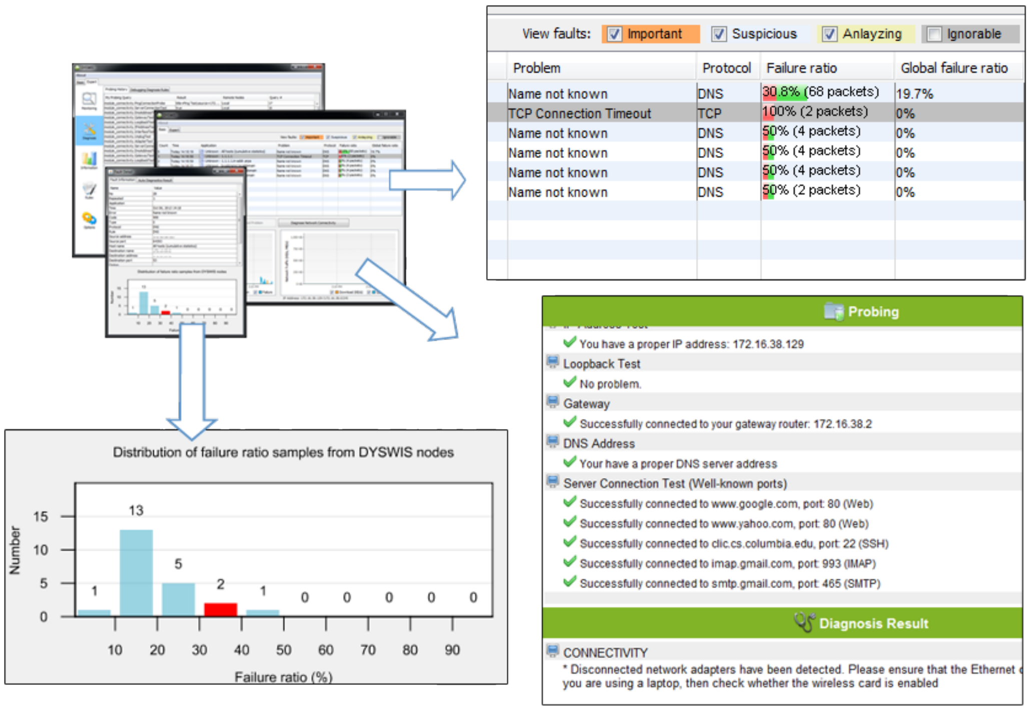
Name	Value
No	28
Repeated	1
Application	
Time	Oct 06, 2013 14:18
Error	Name not known
Code	999
Type	0
Protocol	DNS
Rule	DNS
Source address	[illegible]
Source port	64393
Host name	All hosts (cumulative statistics)
Destination name	[illegible]
Destination address	[illegible]
Destination port	53
Option	

IP Address: 172.16.38.129 (172.16.38.0/24)

Figure 1.5: DYSWIS screen dump

In addition, on top of the framework, we provide various diagnostic packages in order to prove our approach as well as provide sample diagnosis modules for the real-world network problems. Integrating those packages and DYSWIS framework, we provide complete standalone software with user-friendly GUI (on Mac OS X and Microsoft Windows). Figure 1.5 and Figure 1.6 show screen dumps of DYSWIS.

A diagnosis package is a collection of multiple diagnosis modules. Usually, it includes several modules which probe the same protocols such as HTTP, DNS, and TCP. Otherwise, some modules which probe a particular environment such as wireless or NAT can be aggregated into an independent diagnosis package. We use OSGi [40] to handle these



Problem	Protocol	Failure ratio	Global failure ratio
Name not known	DNS	30.8% (68 packets)	19.7%
TCP Connection Timeout	TCP	100% (2 packets)	0%
Name not known	DNS	50% (4 packets)	0%
Name not known	DNS	50% (4 packets)	0%
Name not known	DNS	50% (4 packets)	0%
Name not known	DNS	50% (2 packets)	0%

Probing

✓ You have a proper IP address: 172.16.38.129

Loopback Test

✓ No problem.

Gateway

✓ Successfully connected to your gateway router: 172.16.38.2

DNS Address

✓ Your have a proper DNS server address

Server Connection Test (Well-known ports)

✓ Successfully connected to www.google.com, port: 80 (Web)

✓ Successfully connected to www.yahoo.com, port: 80 (Web)

✓ Successfully connected to clic.cs.columbia.edu, port: 22 (SSH)

✓ Successfully connected to imap.gmail.com, port: 993 (IMAP)

✓ Successfully connected to smtp.gmail.com, port: 465 (SMTP)

Diagnosis Result

CONNECTIVITY

* Disconnected network adapters have been detected. Please ensure that the Ethernet
you are using a laptop, then check whether the wireless card is enabled

Figure 1.6: DYSWIS screen dump

diagnosis packages. OSGi is a java-based framework which protects each Java class from another class's accessing its variables and methods. Using OSGi, DYSWIS protects each diagnosis packages from other packages as we expect programmers would participate in building different diagnosis packages. We also leverage this technology to update diagnosis packages dynamically and automatically.

The rule system enables users add or modify existing rules without re-compiling the source code. Also, rule developers can easily create new rules without analyzing the source code. We expect this feature encourages not only programmers but also administrators without knowledge of programming to participate in writing rules.

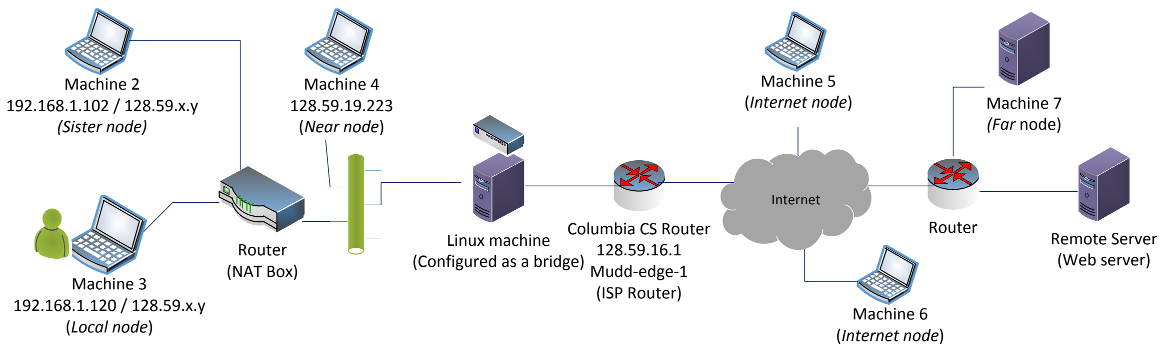


Figure 1.7: A fault diagnosis testbed for injected failure scenarios

1.6 Evaluation

An experimental testbed

We set up a testbed that contained a NAT box, a bridge, remote servers, and collaborative nodes. As illustrated in Figure 1.7, we placed *near nodes* inside the campus network, *Internet nodes* in various external networks, and a web server and *far nodes* on the Amazon EC2 network. We simulated Internet service provider (ISP) network failures by injecting network delays or dropping packets on the bridge between the NAT box and the campus network.

Common network failures

We compared the diagnostic accuracy of DYSWIS with four diagnostic tools, two tools provided by operating systems (Windows 7 and Mac OS X) and two commercial tools (Network Magic Pro 5.5 from Cisco Systems [38] and HomeNet Manager 3.0.8 from SingleClick systems [28]). We ran each tool in the testbed with injected faults and evaluated the diagnostic result. The failure scenarios were adopted from other studies [3, 23],

Table 1.4: The diagnosis results of each problem diagnostic tool for injected fault scenarios.

No.	Injected faults	Windows 7 diagnostic tool	Mac OS X diagnostic tool	Network Magic Pro	HomeNet Manager	DYSWIS
1	Ethernet cable unplugged	O	O	O	O	O
2	Network adapter disabled	O	O	O	O	O
3	IP address conflicts	O	O	X	X	△
4	Incorrect gateway address	△ (DHCP is not enabled)	△ (reboot the router)	X	X	△
5	DNS address misconfigured	O	X	X	X	O
6	Server down (Web or SSH server)	△ (No connection)	X	X	X	O
7	A NAT blocks a server	△ (No connection)	X	X	X	O
8	An ISP blocks a server	△ (No connection)	X	X	X	O
9	Port blocking by NAT (e.g., SSH and BitTorrent)	X	X	X	X	O
10	Port blocking by ISP	X	X	X	X	O
11	A web server is too slow	X	X	△	△	△

which investigated common network failures obtained from surveys on end-user environments. We merged them and inserted several additional scenarios to create our test list (Table 1.4). In this table, O implies that the diagnostic result is correct, $\triangle$ indicates that the result is helpful but imprecise, and $\times$ denotes that the tool has no capability to diagnose the fault or that it outputs an incorrect answer. The first five failures listed in the table were caused by misconfigurations, and the last six were due to a service outage

Table 1.5: The diagnostic results of DYSWIS

No.	Injected faults	The results of DYSWIS
1	Ethernet cable unplugged	O
2	Network adapter disabled	O
3	IP address conflicts	△ (Invalid IP address)
4	Incorrect gateway address	△ (Your local gateway router is down or refusing your request)
5	DNS address misconfigured	O (Configure a proper DNS server. Others do not have this problem.)
6	Server down (Web or SSH server)	O (The server is not working.)
7	A NAT blocks a server	O (Your router blocks the server.)
8	An ISP blocks a server	O (Your ISP blocks the server.)
9	Port blocking by NAT (e.g., SSH and BitTorrent)	O (The port X is blocked by your router.)
10	Port blocking by ISP	O (The port X is blocked by your ISP.)
11	A web server is too slow	△ (Pinpoint possible congestion points with additional steps.)

or port blocking. Although the commercial tools provided many powerful functions such as network monitoring and convenient user interface for network settings, they exhibited limited capabilities in diagnosing our fault scenarios. The tools embedded in each OS also failed to diagnose most scenarios as described in Table 1.4. The tools performed better in the scenarios of misconfiguration faults; however, they failed to correctly diagnose the outage and port blocking scenarios. This is not surprising since there is no good way to investigate the network infrastructure (NAT, ISP, or remote server) for tools running on end-user machines.

In contrast, DYSWIS successfully identified the root causes in seven out of eleven scenarios taking advantage of the assistance of other nodes located in different networks.

For example, the blocking of a website by the ISP could be diagnosed by comparing probe results from multiple *near* and *Internet nodes*. If every *near node* failed to connect to a particular server while the *Internet nodes* could connect to the server, we inferred that the traffic between the server and the ISP was constrained.

Similarly, we diagnosed the port blocking problems, which are common in home networks. If a home router blocks a particular inbound or outbound port, applications that use the port will not function properly. To diagnose these problems, NetPrints [3] used current configurations on home routers and nodes. Although this attempt can pinpoint misconfigured settings, it is difficult to identify the root cause when packets are blocked by an ISP or remote servers, which usually do not expose their policies. Figure 1.8 describes the approach of DYSWIS for this issue.

By comparing probe results from *sister*, *near*, and *Internet nodes*, we determined whether a particular outbound port was blocked by a local router or an ISP. Further, by asking other nodes to send packets to the local machine via a specific port and comparing the results from different types of nodes, we could determine whether the user needed to reconfigure the router or consult the ISP about the port issue.

Another advantage of this collaboration is that we can obtain alternative solutions. For example, if a local DNS does not function properly, we can temporally configure other DNS servers recommended by external nodes until the local server is recovered. If the outside DNS servers refuse queries from the node because of a security concern, we can also request the collaborating nodes to query the domain to their DNS servers and resolve the IP address on behalf of the *local node*. However, there is a security issue that malicious nodes might provide compromised information. To mitigate this risk, DYSWIS

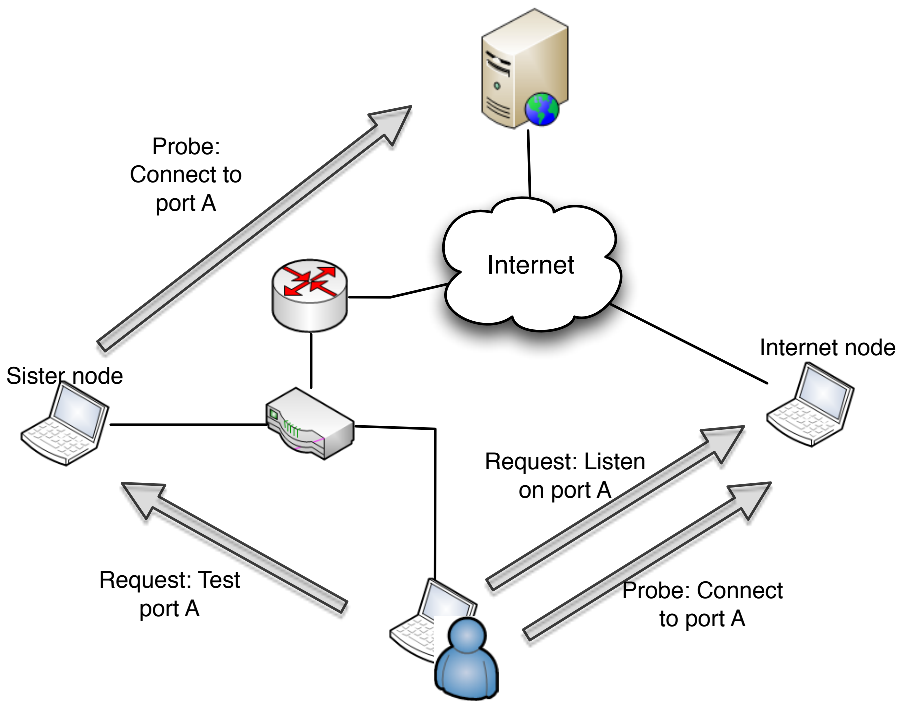


Figure 1.8: Diagnosis example: Port blocking test

asks multiple nodes to collect multiple alternative solutions and provide the most frequently answered solutions to the users because it is very rare for random collaborative nodes to provide the same compromised information.

Detecting performance bottlenecks

In this section, we describe the detailed diagnostic results of problem #11 (“A web server is slow”) listed in Table 1.4. This kind of performance problem is challenging to diagnose since there are a number of possible points where bottlenecks may be located. We assumed that there were seven candidate congestion points on the path from the client to the remote server. Then, our project members wrote multiple rules independently as described in Section 1.4. For example, if round-trip time (RTT) between the *local node* to the

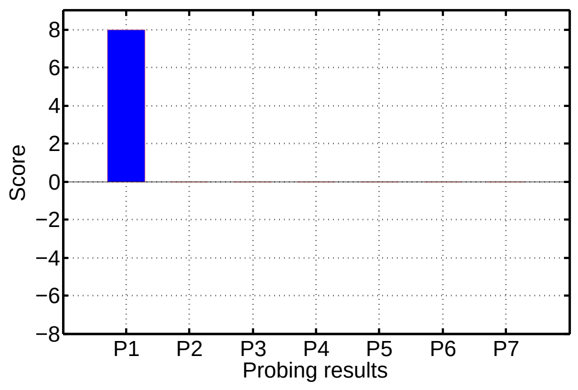
ID	Fault scenarios
P1	Network adapter disabled
P2	Problems on the link between the user and the router
P3	Problems on the router
P4	Problems on the ISP
P5	Problems on the link between the ISP and the Internet
P6	Problems on the service provider network
P7	Problems on the remote web server

Table 1.6: Possible bottlenecks of the network

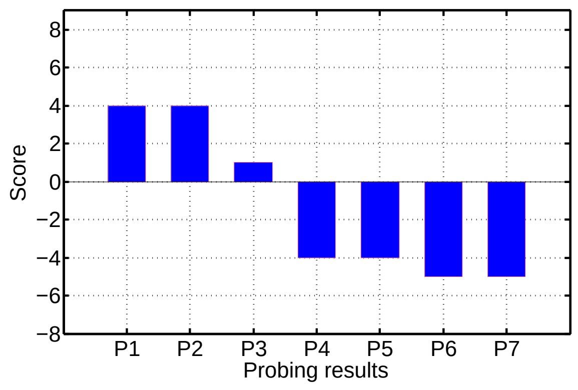
web server is very high while the RTT between a *sister node* and the server is considerably lower, we increase the score of P1 in Table 1.6 and decrease the other scores.

To evaluate the accuracy, we artificially generated bottlenecks by configuring the packet delay on each device or link. Table 1.6 describes the possible bottleneck points.

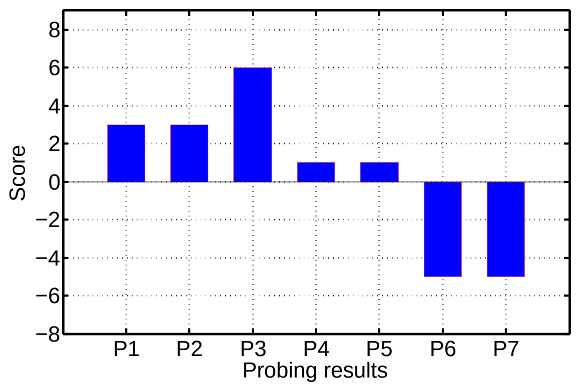
Figure 1.10 shows bar graphs, which are the results of DYSWIS obtained from each experiment with injected bottlenecks. The bars indicate the final scores obtained after running the rules. The cause that gained the highest score is the most probable cause. In six out of seven scenarios, the actual point where the delay was injected gained the highest score, which implies that DYSWIS can pinpoint the bottleneck point correctly. However, in three cases (P2, P6, and P7), there exist two tied entries that gained the same scores. The addition of more rules is helpful to narrow down the root causes of these cases. For example, Figure 6(e) shows that P6 and P7 gained the highest score, which implies that DYSWIS could not determine whether the high latency of the web server was caused by the provider network (e.g., Amazon EC2) or by the remote server. In this case, we can request a far node, located in the same provider network, to measure RTT to the target server. If the RTT is high, we can infer that the service provider network may have a



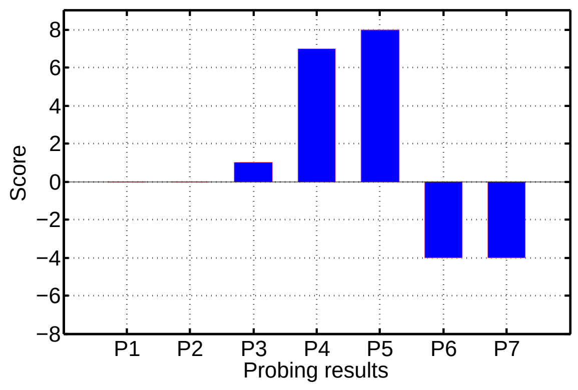
(a) P1



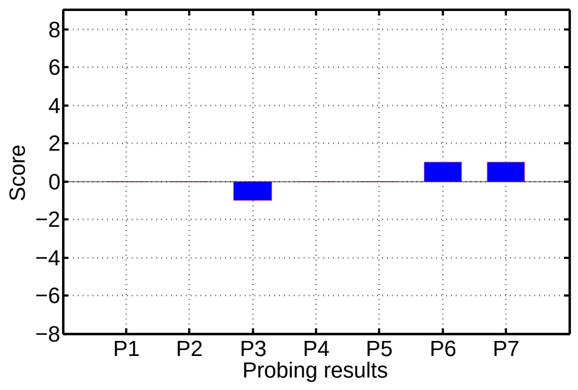
(b) P2



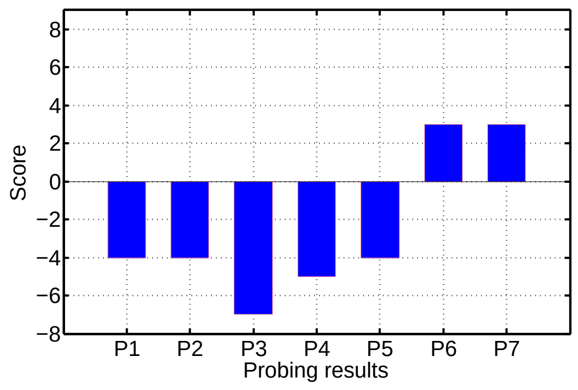
(c) P3



(d) P4 and P5



(e) P6



(f) P7

Figure 1.10: Probing results of each scenario

problem. Therefore, we can add the following rule – if the RTT from a far node to the target server is high, increase the score of P6. By adding this rule, we ensure that P6 will gain a higher score and DYSWIS can finally narrow down the actual cause appropriately. This process can be repeated and applied to other scenarios by crowdsourcing. We believe that the larger number of rules that are aggregated, the higher the system accuracy will be.

1.7 Related work

Network fault detection and diagnosis have been an area of interest for a number of years. A number of studies discuss home network environments. For example, HomeNet Profiler [20] measured several characteristics of home networks such as the quality of home Wi-Fi networks and the deployment of auto-configuration protocols. Cui et al. [19] identified the root cause of high web page loading time by capturing packets and correlating various metrics such as DNS query time, TCP RTT, and data transfer period. Also, several studies use the collaboration of different machines to diagnose problems. WebProfiler [1] aggregated observations of multiple machines to discover network elements involved in failures, Netprints [3] diagnosed and resolved problems in home router configurations using shared knowledge of labeled (good or bad) configurations collected from multiple machines, and WiFiProfiler [16] relies on cooperation among wireless clients to diagnose and resolve problems. Aggarwal et al. [2] developed a network diagnostic tool that uses a signature-based learning technique. Also, Dong et al. [23] wrote an argumentation-based algorithm for home network diagnosis. In their system, *arguments* are possible conclusions of the diagnosis, and *assumptions* are used to eliminate wrong *arguments* in the reasoning process of the argument-based algorithm.

The main difference of DYSWIS's approach from the studies above is that DYSWIS not only uses the failure history of others, but also leverages end-users' active probing in real-time while others rely on passive observations from the users. By combining the passive and active probings, we filter out false positive failures and diagnose the filtered problems more accurately. Furthermore, in our best knowledge, DYSWIS is the first platform that suggests a practical method that supports a crowdsourced-rule repository for network problem diagnosis.

There are several proposals that use user-based diagnosis. For example, Glasnost [22] discovers service differentiation by ISP based on traffic analysis between an end point and another controlled end point in the network. Choffnes et al. [17] proposed a methodology to detect network events based on users' experiences. They aimed to detect events impacting user-perceived application performance. Zhang et al. [57] proposed end user based collaborative active probing to diagnose significant routing events. Tulip [35] probed routers to localize anomalies such as packet reordering and loss. Dasu [46] developed a platform that enables network researchers to experiment network-related issues using a huge number of end users. These studies focus more on investigating the network core elements while DYSWIS focuses on diagnosing end-user problems.

AutoMON [12] uses a P2P-based solution to test network performance and reliability. The distributed testing and monitoring nodes are coordinated by using a DHT, which helps in locating resources or agents. This study focuses on testing and monitoring while DYSWIS is designed to diagnose the root cause of failures.

In addition, DYSWIS shares the idea of distributed measurements with the “framework for large-scale measurements” [24] which was recently proposed by the Large-Scale Measurement of Broadband Performance (LMAP) working group. While DYSWIS focuses on assisting end users, this framework proposes a measurement system that can be used by ISPs and regulators as well. However, we believe that DYSWIS and the LMAP framework can support each other and create a synergy when used together. Since the LMAP framework proposes the detailed mechanisms of collecting and reporting data from distributed measurement peers, DYSWIS can take advantages of its existing model to obtain useful data for diagnosing end-user problems. Also, DYSWIS can be a part of the framework participating as measurement peers to provide end-user data to contribute the LMAP framework.

1.8 Discussion

Because our approach employs the collaboration among peers, it is susceptible to security issues found in P2P networks [50], which are vulnerable to malicious users who try to attack others by providing malformed data (e.g., file poisoning) or by using manipulated identities (e.g., Sybil attack). Furthermore, in P2P systems, a user’s IP address is exposed to others. This makes it easy for malicious users to target a user through denial of service attack, in addition to the privacy issues that such exposure entails. In this section, we discuss the potential security problems in our approach and suggest several solutions.

Security issues

Because DYSWIS's network protocol and APIs are open to public, it is allowed to create another application that participates in the DYSWIS network. However, a disadvantage exists in that a user could contact DYSWIS nodes in order to initiate malicious probes against a normal service. There are two attack scenarios.

The first scenario is a DoS attack: A malicious node can simply send a large number of probe requests to a target node, which will then become busy handling these probes. This attack can be prevented by counting the number of requests from other nodes and simply restricts the maximum number of probing requests per node within a particular period.

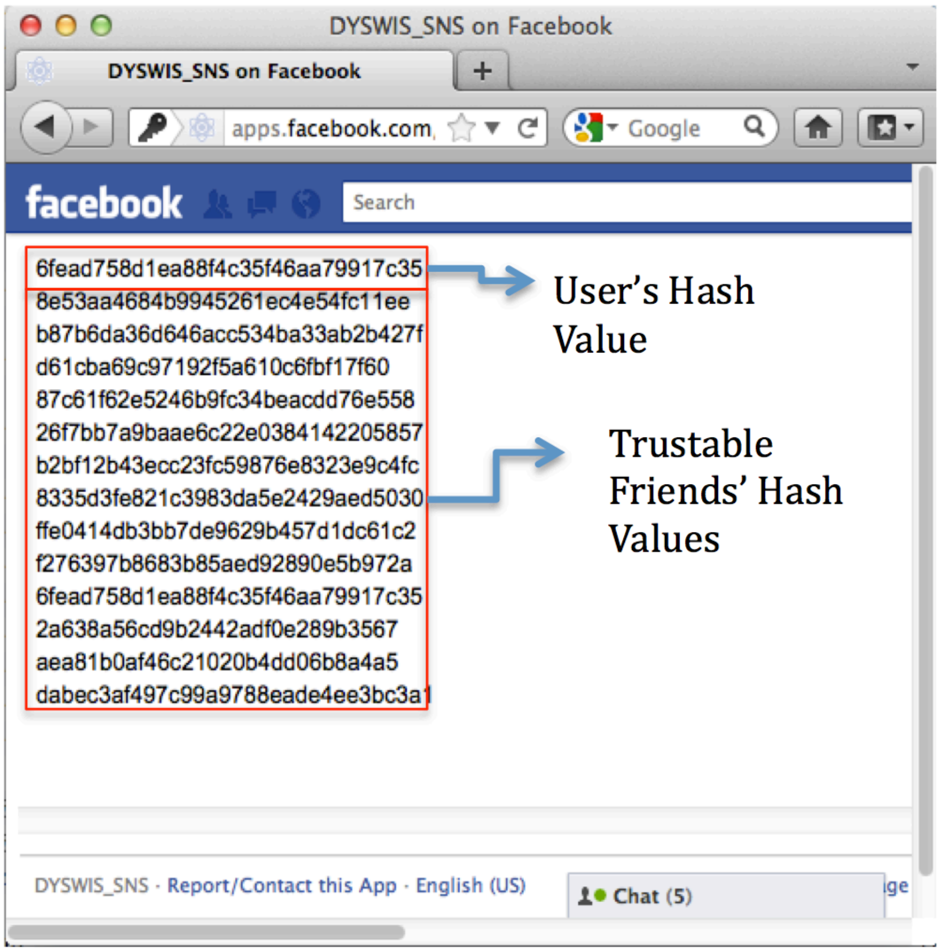
The second scenario is a Distributed Denial of Service (DDoS) attack. When a malicious user uses multiple DYSWIS nodes to launch a DDoS attack by requesting them to probe the same node or web server. For example, the malicious user first collects as many peers as possible and then requests them to execute a "TCP connection check" to a target IP address. Because the peers are not aware that these requests are being sent to multiple users by the malicious user, they will execute the requests as usual – open a TCP connection to the target – in a manner similar to how compromised nodes in a typical botnet behave.

In order to prevent this attack, every node that is requested to perform a probe looks up the probe history to check whether the host or service has been probed recently and a usable result exists. This will prevent redundant probes from being performed. However, for this to be effective, every probe transaction performed by each node should be stored.

This is not recommended because the database (DHT, in our system) can be flooded with probing transactions. DYSWIS reduces the history size by randomly storing only a small portion (e.g., 10%) of the entire transactions in the DHT because an estimated number of probes is enough for our mechanism. For example, if ten recent probes are detected by querying the DHT, it implies that around 100 probes have been performed recently. If the number exceeds a certain limit, DYSWIS considers it to be a part of an attack and refuses to perform the probe. In this case, the malicious user cannot harm the target, but a normal user can still obtain probe results from other nodes.

Social Network Peers

Another challenging problem exists, namely, that of whether we can trust the probe results from other nodes. This is because a user might be malicious and could therefore be providing wrong results. In this section, we suggest a mechanism to distinguish genuine users from potentially malicious nodes by recommending *social peers* registered on the friend list in a social network service (e.g., Facebook). This approach is based on the actual human social interactions. When someone needs the answer to an important question, they first ask their friends before asking, say, some random, anonymous person on the street, because they trust their friends more. Similarly, we assume that if we choose collaborative peers among close friends in the social network service, the probability of obtaining trustable peers is much higher than the case of simply obtaining random nodes in a DHT. Thus, if DYSWIS discovers peers who are on the friend list of the user, it recommends those social peers to the user. The user can finally determine whether to choose



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6fead758d1ea88f4c35f46aa79917c35
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aea81b0af46c21020b4dd06b8a4a5
dabec3af497c99a9788eade4ee3bc3a1
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Figure 1.11: Searching Social Network Peers using Facebook API

random or social peers. Because DYSWIS requires only a couple of nodes for fault diagnostics, we do not need to collect hundreds of peers as does a typical P2P file sharing system. In our current diagnosis rules, six nodes are even sufficient to run a diagnosis; this number is reasonably small and this many nodes could easily be retrieved from a user's friend list in a social network. One of the challenges of this system is determining who a user's close friends are. DYSWIS calculates the proximity scores of each friend in Facebook by using the number of wall posts and messages that they have exchanged. This algorithm is heuristic, yet it adequately distinguishes actual friends from fake ones.

However, we also need to consider the privacy issue. It is possible that the IP address of a particular friend could be exposed in this approach. Our goal is to provide the contact points (IP addresses) of social peers without revealing the matches that indicate who has a specific IP address.

We have implemented this system (Figure 1.11) using the Facebook API as a proof of concept and integrated it into the DYSWIS framework. It first generates an identification key for each node. The identification key is a unique MD5 hash string generated from a Facebook user ID and a secret key of the application. Because the secret key is not exposed to the public, it is impossible to reproduce the identification key using the names of friends. Thus, only the user and the Facebook application know the secret key. After receiving the identification key from the Facebook application, DYSWIS registers the (key, IP address) pair in the DHT. When another user requests a social peer list, the Facebook application calculates the proximity of the requested user and returns the closest friends from the Facebook friend list of the user. For this purpose, it is necessary for the user to pass the authentication process beforehand. Note that the application does not return the names of friends or user IDs. Instead, it returns the hash strings that were generated with a user ID along with a secret key. In the last step, DYSWIS queries the DHT to check whether the received keys are registered. In other words, it checks whether the friends have installed DYSWIS and are currently running it. Consequently, through these steps, DYSWIS can obtain the IP addresses of close friends who are running DYSWIS without revealing the actual owner of the IP addresses. It is difficult to convert the IP address to the corresponding user because DYSWIS users only obtain the hashed keys of the user

IDs.

1.9 Conclusion

DYSWIS diagnoses complex network problems for end users using end-user collaboration. We provide a new framework for a collaborative approach and diagnosis strategies for various fault scenarios. We provide a detailed design to discover and communicate with collaborating nodes. Also, we provide a crowdsourcing framework for administrators and developers to participate in expanding the diagnostic system.

We have implemented DYSWIS framework, diagnostic rules, and probing modules that diagnose several common network faults. We set up these scenarios with real network devices and diagnosed them using DYSWIS. While local probing with traditional diagnostic tools fail to point out the cause of these fault scenarios, our evaluation shows that DYSWIS can effectively narrow down the problematic regions and pinpoint the root causes.

Chapter 2

WiSlow: diagnosing Wi-Fi performance degradation

2.1 Introduction

Today, it is common for households to build home networks with a private wireless router (access point) that supports multiple wireless devices. However, the increasing usage of wireless networks using shared unlicensed spectrum inevitably results in more contention and interference, which causes unsatisfactory Wi-Fi performance. Furthermore, non-Wi-Fi devices such as microwave ovens, cordless phones, and baby monitors severely interfere with many Wi-Fi networks because these devices operate on the same 2.4 GHz spectrum as 802.11b/g [26].

Although these problem sources can be easily removed in many cases (e.g., by relocating the interfering device, choosing a different channel, or moving to the 5 GHz band), it is difficult for technically non-savvy users to even notice the existence of channel contention or interference caused by non-Wi-Fi devices. Instead, properly working routers or service providers are frequently misidentified as the culprit while the actual root cause remains unidentified.

Isolating the root causes of poor Wi-Fi performance is nontrivial, even for a network expert, because they show very similar symptoms at the user level, and special devices are required in order to investigate the lower layers of the protocol stack.

In this chapter, we present WiSlow, a software tool that diagnoses the root causes of poor Wi-Fi performance with user-level network probes and leverages peer collaboration to identify their physical locations. The goal of this tool is to report the problem source and its approximate location to users such as "It appears that a baby monitor located close to your router is interfering with your Wi-Fi network." We focus on building software that does not require any additional spectrum analysis hardware (unlike, e.g., WiSpy [53], AirSleuth [5], or AirMaestro [4]). In addition, WiSlow does not depend on a specific network adapter such as the Atheros chipsets, which were used to achieve similar goals in other studies [44, 45]. These features enable WiSlow to run on common end-user machines that do not have special hardware.

First, we investigate behaviors of 802.11 networks such as retries, Frame Checksum Sequence (FCS) errors, packet loss, and bit rate adaption, which can be observed on ordinary operating systems. Our experimental results show that the statistical patterns of the above variables vary depending on the problem sources. For example, with the interference that caused by non-Wi-Fi devices, we observed a greater number of retried packets, fewer FCS errors, and larger variations in the bit rates compared to channel contention. Correlating these variables, we can categorize the sources of performance problems into several distinct groups. In addition, the non-Wi-Fi devices such as baby monitors, cordless phones, and microwave ovens show different patterns when the number of UDP packets and 802.11 ACKs are plotted over time.

Based on our observations, we developed two methods to identify the root causes: packet loss analysis and 802.11 ACK pattern analysis. These methods successfully distinguish channel contention from non-Wi-Fi interference and infer the product type of the interfering device. We believe that this technology will be useful to end users since it can inform them of what needs to be done in order to improve the performance of their networks—whether to change the Wi-Fi channel or remove a device that is emitting the interference.

In non-Wi-Fi interference scenarios, another goal is to identify the physical location of the source of interference. Although it is difficult to pinpoint the exact physical location of the source without a spectrum analyzer or additional support of APs, we showed that it is possible to infer the relative location of the problem source by collaborating with other end users connected to the same wireless network. WiSlow collects probing results from peers and determines whether others observe the interference. If all the machines observe the same interference, it is highly likely that the problematic source is close to the wireless AP. However, if only one of the peers observes the interference, the source is likely to be located close to that peer. Our experimental results show clearly that this approach is feasible.

In summary, WiSlow (i) distinguishes channel contention from non-Wi-Fi interference, (ii) infers the product type of the interfering device (e.g., a microwave oven, cordless phone, or baby monitor) by analyzing network packets, and finally (iii) points out the approximate location of the source of interference by exploiting user collaboration. We evaluate WiSlow with various interference sources and show that its diagnostic accuracy is quite high. We also prove that our approach locating the interference source is feasible.

2.2 Background

Common sources that cause Wi-Fi performance degradation include:

- **Wi-Fi channel contention** reduces throughput when the channel is crowded by multiple Wi-Fi devices that compete to transmit data through wireless access point (AP). It also includes interference due to nearby APs that are using the same channel or adjacent channels.
- **Non-Wi-Fi interference** refers to interference caused by non-Wi-Fi devices that use the same spectrum as the 802.11 networks. The devices include microwave ovens, cordless phones, baby monitors, and Bluetooth devices.
- **Weak signal** means that the radio signal is not strong enough due to distance or obstacles. In this environment, packets can be lost or corrupted frequently.

Although the extent varies, all the above sources result in severe performance degradation—some of them even drop the TCP/UDP throughput to almost zero [44]. In this thesis, we focus on Wi-Fi channel contention and common non-Wi-Fi interference sources.

2.3 Challenges

In this section, we describe the reasons why analyzing wireless networks is difficult for end users.

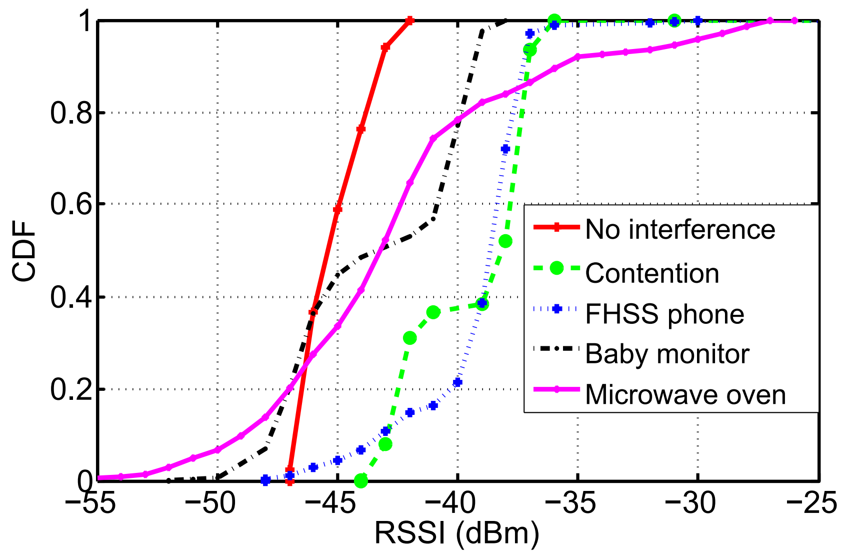
Inaccurate RSSI and SINR measurements

Received signal strength indication (RSSI) and Signal-to-interference-plus-noise ratio (SINR) are generally considered to be the key factors that indicate the quality of a wireless link. However, according to Vlavianos et al. [51], RSSI inaccurately captures the link quality and it is difficult to accurately compute SINR with commodity wireless cards. We also observed a similar result when monitoring RSSI and SINR values in our own experiments. We placed various types of interference sources close to the AP and measured the values on a general-purpose client machine[1]. In Figure 2.1a, RSSI values with a baby monitor as interference were consistently higher than those with a cordless phone, but the measurement result showed lower throughput for the baby monitor. In Figure 2.1b, the SINR values with a cordless phone were higher than even a no-interference case. Furthermore, these results varied for each experiment. Based on this observation, we conclude that RSSI and SINR values captured by a general wireless card do not represent the level of interference correctly. Therefore, we do not use these metrics for purposes other than as a hint in the case of an extremely weak signal.

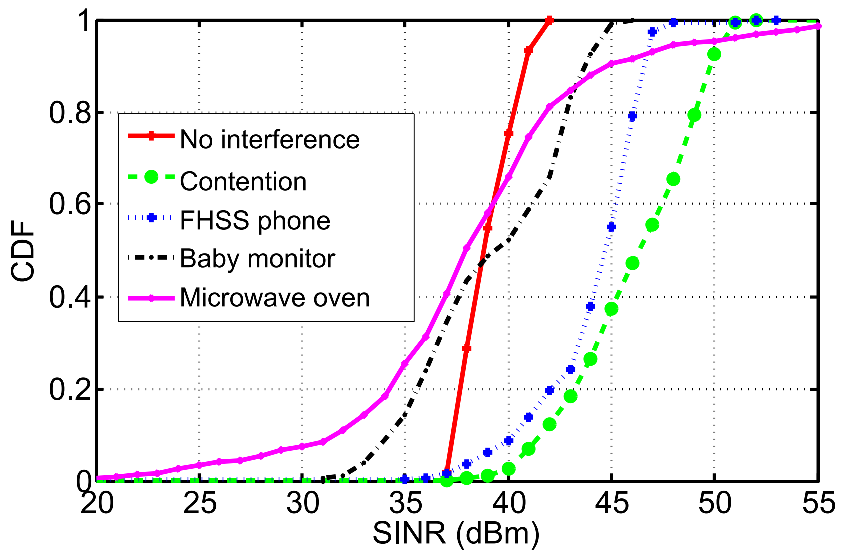
No specific network adapter or driver

We do not make any assumptions about the specific network adapters or drivers that end users may have. Some Atheros chipsets, which are widely used in other research studies, support a *spectral scan* that provides a spectrum analysis of multiple frequency ranges. Rayanchu et al. developed Airshark [44] and WiFiNet [45] leveraging this feature

[1]We used a MacBook Pro 2013 (network card: AirPort Extreme, chipset: Broadcom BCM43 series) in this measurement.



(a) RSSI measurement



(b) SINR measurement

Figure 2.1: The CDFs of RSSI and SINR values. The values are measured on a general-purpose client machine while various interference sources are placed between the machine and the access point.

to distinguish non-Wi-Fi interferers using a commodity network card without specialized hardware.

Although this approach achieved quite high accuracy in identifying the interfering devices, to the best of our knowledge, only a few chipsets (e.g., Atheros) currently provide this feature. In addition, we failed to discover references to this feature for any OS other than Linux. Since there are hundreds of products that use a different chipset or OS, it is impractical to assume that a general end user has this specific setup. Therefore, we focus instead on analyzing the quality of a link observing user-accessible packets such as UDP and 802.11 packets. Because the mechanisms of these protocols are the same across Wi-Fi devices, we believe WiSlow can help a wider range of end users.

Lack of monitoring data

Another restriction in the end-user environment is the lack of a monitoring history. If we assume that we have been monitoring the machine up to the moment when a performance problem happens, the diagnosis will be easier because we can obtain several important clues such as the average quality of the link, the time when the problem started, and whether it has happened in the recent past. However, although the overhead of network monitoring is not heavy on modern machines, it is unrealistic to expect that end users will continuously run such a tool. The more common scenario is that a user launches a troubleshooting tool like WiSlow to request a diagnostic only after he/she has noticed a severe performance problem. Therefore, we need to design the tool assuming little or no previous monitoring data. In the next section, it is explained how WiSlow estimates the problem source without running in background, which implies that no information about the quality of the underlying network is provided.

2.4 Architecture

In this section, we elaborate on the details of probing methods for identifying the root causes of network interference. First, to investigate the behavior of Wi-Fi networks in each problem scenario, we artificially inject problems while transmitting UDP packets between a client (laptop) and an AP. We capture every packet on the client machine, and then trace the transport layer (UDP), the 802.11 medium access control (MAC) layer, and some user-accessible 802.11 physical layer (PHY) information to ascertain each problematic scenario's interference levels and characteristics.

To capture 802.11 packets, WiSlow uses the *monitor mode* of wireless adapters. Monitor mode provides the Radiotap [43] header, a standard for 802.11 frame information. The headers are used to extract low layer information such as frame check sequence (FCS) errors and bit rates. Sniffing wireless packets is supported by most Linux and all Mac OS X machines without additional drivers or kernel modification. Therefore, if we can successfully characterize each performance-degrading source by probing the transmitted packets, the same probes will enable WiSlow to identify the problem sources on most platforms. However, it is not always possible to capture wireless packets on some types of OS, e.g., Microsoft Windows [52]. Instead, both Windows 7 and Windows 10 provide *Native WiFi APIs* [54] that report 802.11 packet statistics to user applications. Those APIs enable WiSlow to run on Windows because they provide all the information that WiSlow must extract from the 802.11 packets.

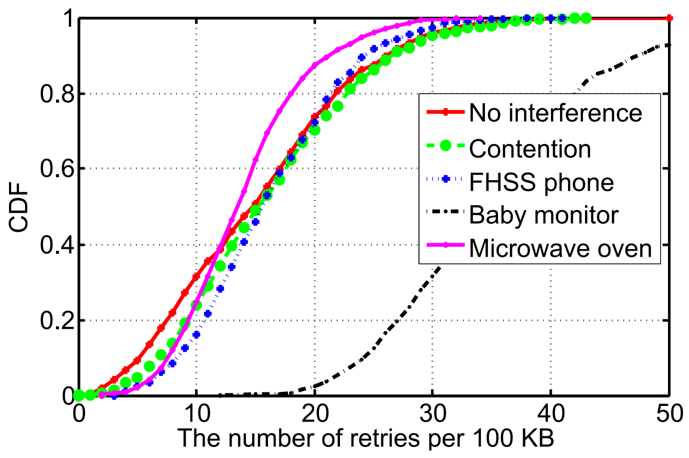
In the following sections, we explain WiSlow's two main diagnostic methods: packet loss analysis and 802.11 ACK pattern analysis.

2.5 Analysis method 1: packet loss analysis

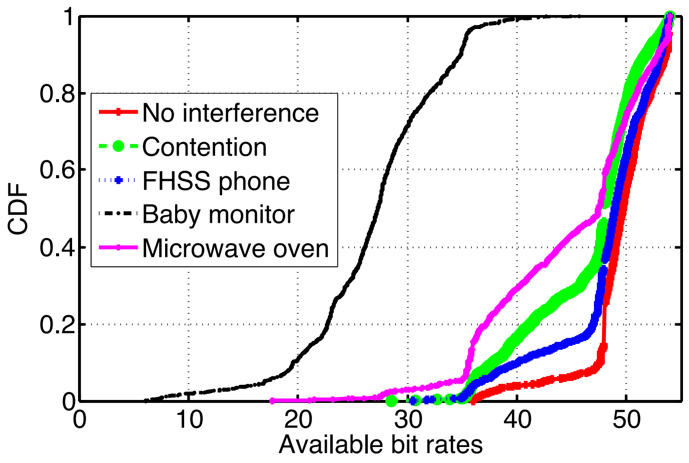
First, we found that each problem source varies in their packet loss characteristics, represented by three statistics: i) the number of 802.11 retries, ii) the available bit rates, and iii) the number of FCS errors. In each experiment, we measured these values on a client laptop while downloading UDP packets from an AP. The values were recorded for each 100 KB of UDP packets. We repeated this experiment for different scenarios including channel contention and non-Wi-Fi interference. To simulate channel contention, we set up several laptops sending bulk UDP packet streams to the AP. To generate non-Wi-Fi interference, we placed each interfering device (baby monitors, microwave ovens, and cordless phones) close to the AP (about 20 cm away) and measured the effect on the client placed at various distances from the AP. [2] Note that the client downloaded 100 MB of UDP packets for each experiment to collect a statistically meaningful amount of samples, but when actually probing on an end user's machine, WiSlow only needs to transmit 5 MBytes of UDP packets to identify the root cause, which takes a reasonable amount of time (10–40 s).

- **Retry and available bit rate**: Since an 802.11 retry and bit rate reduction are both initiated by a packet loss, their temporal changes are closely correlated; when a

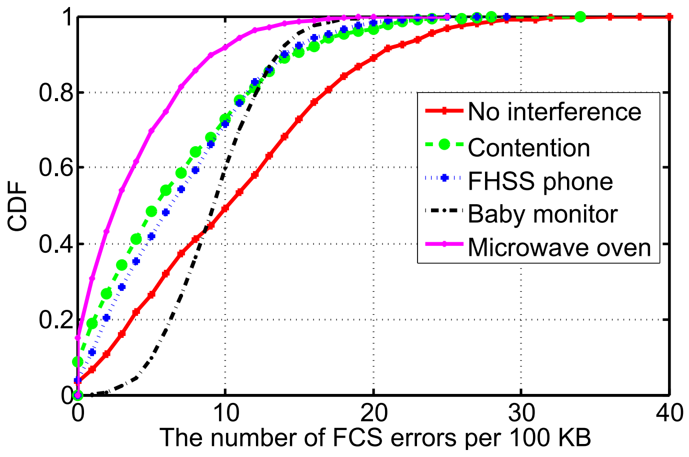
[2]In this study, we do not consider the combined interference of multiple devices.



(a) The CDF of 802.11 retries



(b) The CDF of available bit rates



(c) The CDF of FCS errors

Figure 2.2: 802.11 statistics with various interference sources

packet loss occurs, the 802.11 rate adaptation algorithm [11] decreases the bit rate. The probability of packet loss then decreases due to the reduced bit rate, which lowers the number of retries. After that, the bit rate gradually increases again owing to the reduced packet loss, which leads to a higher probability of packet loss and retries. In other words, if contention or interference exists, it causes packet losses, and then the bit rate and the number of retried packets repeatedly fluctuate during the subsequent data transmission. Because of this fluctuation, the measured statistics of retries and bit rates do not represent the characteristics of interference sources correctly. Figure 2.2a and 2.2b shows that the cumulative distribution functions (CDFs) of the values do not differ any interference sources except for the baby monitor.

- **Frame check sequence errors**: Another variable that we trace is the number of FCS errors per byte. In our experiments, we counted the number of FCS errors per 100 KB of data. Intuitively, it can be predicted that non-Wi-Fi interference introduces more FCS errors than channel contention or a no-interference environment because the packet corruptions are likely to occur more frequently when a medium is noisy. However, in our experiment, it turned out that a large number of FCS errors are not necessarily correlated with severe interference. On the contrary, we often observed that fewer FCS errors occur in a severe interference environment (e.g., interference from a baby monitor) than in a no-interference environment (Figure 2.2c). This paradox can be explained by the low bit rates in the interference case. This implies that a smaller number of bits are transmitted in the same bandwidth. Consequently, the number of FCS errors per byte alone is not sufficient to characterize interference sources.

Packet loss estimation

As we stated above, although the number of retries, bit rate, and FCS errors are affected by the current state of the wireless network, they often show very different statistics for each experiment set. We conjecture several reasons; the environment is not exactly the same in every experiment, the occurrence of packet loss is probabilistic rather than deterministic, and the individual variables fluctuate over time, affecting each other and leading to different statistics for a certain period of time. Therefore, it would be more reasonable to compare the combinations of these statistics together instead of investigating each variable individually. This is discussed in detail in the next section.

There are two cases that can cause a retry. First, a packet was not delivered, i.e., it was lost. Second, a packet was delivered but it had an FCS error. We can estimate the number of packets lost (the first case) by subtracting the number of FCS errors from the number of retries (Eq. 2.1).

$$N_{PacketLoss} = N_{Retries} - N_{FCSerrors} \tag{2.1}$$

Packet losses in this measurement is equivalent to serious corruption, i.e., the packet could not even be detected. We found that this estimated number of packet losses represents the level of interference more reliably than the individual statistics of retries, bit rates and FCS errors. In other words, the number of packet losses provides relatively consistent results in repeated experiments, while the others varied for each experiment.

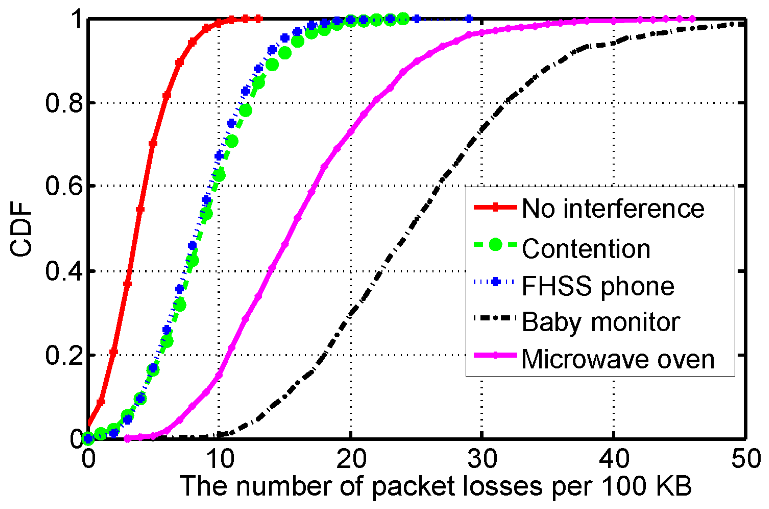
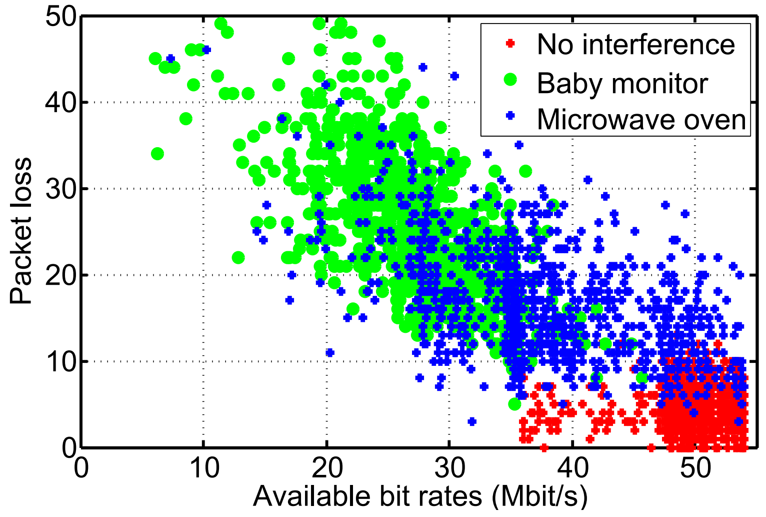


Figure 2.3: The CDFs of the number of estimated packet losses

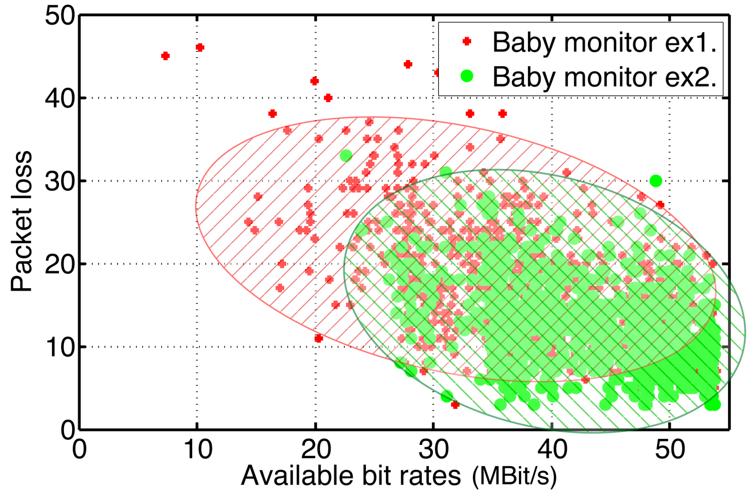
Figure 2.3 shows that the CDF of the estimated number of packet losses clearly distinguishes each device compared to the CDFs in Figure 2.2. It can be seen that a baby monitor causes the most severe amount of packet loss while cordless phones cause a relatively small amount of packet loss. Since baby monitors send video and audio data at the same time, they use more bandwidth than cordless phones that send audio only, thus causing more interference. Channel contention shows less packet loss because of the 802.11 collision-avoidance functions such as random back-off and RTS/CTS that force each client to occupy the medium in separate time slots. In this case, the degradation of throughput is caused by the shared medium rather than noise from other sources.

Correlation of variables

Finally, we explain that the correlation between bit rate and the estimated number of packet losses shows clearer differences among various problem sources. In Figure 2.4a, the majority of the samples from a clean environment are distributed in a healthy zone (higher bit rate and lower packet loss) while the samples of baby monitors and microwave ovens are widely dispersed. WiSlow uses the correlation of these two variables to distinguish the level of interference.



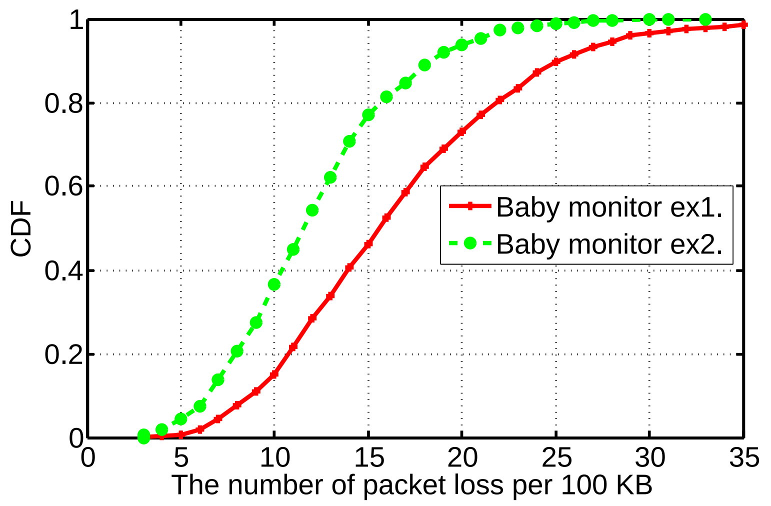
(a) Different interference sources, a baby monitor and a microwave oven



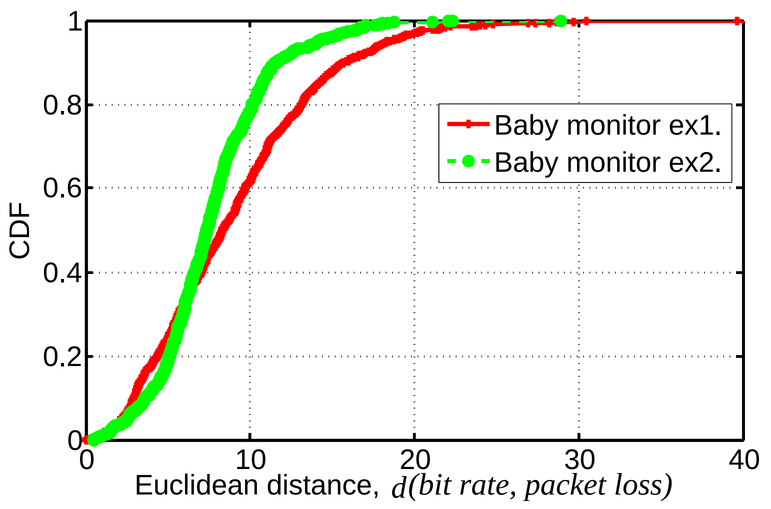
(b) The same device, a baby monitor, in different environments

Figure 2.4: The distribution of the correlation of bit rates and the estimated packet loss for various types of interference sources

As described above, the problem sources each have their own distribution patterns on



(a) The estimated number of packet loss (two experiments with a baby monitor)



(b) The Euclidean distance between each sample and the mean

Figure 2.5: The CDFs obtained from two experiments with the same baby monitor in different environment.

the scatter plot. However, an end user cannot infer a root cause by simply matching the measured statistics with the results of our experiments. This is because the measurement of a wireless network is highly affected by the client's own environment such as a distance from the AP, signal power, or fading (multi-path and shadowing). In other words, even though they have the same type of problem, the statistics of the measured metrics can vary depending on each end user's own situation. Note that this is the reason why simple measurements such as the higher-layer throughput (e.g., TCP or UDP) or number of 802.11 retries are not enough to identify the level of interference and the type of interferers.

Therefore, it is necessary to find a metric that only depends on the interference source, not the underlying environments. To achieve this, we focused on evaluating the variance of the measured samples rather than their values. On the scatter plot described above where x-axis is the available bit rates and y-axis is the number of packet losses, we found that *even if the underlying environment changes, the extent of the area over which the samples are placed does not change significantly if the problem source is the same*, which implies that the variance of the samples are consistent across different environments. Figure 2.4b shows that even though the two groups of samples from discrete environments are distributed on different spots on the coordinate plane, their extent is similar. Thus, we first quantify how widely the samples are dispersed by calculating the Euclidean distances between each sample and the mean. We use the following formula to calculate the distance: $distance = \sqrt{(M_x - S_x)^2 + (M_y - S_y)^2}, mean = (M_x, M_y), sample = (S_x, S_y)$, where $x =$ available bit rate (Mb/s), $y =$ the number of packet losses per $100KB$ of data. Note that the units of the sample data are best chosen to balance the magnitude of the variance of x-axis values and that of y-axis values to avoid only one of them impacting the result. Therefore, the distance value itself is not meaningful, but a set of the distance values are useful to compare the level of interference and identify the interference source. Figure 2.5 compares the CDFs obtained from two experiments that were conducted with the same baby monitor in two discrete environments. The CDFs of packet loss estimation (Figure 2.5a) show different distributions while the CDFs of the Euclidean distances between the samples and the mean show similar distribution (Figure 2.5b).

Therefore, WiSlow can use the CDFs of the Euclidean distances to identify the root causes of network interference. We prepare these CDFs of each problem source in advance, which are obtained from our experiments. Then, WiSlow traces the wireless packets on an end user's machine, generates a CDF of the distances, and compares it to the pre-calculated CDFs of each problem source. For the convenience of identification, we group the problem sources into three groups by the shape of the CDFs: no interferers (group 1), light interferers (group 2), and heavy interferers (group 3). Each group has its representative CDFs that are determined by multiple experiments (Figure 2.6). In our data sets, group 1 indicates a no-interference environment, group 2 includes channel contention and cordless phones that use frequency-hopping spread spectrum (FHSS), and group 3 contains microwave ovens and baby monitors. WiSlow examines which representative CDF is the most similar one to the CDF measured on the user's machine. To compare the CDFs, WiSlow uses the two-sample Kolmogorov-Smirnov test (K-S test), a widely used statistical method that tests whether two empirical CDFs obtained from separate experiments have the same distribution [36]. If the p-value of this test is close to 1, the two CDFs are likely to come from the same distribution, however, if the p-value is close to 0, they are likely to come from different distributions. Since the K-S test not only considers the average and variance of the samples but also takes into account the shape of the CDFs, it best fits the purpose of WiSlow where it is used to pick the most similar distribution from multiple data sets. Our evaluation proves that the approach explained above successfully distinguishes these groups, minimizing the impact of the end user's

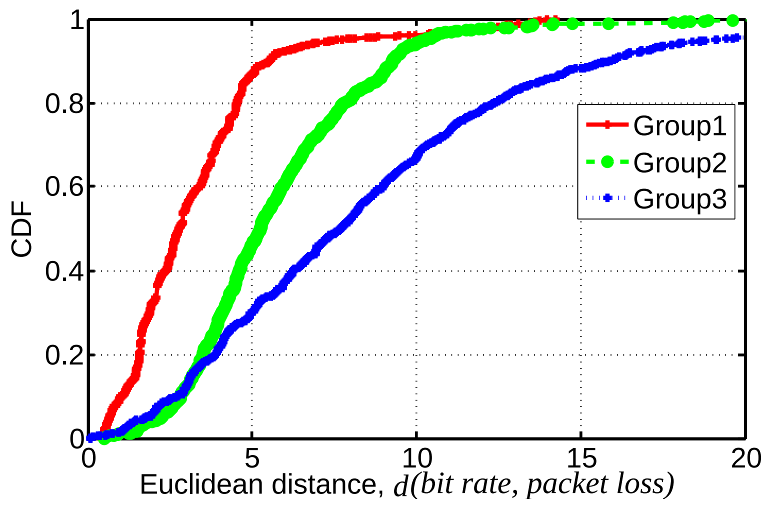


Figure 2.6: Three groups categorized by the packet loss analysis: 1) a no-interference environment, 2) contention and FHSS cordless phones, and 3) microwave ovens and baby monitors. The units of the sample data are best chosen to balance the magnitude of the variance of x-axis values and that of y-axis values.

underlying environment.

2.6 Analysis Method 2: 802.11 ACK pattern analysis

The first method is able to determine which type of loss pattern a problem source has. However, because multiple problem sources are categorized into each group, we need another method that further narrows down the root causes. In this section, we explain the second method, designed to distinguish several detailed characteristics of non-Wi-Fi devices such as frequency hopping and duty cycle.

WiSlow sends bulk UDP packets to the AP and counts the received 802.11 ACKs to check the quality of a wireless link within a given period. In order to detect patterns on the scale of milliseconds, we use a very small size of UDP packets (12 bytes) that reduces potential delays such as propagation and processing delays, and we transmit as many UDP packets as possible to reduce the intervals between samples. As a result, we observed maximum seven ACKs per millisecond.

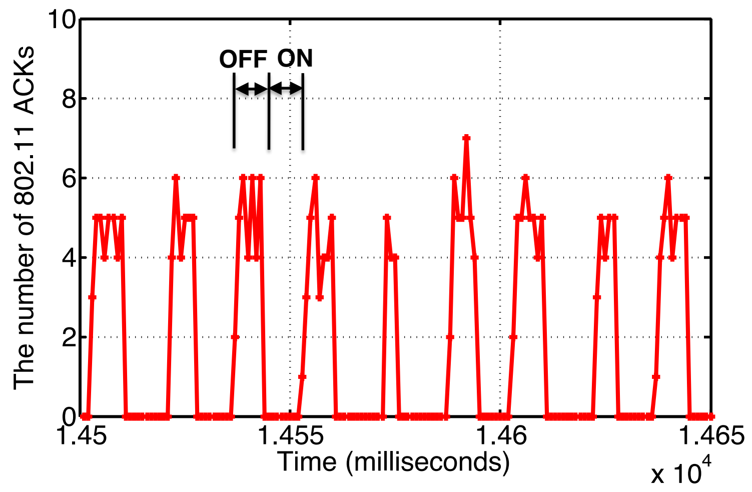
In the following sections, we describe the results of the above method when performed with various non-Wi-Fi interferers, and we explain how WiSlow identifies the devices based on the results.

Duty cycle (microwave ovens)

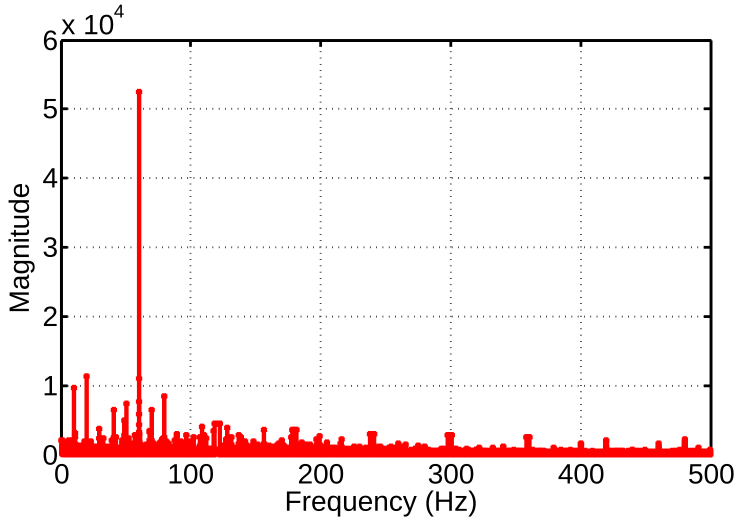
Microwave ovens generate severe interference in almost every channel of the 2.4 GHz band. We identify this heavy interferer using its duty cycle, which is the ratio of the active duration to the pulse period. It is known that the duty cycle of microwave ovens is 50% and the dwell time is 16.6 ms (60 Hz)[3] [30]. This implies that it stays in the ON mode (producing microwaves) for the first 8.3 ms and the OFF mode for the next 8.3 ms. This feature can be observed by various means such as using a spectrum analyzer [53] or signal measurement [44].

Our hypothesis was that a user-level probe could also detect this *on-off* pattern if the network packets were monitored on a millisecond timescale because the packets would be lost only when the interferer was active (*on* mode). To validate this assumption, we implemented the above method and plotted the number of successfully received 802.11 ACKs per millisecond. As a result, a clearly perceptible waveform with a 50% duty cycle is observed in Figure 2.7a; the average number of ACKs is greater than five for the first 8 ms and zero during the next 8 ms. This pattern repeats while the microwave oven is running.

[3]This frequency could be 50 Hz in other countries (e.g., Europe and most of Asia) where 50 Hz AC power is used.



(a) Time domain



(b) Frequency domain

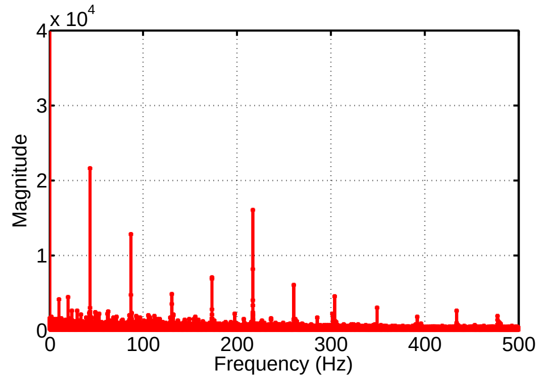
Figure 2.7: The number of 802.11 ACKs with interference of a microwave oven

This result becomes clearer when it is converted to the frequency domain (Figure 2.7b) using a fast Fourier transform (FFT). The highest peak is at 60 Hz, which means the cycle is 16.6 ms. This number is exactly the same as the known duty cycle of microwave ovens.

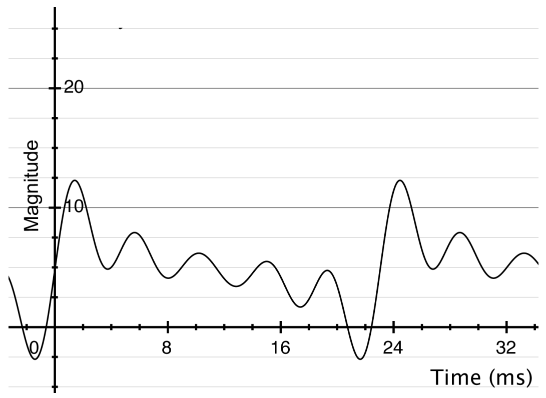
Consequently, if a perceptible cycle is detected from this probing method and the period matches a well-known value, WiSlow determines that the current interference is due to a particular type of device (e.g., 60 Hz for microwave ovens).

Frequency hopping (baby monitors and cordless phones)

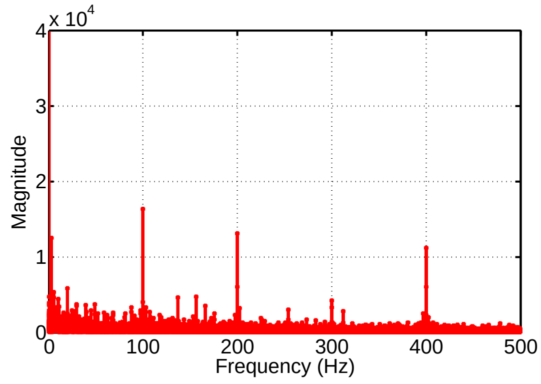
The duty cycle of typical audio and video transmitters such as baby monitors is known to be 100%. It means that they send and receive data constantly, implying that they continuously interfere with Wi-Fi networks without any *off* period. Therefore, intuitively, we do not expect to observe similar ACK patterns as those observed in the microwave oven experiment. However, when converting the plot from the time domain to the frequency domain, we observe another notable pattern. Figure 2.8a shows that there are multiple high peaks set apart by a specific interval, i.e., 43 Hz (occurring at 43, 86, 129, and 172 Hz). This is in contrast to the microwave ovens that showed only one significant peak at 60 Hz (Figure 2.7b). We conjecture that these peaks are caused by frequency hopping; a frequency hopper switches its frequency periodically, and interference occurs when it hops to a nearby frequency of the current Wi-Fi channel. However, the frequency-hopping device does not necessarily return to the same frequency at a regular period because the frequency of the next hop is decided by a pseudorandom sequence. This pseudorandomness instead creates diverse cycles with different periods. However, these periods are multiples of a specific number due to the fixed hopping interval. For clarity, we plot a quantized time-domain graph (Figure 2.8b) that is converted back from the frequency-domain graph. We used the 10 highest frequencies from Figure 2.8a. In the time-domain graph, the number of ACKs (y-axis) fluctuates periodically, however, note that the heights of the peaks vary. The possible explanation is as follows: the number of ACKs is large when the device hops far from the current Wi-Fi channel and is relatively small when it hops to a nearby frequency. If the device hops into the exact range of the



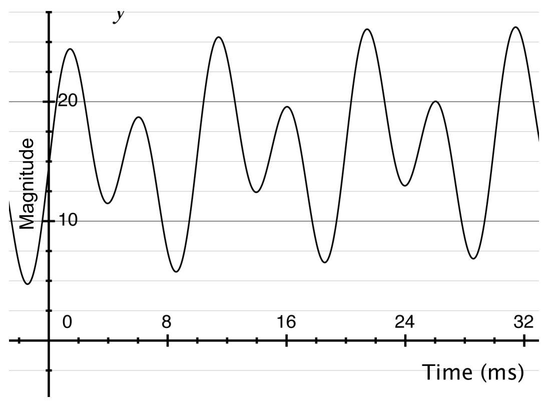
(a) A baby monitor: frequency domain



(b) A baby monitor: time domain - top 10 frequencies



(c) An FHSS cordless phone: frequency domain



(d) An FHSS cordless phone: time domain - top 10 frequencies

Figure 2.8: The number of 802.11 ACKs per 100 KB of UDP packets with a baby monitor and a cordless phone

Wi-Fi channel, the number of 802.11 ACKs drops almost to zero. In other words, there are multiple levels of interference which depend on how closely in frequency the device hops to the frequency used by the Wi-Fi channel. These multiple levels of interference create several pulses that have different magnitudes and frequencies. Finally, because the hopping interval is fixed, the frequencies of the created pulses are synchronized such that the periods of the cycles are multiples of a specific value.

The FHSS cordless phone, which also uses the frequency hopping technique, showed a similar result — multiple peaks spaced by a fixed interval of 100 Hz (Figure 2.8). This verifies that our method is suitable to identify frequency hopping devices.

Consequently, we can distinguish frequency-hopping devices by determining whether the number of 802.11 ACKs has multiple high peaks with a certain interval in the frequency domain. We check this by linear regression of the peak frequencies; if the correlation coefficient is greater than 0.99, we consider it to be a frequency-hopping device.

Fixed frequency (analog cordless phones)

Since many analog cordless phones use a fixed frequency, they usually interfere only with a small number of channels. (The analog phones we tested only interfered with Channel 1.) Because they do not change frequency, severe interference occurs if the current Wi-Fi channel overlaps with the frequency of the phone. In addition, their duty cycle is close to 100%, which implies that the pattern of ACK rates does not exist. In our experiments, the UDP throughput stayed very low and no explicit pattern of received ACKs was observed as expected. This implies that the device does not use the frequency-hopping mechanism. Therefore, WiSlow concludes that an analog cordless phone is the interferer if there is heavy interference pattern but no explicit ACK cycle or duty cycle is detected. Then, we can inform the user that switching the Wi-Fi channel can improve the performance in this case because we know that this kind of devices only affects a few channels.

Mixed-mode devices with frequency hopping and partial duty cycle

A Frequency Hopping Spread Spectrum (FHSS) phone is another example of a device that explicitly shows the hopping patterns that we described above. In addition, it is known that some FHSS phones have a specific pulse interval, which was verified by Rayanchu et al. [44] using signal measurement. We also confirmed this feature with our user-level probes. Figure 2.8c shows 802.11 ACKs in the frequency domain. It shows similar patterns as the microwave ovens (low duty cycle devices) rather than the baby monitors (frequency-hopping devices) even though it also uses frequency hopping. This is because the duty cycle influences the shape of the waveform more than the hopping effect. Therefore, it is possible to use this duty cycle to distinguish the FHSS cordless phones as we did for the microwave ovens. In this case, we use the frequencies, 100 and 200 Hz, to determine the FHSS cordless phone interference. However, to the best of our knowledge, there is no standard regarding the period of the duty cycle for FHSS cordless phones. This means it can vary depending on the product. Therefore, if a duty cycle is detected but the period is an unknown value, WiSlow fails to identify the exact product type. In this case, we provide our best estimate of the problem source by listing a possible set of candidates.

Bluetooth

Bluetooth is another widely used wireless standard that operates in the 2.4 GHz spectrum. Hopping within the entire 2.4 GHz band, it interferes with every channel of an 802.11 network. However, algorithms such as Adapted Frequency Hopping (AFH), which is used to automatically avoid busy channels, mitigate this interference. Consequently,

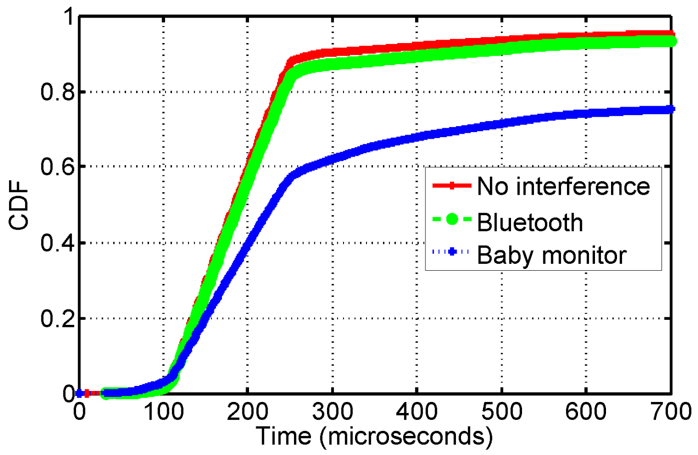


Figure 2.9: 802.11 Inter-frame period with Bluetooth interference

Bluetooth affects the performance of 802.11 networks only marginally. In a measurement by Rayanchu et al. [44], Bluetooth was shown to degrade the UDP throughput by about 10% in the worst case. Investigating the 802.11 backoff period, we verified this more accurately. We measured the inter-frame period (T_i) of UDP packets, which is a sum of the higher-layer processing time (T_h), 802.11 DIFS (T_d), and the backoff time (T_b). T_d is fixed as 20 μs in 802.11g and T_h is stable ($T_d + T_h$ was about 110 μs in our environment). Therefore, T_i mostly depends on T_b (backoff time), which is affected by interference. This is because T_b increases when the channel is not idle based on the 802.11 protocol. $T_b = 9\ (\mu s) \times$ CW, where CW (contention window) is randomly chosen to be between 1 and 15 when there are no lost packets. Thus, in theory, if there is no interference, T_i should be determined to be between 120 μs and 245 μs in our environment.[4]

The CDF (Figure 2.9) shows that 90% of inter-frame periods are evenly distributed between 120 μs and 250 μs in a no-interference environment. We can infer that CW in-

[4]$T_i = T_h + T_d + T_b, T_h + T_d = 110\ (\mu s)$, and $9\ (\mu s) \le T_b \le 135\ (\mu s)$. Therefore, $119\ (\mu s) \le T_i \le 245\ (\mu s)$.

creased owing to the ACK timeout (lost packet) in the other 10% of the cases. With the presence of a baby monitor, 40% of T_i were greater than 246 μs. However, the Bluetooth and no-interference cases show almost the same distribution (only 10% are greater than 250 μs), which implies that Bluetooth does not interfere much with 802.11g networks. For this reason, we excluded Bluetooth in both our experiment and the evaluation scenario.

2.7 Classification

WiSlow takes into account the combination of the results from the first method (packet loss analysis) and the second method (ACK pattern analysis) to identify the device product type precisely. For example, if the result of the first method is Group 3 and that of the second method is frequency-hopping, we consider the problem source to be a baby monitor. In addition, WiSlow looks into the source and destination addresses of the captured 802.11 packets in order to examine the channel occupancy rate. If the channel is highly occupied by other clients or nearby APs, but WiSlow does not detect any non-Wi-Fi interference, it considers the root cause to be channel contention.

Figure 2.10 describes the classification algorithm that WiSlow uses to arrive at the root cause.

2.8 Locating interfering devices

A number of research studies on indoor location tracking have attempted to pinpoint the location of laptops or smartphones through various methods [6, 27, 56]. While these

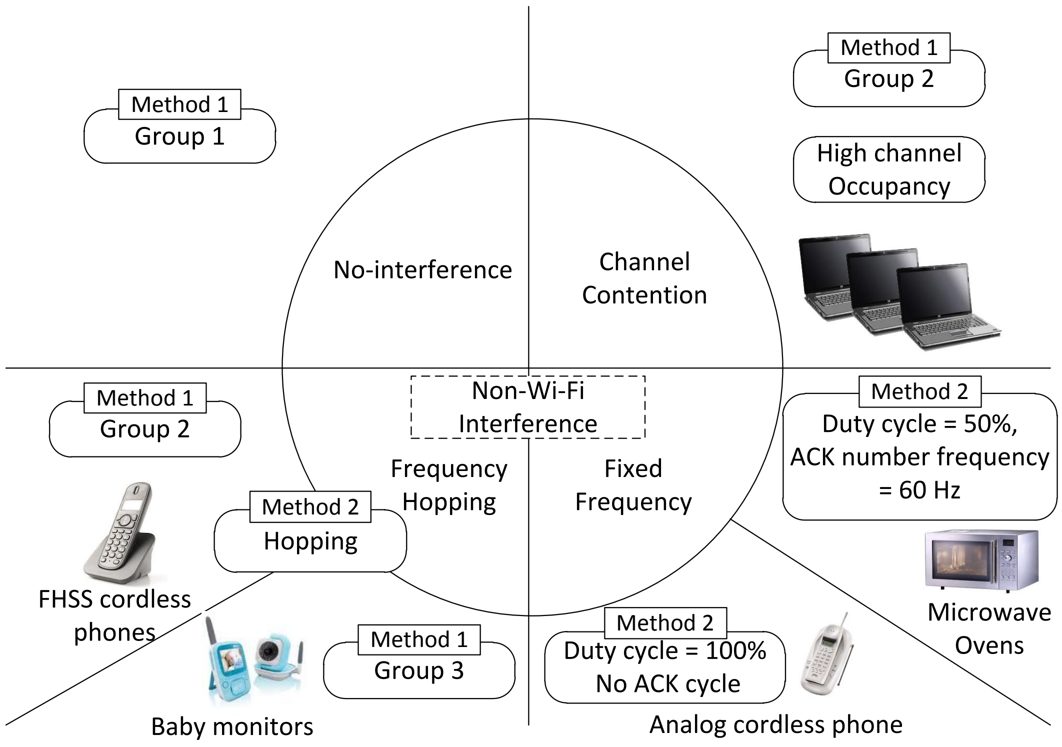


Figure 2.10: The classification of problem sources by WiSlow's diagnostic methods

studies focus on locating *client devices* using signal information such as RSSI and SINR values, we focus on locating *interference sources* using multiple collaborating end-user devices. Compared to locating Wi-Fi devices, there are several difficulties in locating non-Wi-Fi devices for end users. First, it is impossible to obtain measurement data such as RSSI and throughput from such devices (e.g., microwave ovens neither monitor signals, nor communicate with Wi-Fi devices). Second, owing to the limited capability of the hardware, end-user devices cannot detect signals emitted from the devices precisely. To overcome these circumstances, we leverage multiple Wi-Fi devices; a probing client (end-user machine) requests cooperative clients to perform a WiSlow diagnostics as described in previous sections. It then receives the diagnostic result containing the type of the detected device (e.g., microwave oven) and its *interference strength* from each client. We calculate the *interference strength* using the magnitude of the pattern of the number of received ACKs which was used to detect the device, as described in the previous section. For example, the *interference strength* of a microwave oven can be determined based on a magnitude of 60 Hz in the FFT of the number of ACKs. In the case of an FHSS device, it can be determined by the sum of the magnitudes of the multiple frequencies caused by the frequency hopping pattern. After collecting the strength values from the clients, we use the same method of obtaining the center of mass to find the location of the interference. If the *interference strength* detected by a particular client is greater than that detected by other clients, it means that the interference source is closer to that client. Therefore, *interference strength* can be considered equivalent to the mass in the formula of the center of mass. WiSlow first obtains the coordinates of cooperative clients based on the input from end users and calculates the coordinates of the interference source using the formula.

The basic mechanism is that an end user (probing client) first requests multiple cooperative clients to perform WiSlow diagnostics as described in previous sections. Then it checks whether the other client machines observe the same interference. If all the cooperative client machines observe a particular type of interference at the same time, it is likely that the problematic source is close to the AP because this would affect the entire wireless network. However, if only one of the clients observes the interference, the source is highly likely to be located close to that client.

$$M_i = \sum_{k=1}^{m} f_i(kx), \qquad \boldsymbol{R} = \frac{1}{\sum\limits_{i=1}^{n} M_i} \sum_{i=1}^{n} M_i \boldsymbol{r_i} \tag{2.2}$$

M_i is the strength of interference on the ith client and f_i denotes the function of the measured magnitudes for each frequency, kx, where x is the smallest frequency caused by the interfering device. The coordinate of the interference source, $\boldsymbol{R}$, can be calculated based on the sum of each client's weighted (M_i) coordinates ($\boldsymbol{r_i}$). We evaluate this approach in Section 2.9.

2.9 Evaluation

In this section, we evaluate the accuracy of WiSlow. First, we placed a laptop 8 m away from an AP, sufficiently close so that Wi-Fi performance is not affected by weak signal strength. Then, we located the interfering devices between them, one at a time. We repeated the experiments altering the distance between the interfering device and the AP. We ran WiSlow on the laptop 15 times each at six different locations (a total of 90 measurements for each interfering device) and counted the number of times that WiSlow correctly diagnosed the root cause. First, without considering the type of the non-Wi-Fi device, we tested the capability of WiSlow to distinguish between no-interference, channel contention, and non-Wi-Fi interference.

We evaluate the *diagnostic accuracy* and the *false positive* rate (type-I error) of WiSlow for each problem source. The diagnostic accuracy of a problem source P is the ratio of the number of correct diagnostics to the total number of experiments in which P is injected as a problem source. The false positive rate of P is the ratio of the number of cases that the cause is misidentified as P to the total number of experiments in which P is not actually the cause.

Table 2.1 shows that WiSlow successfully distinguishes them with high accuracy (over

90% for no-interference and channel contention cases). In the non-Wi-Fi interference case, the accuracy was also over 90% when the interfering device was close to the AP; however, it notably decreased when the distance between the AP and the device increased. We found that this inaccuracy was mostly caused by the FHSS cordless phones. In the following sections, we explain the reason for this inaccuracy and the method WiSlow employed to reduce it.

Identifying the root cause

Table 2.2 shows the detailed diagnostic results of identifying each type of non-Wi-Fi device. First, WiSlow could clearly detect interference caused by a microwave oven regardless of the distance (average 98%). In our extra experiments, WiSlow could detect the duty cycle of the microwave oven even when located relatively far from the AP and laptop (11 m and 16 m). However, in these cases, the microwave oven did not severely interfere with the Wi-Fi network, thus we do not elaborate further on the results.

Second, the diagnostic accuracy of detecting baby monitors was also very high when it was close to the AP. However, it dropped to under 6.7% when the distance was greater than 1 m (Table 2.2). In most cases, it was misidentified as a FHSS cordless phone, which contributed the high false positive rate of this device (24.8%). This result occurred because these two devices have the same characteristic (frequency hopping), and WiSlow partially considers their level of interference to distinguish them. In other words, if a baby monitor is far from a Wi-Fi device and causes less interference, it can mislead WiSlow's identification. The accuracy of detecting FHSS cordless phones was also low when it was not close

Injected Problem	Distance from the AP	Accuracy	False Positive
No interference	-	100.0%	14.1%
Channel contention	-	92.2%	1.5%
Non-Wi-Fi interference (baby monitor, cordless phone, and microwave oven)	0.0 m	100.0%	3.9%
	0.5 m	97.8%	
	1.0 m	82.2%	
	1.5 m	82.2%	
	2.0 m	73.3%	
	2.5 m	68.9%	

Table 2.1: The accuracy of WiSlow for distinguishing between a clean environment, channel contention, and non-Wi-Fi interference

to the AP (6.7% at 2.5 m). However, this was because the cordless phone caused insignificant interference at this spot; the average UDP throughput was 13.28 Mb/s at 2.5 m (the average throughput with no interference was 14 Mb/s in the same environment). With this small interference, WiSlow did not observe the expected hopping patterns. As a result, the majority of incorrect diagnostic results were "no interference," which explains its high false positive rate (14.1%) shown in Table 2.1.

The low accuracy of detecting baby monitors and FHSS cordless phones can be improved if we take into account their specific pattern of the number of successful ACKs (hopping pattern), which were discussed in Section 2.6. Recall that the pattern of the number of ACKs of the baby monitor were a multiple of 43 Hz, and that those of the FHSS cordless phone were a multiple of 100 Hz. When WiSlow is adapted to consider these specific numbers, the detection accuracy increases dramatically. With this approach, the fi-

Non-Wi-Fi Interference	**Distance from the AP**	**Avg. Throughput**	**Diagnostic Accuracy**	**False Positive**
Microwave oven	0.0 m	7.54 Mb/s	100 %	0.4 %
	0.5 m	8.52 Mb/s	100 %	
	1.0 m	8.96 Mb/s	100 %	
	1.5 m	9.33 Mb/s	100 %	
	2.0 m	9.30 Mb/s	100 %	
	2.5 m	8.91 Mb/s	93.3 %	
Baby monitor	0.0 m	0.51 Mb/s	100 %	1.1 %
	0.5 m	3.16 Mb/s	73.3 %	
	1.0 m	4.79 Mb/s	6.7 %	
	1.5 m	4.49 Mb/s	6.7 %	
	2.0 m	4.81 Mb/s	6.7 %	
	2.5 m	5.17 Mb/s	0.0 %	
FHSS Cordless phone	0.0 m	6.76 Mb/s	80.0 %	24.8 %
	0.5 m	9.65 Mb/s	86.7 %	
	1.0 m	10.02 Mb/s	40.0 %	
	1.5 m	10.05 Mb/s	40.0 %	
	2.0 m	12.44 Mb/s	13.3 %	
	2.5 m	13.28 Mb/s	6.7 %	

Table 2.2: The accuracy of WiSlow for identifying non-Wi-Fi devices

nal diagnostic accuracy was 100% most of the time, except when the FHSS cordless phone was placed at locations farther than 1.5 m from the AP[5]. However, the disadvantage of this approach is that WiSlow needs to learn the hopping pattern of the particular product in advance because the pattern depends on each model. It seems impractical to collect the patterns from every product. However, we found that different products likely have common characteristics. For example, we tested four FHSS cordless phones produced by two different manufacturers (Motorola and Panasonic), and each one showed the same

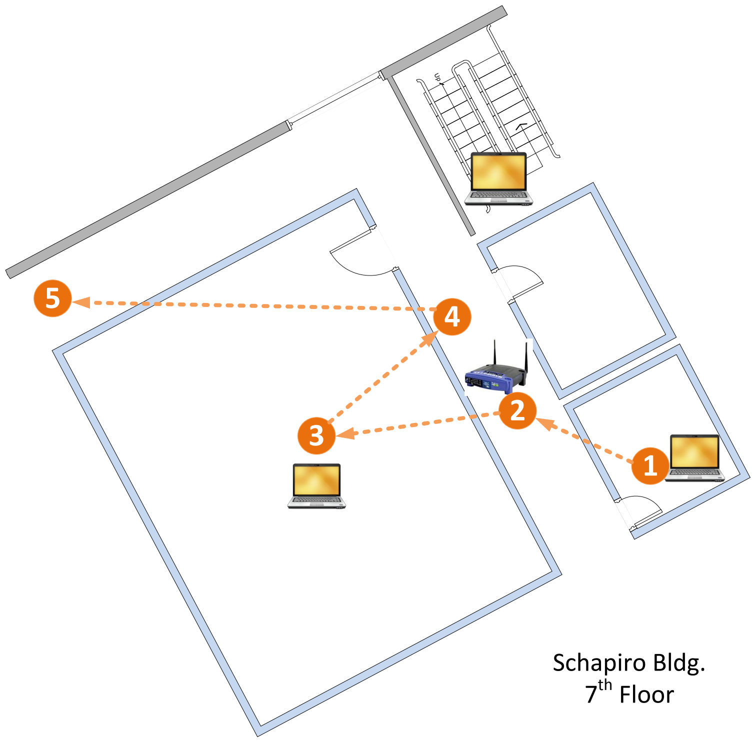
[5]These inaccuracies can be ignored because the throughput shows there was actually “no interference” even though the cordless phone was active.

pattern of the number of ACKs (multiples of 100 Hz). In this particular case, the pattern is caused by the DECT (Digital Enhanced Cordless Telecommunications) standard [21] which specifies the frame time as 10 ms. Therefore, we believe that collecting a small amount of information can cover the majority of devices if they follow the industry standards or use similar technologies.

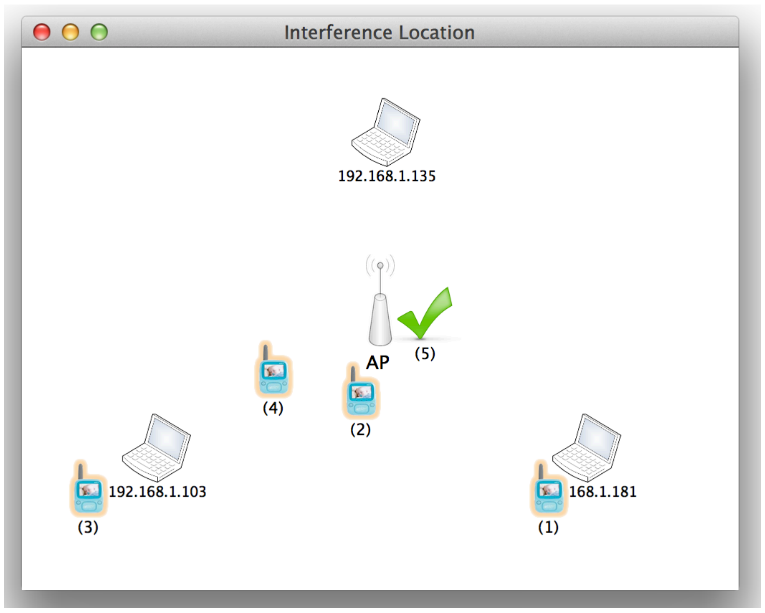
In conclusion, WiSlow successfully detected the root cause of Wi-Fi performance degradation with a high probability (over 90%) in most cases, although it frequently misidentified the type of certain non-Wi-Fi interfering devices when they were not located near the Wi-Fi device. However, this inaccuracy can be removed if we take into account the pre-obtained pattern of the number of received ACKs of each device.

Locating interfering devices

We set up three laptops and one 802.11g AP in a building at Columbia University. We placed a baby monitor between them and changed its location over time. Figure 2.11a illustrates our experimental scenario. The circled numbers indicate the movement path of the baby monitor. We ran WiSlow each time the location was changed. Figure 2.11b shows an actual real-time screenshot of WiSlow detecting the location of the baby monitor. For the first location, laptops A and B reported no interference, but laptop C detected the baby monitor successfully. For the second location, the three laptops all detected the baby monitor and reported similar *interference strengths* because the interference source was close to the AP, and thus the entire wireless network was affected by the baby monitor. In this particular case, WiSlow could infer that the problem source was likely to be a device



(a) Experiment scenario of locating interference



(b) A real-time result of WiSlow

Figure 2.11: Locating the interference source

placed near the AP. For the third location, only laptop B detected the baby monitor, and thus WiSlow placed the baby monitor icon close to laptop B. For the fourth location, the three laptops all detected the baby monitor, but the measured *interference strengths* were distinct. Therefore, based on the formula of the center of mass, WiSlow pointed the location of the baby monitor as being relatively close to laptop B. For the last spot, since none of the laptops detected any interference, only a green check icon was displayed, which indicates that the state of the network is good.

This experiment proves that our approach is feasible for determining the relative location of an interfering device. Although WiSlow shows errors of several meters in pinpointing a location, we believe that this level of error is not critical for a home network environment since users typically have only one cordless phone or baby monitor. (They do need to distinguish between their own device and that operated by a neighbor.)

2.10 Related work

Airshark [44] uses a commodity Wi-Fi network adapter using Atheros chipsets to identify the source of interference. It leverages a spectral scan to obtain signal information from multiple frequency ranges. It identifies the interference sources very accurately (over 95%) by analyzing the spectrum data using various methods. However, it is not easy to apply this approach for typical end users because collecting high-resolution signal samples across the spectrum is impossible if the network card does not support this functionality. WiFiNet [45] identifies the impact of non-Wi-Fi interference and finds its location using observations from multiple APs that are running Airshark. Although the authors briefly mention that WiFiNet can be used by end users, they focus more on pinpointing the location of the interference source using multiple APs, which is difficult to be used in a home network environment that usually has a single AP. In contrast, WiSlow focuses on identifying the location of the interference source by exploiting cooperation between end users.

Kanuparthy et al. [31] propose an approach similar to WiSlow in terms of using user-level information. They distinguish congestion (channel contention) from hidden terminals and low SNR by measuring the one-way delay of different packet sizes. They then investigate the delay patterns to distinguish hidden terminals from low SNR. While their approach intentionally avoids using layer-2 information, WiSlow actively exploits 802.11 information in order to obtain a more detailed identification (e.g., device type causing the interference). Spectrum MRI [10] also isolates interference problems. The authors discuss that the link occupancy and retransmission rate differs depending on the sources of interference. They measure and compare those metrics to identify Bluetooth, channel congestion and the "slow link on same AP" problem by measuring the link occupancy and retransmission rate and using a spectrum analyzer, Wi-Spy [53].

Sundaresan at el. [47] present a tool that identifies whether a performance bottleneck exists inside the home network or on the access link by measuring variation of packet inter-arrival time and TCP RTT between a device and an access point. It also evaluates the state of the wireless link by monitoring the bitrate and throughput on an AP. While this tool focuses on identifying where a bottleneck exists, WiSlow focuses on identifying the type of interference source within the wireless network.

2.11 Discussion

802.11n

We have focused on interference in 802.11g networks (2.4 GHz). However, 802.11n, which uses both 2.4 and 5 GHz bands, has become popular. Although fewer non-Wi-Fi devices are operating at 5 GHz, and thus less interference presently exists at that band, Cisco has anticipated that more devices will use the 5 GHz band in the future, and therefore a similar interference will likely occur [18, 49]. We believe that our basic approach will also be feasible for discovering non-Wi-Fi interference sources at 5 GHz if customized to an 802.11n environment.

Ad-Hoc mode and mobile devices

We also tested WiSlow on an ad-hoc network using two laptops, which enables WiSlow to run independently without communicating with an AP. Since ad-hoc networks also use the same 802.11 protocol, we did not see any differences from the experiments with an AP. We expect that using WiSlow with ad-hoc networks will be especially helpful in independently discovering nearby interference sources when used with multiple mobile devices such as smartphones.

2.12 Conclusion

We designed WiSlow, a Wi-Fi performance trouble shooting application, specialized to detect non-Wi-Fi interference. WiSlow distinguishes 802.11 channel contention from non-

Wi-Fi interference, and identifies the type of interfering devices present. WiSlow was designed to exploit user-level probing only, which enables a software-only approach. For this purpose, we developed two novel methods that use user-accessible packet information such as UDP throughput and 802.11 ACKs.

The accuracy of WiSlow exceeds 90% when the sources are close to a Wi-Fi device while it becomes less accurate when the interfering devices are located farther from the Wi-Fi devices. However, this inaccuracy can be removed if we take into account the known characteristics of each device. Also, we proved that the collaborative approach is feasible for determining the relative location of an interfering device.

Chapter 3

MoT: A Collaborative Network Troubleshooting Platform for the Internet of Things

3.1 Introduction

Today, not only smartphones and laptop computers but also traditional household devices such as TVs, air conditioners, lamps, and door locks are networked (smart objects). Although the Internet grants powerful functionality to these smart objects, the convenience instantly turns into a nuisance when the network does not function properly and the cause remains hidden. Troubleshooting network problems on such devices is not easy because most devices have insufficient computing power to run sophisticated diagnostic tools and have no user interfaces to debug the problem directly. According to Sundaresan et al. [48], service calls to Internet Service Providers (ISPs) for network troubleshooting are costly ($9–$25 per call). If the Internet of Things (IoT) environment further penetrates the home and every household device is connected to the Internet, this cost will increase drastically in the near future.

For general end-user computers, the diagnostic tools for network problems can be useful to mitigate the pain of the troubleshooting process. Existing tools include traditional command line tools (e.g., `ping` and `traceroute`), network diagnostic software embedded in each operating system, and several third-party diagnostic tools (e.g., Network Magic and HomeNet Manager described in Section 1.6). However, these tools are not only difficult to use for technically non-savvy users, but also inappropriate for home devices because they require user interfaces such as keyboards and monitors. Moreover, some tools may execute arduous tasks such as packet sniffing to trace and analyze the network packets [39], which requires more memory, storage, and CPU power than the small devices usually possess. For example, it is impractical to connect a monitor and keyboard physically to a networked door lock and execute `ping`, `nslookup`, and `tcpdump` in order to identify the cause of its network problem. Therefore, it is necessary to build a lightweight and user-friendly network diagnostic tool for home networks.

We propose MoT ("Medic of Things"), a network problem diagnosis platform that leverages the collaboration of smart objects, smartphones, and computers. The main idea is that when a device suffers from network problems such as DNS resolution errors, misbehavior of a Network Address Translation (NAT) box, port blocking, and DHCP problems, it offloads the troubleshooting task to other devices that have more capabilities (e.g., network accessibility or computing power). However, there is an issue of how to inform the other devices that the problem has occurred if the network is faulty. We note that most recent smart objects (e.g., smart TVs) have been designed to support extra communication protocols such as Bluetooth, ZigBee, Wi-Fi Direct, or NFC (Near Field Communication) in addition to Wi-Fi. Therefore, even if a device has a problem with a Wi-Fi network, the problem can be reported to nearby devices via other available communication interfaces. When another device receives the problem report, and that device has diagnostic functionality, it can start the diagnostic process to examine the problematic device and the network. Otherwise, it can simply forward the task to a more suitable device. For example, if a networked refrigerator has a problem with a Wi-Fi network, it sends a diagnosis request (like a distress message) to a nearby laptop computer that has no network problem. The laptop has enough memory, CPU, and user interfaces to run a dedicated diagnostic tool and thus is better able to diagnose the current network status.

We propose a common message format as the means through which heterogeneous devices communicate with each other to send, forward, and receive reports of network problems. Moreover, a device that diagnoses a problem can send probe requests to other devices to obtain different information about the current network state from multiple devices. To separate the modules for rules and probing, we designed two layers: The *logic layer* and the *probe layer*. This enables some devices that have less computing power to have only the probe functionality and others that have sufficient computing power (e.g., laptop computers and tablets) to have both diagnostic and probe functionality. We implemented a prototype of this platform, including applications for Android devices and general computers. The Android application uses native APIs to implement the *probe layer* and adopt a Web application technology for the *logic layer*. In order to obtain probe results from other nodes located outside the home network, we use DYSWIS presented in Chapter 1. We also suggest using instances in public clouds if a user worries about privacy in using peer-to-peer nodes. To prove the feasibility, we introduce a sample rule for diagnosis of push notification faults on Android devices.

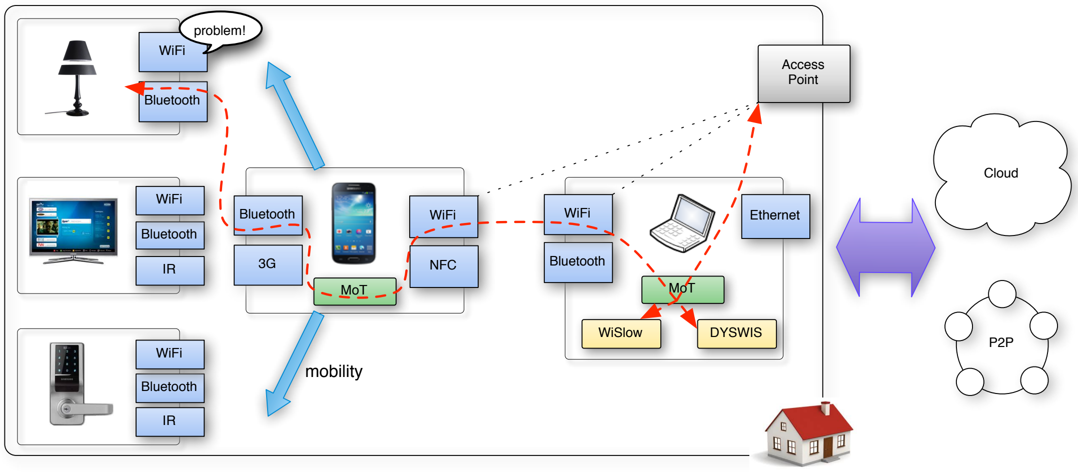


Figure 3.1: The architecture of MoT

3.2 MoT architecture

The main goal of MoT is to diagnose network problems of IoT devices in home networks. The diagnostic process is conducted using the collaboration of nodes in a home network and, if needed, MoT connects to other collaborators in external networks to request probes for problem diagnosis. We use a straightforward communication protocol that enables the devices to exchange problem profiles and diagnostic results with each other.

Device types

We define three roles in the MoT system: a *client device* is a smart object that has a network problem, a *forwarding device* passes probe requests from the *client* device to a *diagnostic device*, and a *diagnostic device* actually helps the *client device* diagnose the problem.

Each device in a home network has one or more roles, depending on its computing power (memory and CPU) and its attached user interfaces. For example, a laptop computer, which has ample computing power and user interfaces such as a mouse and a screen, will be a *diagnostic device* because it can run diagnostic software. The laptop may also be a *client device* since it can request a diagnosis from other devices when it has a network problem. Most other devices have roles as both *client devices* and *forwarding devices*. The forwarding is necessary when a *client device* is not physically close enough to the *diagnostic device* to communicate via Bluetooth, NFC, Wi-Fi direct or ZigBee.

Device registration

Each device first uses a service discovery technology (e.g., Bonjour) to discover a directory server and registers its attributes with the server when they are connected to the network. These attributes include which network interfaces it has (e.g., Wi-Fi, Bluetooth, ZigBee, or 3G/LTE), whether it can be mobile (e.g., smartphones and tablets), and whether it has a capability to run diagnostic software. A *diagnostic device*, which is usually a desktop or laptop, runs a MoT server that maintains a device directory based on these profiles and uses this when it diagnoses a problem. For example, if a cellular network is required to diagnose a particular problem, it first looks up which devices can connect to a cellular network (e.g., smartphones), and if such a device is currently reachable, it sends the probe request to the device via intermediate network available (e.g., Wi-Fi or Bluetooth). We describe this scenario in Section 3.3.

Problem description

When a device detects a network problem, it first creates a problem description that contains failure symptoms (e.g., it cannot connect to the wireless access point (AP), or the

TCP latency to servers in the Internet is too long). Then, it sends a diagnosis request that contains the problem description to the *diagnostic device*. The problem description includes the following parameters.

```
problem description := (deviceId, problemId, timestamps, problematic
interface type, MAC address, application name, protocol, port,
problem symptoms)
```

However, when a device is located too far from a *diagnostic device*, it cannot send the diagnosis request to the *diagnostic device* via Bluetooth or ZigBee. In this case, our suggestion is that the diagnosis request can be forwarded (broadcasted) to other devices that are in the vicinity of the faulty device. The devices that receive the diagnosis request are responsible for sending it to the *diagnostic device* or forwarding it to other devices that have a connection to the *diagnostic device*.

Mobile devices

When a device has a problem with the Wi-Fi network and has no nearby *forwarding device*, it cannot send the diagnosis request to another device. In this case, mobile devices such as smartphones and tablets have important roles. We take advantage of their portability in order to collect diagnosis requests from problematic devices. The devices that are large or fixed, such as refrigerators, lights, and door locks, cannot be moved and often are located far from other devices (e.g., lights at the ceiling). Therefore, when these devices have problems with the Wi-Fi network, the devices may fail to reach others because of their limited communication range, even if they have active communication interfaces other than Wi-Fi. In this case, a mobile device can be a *forwarding device* or a *diagnostic device*. A user carries the mobile device close to the problematic device and pairs via Bluetooth[1]. Then, the problematic device notices that a forwarding (or diagnostic) device, which is portable, is nearby and sends it the diagnosis request.

Diagnosis

The diagnostic processes are driven by predefined diagnostic rules. We adopt the rule system from DYSWIS, so the rules can be crowdsourced and updated via a central rule repository server. The basic rule starts with a check of whether the same problem has been reported by other devices. If there has been no report of the problem, we attempt to communicate with other devices to determine whether those are reachable without any network problems. If it turns out that the same problem occurs for multiple devices in the network, we infer that the problem is caused by the home network infrastructure (e.g., an AP). In this case, we run other diagnostic software such as DYSWIS and WiSlow to check whether DNS, DHCP, TCP/UDP, and Wi-Fi are functioning properly. If other devices do not observe the problem, then MoT interacts with the problematic device again via an alternative communication interface and requests that the probe modules indicated by the diagnostic rule be executed. We define a simple message syntax for this request. The message contains the name of the probing module that should be executed and the parameters that should be passed to the module. The return value will be sent back in a similar format. As an example, JSON-format messages are illustrated below.

[1]Currently, the Bluetooth paring process is done manually in our prototype.

```
request = {“module”: “TCP listen”, “parameters”: {“port: 80”}}

response = {“status”: “success”}

request = {“module”: “ping”, “parameters”: {“host”: “192.168.1.1”}}

response = {“status”: “success”, “result”:“5ms”}
```

These messages are used between different types of devices in order to exchange probe requests and responses.

External nodes

When a device fails to connect to a server outside the home network (e.g., a web service or IoT management server[2]), it is necessary to obtain probe results from external collaborative nodes. For example, if a device fails to connect to the central management server, it is useful to know whether other devices or computers in different networks (other households) have the same problem. Accordingly, we can use the P2P network that DYSWIS provides, which originally was designed to help general computer users with problem diagnosis. As described in Chapter 1, DYSWIS supports a distributed network composed of multiple peer nodes that voluntarily participate in a fault diagnosis process. The nodes run the probes requested to diagnose the network problems of end users. In a similar way, MoT asks other nodes in the DYSWIS network in order to determine whether the management server is working properly for those nodes. Moreover, collaborative nodes in outside networks can send network packets to the home devices in order to confirm

[2]For example, devices need to connect to a SECE [13] server, which is a central management server for networked devices. SECE is a general IoT platform developed at Columbia University.

that incoming packets are received correctly.

However, a user may well be concerned about the privacy of using P2P networks, because information on the problem is revealed to other users when probes are requested. If a user prefers a private method to diagnose the problem, the alternative method that we suggest is the use of virtual instances in public clouds. Since public clouds now offer instances in multiple geographical locations (e.g., Amazon EC2 offers instances in 16 geographic regions around the world), it is even possible to run probe processes in multiple different networks without the help of a P2P network or a distributed shared network such as PlanetLab [41]. Figure 3.1 illustrates the collaboration of cloud instances to diagnose home network devices. When a suspicious network behavior is observed, we launch instances from a prepared image that contains probing modules to assist in the problem diagnosis. The instances can be operated by a trustworthy third party, or users can run their own isolated instances using their accounts on the cloud service providers.

3.3 Diagnosis scenarios

In this section, we describe several sample scenarios of the problem diagnosis process using MoT.

Device diagnostics using history

Suppose that the bandwidth of a device is capped by a firewall at an AP for security reasons. Because of this, the device has difficulty connecting to the network and sends a diagnosis request to a nearby laptop via Bluetooth. Then, the laptop starts the diagnostic process by sending probe requests to other devices to determine whether those have the same problem. Then, MoT compares the problem description received from the problematic device with probe results received from other devices to identify the cause of the problem. In this case, since other devices observe no network problem, MoT can infer that the AP is functioning correctly, but only this device suffers from the bandwidth problem. If the past log of the bandwidth measured on the device showed no problem consistently, we can infer that a configuration at the AP might be the cause of the problem.

Device diagnostics using active probing

Suppose that a device suffers from performance degradation due to severe Wi-Fi interference. The Wi-Fi interference can be caused by channel contention or nearby non-Wi-Fi devices [44] as discussed in Chapter 2. In this case, the problematic device may even fail to report the problem to a diagnostic node. Therefore, our approach is that a mobile device with a forwarding capability (e.g., smartphone) collects the problem description from the problematic device using an alternative communication protocol such as Bluetooth and then forwards the message to the diagnostic node when the nodes move into areas where the Wi-Fi network is accessible with no problem. Then, the diagnostic node runs specialized diagnostic software such as WiSlow to detect the root cause of the Wi-Fi interference.

Smartphone diagnostics

Another example is the diagnosis of a problem with a smartphone. Suppose that a smartphone application has a network problem but the source of the problem is not known. For example, many Android applications use push notifications to send network packets to mobile devices. To test whether these notifications work correctly, the diagnostic application on a smartphone sends probe requests to a laptop via Bluetooth or any other short-range communication methods available. The laptop diagnoses the problem using predefined diagnostic rules. These diagnostic rules entail further probes into the smartphone via Bluetooth to proceed with the diagnosis. We tested this scenario with an Android application that we implemented (Section 3.4 and 3.5).

Computer diagnostics

Another possible scenario is the reverse of the previous scenario. A laptop computer has a network problem, and thus it cannot contact external nodes in other networks. For example, suppose that an ISP has a temporary outage and its customers have no Internet connection. In this case, the laptop becomes completely isolated and there are not many methods to diagnose the causes. With MoT, the laptop first detects that there is a device (smartphone) connected to a cellular network. Then, the laptop sends a diagnosis request to the smartphone which connects to the Internet via the cellular network and diagnoses the problem. Although the cellular and Wi-Fi network use different ISPs and network paths, the cellular network can still assist the diagnosis. For example, the smartphone can obtain real-time service interruption records from the websites that maintain the list of services that are down[3]. Moreover, it can send probing requests to external nodes that are connected to the same ISP to ascertain what is actually happening in the Internet and the service provider network.

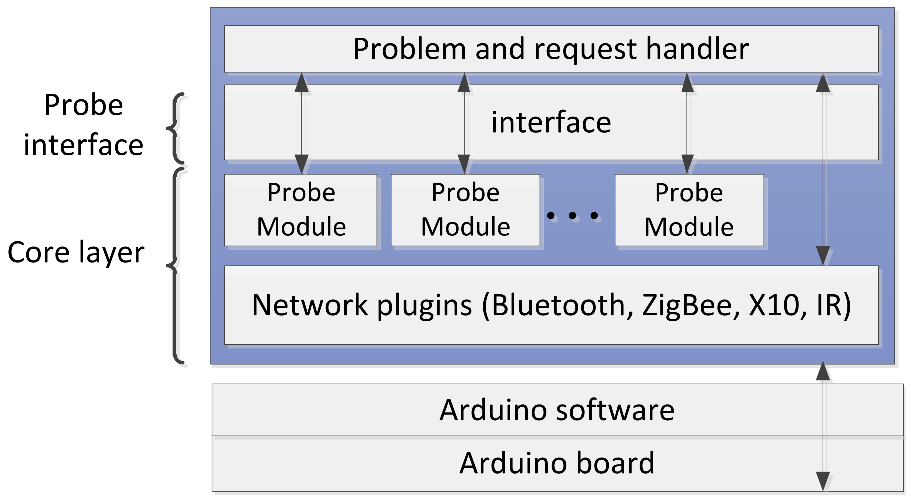
3.4 Implementation

As a proof of concept, we implemented and tested a prototype of a network troubleshooting tool based on the MoT platform. This implementation includes two applications, one for Android devices and the other for computers. The applications communicate via Bluetooth in this example. The algorithm described in Figure 3.3 diagnoses the "Smartphone diagnostics" scenario described in Section 3.3.

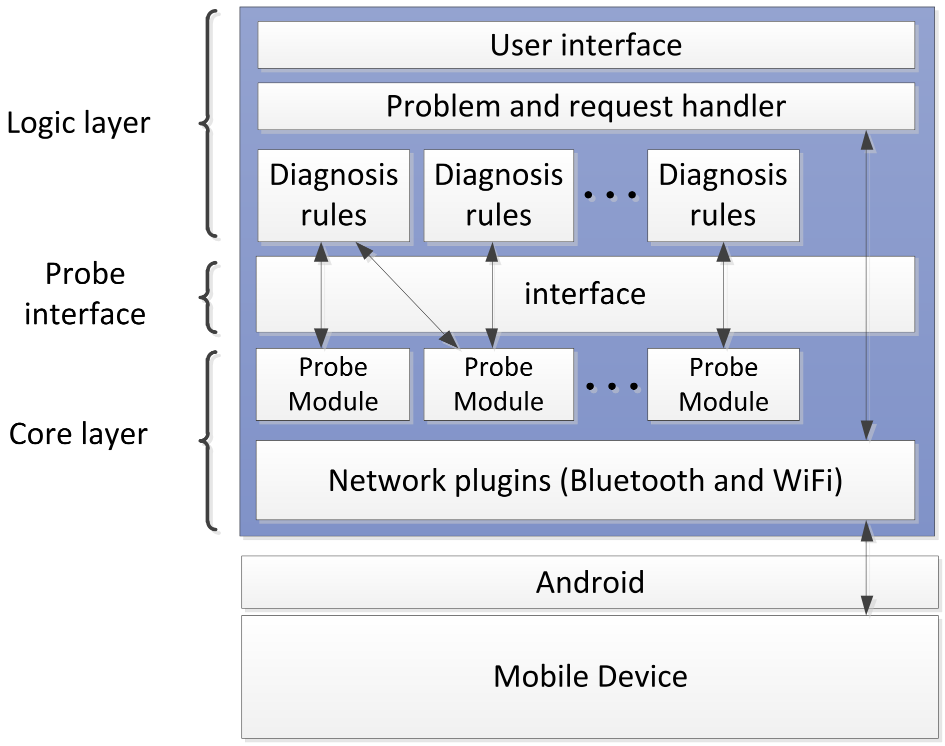
The challenges to implementation are twofold. First, we need to create a framework that is generally applicable to heterogeneous devices. Therefore, it is necessary to have a platform-independent interface. Second, it should be possible to change the diagnostic strategies easily without rewriting software, since the diagnostic logic may be updated frequently. To achieve these goals, we divide the system into two layers (Figure 3.2): the core layer, which is rarely updated, and the logic layer, which can be updated flexibly. These two layers communicate with each other using the probe messages.

We aggregate platform-dependent modules and place these in the core layer to avoid rebuilding the software when diagnostic algorithms are updated. As a result, probe modules (e.g., `ping`, `traceroute`, and the TCP connection checker) and network communication modules (e.g., for Bluetooth and TCP) are included in the core layer since these

[3]For example, http://www.downdetector.com



(a) MoT client for Arduino (microcontroller)



(b) MoT client for Android

Figure 3.2: MoT implementation

functions use the native APIs supported by the underlying platform. Although the modules in the core layer should be developed separately for each type of device, these rarely need to be updated once implemented. The core layer modules that we developed for the Android application include a Bluetooth sender and receiver, a TCP and UDP tester, a DNS tester, and wrappers for traditional tools such as `ping` and `traceroute`.

The logic layer includes diagnostic rules and a user interface. These modules need to be updated frequently, whenever new diagnosis rules are designed. Therefore, a mechanism that dynamically loads and updates new modules is needed.

In the MoT client for Android, we adopt the hybrid-application approach, which is popular with mobile application developers because it makes the development cycle faster and updates easier [29]. Thus, we implement the core layer in the native language of Android (i.e., Java), and the logic layer using web applications (i.e., HTML5 and Javascript). This technology is used to separate core network probing modules from diagnostic rules. As a result, we can independently develop and reuse the logic layer without modifying the original application. Thus, by simply writing HTML files and Javascripts, new rules and user interfaces can be added to the application. As described in Section 3.2, the modules within each layer communicate with each other using messages formatted in JSON that contain the names and parameters of probe functions.

More importantly, another advantage of dividing the system into two layers is that some devices do not need to have both layers. Although our implementation for Android has both layers, the logic layer is not necessarily installed on small devices that have less computing power and no user interface. Figure 3.2a describes the prototype of MoT for such devices, which is implemented on top of the Arduino microcontroller [9]. In this model, the device has only the core layer, which communicates with the logic layer of another device to diagnose its own network problem or help the other device with a diagnosis. The messages used between two layers within the same device are also used across different devices when probe requests and responses are exchanged.

3.5 Evaluation

In Android framework, it is common that Android application servers send messages to the target Android device using Google's messaging services such as Google Cloud Messaging (GCM) or Cloud to Device Messaging (C2DM). These services enable application developers to send messages from their servers to the client applications on the Android devices using HTTP connections [15, 25]. Although a number of Android applications use these services, the users have no good way to diagnose a problem if they suspect that their applications do not receive the notifications properly.

We implemented the Android network diagnostic tool which can determine whether a mobile device is able to receive a push notification correctly. When the push notification system is not functioning properly, there are four possible cases:

- A problem in the GCM or C2DM servers
- A problem with the connection to the ISP
- A problem in the local network
- A non-network problem

We assume that the device is using a Wi-Fi network. To identify the cause of the

```
function PROBE($failure$)
    $D \leftarrow$ the problematic Android device
    Request(C2DM Server, send a message to $D$)
    if $D$ received C2DM message then
        return “A non-network problem”
    else
        $N_e \leftarrow$ an external node
        Request($N_e$ open a TCP port)
        Request($D$, send TCP packets to $N_e$)
        if $D$ successfully sends packets to $N_e$ then
            return “A problem in the GCM or C2DM servers”
        else
            $N_i \leftarrow$ an internal node
            Request($N_i$ open a TCP port)
            Request($D$, send TCP packets to $N_i$)
            if $D$ successfully sends packets to $N_i$ then
                return “A problem with the connection to the ISP”
            else
                return “A problem in the local network”
            end if
        end if
    end if
end function
```

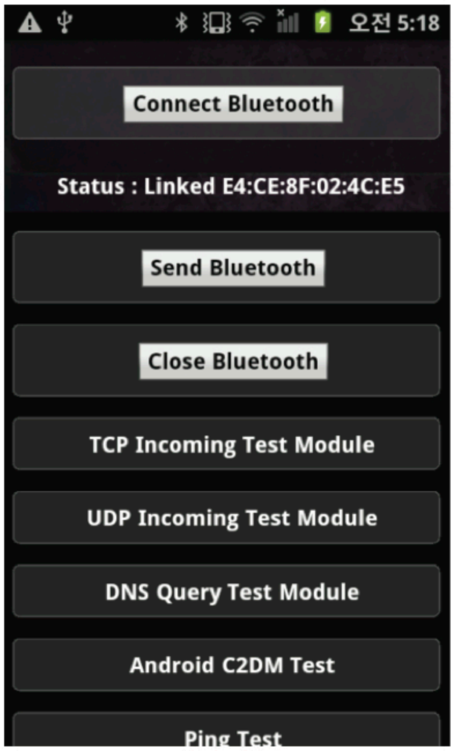
Figure 3.3: Algorithm for the C2DM test

network problem, our Android application first sends a diagnosis request to a laptop via Bluetooth, since we cannot be sure that the Wi-Fi network is functioning correctly in this example. On behalf of the Android device, the laptop runs a diagnostic algorithm (Figure 3.3). First, it requests the Google server to send a push notification to the Android device. If the device fails to receive this notification, the second test is performed to determine whether the device can exchange TCP packets with an external node in the Internet. We use P2P nodes or cloud instances for this test as described in Section 3.2. If this succeeds, we can infer that there is no problem in connecting to the Internet from the device. Then, we attempt to send packets to the device from the laptop to determine whether the local area network is faulty. If everything works but the device still cannot receive the push notification, we can infer that the push notification servers are the cause rather than other networks. We tested the tool using our testbed, which artificially injects local network connectivity faults. Also, we simulated the outage of C2DM servers by using our own servers instead of Google servers in our testbed. The tool successfully distinguished the local network problems from the push notification fault in our testbed. Figure 3.4 shows the screenshots of the tool for Android.

3.6 Related work

A number of researchers have studied home network troubleshooting. As described in Section 1.7, there are many home network diagnostic tools and studies such as HomeNet Profiler, WebProfiler, NetPrints, Deja vu, and WiFiProfiler.

In contrast to the studies above, we have focused on networked home devices in this



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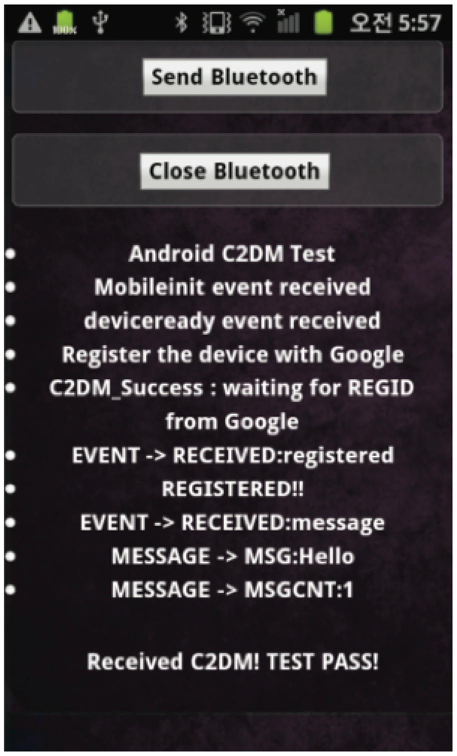
(a) A GUI of test modules



- Android C2DM Test
- Mobileinit event received
- deviceready event received
- Register the device with Google
- C2DM_Success : waiting for REGID from Google
- EVENT -> RECEIVED:registered
- REGISTERED!!
- EVENT -> RECEIVED:message
- MESSAGE -> MSG:Hello
- MESSAGE -> MSGCNT:1

Received C2DM! TEST PASS!

(b) Android C2DM test

Figure 3.4: An MoT application for Android devices

chapter. Since these devices are different from general computers in terms of user interface and computing power, existing studies are unlikely to be applicable for these devices. We adopt the rule system of DYSWIS and its collaborative method, and suggest additional mechanisms to support home devices. Wustner et al. [55] suggested a similar idea as MoT in terms of collaboration of home network devices for troubleshooting network problems. When a user suffers from the low performance of a network, the authors suggested to correlate the different recorded metrics such as RTT, jitter, throughput, and packet retransmission. They determine which metric is related to the poor performance. Our approach shares this idea of cooperation between devices; however, we use real-time probing with predefined diagnostic rules instead of correlating metrics. Thus, our approach does not require devices to record network states. Furthermore, we suggest practical mechanisms such as discovering, forwarding, and probing that support the collaboration of devices effectively.

3.7 Conclusion

We proposed a network troubleshooting system, MoT, which supports the collaboration of home devices (smart objects) and end-user devices such as laptop computers and smartphones. We take advantage that recent devices have multiple communication interfaces. Therefore, when a device has a problem with one interface, it can send a probe request to other devices using an alternative interface. Moreover, we focused on a mobile device that is able to move physically close to other problematic devices and collect problem profiles. Finally, the system adopts collaborative mechanisms to diagnose the root cause of a network problem. It can use cooperation from internal nodes or send requests to external P2P nodes or cloud instances. We demonstrated the feasibility of this approach by implementing an Android application and an algorithm that diagnoses the push notification failure.

Conclusion

This thesis presents three studies focusing on troubleshooting network failures for end users. They include new architecture and algorithms that identify the root causes of failures related to Internet connectivity and poor network performance.

DYSWIS is a framework that supports diagnostic applications for complex network problems using collaboration of end-user machines. We suggested a detailed mechanism to discover and communicate with cooperative peers, built a framework that enables administrators and developers to contribute to the expansion of the diagnostic system, and finally implemented diagnostic tools based on the cooperative probing algorithms and rules. We also demonstrated the ease with which participants could add new rules and modules on top of the framework in order to diagnose common network failures. In our experiments, DYSWIS successfully identifies the root cause in seven out of eleven scenarios.

In addition, this thesis presents WiSlow, a Wi-Fi performance troubleshooting application specialized to detect non-Wi-Fi interference. WiSlow distinguishes 802.11 channel contention from non-Wi-Fi interference and identifies the type of interfering devices present. It is designed to exploit user-level probing only, enabling a software-only approach. WiSlow contains novel diagnostic methods and algorithms which rely on user-accessible packet information. The accuracy of detecting interference sources using WiSlow exceeds 90% when the sources are close to a Wi-Fi device.

Furthermore, inspired by lessons learned from the above studies, we expanded the collaborative approach to the IoT environment and proposed a network diagnosis platform for home devices. This platform takes advantage of the built-in features of new devices such as multiple communication interfaces. When a device has a problem with an interface, it can send a probe request to other devices using an alternative communication interface. As a result, the proposed system is able to use cooperation between both internal devices and remote machines.

The studies presented in this thesis attempt to solve problems in different areas, but share one key concept — machines are able to help each other to diagnose complex network issues. We have designed and built diagnostic tools based on this approach and performed various experiments to show the idea is feasible.

Today, both network infrastructure and consumer products are still evolving rapidly. In the near future, since almost every product will be connected to Internet, technologies that are able to resolve network issues quickly and correctly will become more important. I believe the concepts, system designs, and discussions presented in this thesis contribute to upgrading the Internet by taking one step forward and towards trouble-free networks for end users.

Bibliography

[1] Sharad Agarwal, Nikitas Liogkas, Prashanth Mohan, and Venkata N. Padmanabhan. "WebProfiler: cooperative diagnosis of Web failures." In: *Proc. of COMSNETS*. Bangalore, India, Jan. 2010.

[2] Bhavish Aggarwal, Ranjita Bhagwan, Lorenzo De Carli, Venkat Padmanabhan, and Krishna Puttaswamy. "Deja vu: fingerprinting network problems." In: *Proc. of CoNEXT '11*. Tokyo, Japan, Dec. 2011.

[3] Bhavish Aggarwal, Ranjita Bhagwan, Tathagata Das, Siddharth Eswaran, Venkata N. Padmanabhan, and Geoffrey M. Voelker. "NetPrints: diagnosing home network misconfigurations using shared knowledge." In: *Proc. of NSDI*. Berkeley, CA, USA, Apr. 2009.

[4] *AirMaestro*. `http://www.bandspeed.com/products/products.php`. [Online; accessed May 2013].

[5] *AirSleuth*. `http://nutsaboutnets.com/airsleuth-spectrum-analyzer/`. [Online; accessed May 2013].

[6] Adel Ali, LA Latiff, and Norsheila Fisal. "GPS-free indoor location tracking in mobile ad hoc network (MANET) using RSSI." In: *Proc. of IEEE RFM*. Selangor, Malaysia, Oct. 2004.

[7] A. Amirante, S. P. Romano, K. H. Kim, and H. Schulzrinne. "Online non-intrusive diagnosis of one-way RTP faults in VoIP networks using cooperation." In: *Proc. of IPTComm '10*. Munich, Germany, Oct. 2010.

[8] Apple inc. *Bonjour*. http://www.apple.com/support/bonjour/.

[9] *Arduino*. `http://www.arduino.cc/`. [Online; accessed November 2016].

[10] A. Baid, S. Mathur, I. Seskar, S. Paul, A. Das, and D. Raychaudhuri. "Spectrum MRI: Towards diagnosis of multi-radio interference in the unlicensed band." In: *Proc. of IEEE WCNC*. Quintana-Roo, Mexico, Mar. 2011.

[11] S. Biaz and Shaoen Wu. "Rate adaptation algorithms for IEEE 802.11 networks: A survey and comparison." In: *Proc. of IEEE ISCC*. Marrakech, Morocco, July 2008.

[12] Andreas Binzenhöfer, Kurt Tutschku, Björn auf dem Graben, Markus Fiedler, and Patrik Arlos. "A P2P-Based Framework for Distributed Network Management." In: *Proc. of EuroNGI Workshop*. Villa Vigoni, Italy, July 2005.

[13] O. Boyaci, V. Beltran, and Henning Schulzrinne. "Bridging communications and the physical world: Sense Everything, Control Everything." In: *Proc. of GLOBECOM Workshops '10*. Florida, USA, Dec. 2010.

[14] E. Bozdag, A. Mesbah, and A. van Deursen. "A Comparison of Push and Pull Techniques for AJAX." In: *Proc. of WSE 2007*. Paris, France, Oct. 2007.

[15] *C2DM*. `https://developers.google.com/android/c2dm/`. [Online; accessed Sep 2013].

[16] Ranveer Chandra, Venkata N. Padmanabhan, and Ming Zhang. "WiFiProfiler: Cooperative diagnosis in wireless LANs." In: *Proc. of MobiSys*. Uppsala, Sweden, June 2006.

[17] David R. Choffnes, Fabian E. Bustamante, and Zihui Ge. "Crowdsourcing service-level network event monitoring." In: *Proceedings of ACM SIGCOMM*. New Delhi, India, Sept. 2010.

[18] Cisco. *20 Myths of Wi-Fi Interference*. White Paper, `http://goo.gl/E2Qmib`. [Online; accessed April 2017].

[19] Heng Cui and Ernst Biersack. "Trouble shooting interactive Web sessions in a home environment." In: *Proc. of HomeNets*. Toronto, Ontario, Canada, Aug. 2011.

[20] L. DiCioccio, R. Teixeira, and C. Rosenberg. "Measuring home networks with homenet profiler." In: *Proc. of PAM*. Hong Kong, China, Mar. 2013.

[21] *Digital Enhanced Cordless Telecommunications*. `http://www.etsi.org/technologies-clusters/technologies/dect`. [Online; accessed April 2017].

[22] Marcel Dischinger, Massimiliano Marcon, Saikat Guha, P. Krishna Gummadi, Ratul Mahajan, and Stefan Saroiu. "Glasnost: Enabling End Users to Detect Traffic Differentiation." In: *Proceedings of NSDI*. San Jose, CA, USA, Apr. 2010.

[23] Changyu Dong and Naranker Dulay. "Argumentation-based fault diagnosis for home networks." In: *Proc. of HomeNets*. Toronto, Ontario, Canada, Aug. 2011.

[24] Philip Eardley, Al Morton, Marcelo Bagnulo, Trevor Burbridge, Paul Aitken, and Aamer Akhter. *A Framework for Large-Scale Measurement of Broadband Performance (LMAP)*. RFC 7594. Sept. 2015. DOI: `10.17487/rfc7594`. URL: `https://rfc-editor.org/rfc/rfc7594.txt`.

[25] *GCM*. `http://developer.android.com/google/gcm/`. [Online; accessed November 2016].

[26] Shyamnath Gollakota, Fadel Adib, Dina Katabi, and Srinivasan Seshan. "Clearing the RF smog: making 802.11n robust to cross-technology interference." In: *Proc. of ACM SIGCOMM*. Toronto, Ontario, Canada, Aug. 2011.

[27] Jeffrey Hightower, Roy Want, and Gaetano Borriello. "SpotON: An indoor 3D location sensing technology based on RF signal strength." In: *Technical Report, UW CSE 00-02-02, University of Washington, Seattle, WA* (2000).

[28] *HomeNet Manager*. `http://www.homenetmanager.com/`. [Online; accessed Dec 2013].

[29] *Hybrid Apps*. `http://www.nngroup.com/articles/mobile-native-apps/`. [Online; accessed November 2016].

[30] A. Kamerman and N. Erkocevic. "Microwave oven interference on wireless LANs operating in the 2.4 GHz ISM band." In: *Proc. of PIMRC*. Helsinki, Finland, Sept. 1997.

[31] Partha Kanuparthy, Constantine Dovrolis, Konstantina Papagiannaki, Srinivasan Seshan, and Peter Steenkiste. "Can user-level probing detect and diagnose common home-WLAN pathologies." In: *Computer Communication Review* 42.1 (2012), pp. 7–15.

[32] Kyung-Hwa Kim, Hyunwoo Nam, and Henning Schulzrinne. "WiSlow: A Wi-Fi Network Performance Troubleshooting Tool for End Users." In: *Proc. of IEEE INFOCOM*. Toronto, Canada, Apr. 2014.

[33] Kyung-Hwa Kim, Hyunwoo Nam, Vishal Singh, Daniel Song, and Henning Schulzrinne. "DYSWIS: Crowdsourcing a Home Network Diagnosis." In: *Proc. of ICCCN*. Shanghai, China, Aug. 2014.

[34] Kyung-Hwa Kim, Hyunwoo Nam, Jin-Hyung Park, and Henning Schulzrinne. "MoT: A Collaborative Network Troubleshooting Platform for the Internet of Things." In: *Proc. of IEEE WCNC*. Istanbul, Turkey, Apr. 2014.

[35] Ratul Mahajan, Neil Spring, David Wetherall, and Thomas Anderson. "User-level internet path diagnosis." In: *Proceedings of ACM SOSP*. New York, NY, USA, Oct. 2003.

[36] Frank J Massey Jr. "The Kolmogorov-Smirnov test for goodness of fit." In: *Journal of the American statistical Association* 46.253 (1951), pp. 68–78.

[37] Hyunwoo Nam, Bong Ho Kim, Doru Calin, and Henning Schulzrinne. "Mobile Video is Inefficient: A Traffic Analysis." In: *Columbia Technical Report cucs-018-13.* June 2013.

[38] *Network Magic Pro.* `http://tinyurl.com/n6hh7ka`. [Online; accessed Dec 2013].

[39] *Network diagnostics in Windows 7.* `https://technet.microsoft.com/en-us/library/ff625276.aspx`. [Online; accessed November 2016].

[40] OSGi Alliance. *OSGi.* http://www.osgi.org/Main/HomePage.

[41] *PlanetLab.* `https://www.planet-lab.org/` . [Online; accessed Jan 2014].

[42] B Pourebrahimi, K Bertels, and S Vassiliadis. "A survey of peer-to-peer networks." In: *Proc. of ProRisc.* Veldhoven, The Netherlands, Nov. 2005.

[43] *Radiotap.* `http://www.radiotap.org/`. [Online; accessed May 2013].

[44] Shravan Rayanchu, Ashish Patro, and Suman Banerjee. "Airshark: Detecting non-WiFi RF Devices Using Commodity WiFi Hardware." In: *Proc. of ACM IMC.* Berlin, Germany, Nov. 2011.

[45] Shravan Rayanchu, Ashish Patro, and Suman Banerjee. "Catching Whales and Minnows Using WiFiNet: Deconstructing non-WiFi Interference Using WiFi Hardware." In: *Proc. of USENIX NSDI.* San Jose, CA, USA, Apr. 2012.

[46] Mario A. Sánchez, John S. Otto, Zachary S. Bischof, David R. Choffnes, Fabián E. Bustamante, Balachander Krishnamurthy, and Walter Willinger. "Dasu: Pushing Experiments to the Internet's Edge." In: *Proc. of NSDI.* Lombard, IL, Apr. 2013.

[47] Srikanth Sundaresan, Nick Feamster, and Renata Teixeira. "Home Network or Access Link? Locating Last-mile Downstream Throughput Bottlenecks." In: *Proc. of PAM.* Heraklion, Greece, Mar. 2016.

[48] Srikanth Sundaresan, Yan Grunenberger, Nick Feamster, Dina Papagiannaki, Dave Levin, and Renata Teixeira. "WTF? Locating Performance Problems in Home Networks." In: *SCS Technical Report GT-CS-13-03.* June 2013.

[49] *Ten myths of Wi-Fi interference.* `http://searchmobilecomputing.techtarget.com/feature/Ten-myths-of-Wi-Fi-interference`. [Online; accessed November 2016].

[50] Guido Urdaneta, Guillaume Pierre, and Maarten Van Steen. "A survey of DHT security techniques." In: *ACM Comput. Surv.* 43.2 (Feb. 2011), 8:1–8:49. ISSN: 0360-0300. DOI: `10.1145/1883612.1883615`.

[51] Angelos Vlavianos, Lap Kong Law, Ioannis Broustis, Srikanth V. Krishnamurthy, and Michalis Faloutsos. "Assessing link quality in IEEE 802.11 Wireless Networks: Which is the right metric?" In: *Proc. of PIMRC*. Cannes, France, Sept. 2008.

[52] *WLAN packet capture*. `http://wiki.wireshark.org/CaptureSetup/WLAN`. [Online; accessed May 2013].

[53] *Wi-Spy*. `http://www.metageek.net/`. [Online; accessed November 2016].

[54] *Windows Native WiFi API*. `https://msdn.microsoft.com/en-us/library/windows/desktop/dd439487(v=vs.85).aspx`. [Online; accessed April 2017].

[55] Stéphane Wustner, Diana Joumblatt, Renata Teixeira, and Jaideep Chandrashekar. "Automated home network troubleshooting with device collaboration." In: *Proc. of CoNEXT Student '12*. Nice, France, Dec. 2012.

[56] G.V. Zaruba, M. Huber, F.A. Kamangar, and I. Chlamtac. "Indoor location tracking using RSSI readings from a single Wi-Fi access point." In: *Wireless Networks* 13.2 (Apr. 2007), pp. 221–235. ISSN: 1022-0038.

[57] Ying Zhang, Zhuoqing Morley Mao, and Ming Zhang. "Effective Diagnosis of Routing Disruptions from End Systems." In: *Proceedings of NSDI*. San Francisco, CA, USA, Apr. 2008.