US009104871B2

(12) **United States Patent**
Tuvell et al.

(10) **Patent No.: US 9,104,871 B2**
(45) **Date of Patent: Aug. 11, 2015**

(54) **MALWARE DETECTION SYSTEM AND METHOD FOR MOBILE PLATFORMS**

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(*) Notice: Subject to any disclaimer, the term of this patent is extended or adjusted under 35 U.S.C. 154(b) by 1486 days.

(21) Appl. No.: **11/697,647**

(22) Filed: **Apr. 6, 2007**

(65) **Prior Publication Data**

US 2007/0240218 A1 Oct. 11, 2007

Related U.S. Application Data

(60) Provisional application No. 60/789,766, filed on Apr. 6, 2006, provisional application No. 60/789,748, filed on Apr. 6, 2006, provisional application No. 60/789,749, filed on Apr. 6, 2006, provisional application No. 60/789,746, filed on Apr. 6, 2006, provisional application No. 60/789,744, filed on Apr. 6, 2006, provisional application No. 60/789,745, filed on Apr. 6, 2006, provisional application No. 60/789,743, filed on Apr. 6, 2006, provisional application No. 60/789,958, filed on Apr. 6, 2006, provisional application No. 60/824,649, filed on Sep. 6, 2006, provisional application No. 60/828,491, filed on Oct. 6, 2006.

(51) **Int. Cl.**

G06F 12/14	(2006.01)
G06F 21/56	(2013.01)
H04L 29/06	(2006.01)
H04W 12/12	(2009.01)
H04W 12/10	(2009.01)

(52) **U.S. Cl.**

CPC ***G06F 21/566*** (2013.01); ***G06F 21/56*** (2013.01); ***G06F 21/562*** (2013.01); ***G06F 21/563*** (2013.01); ***G06F 21/564*** (2013.01); ***G06F 21/565*** (2013.01); ***H04L 63/145*** (2013.01); ***H04L 63/1441*** (2013.01); ***H04W 12/12*** (2013.01); *H04W 12/10* (2013.01)

(58) **Field of Classification Search**

CPC G06F 21/56; G06F 21/262; G06F 21/563; G06F 21/564

USPC 726/9, 26, 27, 28, 29; 709/224, 201, 709/212, 213, 220, 223; 707/E17.014, 707/E17.002, 769; 719/318, 330; 380/270, 380/255, 247

See application file for complete search history.

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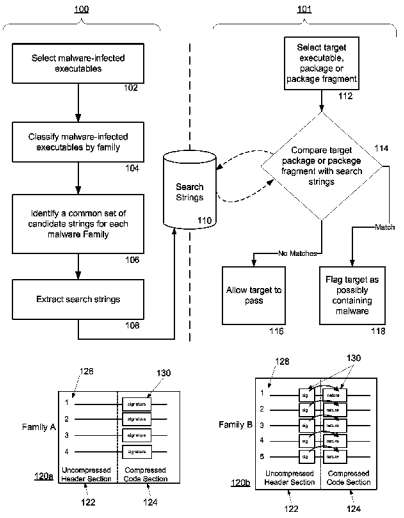
(57) **ABSTRACT**

A system and method for detecting malware optimized for mobile platforms. The system and method compares hashed portions of one or more malware signatures to hashes hashed from a suspect application, to determine whether the suspect application is malware-free. A second stage robust hash and splatter set of pseudorandomly selected blocks of the malware signatures reduce false positives allowing for improved detection of malware.

16 Claims, 13 Drawing Sheets



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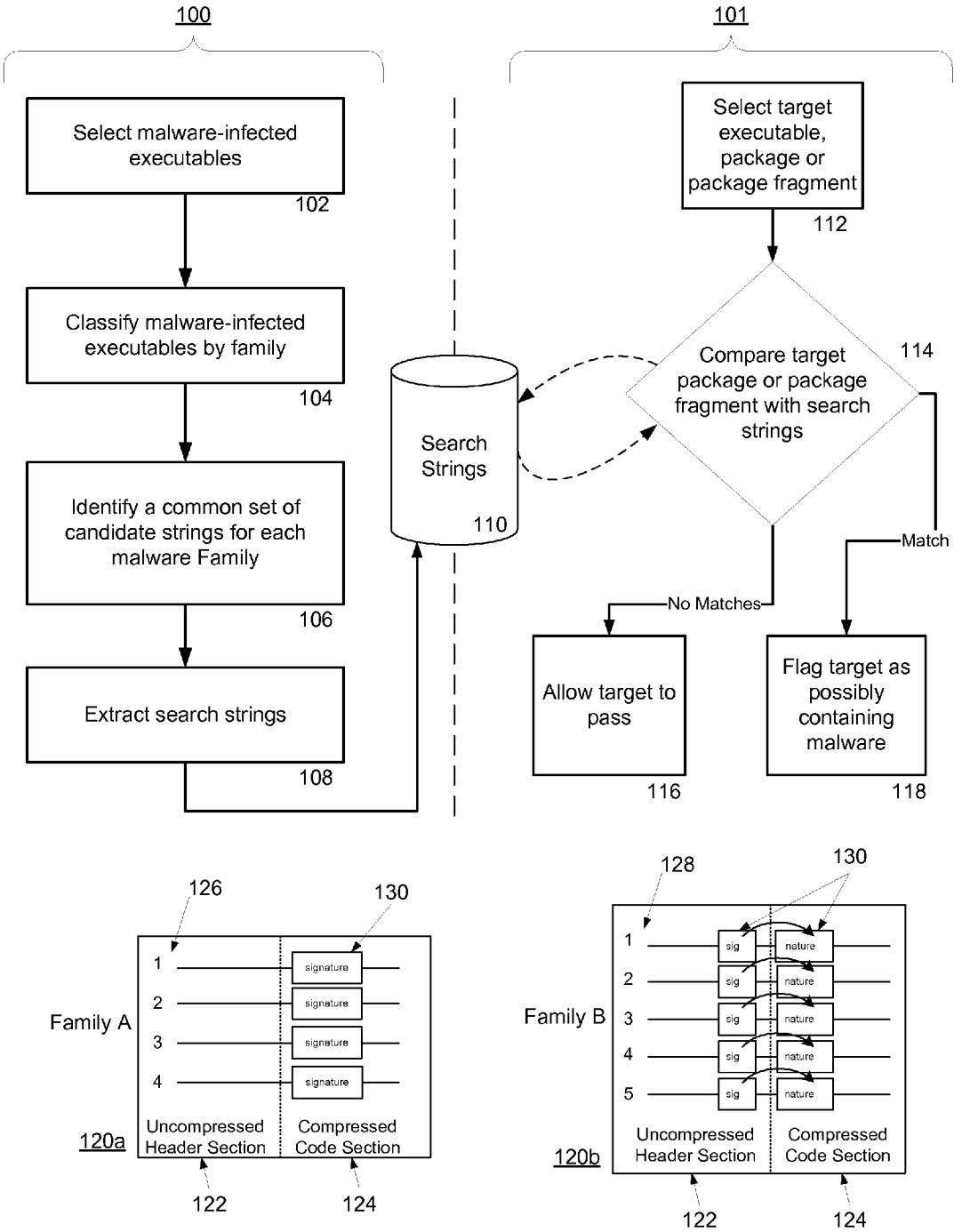

100
101
Select malware-infected executables
102
Classify malware-infected executables by family
104
Identify a common set of candidate strings for each malware Family
106
Extract search strings
108
Search Strings
110
Select target executable, package or package fragment
112
Compare target package or package fragment with search strings
114
Match
No Matches
Allow target to pass
116
Flag target as possibly containing malware
118
126
130
Family A
signature
120a
Uncompressed Header Section
Compressed Code Section
122
124
128
130
Family B
sig
nature
120b
Uncompressed Header Section
Compressed Code Section
122
124

Fig. 1

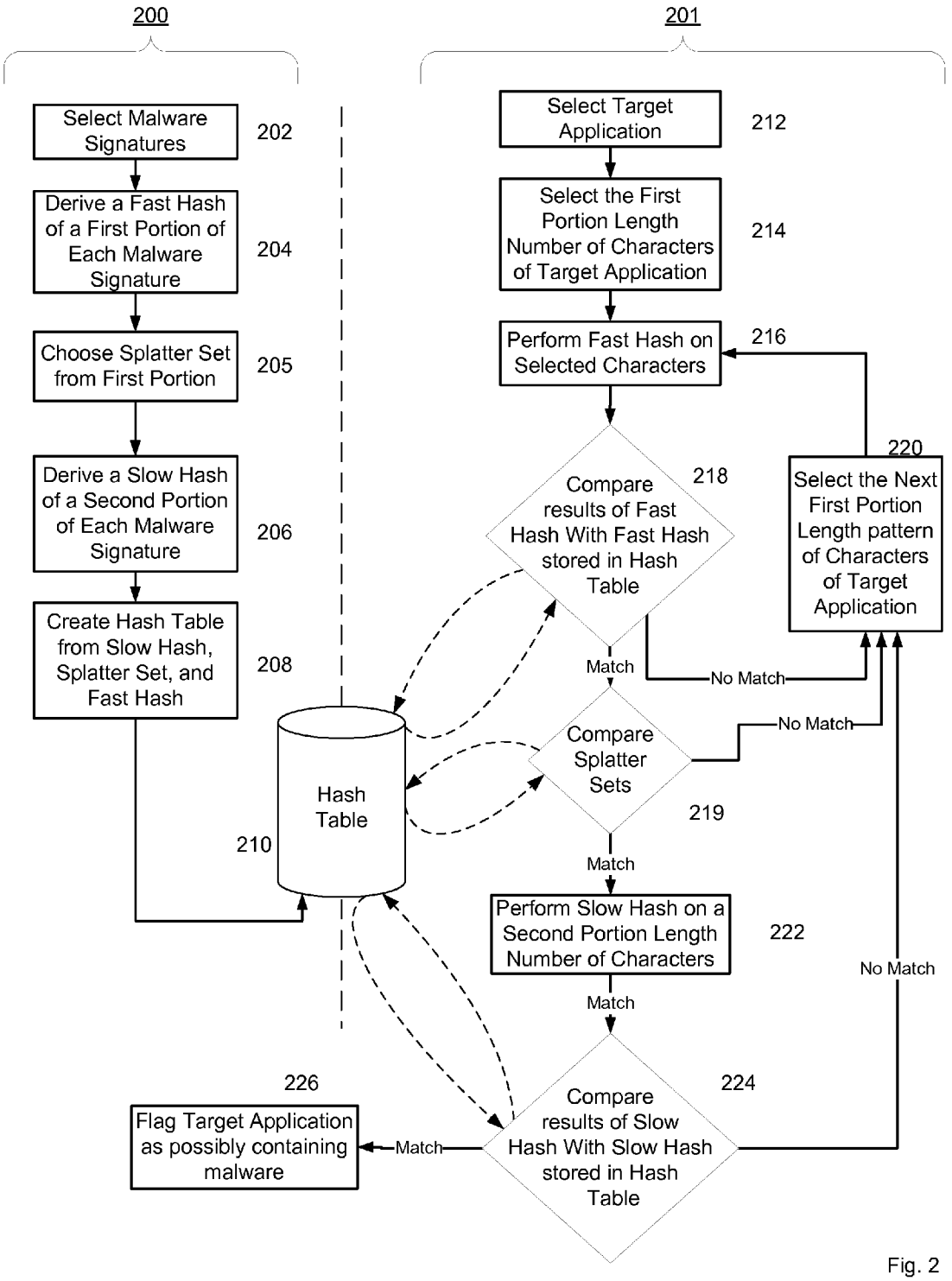

200
201
Select Malware Signatures
202
Derive a Fast Hash of a First Portion of Each Malware Signature
204
Choose Splatter Set from First Portion
205
Derive a Slow Hash of a Second Portion of Each Malware Signature
206
Create Hash Table from Slow Hash, Splatter Set, and Fast Hash
208
Hash Table
210
Select Target Application
212
Select the First Portion Length Number of Characters of Target Application
214
Perform Fast Hash on Selected Characters
216
Compare results of Fast Hash With Fast Hash stored in Hash Table
218
Select the Next First Portion Length pattern of Characters of Target Application
220
Match
No Match
Compare Splatter Sets
219
No Match
Match
Perform Slow Hash on a Second Portion Length Number of Characters
222
No Match
Match
Compare results of Slow Hash With Slow Hash stored in Hash Table
224
Match
Flag Target Application as possibly containing malware
226

Fig. 2

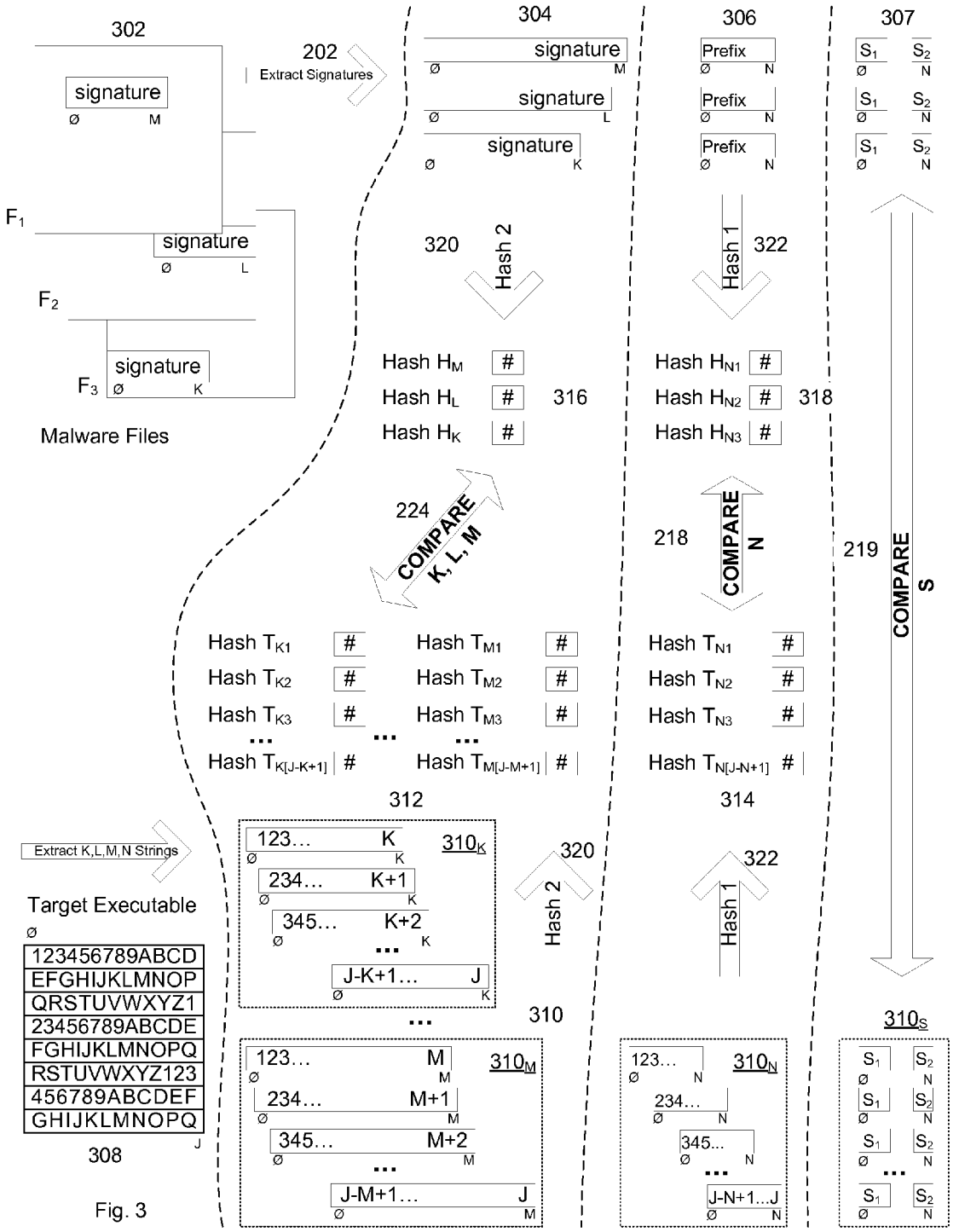

302
signature
Ø M
F1
signature
Ø L
F2
signature
F3 Ø K
Malware Files
202
Extract Signatures
304
signature
signature
signature
306
Prefix
Prefix
Prefix
307
S1 S2
320
Hash 2
322
Hash 1
Hash HM #
Hash HL # 316
Hash HK #
Hash HN1 #
Hash HN2 # 318
Hash HN3 #
224
COMPARE K, L, M
218
COMPARE N
219
COMPARE S
Hash TK1 #
Hash TK2 #
Hash TK3 #
Hash TK[J-K+1] #
Hash TM1 #
Hash TM2 #
Hash TM3 #
Hash TM[J-M+1] #
Hash TN1 #
Hash TN2 #
Hash TN3 #
Hash TN[J-N+1] #
312
314
Extract K,L,M,N Strings
Target Executable
123456789ABCD
EFGHIJKLMNOP
QRSTUVWXYZ1
23456789ABCDE
FGHIJKLMNOPQ
RSTUVWXYZ123
456789ABCDEF
GHIJKLMNOPQ
308
123… K
234… K+1
345… K+2
J-K+1… J
310K
310
123… M
234… M+1
345… M+2
J-M+1… J
310M
123…
234…
345...
J-N+1...J
310N
310S

Fig. 3

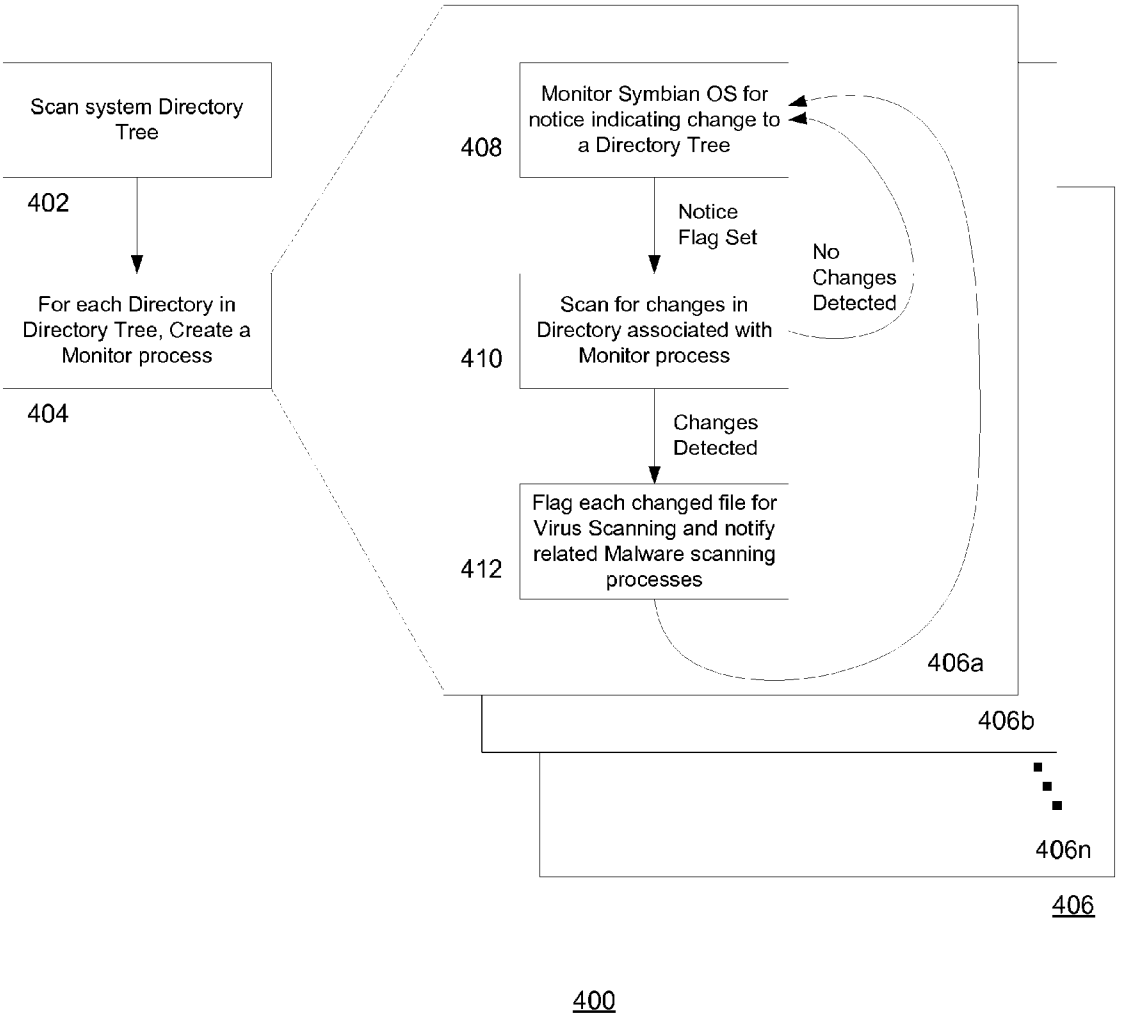

Scan system Directory Tree
402
For each Directory in Directory Tree, Create a Monitor process
404
Monitor Symbian OS for notice indicating change to a Directory Tree
408
Notice Flag Set
Scan for changes in Directory associated with Monitor process
410
No Changes Detected
Changes Detected
Flag each changed file for Virus Scanning and notify related Malware scanning processes
412
406a
406b
406n
406
400

Fig. 4

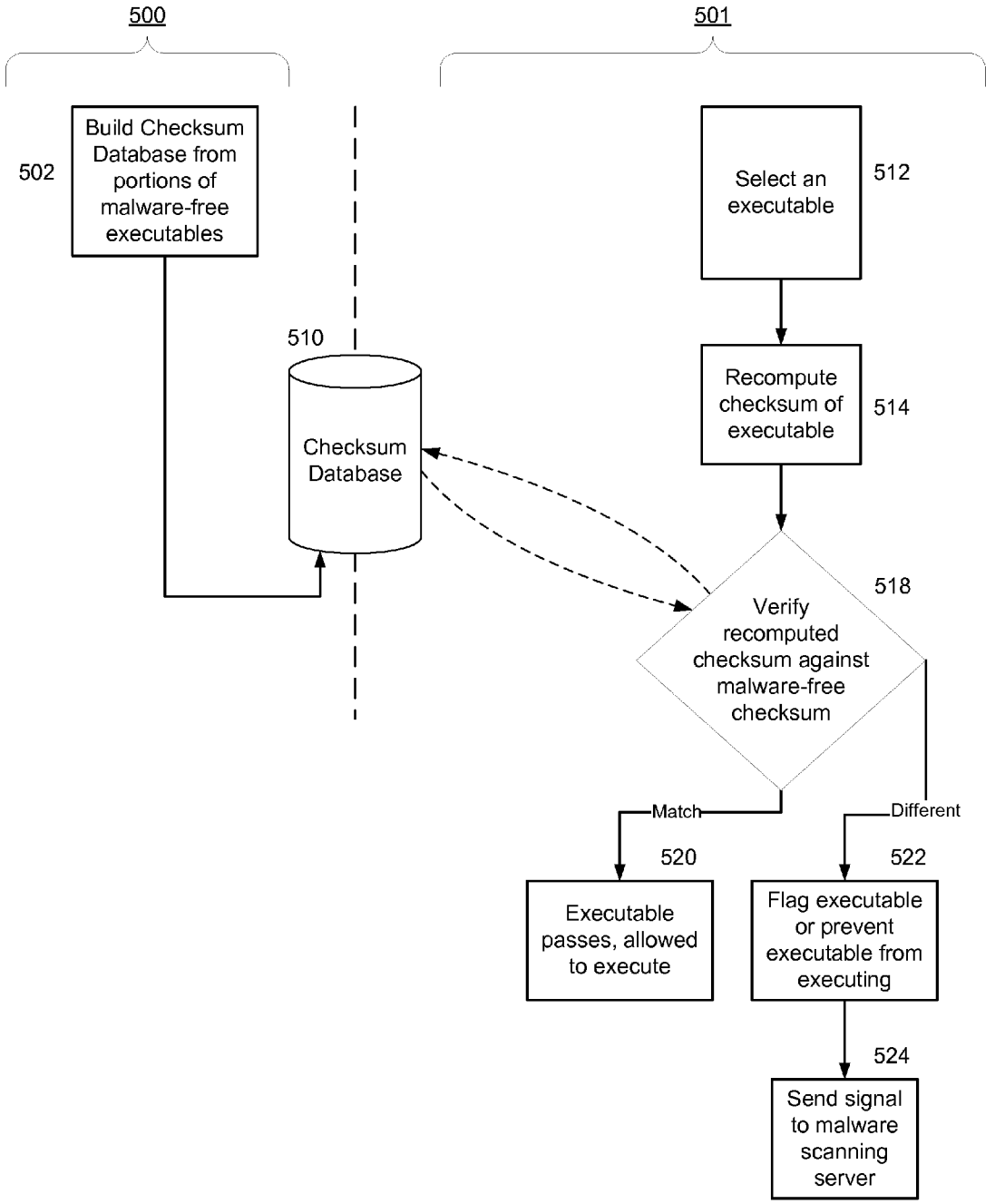

500
501
502
Build Checksum Database from portions of malware-free executables
510
Checksum Database
Select an executable
512
Recompute checksum of executable
514
Verify recomputed checksum against malware-free checksum
518
Match
Different
520
Executable passes, allowed to execute
522
Flag executable or prevent executable from executing
524
Send signal to malware scanning server

Fig. 5

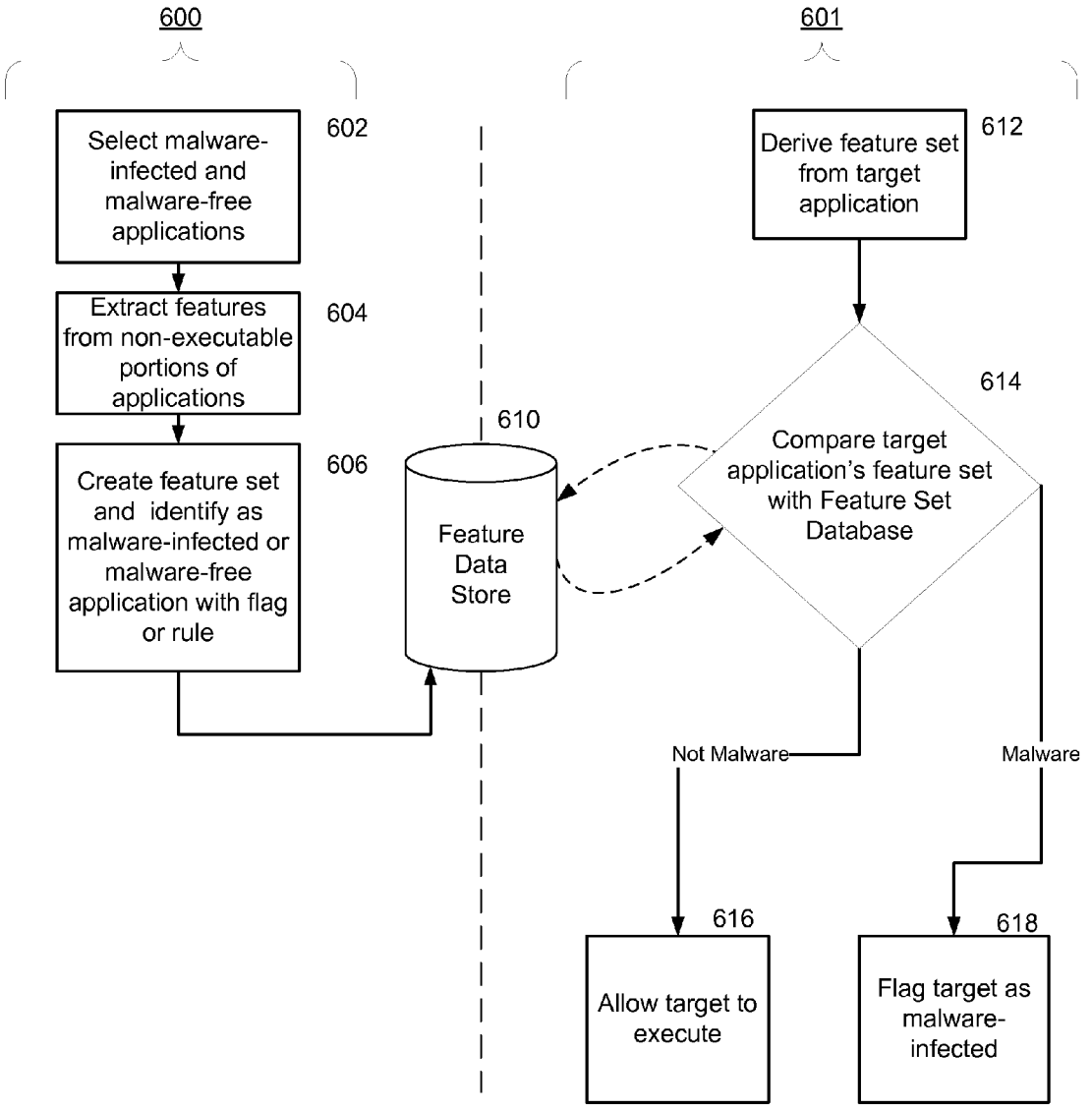

600
601
Select malware-infected and malware-free applications
602
Extract features from non-executable portions of applications
604
Create feature set and identify as malware-infected or malware-free application with flag or rule
606
610
Feature Data Store
Derive feature set from target application
612
614
Compare target application's feature set with Feature Set Database
Not Malware
Malware
616
Allow target to execute
618
Flag target as malware-infected

Fig. 6

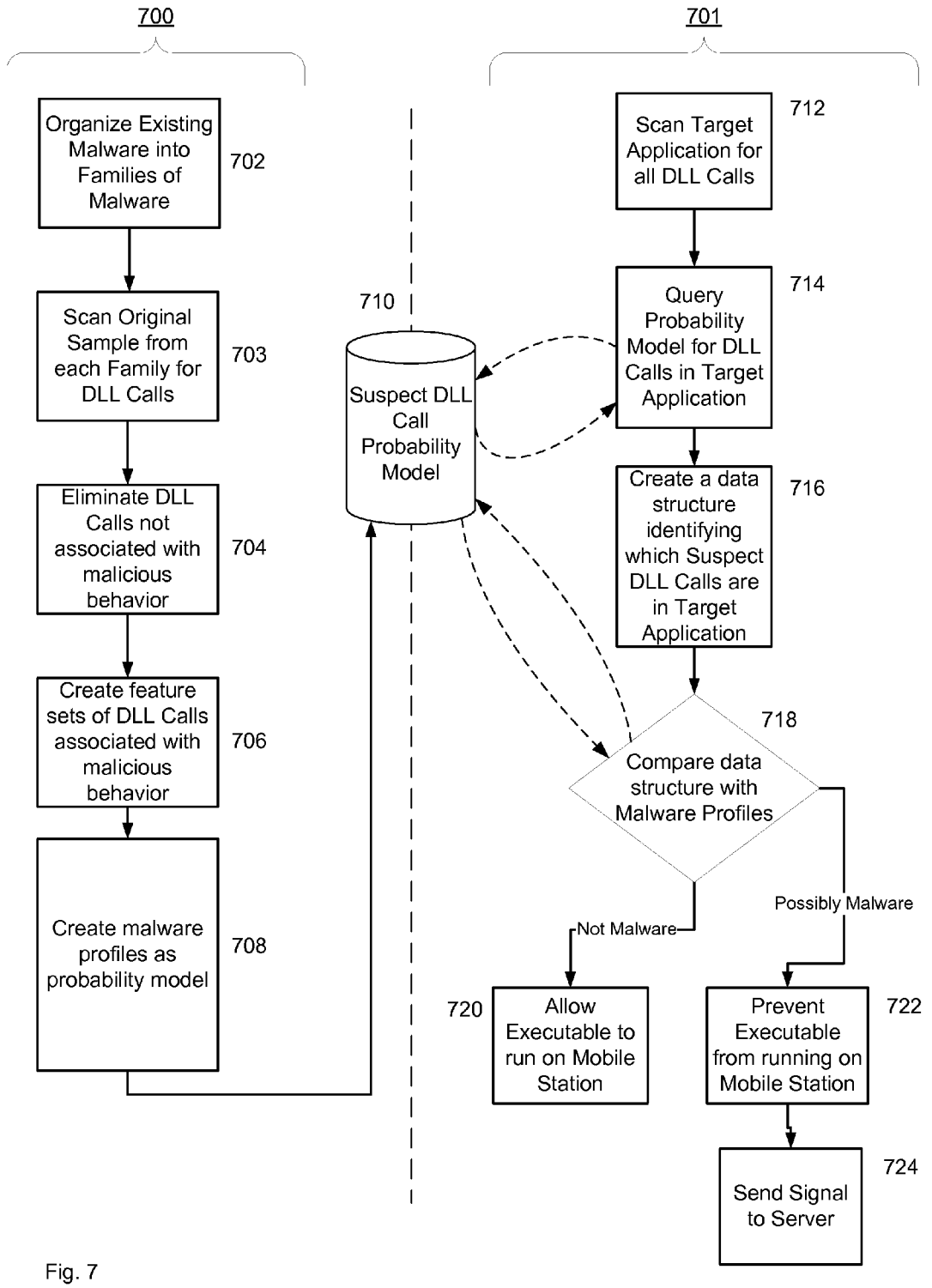

700
701
Organize Existing Malware into Families of Malware
702
Scan Original Sample from each Family for DLL Calls
703
Eliminate DLL Calls not associated with malicious behavior
704
Create feature sets of DLL Calls associated with malicious behavior
706
Create malware profiles as probability model
708
710
Suspect DLL Call Probability Model
Scan Target Application for all DLL Calls
712
Query Probability Model for DLL Calls in Target Application
714
Create a data structure identifying which Suspect DLL Calls are in Target Application
716
Compare data structure with Malware Profiles
718
Not Malware
Possibly Malware
720
Allow Executable to run on Mobile Station
Prevent Executable from running on Mobile Station
722
Send Signal to Server
724

Fig. 7

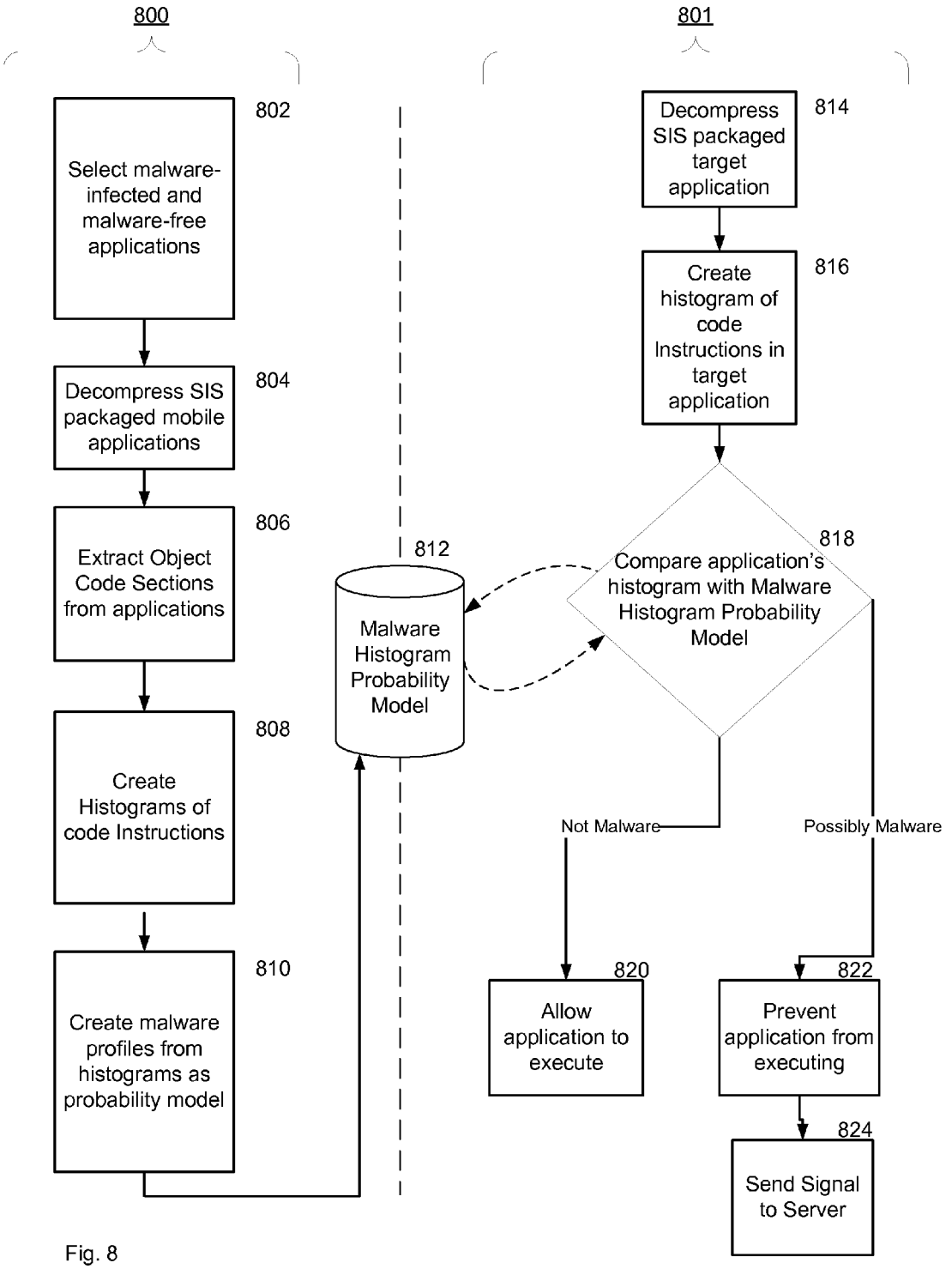

800
801
802
Select malware-infected and malware-free applications
804
Decompress SIS packaged mobile applications
806
Extract Object Code Sections from applications
808
Create Histograms of code Instructions
810
Create malware profiles from histograms as probability model
812
Malware Histogram Probability Model
814
Decompress SIS packaged target application
816
Create histogram of code Instructions in target application
818
Compare application's histogram with Malware Histogram Probability Model
Not Malware
Possibly Malware
820
Allow application to execute
822
Prevent application from executing
824
Send Signal to Server

Fig. 8

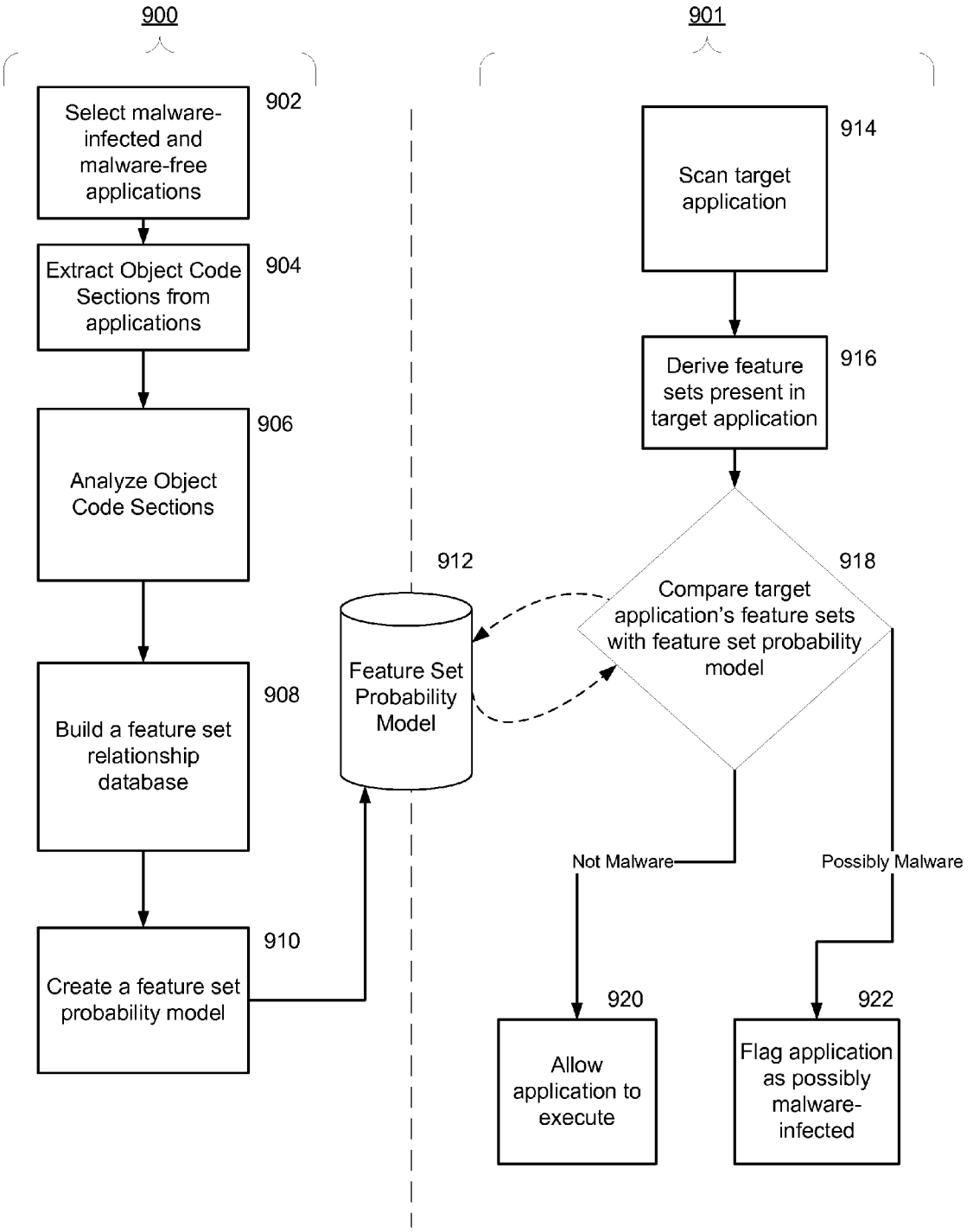

900
901
Select malware-infected and malware-free applications
902
Extract Object Code Sections from applications
904
Analyze Object Code Sections
906
Build a feature set relationship database
908
Create a feature set probability model
910
Feature Set Probability Model
912
Scan target application
914
Derive feature sets present in target application
916
Compare target application's feature sets with feature set probability model
918
Not Malware
Possibly Malware
Allow application to execute
920
Flag application as possibly malware-infected
922

Fig. 9

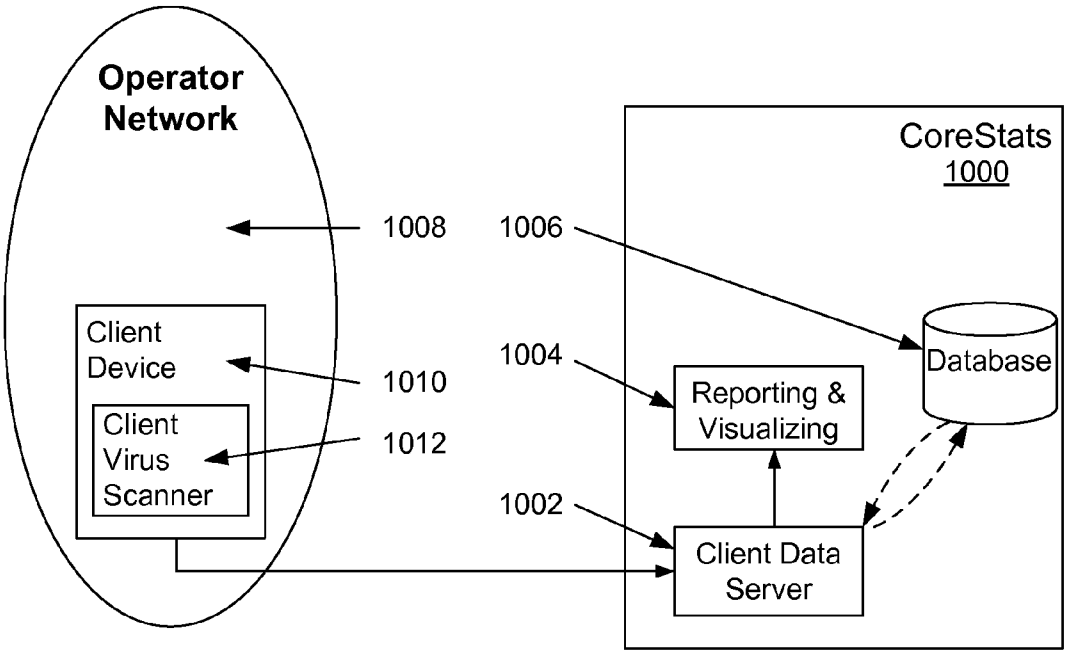


Fig. 10a

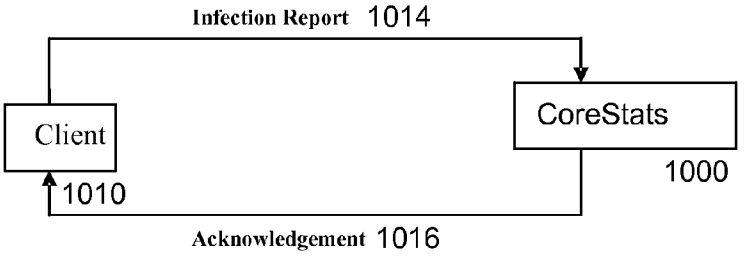
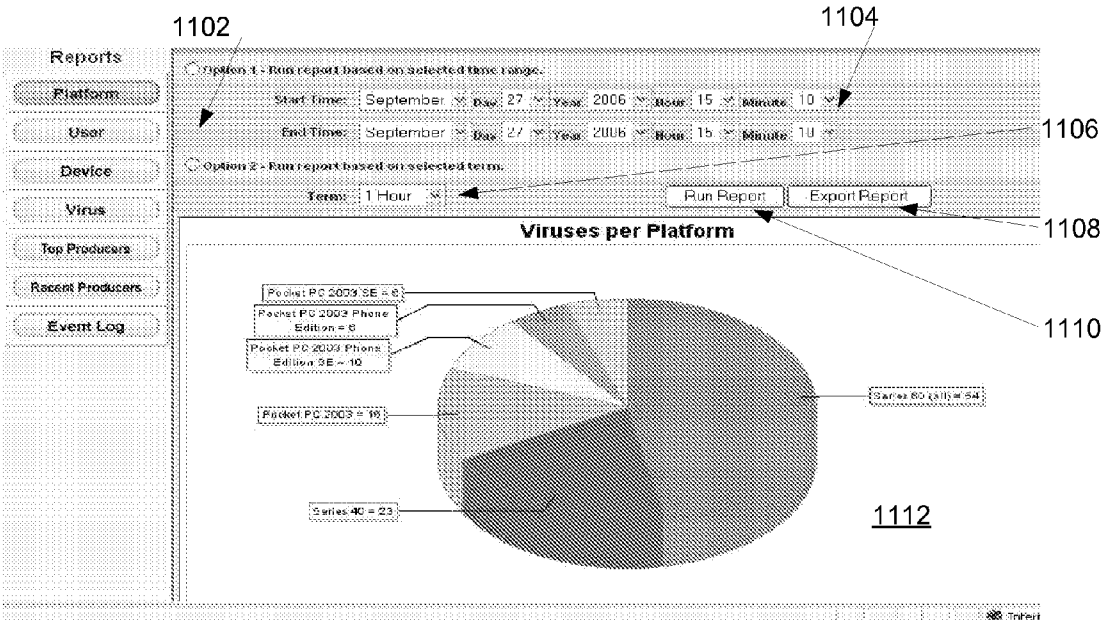
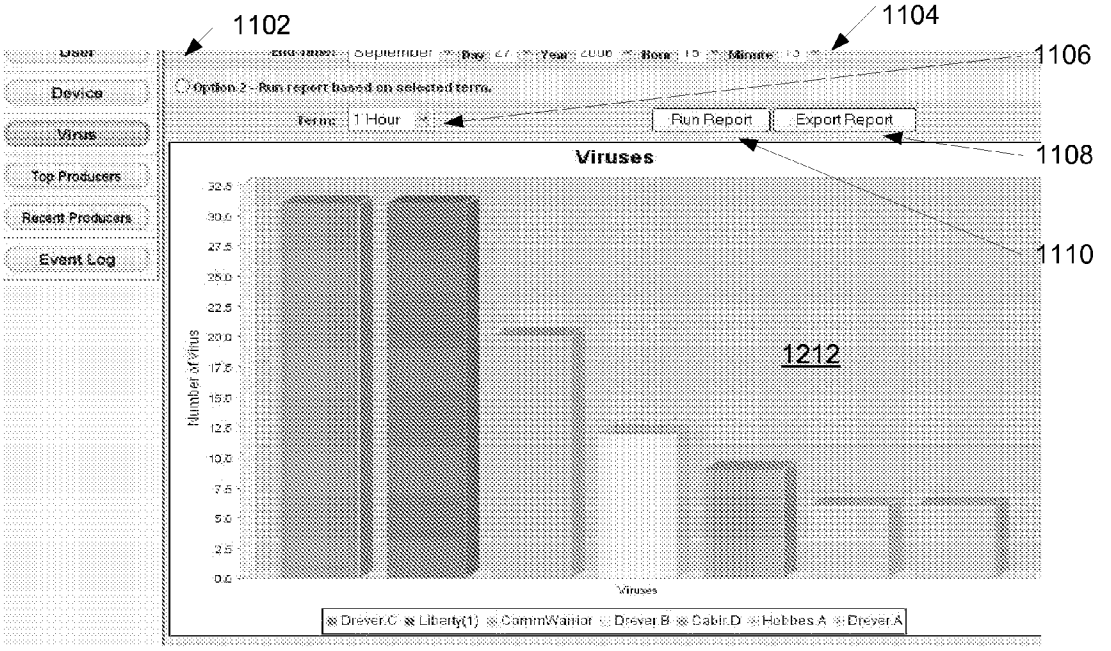


Fig. 10b



1100

Fig. 11



1200

Fig. 12

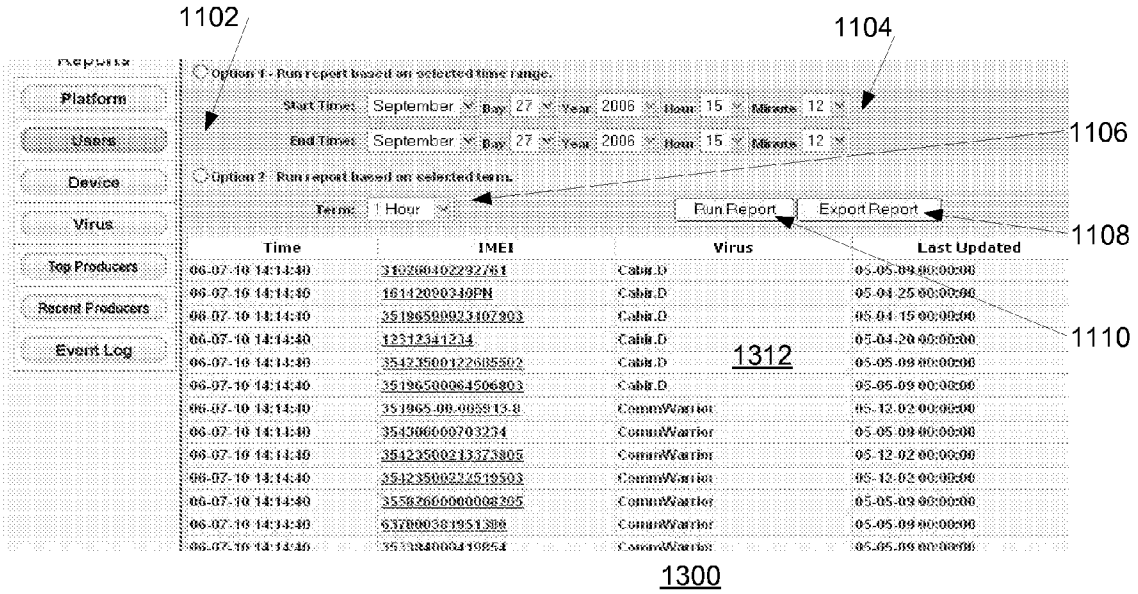

1102
1104
1106
1108
1110
1312
1300
Platform
Users
Device
Virus
Top Producers
Recent Producers
Event Log
Option 1 - Run report based on selected time range.
Start Time: September Day 27 Year 2006 Hour 15 Minute 12
End Time: September Day 27 Year 2006 Hour 15 Minute 12
Option 2 - Run report based on selected term.
Term: 1 Hour
Run Report
Export Report
Time
IMEI
Virus
Last Updated

Fig. 13

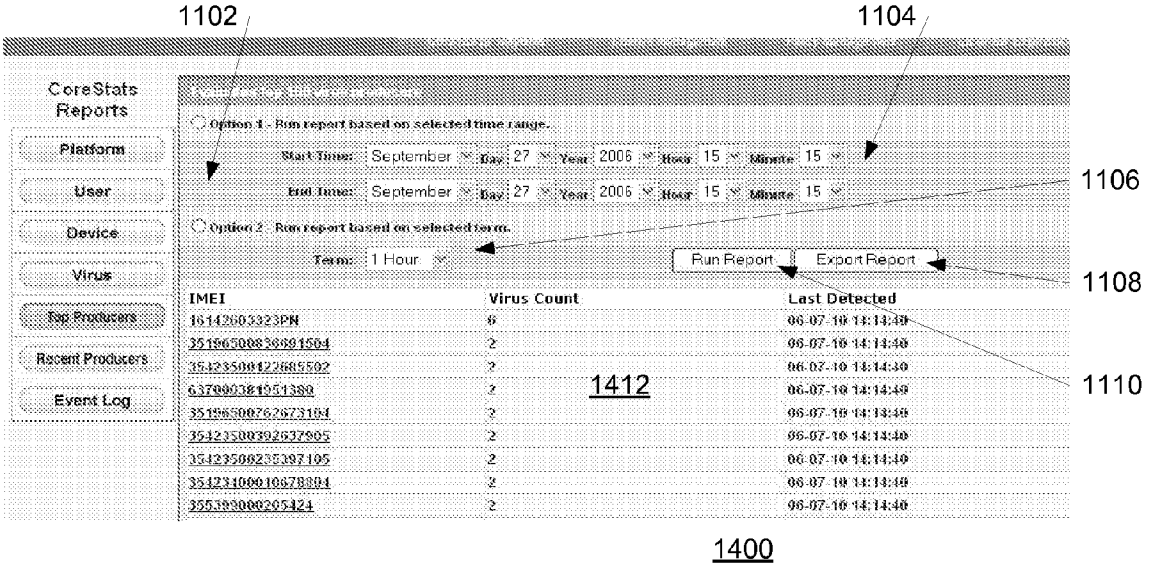

1102
1104
1106
1108
1110
1412
1400
CoreStats Reports
Platform
User
Device
Virus
Top Producers
Recent Producers
Event Log
Option 1 - Run report based on selected time range.
Start Time: September Day 27 Year 2006 Hour 15 Minute 15
End Time: September Day 27 Year 2006 Hour 15 Minute 15
Option 2 - Run report based on selected term.
Term: 1 Hour
Run Report
Export Report
IMEI
Virus Count
Last Detected

Fig. 14

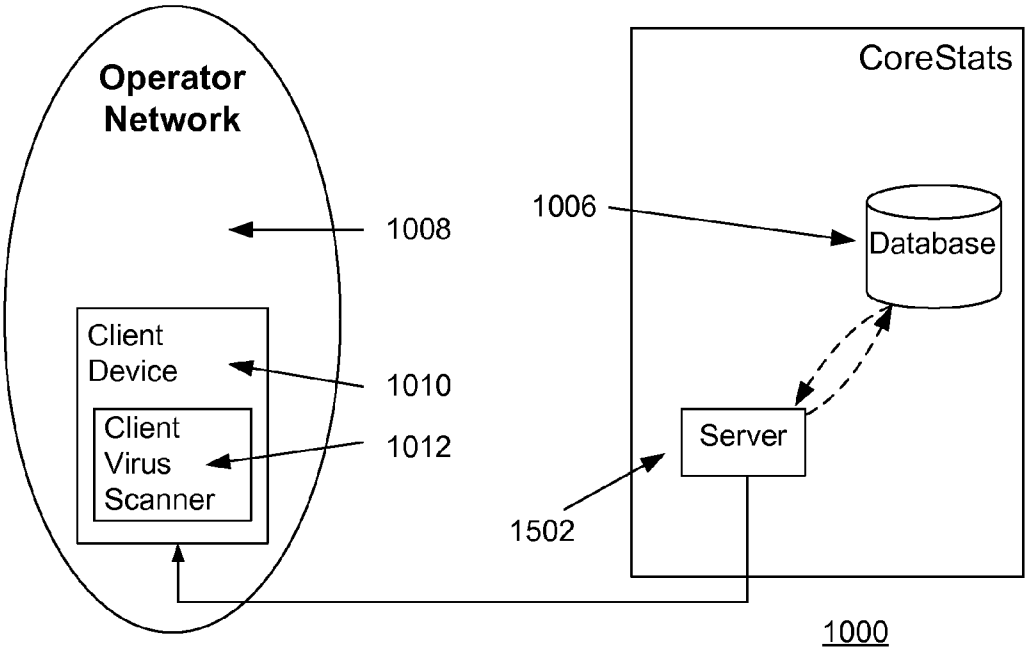

Operator Network
CoreStats
1006
Database
1008
Client Device
1010
Client Virus Scanner
1012
Server
1502
1000

Fig. 15

MALWARE DETECTION SYSTEM AND METHOD FOR MOBILE PLATFORMS

CROSS REFERENCE TO RELATED APPLICATIONS

This application claims the benefit of U.S. Application Nos. 60/789,766, filed Apr. 6, 2006; 60/789,748, filed Apr. 6, 2006; 60/789,749 filed Apr. 6, 2006; 60/789,746, filed Apr. 6, 2006; 60/789,744, filed Apr. 6, 2006; 60/789,745, filed Apr. 6, 2006; 60/789,743, filed Apr. 6, 2006; 60/789,958, filed Apr. 6, 2006; 60/824,649, filed Sep. 6, 2006; and 60/828,491, filed Oct. 6, 2006.

TECHNICAL FIELD

The present invention relates generally to systems, devices, and methods for detecting malware in mobile networks and mobile devices.

BACKGROUND OF THE INVENTION

Traditional malware signature detection methods extract signatures from an invariant portion of the actual executable part of a target application being scanned for malware. However, these detection methods present numerous problems when implemented in mobile networks and on mobile platforms.

A major constraint of scanning within a network is fragmented data. Generally, mobile phone applications contain executables which are compressed and divided into multiple packages for facilitating transmission of such executable in a mobile network. These data packages must then be re-assembled and uncompressed prior to installation and execution. For example, software installation files (SIS packages) in the Symbian® operating system and CAB packages in the Windows Mobile® operating system, have to be re-assembled and "uncompressed" to obtain the executables. Therefore, while scanning for malware, it is not possible to obtain the entire data corresponding to a malicious application because the malicious application may exist across multiple packages in a compressed format. Also, it is cumbersome and time consuming to attempt to re-assemble and uncompress such data packets as they pass through the mobile network due to the latency these operations would introduce.

Also, comprehensive signature matching as a virus or malware detection method on memory-constrained devices, like mobile phones, is difficult to efficiently implement due to the need for a large database of identified malware signatures. String matching is also processor intensive and results in a high computational tax on a mobile device wherein such mobile platforms have relatively low processing power such that large processing and memory requirements results in lowered performance and excessive battery drain.

When files in file systems are modified, it is good practice to run malware checks on any changed files. However, some mobile device operating systems provide only a flag to indicate that a file somewhere in the file system has change. Therefore, it is difficult to determine which file to scan for malware.

Malware checking using signatures is often processor and memory intensive. Malware also changes constantly, requiring continual updates to stay current. Therefore, some of the best and most advanced programs for detecting malware are usually running at network operations centers and may not be available for running on mobile handsets. Mobile handsets, especially those with limited processing capability and operating systems or those that do not permit memory access for malware scanning, will require some other method of verifying that resident applications are free of malware.

In some mobile devices, e.g., BlackBerry® type devices by Research In Motion® and some Palm® devices, access to the binary code of an installed program is prohibited by the operating system. Access to the binary code in other devices may also be limited due to constraints such as power, permissioning, or other limitations. Therefore, one cannot always apply the traditional binary, signature-based methods of scanning binary code to detect malware in such devices.

Using traditional signature detection, every malware variant will have its own signature. Polymorphic viruses, i.e., viruses that change their signatures every time they replicate, may create undetectable variants. Scalability is also a concern for these signature-based detection algorithms since a new signature needs to be added for every new malware variant in the worst case.

Even though each new malware variant tends to perform the same or similar kind of malicious behavior, traditional signature detection can only detect a new malware variant by adding a new signature to its list and scanning for the new signature. As the list of variants grows, the number of signatures grows, further taxing a system's computational and storage capacity.

Signature-based detection requires both storage of a large number of known malware signatures and processing capacity to search for suspected malware programs with those signatures. Mobile devices however are limited in both storage space and computational ability, thus making them difficult platforms for using existing methods of malware detection that were designed for more robust computing platforms such as desktop and laptop systems.

Most malware, whether worm or virus, share a common characteristic: they tend to spread over time from one device to another device if not contained. The ability to get up-to-date and real-time metrics on mobile networks is valuable to network administrators tracking worm and other virus attacks. There is a need to assimilate statistical information about potential malware on the network and present it to network administrators in a meaningful way so they can quickly become apprised of worm and other virus attacks before they have had a chance to widely proliferate.

New malware and malware variants are constantly appearing. Once new malware has been identified, service providers need a way to update mobile devices in the network so that they can remove the new malware from the mobile devices or prevent other mobile devices from becoming infecting. With most malware prevention systems, users manually initiate a process to update their malware prevention system with a server. In the interim, however, their systems remain vulnerable to the new malware. With the growing popularity of smart phones and the potential for greater interaction between mobile phones, there is a need to be able to update mobile devices as soon as new malware is identified.

SUMMARY OF THE INVENTION

The present invention meets the above and other needs. The following embodiments represent various aspects of a malware detection system and method of the present invention.

Malware Signature Detection Using a Mobile Application's Header and Compressed Code

Detection of malware using intelligently generated signatures catches a large number of new malware variants. The approach is to generate unique signatures for different classes or families of malware rather than one for each specific mal-

ware variant. This makes signature detection more reliable when detecting variants of a virus. Mobile malware are classified into families based on their functionality. The present system and method exploits the similarity in data among members of one malware family based on the assumption that some parts of the compressed data remain similar when minor changes are made to the uncompressed data. The system and method extracts generic signatures from "compressed data" and the non-compressed part of the data or packets. This system and method is ideal for in-network malware detection because a target application or data packet does not have to be uncompressed prior to detecting malware.

Malware Detection Using Hashing Algorithms

Detection of malware using a hash pattern matching algorithm is effective for low-power/low-memory mobile platforms. A two-part hash in conjunction with a set of heuristics helps to eliminate malware signature mismatches faster, resulting in faster search characteristics. This platform independent system and method minimizes the amount of memory required to store malware signature patterns and efficiently uses the limited computational resources found on a mobile platform.

On-Write Malware Scanning Framework

An on-write malware scanning framework augments operating systems that provide only a flag indicating whether or not a file has changed in a system. The framework provides a flexible, lightweight means for efficiently monitoring each directory node in separate, yet interconnected, processes. Each process independently monitors the system flag and is responsible for monitoring the files in its own local node for changes and reporting any changes to the malware checking process.

Checksum Application Integrity Checking

A checksum application integrity checking system and method uses checksums to perform integrity checks of executables used by a mobile platform, such as a mobile phone. This checksum based approach is ideal for malware detection when changes are made to executable content or system libraries on the mobile device itself. Initially, the system and method stores the checksums from a clean device with applications that are known to be malware-free. Any changes to a checksum value indicates that the executable as possibly being malware-infected. The checksum is easily re-computable and represents the integrity of the entire executable.

Malware Detection on Limited Access Devices

A feature based system and method uses information about the application to distinguish and detect malware. Generically called features, this other information varies in accordance with the system being scanned, the files present, and the program itself. In different embodiments a variety of different combinations of these features are aggregated to create a feature set that acts as an identifier for a specific application. In this way, a unique identifier for a malware program is created that has a distinctive feature set that distinguishes it from safe programs which are malware-free. For any newly identified malware, a feature set is extracted after analysis and stored as a malware identifier. These malware identifiers can be created off-line or using a variety of on-line methods and then distributed to malware or anti-virus detection systems. These malware detection systems may be located on individual mobile platforms and implement the present system and method for detecting malware. The feature based system and method detects malware by extracting a combination of features, or feature set, from the target application which it then compares to pre-defined feature sets that define malware programs. A complete match indicates that the target application contains a known malware variant.

Heuristic Malware Detection

A heuristic approach to malware detection enables the detection of unknown malware. The solution is based on heuristic rules derived from Bayesian decision theory. Heuristic virus scanning techniques based on features/rules are applied to known malware-infected executables to develop a probability model of the behavior of a malicious application. Specifically, the heuristic rules are derived from a classification based on DLL imports collected from malware-infected executables which are directly linked to the functionality of a program. The system and method exploits common functionality among different virus or malware samples to identify malware without using signatures.

Malware Detection Using Code Histograms

Malware variants tend to perform the same malicious actions, even though they have different identifying signatures. Using statistical analysis, profiles of the code instructions used to perform the malicious actions are developed into a probability model, enabling a malware detection process to search for the profile of the malicious behavior rather than a specific signature variant. The profile is a histogram probability model of the number and frequency of different code instructions in an application that contains malware. The system and method exploits common functionality among different malware to identify malware without using signatures.

Feature Based Malware Detection

It is possible to identify potential malware based on probability models derived from both code analysis and from monitoring the behavior of suspected malware on the mobile platform. In particular, code analysis and associated behavior are used to create feature sets and models of malware behavior. Notably, the system and method is successful in identifying new, never before seen malware without being resource intensive, thereby making it especially adaptable for use on mobile platforms.

Reporting System

The present invention also is a system and method for reporting and visualizing worm and other virus or malware attacks on mobile platforms and networks. The system and method provides a comprehensive means for collecting, reporting, and providing visual depictions of information regarding the propagation and effect of worms, viruses and other malware on a mobile network. Carrier and enterprise network operators and managers use real-time statistics to understand the effect malware has on their mobile networks and the mobile platforms, e.g., mobile phones, connected to their networks.

Updating Malware Protection Using a Device Independent Secure Management Protocol

The present invention is a system and method for enabling service providers to update malware protection on mobile platforms. A device independent secure management protocol, such as the Open Mobile Alliance (OMA) complaint application on a client device (mobile platform), allows malware protection to be managed by a service provider's mobile network server, such as a Device Management (DM) server. Using the device independent secure management protocol, malware protection system updates are performed on mobile platforms in the service provider's network as soon as new malware is detected and identified.

BRIEF DESCRIPTION OF THE DRAWINGS

The accompanying figures depict multiple embodiments of the malware detection system for mobile platforms. A brief

description of each figure is provided below. Elements with the same reference numbers in each figure indicate identical or functionally similar elements. Additionally, as a convenience, the left-most digit(s) of a reference number identifies the drawings in which the reference number first appears.

FIG. **1** is a flow chart diagram of a malware detection method for mobile platforms using search strings derived from the uncompressed headers and compressed code sections of data packages.

FIG. **2** is a flow chart diagram of a malware detection method that uses hashing to optimize malware detection on mobile platforms.

FIG. **3** is a diagram of the hashing process of the malware detection method that uses hashing.

FIG. **4** is a flow chart diagram of a malware detection method for mobile platforms that monitors directories for changed files.

FIG. **5** is a flow chart diagram of a malware detection method for mobile platforms that verifies the checksum of an application against a known malware-free version of the application.

FIG. **6** is a flow chart diagram of a malware detection method for mobile platforms that checks a feature set associated with a target application against a feature data store of feature sets derived from malware-infected and malware-free applications.

FIG. **7** is a flow chart diagram of a heuristic malware detection method for mobile platforms that compares a target application's DLL calls against a probability model of DLL calls profiles associated with malware-infected applications.

FIG. **8** is a flow chart diagram of a malware code histogram detection method for mobile platforms that compares a target application's object code against a probability model of profiles of malware object code.

FIG. **9** is a flow chart diagram of a feature based malware detection method for mobile platforms that compares a target application's code and resource utilization against a probability model of profiles derived from known malware applications.

FIG. **10***a* is a schematic diagram of one embodiment of the reporting system's (CoreStats') architecture.

FIG. **10***b* is a representative diagram of the communications between a client device and CoreStats.

FIG. **11** is a screen snapshot of sample malware per platform report on CoreStats.

FIG. **12** is a screen snapshot of sample malware spreading report on CoreStats.

FIG. **13** is a screen snapshot of sample user infection report on CoreStats.

FIG. **14** is a screen snapshot of sample virus producer report on CoreStats.

FIG. **15** is a schematic diagram of one embodiment of the CoreStats' architecture for updating a mobile client device's malware signatures using a device independent secure management protocol.

DETAILED DESCRIPTION

Exemplary embodiments of the present invention are detailed in FIGS. **1-15**.

Malware Signature Detection Using a Mobile Application's Header and Compressed Code

Mobile applications are transported to mobile platforms across mobile networks using software installation files or SIS packages in the case of Symbian®, and CAB packages in the case of Windows Mobile®. These data packages are compressed before being sent across the mobile network and due to their large size they are often fragmented by the network in the process of being transported. The following detailed description discloses a method and system for detecting malware in these compressed and fragmented data packages without necessitating concatenating all the fragments back together or first decompressing the package in its entirety on a receiving mobile platform. For convenience, a mobile platform is a mobile telephone, a smart phone, a mobile computing device, a smart handheld device, a network element, or any comparable mobile device.

Referring now to the flowchart diagram of a compressed signature method depicted in FIG. **1**, a signature extraction system and method (collectively, method) **100** has the operations of selecting **102** malware infected packages or executables, classifying **104** the malware-infected packages/executables into families, identifying **106** common strings as candidate strings, or candidate signature strings, **130** within a family of malware, and extracting **108** a semi-optimal set from those candidate signature strings **130** as search strings to populate a search string database **110**. For example, as shown for convenience, the malware families, Family A **120***a* and Family B **120***b*, have executables **126**, **128** respectively containing malware from which candidate signature strings **130** are identified **106**; each executable having both an uncompressed header section **122** and a compressed code section **124**.

A signature detection method **101** has the steps of selecting **112** a target executable, package or package fragment and comparing **114** the package contents to the search string database **110** to determine if the package contains a matching search string, and either flagging or identifying **118** the package if a match indicates it is malware-infected, or allowing **116** the target package to pass if it is malware-free.

Signature Extraction:

A signature extraction method **100** builds a search string database **110** containing a semi-optimal set of signature or search strings extracted **108** from the header and code section candidate strings **130**. In one embodiment, the signature extraction method **100** selects **102** a large number of SIS packaged executables (a package or package fragment) **120***a*, **120***b* which are known to contain malware, here represented for illustrative purposes only as malware-infected executables **1-4 126** in Family A **120***a* and malware-infected executables **1-5 128** in Family B **120***b*. The executables **120***a*, **120***b* are then classified **104** by family. To allow detection of all the variants of a malware family, a common set of strings labeled as candidate, or signature, strings **130** for each malware family is identified **106** in either or both the uncompressed header section **122** of the packaged executable **120***a*, **120***b* and the compressed code section **124**. These strings **130** serve as representative signatures for a malware family, and significantly reduce the total number of signatures that need to be searched in order to extract **108** the semi-optimal set later stored in the search string database **110**. Note that due to inter-family code overlap, it is possible that these strings are also used to detect samples from other unrelated malware families as well.

It is desirable to further reduce the number of strings in the set of candidate strings **130** to minimize the total number of strings required to detect all malware samples, but still maintain multiple strings for each malware family to ensure a reasonable probability of detecting new malware variants. New malware variants are assumed to contain at least one of the search strings. In a preferred embodiment, a greedy algorithm is used to compute a semi-optimal set of candidate strings **130** which covers most different malware samples. The candidate strings **130** are ordered in a priority queue (Q)

with the tail of the queue always containing the string that covers (or occurs in) the largest number of strings not covered by any other string. The following is a preferred greedy algorithm finds a semi-optimal set of candidate strings **130** to use as the search strings in the signature detection method **101**.

```
Initially all samples are considered to be uncovered. Each element of the
    queue (Q) comprises the signature string and the set of
    samples it covers.
While (there exist more samples to cover || Q is not empty)
{
    F=Remove_Tail (Q)
    Include F in the result set.
    For every element X in Q
        If (F covers the sample s that X also covers)
        {
            Increment s :: Number of times covered
            If (s :: Number of times covered > threshold), where the
                threshold is a variable defining the number of
                signatures that need to be present in one malware
                sample
            {
                Sample s is considered covered
                Decrement the number of samples covered by X
            }
        }
    End For
}
```

Other types of optimal search strategies may be employed by those of ordinary skill in the art, including for example, heuristic, evolutionary, and dynamic programming approaches among others to compute the candidate strings **130** that comprise the extracted signature strings. Note that although the candidate strings **130** in Family A **120***a* and Family B **120***b* show the candidate strings **130** in identical places for all malware **126**, **128** in each family of malware, the candidate strings **130** may actually be located in different places in the different malware **126**, **128** that comprise a malware family **120***a*, **120***b*. It is common in malware displaying polymorphism for candidate strings **130** to be displaced or fragmented differently from one malware variant **126**, **128** to another.

One aspect of this system and method is the reduction of candidate strings **130**. Allowing every sequence of n bytes as a potential signature or candidate string **130** from the compressed data **124** would create very large numbers of potential signature strings **130**. To reduce the number of potential candidate signature strings **130** in the compressed code section **124**, only strings that are not ASCII text strings from the code portion of the compressed data **124** are identified **106** and extracted **108**. This is done because malware variants sometimes change the text strings for filename, file-path, etc., and using the ASCII text strings would therefore result in signatures that are less robust and less able to detect malware variants. Additionally, the candidate signature strings **130** are identified **106** and extracted **108** as signatures **130** if those strings are present only in malware-infected files and not applications that are malware-free. At least three different strings are extracted **108** and used as the candidate signature strings **130** in the header and code section search string database **110**. Different numbers of candidate signature strings **130** for the header and code section signature search string database **110** can be selected based on the need to balance the desire to use fewer candidate signature strings **130** to reduce the amount of data required to identify malware with the desire to keep the candidate signature strings **130** set large enough to provide good results.

Signature Detection:

The signature detection method **101** first selects **112** a target package or package fragment containing an executable to be scanned. The signature detection method **101** next compares **114** the target package, or executable or package fragment, to the header and code section signature search string database **110**. If a search string is found, the signature detection method **101** flags **118** the target package or package fragment as possibly containing malware. If no signature is found, the signature detection method **101** allows **116** the target package or package fragment to pass through the system as being malware-free.

The header and code section signature search string database **110** containing search strings selected from header and code section candidate strings **130** provides a reduced set of information suitable for scanning target packages or package fragments as they pass through network elements, such as routers and gateways, on either a carrier or enterprise network to a mobile platform or device. By directly scanning the compressed target application, anti-virus actions are taken without the need to uncompress the files passing through the mobile network. The reduced search string set of candidate signature strings **130** also reduces the amount of time necessary to scan a specific target package or package fragment thereby enabling efficient scanning in a network router or mobile device without adding additional latency. The reduced search string set of candidate strings **130** enables efficient scanning of target package fragments as the fragments arrive on a mobile platform, further reducing latency in the model device. The method and system also allows scanning the target package without having to first decompress the package, further reducing the possibility of infection by any malware.

Malware Detection Using Hashing Algorithms

Storing and efficiently searching for an exhaustive list of malware signatures on a mobile platform is difficult given the limited memory, battery, and computational resources of mobile platforms in general. The followed detailed description discloses a method and system for detecting malware that minimizes the amount of memory required to store malware signature patterns and efficiently uses the limited computational resources found on a mobile platform to quickly scan for malware.

Referring now to the flowchart diagram of the hash detection method depicted in FIG. **2**, a hash table generation method **200** has the operations of selecting **202** malware signatures, deriving **204** a fast hash from a first portion of each malware signature, choosing **205** a splatter set from the first portion, deriving **206** a slow hash from a second portion of each malware signature, and creating **208** a hash table from the derived fast hashes, chosen splatter sets, and derived slow hashes to populate a hash table **210**. A hashed signature detection method **201** has the operations of selecting **212** a target application, selecting **214** a set of characters of the same length as the first portion used to derive **204** the fast hash, performing **216** the fast hash on the selected characters, and comparing **218** the result to the fast hash stored in the hash table **210** to see if the hashes match. If there is not a match, then continuing to select **220** a next set of characters by shifting one byte or block in the target application, and repeating steps of performing **216** a fast hash and comparing **218** the result with fast hashes in the hash table **210**. If there is a match, then comparing **219** the splatter set from the first portion stored in the hash table **210** with a splatter set of the selected characters from the target application. If there is a match of the splatter sets then performing **222** a slow hash on a set of characters of the same length as the second portion used to derive **206** the slow hash and comparing **224** the result to the slow hash store in the hash table **210** to see if the hashes match. If there is not a match, then returning to the step of

selecting **220** a next set of characters to fast hash. If there is a match, then identifying or flagging **226** the target application as possibly being malware-infected.

Referring now to the diagram of the hashing process depicted in FIG. **3**, a set of malware files **302** containing malware signatures **304** of lengths M, L, and K are hashed to the malware signature hashes **316** H_M, H_L, and H_K using a second hash (Hash **2**) **320**. Equal-sized portions, or prefixes **306**, of the malware signatures **304** also are hashed to fast hash values **318** H_{N1}, H_{N2}, and H_{N3} using a first hash (Hash **1**) **322**. Pseudorandom splatter sets **307** are chosen from the prefixes **306**.

Continuing to refer to FIG. **3**, a target application **308** of length J contains J−K+1 possible target strings $\mathbf{310}_K$ of length K blocks or bytes, J−L+1 possible target strings $\mathbf{310}_L$ of length L blocks or bytes (not shown for convenience), J−M+1 possible target strings $\mathbf{310}_M$ of length M blocks or bytes, and J−N+1 possible target strings $\mathbf{310}_N$ of length N blocks or bytes. These hash into multiple series of hashes **312** wherein there is one hash value for each of the possible K, L, and M-length target strings $\mathbf{310}_K$, $\mathbf{310}_L$, $\mathbf{310}_M$, using the second hash **320**. A single series of hashes **314** for the N-length possible target strings $\mathbf{310}_N$ is hashed using the first hash **322**. Additionally, a pseudorandom target splatter set $\mathbf{310}_S$ is chosen from the N-length target strings $\mathbf{310}_N$.

Hashing and Heuristic Methods:

Rather than searching for malware signature strings **304** directly in a target application **308**, malware signatures **304** previously extracted from malware-infected files **302** are first selected **202** and hashed by deriving **206** a first hash **322**, and deriving **208** a second hash **320** in a hash table generation method **200** to significantly reduce their size. By hashing the malware signature strings, the comparison steps **224**, **218** become greatly simplified. Instead of searching for long malware strings **304** directly in the target application **308**, the target application **308** is repeatedly hashed into a series of short strings or preferably single values, making the comparison steps **224**, **218** computationally simple and fast. In one exemplary embodiment, the hash is a 64-bit numeric value, but other hash results could also be utilized.

However, hashing is, in general, a computationally expensive process, and therefore the savings in the comparison steps **224**, **218** can be offset by the processor intensive hashing process itself. To improve the performance of the system and method and reduce the computational load on a mobile platform implementing the method, a two-stage hashing process and two exemplary heuristic algorithms are utilized to reduce this computational burden in the hash table generation method **200** and the hash signature detection method **201**. The two-stage hashing process comprises an optimized fast hash (first hash **322**) and a rigorous slow hash (second hash **320**). The heuristic algorithms comprise a minimum prefix match and a pseudorandom splatter set.

Minimum Prefix Matching Heuristic Method:

The minimum prefix match reduces the hashed malware signatures **318** to a common fixed size, or prefix **306**. This significantly reduces the number of comparisons necessary in the first compare step **218** of the hash signature detection method **201**. The minimum prefix can be derived as follows:

Minimum Prefix Match

Let S={S**0**, S**1**, . . . , Sm} be an arbitrary string. We Define S'={S**0**, S**1**, . . . Sk} as a prefix of S

if k<m, k is called the Prefix-length.

Minimum Prefix is a prefix of S with Prefix-Length=lmin, where lmin is the length of the smallest signature in the Rule-Base.

Without the prefix, hashes of the target application **308** would need to be computed for each byte or block offset of the target application **308** for each length of malware signature **304**, which can be of variable lengths, for example K, L, M. Then, each of the hashes would have to be compared **218** with each of the malware signature hash **316** entries in the hash table **210**. Such processing requirements result in an enormous computation expense, involving multiple simultaneous or sequential hashing operations and multiple comparisons. With the minimum prefix match, only a single hash value from the series of hashes **314** of length N for each byte or block offset of the target application **308** is compared **218** to the fast hash value **318** entries in the hash table **210**. Because there can be hundreds of different malware string lengths, this minimum prefix match potentially reduces the computational load in the hashed signature detection method **201** by factor of a hundred or more, or more precisely to 1/x where x is the number of different signature lengths.

Fast Signature Hashing and Fast Hash Signature Detection:

In the hash table generation method **200**, the malware signatures **304** are selected **202** and a first hash **322** is derived **204** from a first portion, or prefix **306**, of the malware signatures **304** using a fast hash called a filter hash. The purpose of the filter hash is to provide a computationally simple hash that can be optimized algorithmically. This filter hash is run once for each first portion length target string $\mathbf{310}_N$ in the target application **308** as a first hash **322** in the hash signature detection method **201**. The filter hash is used to quickly determine to a good degree of probability whether a malware signature **304** is present in the selected string of the target application **308**. An example fast filter hash is provided below.

Let S= {S1S2...Sn} be an arbitrary string of length n.
Filter(Smk) = pos1*[Sm]+pos2*[Sm+1]+...posk*[Sm+k −1], where Filter(Smk) is the Filter-Hash Value for k-lengthed Substring of S starting at position m, [Sn] is the integer value associated with byte Sn, and pos1, pos2...., posm are positive integral values.

This particular fast filter hash algorithmically reduces to the following:

For any arbitrary string S= {S0S2...Sm}
Initialize for any positive integral value k,
Filter(Sik) = Filter(S(i−1)k)−[S(i−1)]+[S(i−1+k)] −(Sum−[S(i−1)])
Sum=Sum+[S(i−1+k)] −[S(i−1)]
Proof:
Let, H(n)=S1*pos1+S2*pos2+.....+Sn*posn
then, H(n+1)=S2*pos1+ ..... +Sn+1*posn
H(n+1)−H(n)=−S1*pos1 + S2*(pos1−pos2)+.....Sn*(posn−posn−1)+ Sn+1*posn
Without loss of generality, we can assume
pos1=1, pos2=pos1+1 and so on
H(n+1)−H(n)=−S1+Sn+1*posn+[S2+.....+Sn]
H(n+1)=H(n)−S1+Sn+1*posn+[S2+....+Sn]
Hence the recursive relation:
H(n+1)=H(n)−[First Element of pattern starting at n]+[Last Element of pattern starting at n+1] −[Sum(elements in pattern starting at n)−[First Element of pattern starting at position n]]

By choosing this particular fast filter hash, the first hash **322** can be performed **216** recursively in the hash signature detection method **201** without having to completely re-compute the entire hash value for each hash in the single series of hashes **314**. Only some elements of the hash value are computed each iteration. This dramatically reduces the computational expense of having to re-compute the entire first hash

322 each time for each first portion length target string 310_N before checking that computed hash value against the fast hash values **318** H_{N1}, H_{N2}, and H_{N3}. Other fast filter hashes could similarly be used.

The prefix **306** defines the first portion of each malware signature **304** to be hashed in deriving **204** the fast hash. This same length is used in performing **216** the fast hash during the hash signature detection method **201**. The system and method next selects **214** a length of characters in the target application **308** identical to the length of characters used to derive **204** the fast hash, and performs **216** the fast hash on those selected characters. The system and method then compares **218** that result with the stored hash values **318** in the hash table **210**. If there is no match, the system and method selects **220** the next pattern of characters to hash by shifting one byte, character, or block further in the target application **308**, and repeats the steps of performing **216** the hash, comparing **218** the result, and selecting **220** the next pattern until there is a match in the compare **218** step or until there are no additional portion-sized **306** patterns left in the target application **308**. An embodiment of the hash signature detection method **201** that utilizes the prefix **306** is therefore as follows, where the second hash in the method, the DJB hash, will be defined and explained in a subsequent section:

```
Let, R = {R1, R2, ...,Rn } be the Set of Rule-Signatures
Input: S = {S0, S1, ...,Sm }
Minimum Prefix Length = m
For i =1 to m
    If(Search(Filter(S_im ),R ) == Found)
    {
      IF(DJB(R_j) == DJB(S_ij ) )
          R' ∪=R_j
    }
End For
Output: R' = {R1, R2, ...,Rk } called the Matched-Set consisting of
rules whose signatures matched substrings in S.
```

The Search function is implemented using Hash-Sort with Filter(S_{im})% m as the Hashing-Index. This Search function also compares the pseudorandom splatter set **307**, described in a later subsection, at that position in the hash table **210** to the target pseudorandom splatter set 310_S derived from that N-length target string 310_N.

Fast Signature Hashing and Detection without Utilizing the Prefix Heuristic Method:

In another embodiment of the present invention, the prefix heuristic method is not employed, and instead the system uses the full length malware strings **304**. An example pattern matching routine without the prefix heuristic method is as follows:

```
Let, R = {R1, R2, ...,Rn }
    L = {L1, L2, ...,Ln }, be the Set of Rule-Signatures and their
    corresponding lengths in the Rule-Base.
Algorithm n-Pattern Match
Input: S = {S0, S1, ...,Sm }
For i = 1 to m
For j = 1 to n
    IF(Filter(R_0Lj ) == Filter(S_ij ))
    {
        IF(DJB(R_0Lj) == DJB(S_ij ) )
            R' ∪=R_j
    }
End For
End For
Output: R' = {R1, R2, ...,Rk } called the Matched-Set consisting of rules
whose signatures matched substrings in S.
```

Note that this n-pattern match algorithm requires generating fast hash values **312** for each n-length malware signature. This method computes n different fast filter hash values (corresponding to n signature lengths) for each input position in the target application **308**, creating multiple series of hashes **312**, and requires individually comparing **218** each element in the multiple series of hashes **312** individually with the corresponding fast hashed malware signature hashes **316** stored in the hash table **210**. Malware signatures **304** can be very long or very short, especially in the case of fragmented polymorphic viruses, where several malware signature fragments together identify a single malware variant. As the size of the hash table **210** increases, the performance of this embodiment decreases proportionally for each additional length of malware signature **304**.

Pseudorandom Splatter Set Heuristic Method:

Because of its simplicity, a fast filter hash will generate some false positives. To eliminate some false positives, a pseudorandom splatter set **307** and a pseudorandom target splatter set 310_S provide an extra level of comparison before performing **222** the more rigorous slow or second hash **320**. The pseudorandom splatter set requires choosing, or deriving, **205** a number of pseudorandom bytes or blocks from the prefix **306** for each malware signature **304** to create a pseudorandom splatter set **307** that is stored along with the hashes in the hash table **210** as part of the hash table generation method **200**. An exemplary pseudorandom splatter set algorithm follows:

```
Pseudorandom Splatter Set

Input: Minimum Prefix Length m
   String S = {S0 S1 ...Sm }
For i=0 to m
   Seed Random Number generator with Filter(S_im)
   Obtain x random positions i1,ix between 0 and m
   {Si1 .... Six } is called the Random Splatter Set R
End For
Output : Random Splatter Set R
```

The pseudorandom target splatter set 310_S consists of the same pattern of pseudorandom points in the target strings 310_N. The pseudorandom points in both the pseudorandom splatter set **307** and a pseudorandom target splatter set 310_S must match in the compare **219** step before performing the rigorous slow hash **320**.

Slow Signature Hashing and Slow Signature Detection:

If at any time there is a match in the fast hash compare **218** step and the pseudorandom compare step **219**, the hashed signature detection method **201** performs **222** a slow hash on a second portion **304** of the target application **308**, starting at the current position and using the same length of characters used in deriving **206** the slow hash. The hashed signature detection method **201** then compares **224** that result with the slow hashes **316** stored in the hash table **210**. If there is not a match, the selecting **220** step continues from where it left off, as if there had been no match during the last compare **218** step. If there is a match in the compare **224** step, the system and method identifies or flags **226** the target application **308** as possibly containing malware.

A second hash **320** is derived **206** using a more rigorous hash called a slow hash. An example slow hash is the DJB hash provided below:

```
Initialize D =5381
For i=m to k
    D = ((D << 5) + D) + [Si]
end For
DJB( Smk )=D
DJB( Smk ) denotes the DJB-Hash value for k-lengthed Substring of
S starting at position m
```

The variable D in the DJB_Hash function is selected as the prime number 5381. Other numbers, including other prime numbers, can be used to initialize the hashing function. The selection of alternative initial values for the variable D may be selected by one of ordinary skill in the art based upon the performance of a given value in hashing the arbitrary string S. The purpose of the slow hash is to ensure that virtually no false positives are likely. The slow hash is performed **222** only if the fast hash generates a positive indication of a match in the fast hash compare **218** step and there is a positive indication of a match in the splatter set compare **219** step.

Because the slow hash compare **224** is performed only a fraction of the number of times the fast hash compare **218** is performed it is somewhat less important to optimize the hashing process for the slow hash. In one embodiment of the present invention, deriving **206** the slow hash is done with the whole portion of each of the malware signature strings **304**. In another embodiment of the present invention, deriving **206** the slow hash is done using the same portion **306** as the fast hash. There are numerous other embodiments, capable of achieving similar results, that would be obvious to one having ordinary skill in the art.

These exemplary embodiments of the present invention are platform independent methods that utilize a two-stage hash in conjunction with a set of heuristics to quickly eliminate malware signature mismatches. The system and method results in a minimized amount of memory required to store malware signature patterns and results in fast malware search characteristics.

On-Write Malware Scanning Framework

The method and system for an on-write malware scanning framework **400** monitors the file system and is shown in FIG. **4**. The on-write malware scanning framework **400** scans the system directory tree **402** and for each directory in the directory tree **402**, it creates **404** a monitor process **406***a*, **406***b*, . . . , **406***n*. Each monitor process, **406***a*, **406***b*, . . . , **406***n*, monitors **408** the operating system file system change notification flag, and when the flag is set, scans **410** the directory associated with the monitoring process for file changes. If no changes are found, the monitor processes **406** go back to monitoring **408** the operating system file system change notification flag. If changes are found, the monitor processes **406** identify or flag **412** each changed file and notify a malware scanning process.

An exemplary embodiment is presented as follows. A file system in a Symbian® OS is organized like Microsoft Windows® (drives, directories, sub-directories and files). Referring now to the flowchart diagram of an on-write detection method depicted in FIG. **4**, the on-write malware scanning framework **400** keeps track of any file or folder change in the file system by creating **404** monitor processes **406** for each directory folder. Each monitor process **406***a*, **406***b*, . . . , **406***n* has a data structure as shown below for its directory folder.

```
Monitor Process
{
    Subfolder_List
    File_List
    Root
    FileServer Session
}
```

Each monitor process **406** contains a Subfolder_List, File_List and a Root that corresponds to the folder which is being watched. The File_List keeps track of the current Files in the Root and the Subfolder_List keeps track of the current subfolders in the Root.

Each monitor process **406***a*, **406***b*, . . . , **406***n* is an active object implemented within the Symbian® OS. The monitor processes **406** have a low priority and maintain an active session with the Symbian® File Server using the function RFs::NotifyChange(Root) which notifies the monitor processes **406** of any change to the root folder. Each monitor process **406***a*, **406***b*, . . . , **406***n* handles the change notification. Each monitor process **406***a*, **406***b*, . . . , **406***n* compares the current state of the Root with the state stored in the File_List and Subfolder_List.

The File_List and Subfolder_List maintain a set of file/folder names along with their timestamps. When a monitor process **406***a*, **406***b*, . . . , **406***n* that is monitoring **408** the Symbian® OS obtains a notification of file system change from the file server, it scans **410** through the current set of files and folders. If no new files/folders exist then the monitor process **406***a*, **406***b*, . . . , **406***n* ignores this notification and goes back to monitoring **408**. If files/folders are missing then it is a notification for deletion and the monitor process **406***a*, **406***b*, . . . , **406***n* updates its lists. If there is a new file/folder found for a particular monitor process **406***a*, **406***b*, . . . , **406***n* then the monitor process **406***a*, **406***b*, . . . , **406***n* handles the notification by flagging **412** the file/folder and notifying the malware scanning processes.

Most new mobile phones, and operating systems including the Symbian® operating system (OS) allow the insertion of memory cards without switching off the device. The root monitor **406***a* lies at the very top level of the file system. When the root monitor **406***a* monitoring **408** the OS obtains a file change notification, it compares a list of active drives to a list that was created when the object was started to see if a new drive was mounted on the device. For the root monitor **406***a* physical drives are its folders, which it treats the same way that other monitors **406** treat folders, with one small exception. For the embodiment on the Symbian® OS, the method and system for an on-write malware scanning framework **400** makes the root monitor **406***a* process protected so the application will not exit when a memory card is inserted into the device.

The on-access or on-write scanner embodiment presented herein preferably monitors file system changes using active objects as implemented within the Symbian® OS. In other operating systems, the on-write scanner is implemented using other comparable objects. For example, in a multi-threaded operating environment, the on-write scanner is implemented as a separate low-priority thread or as a low-priority process.

Checksum Application Integrity Checking

A system and method for application integrity checking on mobile platforms uses checksums to verify that an application is malware-free after a file is modified. In the checksum database building process **500**, a checksum database **510** is built **502** from executables known to be malware-free. When a mobile platform, e.g., a mobile device, tries to execute or modify **512** an executable, the application integrity checking process **501** recomputes a checksum of the executable and

checks **514** to see if the malware-free checksum of the executable is stored on the mobile device. If the malware-free checksum is not stored locally on the mobile device, the mobile device queries **516** a remote checksum database **510** for the malware-free checksum of the executable. The application integrity checking process **501** then verifies **518** that the recomputed checksum of the executable matches the malware-free checksum from the mobile device's database or the checksum database **510**. If it matches, the application integrity checking process **501** ignores **520** the modification to the executable or allows **520** the executable to run. If it does not match, the application integrity checking process **501** identifies, flags and/or prevents **522** the executable from running, and a sends **524** a signal or notice to a malware scanning server. The following details checksum database building process **500** for creating a checksum database **510** and an application integrity checking process **501** for verifying **518** the checksum on a mobile platform.

The system and method for application integrity checking on mobile devices uses a checksum based approach to prevent executable binaries from being modified for malicious activity once they are installed on the device. Referring now to the flowchart diagram of a checksum based method depicted in FIG. **5**, a checksum database building process **500** initially builds **502** a checksum database **510** by collecting data from all the executable files on a device, or from any desired set of executable files, known to be malware-free. In an alternative embodiment, some or all information used to build **502** the checksum database **510** is imported from a known source of pre-computed checksum data, such as from an operational support system.

Much of the information used in the checksum database building process **500** to build **502** the checksum of an executable file is available in the header of an executable and is therefore very easy to extract. In an exemplary embodiment, the checksum built **502** and entered into the checksum database **510** for each executable is a combination of:

1) The sum of all 32-bit values in the code section and import section of the executable;
2) A byte sequence at the entry point in the program;
3) The size of import table; and,
4) The size of the import section.

The sum of all the 32-bit values in the code section and import section partially ensure data integrity. But because it is possible for malware to preserve the same checksum but change the actual code of the executable, additional components are added to increase the robustness of the preferred checksum. The byte sequence at the entry point of the program ensures that malicious code cannot add jump statements when the executable runs. The size of the import table and import section are also separately verified to check for integrity.

In an alternative embodiment, a Cyclic Redundancy Check (CRC) checksum is used instead of the simpler checksum described above. Use of the CRC checksum provides increased robustness at the price of additional complexity. When using a CRC checkup the system and method must re-compute the checksum for a file, e.g., an executable, every time a file write occurs.

A change in checksum indicates that the executable has been changed. This change can be as a result of malware trying to overwrite the file. When a particular executable file has been modified **512**, or when an mobile device attempts to execute **512** an executable, the application integrity checking process **501** checks **514** to see if the checksum is stored locally on the mobile device. The checksum database **510** is stored locally on the mobile device or alternatively, as in the case of an enterprise or network based anti-virus service, an enterprise or network server provides the mobile device with specific application checksum data when queried **516** by a given mobile device. When the checksum database **510** is stored on another server, it is also possible for the mobile platform or device to verify **518** programs already installed on the device during installation. The application integrity checking process **501** then verifies **518** the executable checksum against the checksum from the checksum database **510** or local copy. If it matches, the application integrity checking process **501** ignores **520** the modification to the executable or allows **520** the executable to run. If it does not match, the application integrity checking process **501** identifies, flags and/or prevents **522** the executable from running, and sends **524** a signal or notice to a malware scanning server in the mobile network.

An embodiment of the disclosed system and method for an application integrity checking process **501** on mobile devices and mobile phones using the Symbian® OS is presented herein. The Symbian® kernel performs some basic checks before running an executable file. In particular, it checks if the Uid (a unique identifier for the application) has been tampered with or if the data has been changed. But these checks are very simple to avoid. For example, a malicious programmer can patch the changed data and recomputed checksum to make the infected file look valid.

Another embodiment of the system and method for an application integrity checking process **501** is described for Symbian® E32 format executables. The implementation is based on building a hash table of relevant E32 header information of all installed files and system libraries and using this to periodically check for possible infections. The E32 format already provides all the elements needed for the checksum described above through the E32 header. The E32 header in the Symbian® OS contains the iChecksumCode, iEntryPoint, iImportOffset information. This information can be directly used to check the integrity of the file.

Initially, the checksum database **510** is built on a clean device. The entries in the checksum database **510** are hashed based on the name of the executable. Each entry, following the checksum format described above, contains the following information:

1) iCheckSumCode.
2) 64 bytes starting from ientryoint,
3) Size of import-table at iImportOffset
4) Size of import section=iCodeRelocOffset−iImportOffset

When a file-write event for an executable file occurs, the new checksum elements are compared against the stored ones. The entries in the stored checksum table are updated based on the event that a file is created, deleted or replaced. In particular, when a file is replaced a check is made on the new file to ensure that invalid format or 0 byte executable files do not replace valid ones. The stored checksums are themselves vulnerable to corruption by a virus since they are stored on the device. An integrity check is first made on the stored checksum table by comparing the sum of all bytes from the last store to the present value. If the checksum database **510** itself is corrupted, then it is generated again after cleaning the entire device with a virus scanner.

A checksum application integrity checking system and method uses checksums to perform integrity checks of the executables used by a mobile platform. This checksum based approach is used to keep track of possible changes made to executable content or system libraries on the device. Initially, the system and method stores the checksums from a clean device with applications that are known to be malware-free. Any changes to a checksum value flags the executable as

possibly being malware-infected. The checksum is easily re-computable and represents the integrity of the entire executable.

Malware Detection on Limited Access Devices

Referring now to the flowchart diagram of a limited access malware detection method depicted in FIG. **6**, a high level feature set extraction method **600** has the operations of selecting **602** malware and non-malware infected mobile applications, extracting **604** features from the non-executable portions of the applications, and creating **606** features sets and rules from each application and flagging each on as either malware-infected or malware-free. These feature sets and rules are collected in a feature set database or feature data store **610**. When a target application needs to be checked, the high level feature based malware detection method **601** derives **612** a feature set from the target application and compares **614** the derived **612** feature set with those in the feature data store **610** according to one or more rules defining when a match of such feature sets occurs. If it is similar to an existing malware feature set, as determined by an associated rule, the high level feature based malware detection method **601** flags **618** the executable as possibly containing malware. If it is more similar to a non-malware feature set, as also determined by one of the associated rules, the high level feature based malware detection method **601** allows **618** the executable to execute on the mobile device.

In one exemplary embodiment of high level feature based malware extraction and detection methods **600**, **601**, the information used to detect malware comprises a feature set selected from the list comprising such program information or features as file name, file size, vendor of the program and version of the program. The program information used in the high level feature based malware extraction and detection methods **600**, **601** is referred to generically as features. Any individual feature by itself usually is neither necessary nor sufficient to tell whether or not a program is malicious. The high level feature based malware extraction and detection methods **600**, **601** rather detects malware by using via one or more rules a combination of these features, i.e., to create **606** a feature set or program feature set definition, which is a combination of multiple features to provide the high level feature based malware detection method **601** with sufficient information to distinguish malware-infected from malware-free programs.

Creating Feature Sets

To build a feature data store **610** using the high level feature set extraction method **600**, a large number of applications is selected **602** and their feature sets extracted **604**. The feature sets vary depending on the operating system. For example, an exemplary feature set for one embodiment of high level feature set extraction method **600** for a limited access mobile platform, e.g., a BlackBerry® type device, consists of the following feature elements:

Application Name
Size
Vendor
Version
Description
URL (uniform resource locator)
SHA-1 Hash of Binary (Secure Hash Algorithm-1)
CRC of Binary (Cyclic Redundancy Check)

These features are part of an executable program header, or similar set of encapsulated data, that is readily extracted. The extracted features are also robust i.e., that it is difficult for a malware to change its features dynamically. In the case of the limited access or BlackBerry® type device, the application name, version, description and URL need to be set before program compile time. In order to change any of the features, one needs to recompile the application itself with new parameters. The CRC, SHA-1 and file size are directly related to the program code. Specifically, SHA-1 is a one way hashing algorithm i.e., it generates a unique hash value for the program data. If a small portion of data changes in the application, the SHA-1 value is very different. The CRC is another hash computed from the program data and changes once the data is corrupted or modified. Hence, changing these parameters dynamically is difficult since it would require changing the code section as well, for which there is limited access due to the device's restrictive operating system.

As an example, a first exemplary embodiment of the high level feature set extraction method **600** extracts **602** a feature set with all of the features elements typically available from a BlackBerry® type system program executable to create **606** the feature set definition or rule for matching. Example 1, extract **604** all feature elements from a program to create a program feature set rule (definition):

(a) Extract features from the program
Feature Element - Application Name = "Game"
Feature Element - Size = "53678"
Feature Element - Vendor = "Fun Games"
Feature Element - Version = "1.2"
Feature Element - Description = "This is a game"
Feature Element - URL = "http://www.linktothegame.com"
(b) Combine all the features separating each feature with a "|"
Feature set = Game|53678|Fun Games|1.2|This is a game|http://www.linktothegame.com
(c) Convert the string into hex to create the feature set rule/definition
Feature set rule/definition =
47616d657c35333637387c46756e2047616d65737c312e327c546
869732069732061206716d657c687474703a2f2f7777772e6c696e6b746f74686567616d
652e636f6d

Another example, the second exemplary embodiment details how the high level feature set extraction method **600** processes a blank feature element field in the feature set used to create **606** a program rule or definition. Example 2, extract **604** features and handle missing or empty data:

(a) Extract all available features from the binary
Feature Element - Application Name = "Game"
Feature Element - Size = "53678"
Feature Element - Vendor = "Fun Games"
Feature Element - Version = "1.2"
Feature Element - Description = "This is a game"
Feature Element - URL = NULL - The system and method in this embodiment handles an empty URL feature by replacing it with a string "null." Any feature definition missing from an application is replaced by a string, in this case the string is "null." Other replacement strings can be selected by those of ordinary skill in the

-continued

art to accomplish the same result as the use of the "null" string demonstrated in this exemplary embodiment.
(b) Combine all the features separating each feature with a "|"
Feature Set =Game|53678|Fun Games|1.2|This is a game|null
(c) Convert the string into hex to create the feature set rule/definition
Feature set rule/definition =
47616d657c35333637387c46756e2047616d65737c312e327c546
869732069732061206761 6d657c6e756c6c

The final exemplary embodiment details how the high level feature set extraction method **600** uses a wildcard in a feature element of a rule to capture changes due to polymorphic malware. This embodiment of the system and method enables the detection of malware that modifies or adapts itself during spreading, i.e., malware that exhibits polymorphism. Adaptive malware cloaks itself to make it harder to detect by subtly changing specific features. In this embodiment, the system and method uses partial-matching techniques in order to detect the morphed versions of these malware features. In yet another embodiment, specific features or portions of these program features that are known to remain constant in known malware are emphasized and used to provide a stronger basis for concluding that a specific program is malware. Example 3, extract **604** information and create wildcard(s):

(a) Extract all available features from the binary
Feature Element - Application Name = *
Feature Element - Size = "53678"
Feature Element - Vendor = "Fun Games"
Feature Element - Version = "1.2"
Feature Element - Description = *
Feature Element - URL = *; the * indicates that the data contained in this feature can be effectively anything - such that its data is effectively ignored, creating a wildcard that will enable the system and method to match any entry in that specific feature location in this embodiment.
(b) Combine all the features separating each feature with a "|"
Feature set = *|53678|Fun Games|1.2|*|*
(c) Convert the string into hex to create the feature set rule/definition
Feature set rule/definition =
2a7c35333637387c46756e2047616d65737c312e327c2a7c2a

Other features sets are created **606** from the visible features available on other operating systems, or other implementations of limited access or BlackBerry® type operating systems, as well as subsets of the available features. The feature set is selected by those of ordinary skill in the art using the criteria presented herein in order to obtain sufficient detection rates, (i.e. limited or effectively no false positives, and limited or no false negatives).

Scanning Target Applications

In the preferred embodiment, the high level feature based malware detection method **601** is implemented with two modes of operation. The first mode is an on-demand scanning system whereby malware is detected by scanning all of the device files for malware. The second mode of operation is to detect malware whenever a new application or program is installed by scanning the application/program whenever it is initially installed. Exemplary embodiments as implemented on a BlackBerry® type device, are described below.

On-Demand Scan: A user activated scan that scans all the device files for malware. The high level feature based malware detection method **601** retrieves a list of all the applications installed. Feature sets are derived **612** from all of the applications installed. The feature set of each application is compared **614** against the feature data store **610** comprising feature sets defining known malware. If a match is detected, the application is identified or flagged **618** and then possibly deleted or cleaned. Other appropriate action to contain the malware can also be initiated. If the feature sets do not match, the high level feature based malware detection method **601** allows **616** the executable to run on the mobile platform.

On-Access Scan: This is a background scan that is performed whenever a new application is installed on a mobile platform. Any new installation triggers an event that is caught by the high level feature based malware detection method **601**. The newly installed application is then scanned by the system and method to detect malware using the same method as described for On-Demand scan. The advantage with the On-Access scan is that it is non-obtrusive to a user and immediately detects threats before the malware causes further damage or spreads to other mobile platforms or devices in a network.

Heuristic Malware Detection

Referring now to the flowchart diagram of a heuristic detection method depicted in FIG. **7**, a heuristic malware profile creation method **700** first organizes **702** existing malware based on their functionality into families of malware. In one embodiment, the heuristic malware profile creation method **700** scans **703** the original sample from each malware family to obtain a list of DLL calls used in the malware, then eliminates **704** those DLL calls that are known not to be associated with the core malicious behaviors of the family. Using the DLL calls that remain, the heuristic malware profile creation method **700** creates **706** a feature set of feature elements that is associated with the malicious behaviors of the family. The heuristic malware profile creation method **700** uses training data to create **708** rules and malware profiles as a probability model, populating the suspect DLL call probability model database **710** with rules and profiles of DLL calls used in the different families of malware. When a target application needs to be checked, the heuristic malware profile detection method **701** scans **712** the target applications for DLL calls and then queries **714** the suspect DLL call probability model database **710** for malware profiles that contain those DLL calls and for rules for applying those profiles. A data structure is created **716** that identifies which suspect DLL calls are in the target application, and that data structure is compared **718** with the malware profiles from the suspect DLL call probability model database **710**.

A large percentage of malware in the mobile domain demonstrates common functionality (e.g., deleting system files, sending MMS messages). Malware can be classified into different families or classes based on common functionality. Each family of malware has an original sample and variants derived from code of the original sample. The heuristic malware profile creation and detection methods **700**, **701** exploit the fact that variants in the same family of malware share malicious core behaviors and have similar patterns of DLL calls, or imports. The list of DLL imports used by a malware gives a high-level view of the behaviors of the malware in terms of its functionality. For example, AppDisabler disables device applications whereas Commwarrior sends unwanted MMS messages. However, each variant can add its own specific functionality (e.g., a graphical interface), and therefore detection of each family of malware exploits only the core behaviors. These DLL imports also are easy to extract from the executable files making it an efficient method.

Every executable uses a set of DLL imports. After organizing **702** malware into families, the set of DLL imports is scanned **703** from the original malware sample for a given family of malware. The total number of DLL imports obtained from an executable is usually very large. To reduce this and obtain the core functionality, imports known to occur

commonly in all executables are eliminated **704**. User interface related DLL imports are also eliminated **704** because they generally do not contribute to malicious behavior of viruses. The remaining DLLs are used to create **706** a feature set of DLL calls associated with the malicious behaviors for a family of malware.

The heuristic malware profile creation method **700** creates **706** malware profiles of DLL calls in the suspect DLL call database **710** using a heuristic approach to determine which DLL calls should be used to identify malware. The heuristic malware profile creation method **700** takes the feature set for a family of malware and, using training data and an algorithm to reduce the occurrence of false positives and false negatives, determines how many, or which, of the DLL calls in that feature set are needed to indicate the presence of that core malicious behavior in a target application. The heuristic malware profile creation method **700** uses that information to create **708** a probability model for the malware profile(s) in the suspect DLL call probability model database **710**.

The preferred model for building a classifier for each virus family is a naive Bayesian model. For a new executable file, the following hypotheses is constructed: the hypothesis that a file contains malicious code H_0 and the hypothesis that the code is not corrupted H_1. Let C_{00} be the cost of a virus detection, C_{11} that of a correct rejection, C_{10} that of missing or false rejection, and C_{01} that of false alarm. To minimize the total cost, the following decision rule is used:

$$\frac{P(H_0|A)}{P(H_1|A)} > \frac{C_{01} - C_{11}}{C_{10} - C_{00}} \tag{1}$$

where A is the DLL feature set described above and $P(H_i|A)$ is the posterior probability for H_i.

Further, applying the Bayesian rule, (1) simplifies to:

$$\frac{P(A|H_0)}{P(A|H_1)} > \frac{C_{01} - C_{11}}{C_{10} - C_{00}} \frac{P(H_1)}{P(H_0)} = \alpha \tag{2}$$

where α is a parameter which depends on the prior probabilities as well as the cost functions and $P(A|H_i)$ are the corresponding conditional probabilities.

The cost and prior probabilities of C_{10} and C_{01} are much larger than C_{00} and C_{11}. From a user perspective, false alarms are really undesirable therefore C_{01} is must be much larger that C_{10}. Therefore, α is going to be a large number. Based on user feedback, the value α is generally chosen to be the minimum that yields less than 1% false alarm rate.

The value of alpha can vary for different families of viruses. The only constraint in selecting the value of alpha for a given family is to minimize the number of false positives below a user desired range (i.e. a larger range for minimal false positives, but greater likelihood of a false negative or a smaller range with more false positives, but lower likelihood of a false negative). A person of ordinary skill in the art can balance the rates of false positives and false negatives by selecting different values of α. Exemplary alpha values for common viruses to meet the less than 1% false positive rate described above include:

75 for Cabir family

90 for commwarrior family

40 for doomboot family

Next, the conditional probabilities $P(A|H_i)$ are computed using training data. For one embodiment of the present system and method, it is assumed that the individual features (the DLL import functions in the DLL set) are independent. In other embodiments, specific features of the DLL import functions in the DLL set are correlated and this correlation is used to improve the quality of the training data. The probabilities for the individual features correspond to the frequency of occurrence of the specific DLL import function in the training data, and are captured in the rule(s).

In one example, the system first evaluates a given executable DLL import feature set to create a DLL import feature vector. The feature set represents the DLL imports as a set of feature elements comprising a 1 or 0 depending on whether or not a specific DLL and function is imported or not. Each features vector is represented as a data structure such as a binary string that completely specifies for each of the DLL import functions, a feature element, in the feature set whether the import occurs or not. For example, with a feature set of the following three feature elements {DLL1, DLL2, DLL3} and an input executable that contained only DLL1 and DLL3, the feature vector is {101}. Then, the probability of that specific executable being a virus with the feature vector {101} is then computed from the conditional probability data developed from the training data:

```
Prob_Virus = Prob(DLL1|Virus) * (1−Prob(DLL2|Virus)) *
Prob(DLL3|Virus)
Prob_NonVirus = Prob(DLL1|NonVirus) * (1−Prob(DLL2|NonVirus)) *
Prob(DLL3|NonVirus)
```

The conditional probabilities Prob(DLL1|Virus), Prob(DLL2|Virus), and Prob(DLL3|Virus), as well as the Prob(DLL1|NonVirus), Prob(DLL2|NonVirus), and Prob(DLL3|NonVirus), are computed from the training data. Once the probabilities are calculated, a target executable is classified as a virus according to the following probability model: if Prob_Virus>Prob_NonVirus*alpha.

To determine if malware is present in a target application, the heuristic malware profile detection method **701** scans **712** the target application for all DLL calls, and the suspect DLL call database **710** is queried **714** to determine which of those DLLs should be used to identify the existence of malware. A data structure is created **716** which nominally is one or more feature vectors describing the presence or absence of DLL calls (each being a feature element) associated with each of the malware profiles in the suspect DLL call database **710**. The heuristic malware profile detection method **701** plugs those feature vectors into the above probability model, or algorithm, with the heuristically derived conditional probabilities to compare **718** the feature vectors to the malware profiles in the suspect DLL call database **710**.

An Example Embodiment of a Malware Profile in the Symbian® OS Environment

An embodiment of heuristic malware profile creation and detection methods **700**, **701** on a mobile device with the Symbian® OS follows. Although this particular embodiment is based around Symbian® OS malware and files, the system and method can be generalized by one of ordinary skill in the art to other mobile phone operating systems. In the Symbian® OS framework, all interaction between the user process and the kernel takes place using imported DLL functions. Operations which can be used for malicious purposes, such as the system file deletion operation, use some of these imported functions.

Parsing the SIS File:

Symbian® executable code is of following types: .dll, .app, .exe or .mdl. These files are further compressed and packaged

into a SIS file format for installation on the mobile device. The SIS file may also contain other content such as bitmaps, icon files (AIF) and compiled resource files (.rsc). The SIS file format contains the following sections. First, a file header (68 or 100 bytes long) followed by records describing the data and the data itself which is pointed to by the records. The data pointed to by the records consist of executable code. Next, the file data is de-compressed before extracting the DLL imports from it. The list of DLL import functions used by a specific file are set as input to the classifier.

Extracting DLL Imports:

The executable code in Symbian® uses a special format called E32 format. It consists of the E32 header followed by a code section, initialized and un-initialized data sections, the import section and the relocation section. The import section starts with a header as defined in the E32ImportSection data structure followed by an array of import blocks as defined in E32ImportBlock data structure. Each import block contains the name of the DLL followed by all the imported functions. Each imported function appears as a number which gives the position in the DLL.

Reducing the DLL Import Set:

Using knowledge-based feature reduction, DLLs that are used by almost all executables malicious or not are eliminated as are those DLLs which provide user interface functionality. Specifically, the following DLLs are filtered out:

```
APPARC
AVKON
EIK* (all libraries starting with EIK like EIKCOCTL, EIKCORE, ... ]
AKN* (all libraries starting with AKN like AknNotify)
CKN*
CONE
EUSER
```

Implementation Issues:

One challenge when assigning conditional, or likelihood, probabilities is posed by a limited number of samples in a particular virus class. Due to this problem, it is difficult to assign reliable likelihood probability. To avoid this problem, a uniform high probability is assigned in such cases. This is also used as a tuning parameter in order to avoid false alarms. A high value of this probability means lower chances of false positives. This also means that the feature set becomes less flexible to detecting new variants. The Bayesian classification can result in underflow due to low values of probability. To avoid this problem, the logarithms of the probabilities is used.

Malware Detection Using Code Histograms

Referring now to the flowchart diagram of a histogram detection method depicted in FIG. **8**, the malware histogram creation method **800** requires selecting **802** a good sample space of malware-free and malware infected mobile applications. The malware histogram creation method **800** decompresses **804** each mobile application and the object code sections are extracted **806**. Next histograms of each application are created **808**, and, from those histograms, malware profiles are created **810** and stored in a malware histogram probability model database **812**. To scan a target mobile application, the malware histogram detection method **800** decompresses **814** a target application and creates **816** a histogram of the code sections. This histogram is compared **818** with the malware profiles stored in the malware histogram probability model database **812**.

The malware histogram creation and detection methods **800**, **801** use statistical analysis to extract features from existing virus samples and use them for generic detection of new malware. Because most new malware are variants of existing malware families there is similarity in the object code among existing malware infected files. The malware histogram creation and detection methods **800**, **801** exploit this object code similarity.

Code Histograms in the ARM Processor Environment

In one embodiment of the present invention, these generic features are based on ARM opcode. Most mobile phone operating systems (e.g., Symbian®, Windows Mobile®, Palm®) use the ARM processor architecture. The malware histogram creation method **800**, shown on FIG. **8**, selects **802** a large number of malware-free and malware-infected executables for ARM compatible mobile devices to train the histogram profiles.

Symbian® executable code is of three types: .dll, .app or .exe. These files are further packaged into a SIS file format for installation on a mobile device. The SIS file may also contain other content like bitmaps, icon files (AIF) and compiled resource files (.rsc). The feature extraction is meaningful only if the features are obtained from the executable content (since malicious code is meant to be executed). For each application, the malware histogram creation method **800** decompresses **804** the SIS packages and extracts **806** the object code sections.

The SIS file format contains the following sections: First, a file header (68 or 100 bytes long) followed by records describing the data and the data itself which is pointed to by the records. The malware histogram creation method **800** only uses the data pointed to by the records which consist of the executable files (.app, .dll, .exe). The records also contain pointers to the filename which is used to filter out files not used in the feature extraction. The file data is generally stored in compressed format and needs to be decompressed **804** before it can be used for feature extraction. The following algorithm decompresses **804** the SIS package.

```
Input : a SIS file X
Obtain n the number of files packaged in X.
Get Pointer to first File Record from Header.
while(n>0)
    Obtain Name of File from file record
    If (File obtained is executable)
        Decompress file data pointed to by the File Record
        Store the Decompressed data
    n--
    Goto next file record stored contiguously after the previous one
end while
Output: A set of decompressed data files containing executable code.
```

The uncompressed and decoded executable code is not always 100% relevant. Malware can, and almost always does, inserts random data into the code to hide execution patterns. Removal of unnecessary or garbage data provides for better and more efficient analysis.

The decompressed data files do not only contain executable code. The executable code in Symbian® use a special format called E32 format. It consists of the E32 header followed by a code section, initialized and un-initialized data sections, the import section and the relocation section. The header consists of the offset and the length of the code section which contains the executable instructions. To extract **806** the object code using the E32ImageHeader class provided by Symbian®, the following algorithm is utilized:

```
Input: Set of decompressed Data Files
For each data file in the Input set
    Extract the header using E32ImageHeader class.
```

-continued

```
    Extract E32ImageHeader::iCodeSize length of data from the data
    file - starting
        from E32ImageHeader::iCodeOffset position in the file.
    Store the extracted Code Block
end For
Output: Set of Code-Blocks extracted from Input
```

Histogram Creation

To create **808** a histogram, malware histogram detection method **801** creates **808** an index and a set of histogram data values. The ARM processor has the characteristic that each individual code instruction is a predefined number of bits, e.g., 32 bits, in length. A direct utilization however of this encoding results in a feature set of 232 instructions, meaning a histogram index having 232 members—one for each code instruction.

As an alternative, the code instructions are decoded and divided in broad categories. In an exemplary embodiment, the following set of code instruction categories function as the index to the histogram:

1. AND/OR and addition/subtraction.
2. Multiplication.
3. Store a single value to a virtual address in memory (datatype: unsigned halfword).
4. Load/store a single value from/to a virtual address in memory.
5. Move to ARM register from status register.
6. Move to status register from an ARM register.
7. Branch with exchange (Java enabled).
8. Signed multiply accumulate instructions.
9. Test bits and comparison.
10. Logical bit clear (AND NOT) and logical bitwise OR.
11. Move a 32-bit value or the logical not of it into a register.
12. Branch with exchange/Branch with link and exchange.
13. Count leading zeros.
14. Saturated signed and unsigned arithmetic.
15. Breakpoint.
16. Swap a word in memory with a register, without interruption.
17. The STREX instruction.
18. The LDREX instruction.
19. Load/Store a single value from/to a virtual address in memory.
20. S|Q
21. Pack 16-bit halfwords into a 32-bit word.
22. S|U
23. Select between two source operands based on the GE flags.
24. Reverse bytes within a word or halfword.
25. Unsigned sum of absolute differences.
26. Undefined instruction.
27. Store/Load multiple registers to/from memory.
28. Branch relative.
29. Relative branch with link.
30. Move between coprocessor and the ARM register (MCRR/MRRC).
31. Store/Load to/from coprocessor single or multiple 32-bit values.
32. Coprocessor data processing.
33. Move between coprocessor and the ARM register (MCR/MRC).
34. Software interrupt instruction.
35. Change processor state.
36. Set the endianness for data access.
37. Preload hint instruction.
38. Return from exception.
39. Save return state.
40. Branch with link and exchange.

The following preferred instruction decoding algorithm is used in conjunction with the ARM instruction set encoding table:

```
Input: A 32-bit length instruction.
(1) Check the leading hex digit of the instruction, bits 28 to 31. If this has
a value 0xF, then jump to the end of the table.
(2) Index through the table using the second hex digit, bits 24 to 27.
(3) Depending on context, index through the table using a set of decoding
bits including the following: bit 4, bit 7, bit 23.
Output: An instruction index in the set of instruction categories.
```

The features or data in the histogram are the frequency of occurrence of each of the distinct code instruction categories described above. These features are obtained from each file using the following compute feature histogram algorithm:

Input: The set of extracted instructions.

(1) Map each extracted instruction to one of the 40 labels defined. Sometimes these 4 bytes are strings that do not correspond to any command. In these situations, we simply set the corresponding label to be 0.

(2) Count the total number of each label in all the executable portions of the file.

(3) Let the total number of label i to be N_{ii}, $0 \le i \le 40$.

Output: Histogram A of the labeled features (1-40): $A=(a_0, a_1, \ldots, a_{40})$, $a_i=N_i/\Sigma_{i=0}^{40}N_i$.

Malware Profile Creation

To create **810** a malware profile used to check against an unknown target application, a Bayesian classifier and training data are employed as rule. Let H_0 be the hypothesis that a file contains malicious code and H_1 be the hypothesis that the code is not corrupted. A particular file with feature A is considered malicious if:

$$P(H_0|A)>P(H_1|A).$$

Applying Bayesian rule, we have:

$$p(A|H_0)P(H_0)>p(A|H_1)P(H_1).$$

Modeling the probability density of feature A given each hypothesis as a Gaussian function, that is:

$$p(A \mid H_k) = N\left(A - m_k, \sum_k\right) = \frac{1}{\left|2\pi\sum_k\right|^{1/2}}\exp\left(\frac{1}{2}(A - m_k)\sum_k^{-1}(A - m_k)^T\right),$$

$$k = 0, 1$$

The prior probabilities, $P(H_0)$ and $P(H_1)$, and the parameters, m_k and Σ_k, are estimated from the training data. The training data file is comprised of a large set of non-virus files and about 50% of all known viruses.

Rather than attempting to estimate the above parameters accurately with all the features, a subset A* from the whole feature set is used for classification. A* is obtained using cross-validation with the following algorithm:

(1) Let $A^*=\phi$, i.e., an empty set.

(2) Iteratively add features into A*, until all the features were added to A*:

(3) In each step, among all the features that do not belong to A* find A_i so that the feature set $\{A_i\} \cup A^*$ yields the minimum error rate of classification. Then add A_i to A*.

This process builds the parameters for the trained malware profile. The error rate of a particular feature set is tested by equally dividing all the training files into three groups. Among the three groups, pick two of them for training and the remaining one for testing. Let P_D and P_R be the percentage of detection, i.e., the percentage of malicious files that are detected, the percentage of correct reject, i.e., the percentage of normal files that are classified as not malicious. The error rate is the average of P_D and P_R on the testing set.

The malware histogram probability model database **812** stores the feature set and associated histogram, also known as

the rule, after the probabilities have been computed using the training data. When a target application is to be scanned, the malware histogram detection method **801** decompresses **814** the target application and a histogram of the code instructions is created **816** using the same functions above. The selected feature sets of the histogram of the target application are compared **818** using the associated rule with the trained probabilities of the malware profiles stored in the malware histogram probability model database **812** to determine if malware is present in the target application.

Feature Based Malware Detection

Referring now to the flowchart diagram of a feature based detection method depicted in FIG. **9**, a feature based relationship determining method **900** builds a feature set probability model database **912** of malware probability profiles and associated rules for matching by first selecting **902** malware-free and malware-infected mobile applications, extracting **904** object code from the selected applications, analyzing **906** the code by monitoring ARM branch-link commands, identifying common code procedures, and monitoring activated functions in the mobile device, building **908** feature set relationships and creating **910** malware probability models. To check for the presence of malware, the feature based malware detection method **901** scans **914** a target application's code, derives **916** which feature sets are present in the target application, and compares **918** the derived feature sets to the malware probability models stored in the feature set probability model database **912** via the appropriate rules. If the feature sets match a malware profile according to the rule(s), the system and method identifies and flags **922** the target application as possibly containing malware. Otherwise, the target application is allowed **920** to run on the mobile platform.

The feature based malware extraction and detection methods **900**, **901** use probability models to examine the relationship between a set of basic procedures used by normal non-malicious, or malware-free, programs and a set of procedures typically used by malicious malware. To build **908** a feature set of basic procedures used by malware applications, the feature based relationship determining method **900** selects **902** a number of malicious applications and breaks them down into their respective sequences of basic procedures which are then analyzed **906** for both code and behavior.

Common Malicious Procedures

The detection method identifies procedures that resemble malware behavior in an executable, including but not limited to Self-Replication, Spreading, and System Corruption. These procedures have a high probability of being found in malware.

Self-Replication:

A malware program attempts to make a copy of itself. Once this is done it creates an installation package file so that it can be installed on other devices. This functionality is implemented in a number of ways, but generally the malware follows the following strategy:

- The program issues a call to open its executable file and copy its data to memory
- The program loads a template to memory that includes a pre-defined header format for the installation package
- The program fills the template header with data specific to the executable, e.g., a pointer to executable code
- The program compresses the executable contents and packages it along with the header as an installation file.

Spreading:

A malware program attempts to spread from one device to another. On mobile platforms, the most effective spreading mechanisms for malware include Bluetooth® and MMS. Malware programs that spread over Bluetooth® usually adopt the following strategy:

- Search for nearby Bluetooth devices
- Lock on to a particular device and send its duplicated copy (generated as explained above) to the device
- Repeat the above steps whenever it finds new devices or at random intervals of time

Malware that spreads over MMS can use the phone book addresses on the mobile platform to transmit themselves. In such a case, for a receiving mobile device it appears as though the message has been sent by a trustworthy source resulting in them installing the malware. Another advantage of MMS is that, unlike Bluetooth®, spreading it is not constrained by physical distance. That is, Bluetooth® spreading can only occur when mobile devices are close in proximity to each other whereas this is not necessary for MMS spreading. Malware that spreads over MMS generally adopts the following strategy:

- Open the phone book and read its contents
- Send its duplicated copy to phone numbers read from the phone book
- Repeat the above steps at random intervals in time or at a specific time. For e.g., some malware send the message only at late night.

System Corruption:

A malware program destroys or corrupts application files or system files on the mobile device. Such malware can target specific applications such as anti-virus applications or in general destroy all installed applications. The following general strategy is used to corrupt applications on a device:

- Kill application processes running on the device
- Replace pre-installed applications with dummy files of the same name

Corrupting application files often results in loss of data and the need to reinstall applications. The general approach used to corrupt system files on a device is as follows:

- Replace system files with dummy files, e.g., files used in booting a device, files used for standard device fonts, etc.
- Reboot the device forcibly causing it to crash on reboot due to the absence of certain required files for start-up.

However, malware that corrupts system files can result in the device failing to recover from such an attack by the malware. A hard reset which erases all stored data on the device may be the only way to recover in some cases.

Code Analysis

To analyze **906** the code, the feature based relationship determining method **900** extracts **904** object code for individual procedures, disassembles it into assembly code, and categorizes it. Most malicious procedures such as replication, spreading, and system corruption use system functions, e.g., functions like File Open, File Read, etc. Identifying **906** these functionalities in binary executables allows them to be used as feature elements in a feature set. System functions are provided by the mobile platform for which the malware has been written. Most existing mobile executables are written to run on ARM processors. Whenever a system function call is used, it translates into a Branch-Link command in terms of ARM assembly code. Hence, the use of standard functions is identified by analyzing the parameter of the Branch-Link ARM command in an executable. In particular, the following procedures are identified using this method:

- File System related functions, e.g., read, copy, replace, etc.
- File compression or encryption
- Bluetooth protocol related functionality
- Messaging Related functionality

Socket connections and use of the network stack on the device

Phone/Address book access related functionality

Process related functionality, e.g., Process kill

Device related functionality, e.g., Device restart

Behavior Analysis

To analyze **906** the behavior, the feature based relationship determining method executes individual procedures in a mobile handset environment and monitors **906** the events, or activated functions, that occur from executing the procedures. It is possible that the above mentioned code analysis does not provide all the features of malware. Consider the following example: A malware when installed tries to access an instant messaging application and asks the application to broadcast instant messages to all of its contacts. Since the malware is using the application as intended, code analysis does not reveal its malicious intent such that the malware is achieving its goal indirectly. Hence, apart from analyzing **906** the executables and installation packages of mobile malware, additional procedures (or features) are obtained by observing or monitoring **906** the run-time behavior of malware on a real device by allowing it to execute on the device. For this, a monitoring system is developed on a mobile device to monitor usage of key resources on the device that are capable of being misused by malware. These include accessing communication protocols and system applications. Some of the preferred monitored system resources include:

Bluetooth® protocol data transfer

Wi-fi Interface data transfer

Network interface data transfer

Access to privacy information like address book

Messaging services

System file modification

Email-client applications and browser applications

File system access

Memory consumption due to multiple processes

Feature Set Creation

The feature based relationship determining method **900** uses the information from the code analysis and behavior analysis to build **908** a feature set. Each event and corresponding assembly code make up a feature element and together the feature elements from all known malicious functions or behaviors form a feature set. The feature set is obtained **908** after code/behavior analysis of multiple malware-infected applications. The feature set listed below represents an example feature set. These feature elements of the feature set are listed for convenience only. It would be readily apparent to one of ordinary skill in the art to develop a comparable set of feature elements. Sample feature elements are:

1. File Open: This feature is related to opening replication, i.e., a malware program opens its file and tries to copy itself
2. File Replace: This feature is related to System corruption where a system file is replaced by a malware file programmatically
3. Make Directory: This feature is related to creating an installation package which can be used for replication/spreading
4. Bluetooth® Initialize: This feature identifies an initialization of Bluetooth® functions for spreading
5. Compression: An installation package contains executables that need to be in compressed format. Hence, this feature identifies if a malware is trying to compress its executables
6. SDPAgent: This feature is related to the Bluetooth® spreading functionality
7. Messaging Initialize: We identify the initialization of multimedia messaging for spreading using this feature
8. Socket connection: We identify the socket connections related to spreading using this feature.
9. Phone Reboot: This feature is related to system corruption where a malware corrupts system files and tries to reboot the device
10. Protected Process: This feature is also related to system corruption where the malware makes itself protected and hence is difficult to be deleted/cleaned
11. Kill a Process: This feature is related to system corruption where a malware tries to kill a device process (for example, an anti virus process)
12. Contact Database: This feature is related to Spreading using MMS. Using this feature we identify if a malware tries to access a User's contact database
13. SMS Number Access: This is again related to the spreading using MMS or sending a SMS message to Phone number thereby causing the user financial loss.
14. Suspicious String: This is related to replication. We identify if a malware is trying to copy its own file
15. Template Loading: This feature is related to replication in that it identifies whether a malware is loading a template of a required header format
16. Illegal Format Files: This is related to system corruption.
17. Dummy Files: This is also related to system corruption. Here the malware installation file replaces system files
18. Suspicious Boot Loading: This can occur for any type of malware. Here a malware attempts to start itself on reboot
19. Rom File Replacement: A malware corrupts the device by replacing required system files
20. Font File Replacement: We identify if a malware corrupts the device by adding ill-formatted font files
21. Lock Drive: A malware locks the device memory card by inserting a password
22. Suspicious String (bootloading): A malware tries to load a dummy executable during boot up. Such activity can be detected using a string pattern in the executable.
23. Font File Replacement (no executables present along with this): A malware tries to corrupt system fonts. Hence it contains no executables other than a dummy system font file
24. Get Machine Specific Id: A malware gets the machine id of a device and uses it for malicious purposes
25. More Boot Files Than Executable Files: More boot files than executables suggest that the malware is trying to load executables other than the executables in its own set
26. Premium SMS Numbers Being Used: Premium SMS numbers hard coded in a program may suggest that the malware is trying to automatically send SMS messages to this number
27. Internet Socket: A socket connection indicates network activity
28. Monitor Network Connections: A malware may monitor network connections for malicious reasons, e.g., identifying the data being passed through a connection

Probability Model Creation

Once a malware feature set is sufficiently complete, two probability models are created **910** based on the feature sets: one for malware and the other for benign or malware-free programs. With these probability models, it is possible to compare **918** a target application with the probability models and distinguish malware-infected from malware-free programs using a Bayesian decision rule. An exemplary Bayesian classifier follows:

Let H**0** be the hypothesis that a file contains malicious code and H**1** otherwise. Let A={an} be the feature set characterizing the procedures of a file, where an=1, meaning that the corresponding procedure exists, or 0, meaning the corresponding procedure does not exist. Therefore, this file is malicious if:

$$\frac{P(H_0|A)}{P(H_1|A)} > \frac{C_{01}-C_{11}}{C_{10}-C_{00}}, \tag{1}$$

where $P(H_i|A)$ is the posterior probability of the hypothesis H_i given the input, for i=0 or 1. In a general situation, C_{00} and C_{11} are 0, i.e., there is no cost associated with correct detection and rejection. Hence (1) reduces to,

$$\frac{P(H_0|A)}{P(H_1|A)} > \frac{C_{01}}{C_{10}} \tag{2}$$

It is easy to see that the decision rule is closely related to the costs of false alarm and missing the detection of malware. If the cost of raising a false alarm is much higher than that of missing malware, a quite stringent decision rule is used; that is, only a program that is very likely to be malicious is detected as a virus. Consequently, there are fewer false alarms, but there is also a tendency to miss more viruses.

The task here is to compute the likelihood P(Hi|A). Applying the Bayesian rule [3, 6] to (2), provides:

$$\frac{P(A|H_0)}{P(A|H_1)} > \frac{C_{01}}{C_{10}}\frac{P(H_1)}{P(H_0)} = \alpha, \tag{3}$$

where P(A|Hi) is the corresponding likelihood and α is a parameter that depends on the prior probabilities P(Hi) as well as the cost functions C**01** and C**10**.

Since there is not any explicit formula to compute P(A|Hi) directly, P(A|Hi) is estimated from existing malware samples and benign programs. Let A**0**={0, 1, 1, 0, . . . , 0} be a configuration of A, the most direct way of estimating the value of P(A=A**0**|Hi) is to count the total number of programs that has the same feature configuration as A**0** and then divide the number by the total number of programs. By doing so, with N features, there is a need to evaluate total 2^N individual configurations, which is computationally infeasible for large N.

To simplify the computation of P(Hi|A), additional variables {bm} are introduced. Each variable {bm} characterizes a core function of malware-infected and/or malware-free program, and the entire set {bm} includes all the core functions. Assume that once these variables are given, the posterior probability of whether a file is malicious or not does not depend on the procedure any more, that is,

$$P(H_i|b_1,b_2,\ldots,b_M,A)=P(H_i|b_1,b_2,\ldots b_M) \tag{4}$$

In addition, variables {bm} are assumed to be independent. Therefore,

$$P(b_1, b_2, \ldots, b_M|A) = \prod_m P(b_m|A) = \prod_m P(b_m|A_m) \tag{5}$$

The last step utilizes the fact that a core function is only related to a subset of procedure functions Am. $A_m \subset A$. Therefore, there is:

$$\begin{aligned} P(H_i|A) &= \sum_{b_1}\sum_{b_2}\cdots\sum_{b_M} P(H_i, b_1, b_2, \ldots, b_M|A) \\ &= \sum_{b_1}\sum_{b_2}\cdots\sum_{b_M} P(H_i|b_1, b_2, \ldots, b_M, A) \\ &\quad P(b_1, b_2, \ldots, b_M \mid A) \\ &= \sum_{b_1}\sum_{b_2}\cdots\sum_{b_M} P(H_i|b_1, b_2, \ldots, b_M) \\ &\quad \prod_{b_m} P(b_m|A_m) \end{aligned} \tag{6}$$

Again with the assumption that variable {bm} are independent, there is:

$$\begin{aligned} P(H_i|b_1, b_2, \ldots, b_M) &= \frac{P(b_1, b_2, \ldots, b_M|H_i)P(H_i)}{P(b_1, b_2, \ldots, b_M)} \\ &= P(H_i)\prod_m \frac{P(b_m|H_i)}{P(b_m)} \\ &= P(H_i)^{1-M}\prod_m P(H_i|b_m) \end{aligned} \tag{7}$$

Therefore,

$$P(H_i|A) = P(H_i)^{1-M}\sum_{b_1}\sum_{b_2}\cdots\sum_{b_M}\prod_{b_m} P(H_i|b_m)P(b_m|A_m) \tag{8}$$

Again, use the assumption that once a core function is given, the posterior probability does not depend on the related procedure function any more, that is

$$P(H_i|b_m,A)=P(H_i|b_m) \tag{9}$$

Finally, there is:

$$\begin{aligned} P(H_i|A) &= P(H_i)^{1-M}\sum_{b_1}\sum_{b_2}\cdots\sum_{b_M}\prod_{m=1}^{M} P(H_i|b_m, A_m) \\ &= P(H_i)^{1-M}\sum_{b_1}\sum_{b_2}\cdots\sum_{b_{M-1}}\left[\prod_{m=1}^{M-1} P(H_i|b_m, A_m)\right] \\ &\quad \sum_{b_M} P(H_i|b_M, A_M) \\ &= P(H_i)^{1-M}\sum_{b_1}\sum_{b_2}\cdots\sum_{b_{M-1}}\left[\prod_{m=1}^{M-1} P(H_i|b_m, A_m)\right]P(H_i|A_M) \end{aligned} \tag{10}$$

-continued

$$= P(H_i)^{1-M} \sum_{b_1} \sum_{b_2} \cdots \sum_{b_{M-2}} \left[\prod_{m=1}^{M-2} P(H_i|b_m, A_m) \right]$$

$$P(H_i|A_{M-1})P(H_i|A_M)$$

$$= \cdots$$

$$= P(H_i)^{1-M} \prod_{m=1}^{M} P(H_i|A_m)$$

$$= P(H_i) \prod_{m=1}^{M} \frac{P(A_m|H_i)}{P(A_m)}$$

By applying (10) to (2), there is:

$$\prod_m \frac{P(A_m|H_0)}{P(A_m|H_1)} > \alpha \tag{11}$$

The difference between equations (3) and (11) is that in (11), A is divided into several groups, each of which corresponds to a specific core function. Since a group {Am} usually contains a few features, the corresponding probability P(Am|Hi) can be easily estimated.

Writers of malware code often try to obfuscate their malware by reordering sections of code to escape detection by malware scanners that look for matching signatures or code templates. The probability model described above does not have an order specific limitation, and can therefore detect malware once certain features are recognized as being present, regardless of how they are coded by malware writers.

Feature Set Relationship Database Creation

The malware procedure identification, code/behavior analysis, and development of the Bayesian Classification algorithm are tailored to each manufacturer/model of mobile phone for each service provider data network. However, because many mobile phones have significant overlap in their use of common processors and operating systems, and many data networks use similar protocols, many feature sets and Bayesian formulas are reused to some degree. Once the feature sets and Bayesian formulas (rules) are complete, the feature sets and rules, e.g., formulas, are stored in a feature set probability model database **912** and downloaded into a mobile device.

Malware Detection

To check a target application suspected of containing malicious code, the feature based malware detection method **901** scans **914** the target application's code in the mobile device. Each of the feature elements in a pre-defined feature set are derived **916** from the target application. The result is represented in a binary feature set vector, or feature vector, with a "1" indicating that the procedure is present in the searched executable, and a "0" otherwise. An example is provided below using the above sample feature set:

VeriChat is an always-on, unified Instant Messaging (IM) application for Symbian ® devices. It is a benign program with the following feature set A = {1 0 1 0 0 0 0 1 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 1 0 0 0 0}.
Commwarrior is a Symbian ® Series 60 worm that spreads through Bluetooth or MMS. It has the following feature set A = {1 1 1 1 0 1 1 1 0 1 1 0 0 1 1 0 0 0 0 0 0 0 0 0 1 0 0 0 0}.

Upon comparison of these feature sets, both programs have some common functionality, but it is clear that Commwarrior uses more functions related to malicious behavior. The target application's feature set vector is compared against the malware probability models and if there is a match, according to the associated rule, with one of the malware probability models, the application is flagged **922** as being malicious in nature and possibly containing malware. Otherwise, the application is allowed **920** to run on the mobile device.

Reporting System/CoreStats

Referring now to the schematic diagram of CoreStats depicted in FIG. **10***a*, one embodiment of the system and method for reporting and visualizing viruses on mobile networks, CoreStats **1000**, comprises the following components:

Reporting/Visualization Engine **1004**

Client Data Server **1002**

CoreStats **1000** monitors the Operator's Network **1008** by receiving communications from mobile client devices, or mobile platforms, **1010**. The mobile client devices **1010** in the operator network **1008** contain a client virus scanner **1012** capable of detecting viruses on mobile client devices **1010**. Referring to the schematic diagram of a transaction depicted in FIG. **10***b*, a full circle transaction comprises an infection report **1014** sent from a client device **1010** to CoreStats **1000**, and an acknowledgement **1016** sent from CoreStats **1000** back to the client device **1010**.

Referring now to an exemplary screen shot of CoreStats in FIG. **11**, a sample malware per platform report **1100** in CoreStats **1000** illustrates which mobile platforms are infected with the most malware. Referring now to an exemplary screen shot of CoreStats in FIG. **12**, a sample malware spreading report **1200** in CoreStats **1000** illustrates which malware are spreading the fastest. Referring now to an exemplary screen shot of CoreStats in FIG. **13**, a sample user infection report **1300** in CoreStats **1000** shows recently infected mobile platforms. Referring now to an exemplary screen shot of CoreStats in FIG. **14**, a sample virus producer report **1400** in CoreStats **1000** shows which users, or clients, are responsible for spreading the most malware.

FIG. **10***a* illustrates a deployment of CoreStats **1000** outside of the operator network **1008** but alternatively, it also is deployed effectively at various other points in the mobile network. In one embodiment of CoreStats **1000**, the reporting/visualization engine **1004** uses data from the client data server **1002** to graphically report malware statistics in the network. The client devices **1010** contain virus scanning **1012** algorithms which report back information about any malware to the Client Data Server **1002**.

Detection of Handset Infection

The reporting/visualization component **1004** takes input from the client data server **1002** to generate statistics and dynamic graphs depicting malware activity. Client devices **1010**, usually mobile platforms such as mobile phones, contain virus scanning software, or client virus scanners **1012**, that scan the mobile devices **1010** for malware. In one embodiment of the present invention, a handset upon detecting malware generates an internal log file in plain text containing the name of the infected file and the name of the malware that infected the file as a semi-colon delimited text file. The entries in the log file are as follows: "C:\CinBell_Viruses.zip—Cabir.D(sis);
C:\CinBell_Viruses\3d_oidi500.sis-Cabir.D(sis);
C:\CinBell_Viruses\autoexecdaemon.SIS—Cabir.gen(app);".

The client virus scanners **1012** report back information about any malware to the client data server **1002**. Report generation can be automatically triggered upon finding a

virus, upon a periodic fixed time interval, or in response to polling by the client data server **1002**. The reports are sent, for example, using http, ftp, or any packet data transmission method as would be generally known in the art. Such reports typically comprise information such as, but not limited to detailed virus/threat vector information, device identification including type of mobile device, operating system, software and versions, and user information. In an exemplary embodiment of the invention, a sample report contains the following information:

Product Identification to identify the Client Virus Scanner software. This consists of "productid+majorversion+minorversion+patchversion";

Infected filename;

Firmware of the device i.e. the operating system information;

Software version of the device;

Unique Identifier of the infected application;

Name of the malware infection; and,

Date and time of infection.

Storing of Handset Infection Reports

CoreStats **1000** performs information gathering functions. Embedding within CoreStats **1000** is a database **1006** to store raw information gathered by CoreStats **1000** from the client virus scanners **1012**. User specific information is stored in a secure portion of the database **1006** to maintain customer privacy. In an exemplary embodiment of the present invention, the database **1006** has a log file comprising the following information:

Detection Time;

Virus Name;

Infected File Name;

Infected File Size;

Infected Packet Size;

Infected Packet Number;

Source IP;

Source Port;

Source Phone Number;

Destination IP;

Destination Port;

Destination Phone Number; and,

Protocol name.

Full-Circle Transactions Between CoreStats **1000** and Client Devices **1010**

Referring now to the flowchart diagram of a transaction process depicted in FIG. **10***b*, which illustrates an efficient full-circle transaction between the client device **1010** and CoreStats **1000**. Once the client device **1010** sends an infection report **1014** to CoreStats **1000** (on the network), there is an acknowledgement **1016** sent back to the client device **1010** which causes it to delete its existing infection report **1014** and start creating a new infection report **1014**. This particular implementation has two advantages. First, client devices **1010** do not send duplicated information to the CoreStats **1000** about old virus infections, only current ones. Second, client devices **1010** are less burdened memory-wise since they need to retain infection reports **1014** locally for a small duration of time. This is especially important in the case of mobile devices **1010** since they have limited memory resources.

Infection reports **1014** can be configured to be pushed from the client device **1010** to CoreStats **1000** either ad hoc or periodically at regular intervals; the infection reports **1014** can remain in the client device **1010** until queried (pulled) by CoreStats **1000**; or the infection reports **1014** can be delivered to CoreStats **1000** using some combination of pulling and pushing.

Analysis of Handset Infections

CoreStats **1000** also performs report generating functions. The reporting/visualization engine **1004** uses both stored and real-time information, including individual user information, to generate statistics and dynamic graphs depicting malware activity and relative levels of malware activity. For example, the reporting/visualization engine **1004** generates straightforward visual reports to alert managers and operators as to which platforms are infected with the most viruses, which viruses are spreading the fastest, the most recently infected users, and which infected users are spreading the most viruses.

Reports

Referring to an exemplary screen shot of CoreStats in FIG. **11**, a sample malware per platform report **1100** in CoreStats **1000** illustrates which platforms are infected with the most malware. The sample malware per platform report **1100** comprises option selections **1102** for generating a report regarding a selectable interval of time in the past **1104** or the most current period of time **1106**. The report is run to the screen **1110** or it is exported **1108** in a data structure, for example, a semi-colon delimited text file. When run to the screen **1110**, the data can be presented any number of ways including, for example, a graphical representation **1112** of the number of viruses per platform.

Referring now to an exemplary screen shot of CoreStats in FIG. **12**, a sample malware spreading report **1200** in CoreStats **1000** illustrates which malware are spreading the fastest. The sample malware spreading report **1200** comprises options selections **1102** for generating a report regarding a selectable interval of time in the past **1104** or the most current period of time **1106**. The report can be run to the screen **1110** or it can be exported **1108** in a data structure, for example a semi-colon delimited text file. When run to the screen **1110**, the data can be presented any number of ways including, for example, a graphical representation **1212** of the number of instances of each virus detected in the network.

Referring now to an exemplary screen shot of CoreStats in FIG. **13**, a sample user infection report **1300** in CoreStats **1000** shows recently infected users. The sample user infection report **1300** comprises option selections **1102** for generating a report regarding a selectable interval of time in the past **1104** or the most current period of time **1106**. The report can be run to the screen **1110** or it can be exported **1108** in a data structure, for example a semi-colon delimited text file. When run to the screen **1110**, the data can be presented any number of ways including, for example, a text list **1312** of which platforms are infected by which viruses.

Referring now to an exemplary screen shot of CoreStats in FIG. **14**, a sample virus producer report **1400** in CoreStats **1000** shows which users are responsible for spreading the most malware. The sample user infecting report **1400** comprises option selections **1102** for generating a report regarding a selectable interval of time in the past **1104** or the most current period of time **1106**. The report can be run to the screen **1110** or it can be exported **1108** in a data structure, for example a semi-colon delimited text file. When run to the screen **1110**, the data can be presented any number of ways including, for example, a text list **1412** of which platforms are infected by, and therefore likely to be spreading, the most viruses.

Some additional reports generated by the reporting/visualization engine **1004** include the growth of individual viruses over time, and infected subscriber information. User specific information is stored in a secure portion of the database **1006** to maintain customer privacy. Other functions and metrics can be formed by one of ordinary skill in the art.

Interaction with Other Systems

Another way CoreStats **1000** helps mobile network administrators and operators is by reporting alarms upstream to other operational support systems or OAM&P (Operations, Administration, Maintenance, and Provisioning) systems used by network service providers to manage their networks **1008**. The term "operational support system" is generally understood to include a broad range of computer systems and servers created by many different vendors and used by network operators to manage and control their networks and individual network elements. An operational support system may have centralized or distributed servers. Network elements are those individual systems that are assembled by the network operators to build out a functioning network. Many network elements are managed by one or more operational support system, and are capable of reporting alarms to operational support system, as well as receiving and sending configuration information.

The CoreStats System

In one embodiment, CoreStats **1000** operates as a standalone system with some associated virus scanning modules running independently in user mobile devices **1010** to aid in reporting and visualizing viruses on mobile networks **1008**, and monitoring the current status of virus infections on a mobile network **1008**. CoreStats **1000** can also integrate with other operational support systems, reporting alarms upstream to typical OAM&P (Operations, Administration, Maintenance, and Provisioning) systems used by network service providers to manage their networks **1008**. In other embodiments, CoreStats **1000** is an application that operates inside the operator network **1008**, at the edge of the operator network **1008**, inside a network element of the operator network **1008**, or in a combination of locations. As one familiar in the art would appreciate, these are merely exemplary embodiments of the invention for illustration purposes only, and are not intended to limit the invention to any particular configuration or topology.

Updating Malware Protection Using a Device Independent Secure Management Protocol

Referring now to the schematic diagram of CoreStats depicted in FIG. **15**, a central management server **1502** in CoreStats **1000** uses a device independent secure management protocol, such as a DM protocol, to update malware definitions in client malware scanners **1012** from a database **1006** of the most recent malware definitions. The client malware scanners **1012** reside in mobile client devices **1010** in an operator's network **1008**.

In the preferred embodiment, the SyncML DM standard, as promulgated by the Open Mobile Alliance (OMA), provides a Device Management (DM) protocol for transfer management actions between a client device **1010** or mobile phone client and a central management server **1502**. SyncML DM enables an operator in the enterprise or carrier network **1008** to remotely manage the settings of the mobile client devices **1010** using the DM management objects. Those settings can, in principle, be of any kind, including but not limited to, anti-virus definitions, security parameters and other information to mobile client devices **1010** or phones connected to the enterprise or carrier network **1008**. The description of the present invention in terms of the OMA/DM framework is for convenience only and describes the preferred embodiment of the present invention. The system and method of the present invention applies equally to any network communication scheme employing a device independent secure management protocol.

The OMA DM framework builds upon the principles of data synchronization. Data synchronization is typical two-way synchronization, where one central database is synchronized with one or several remote databases. Changes can happen in both places. OMA DM is characteristic in the way that the original data is always in a database **1006** accessible from a central management server **1502**, for example in CoreStats **1000**, and may be placed in the operator's network **1008** and owned by a service provider or an operator (shown in FIG. **15** as outside the operator's network **1008**.) Settings data are applied from the central place to the remote place. This must be done in a controlled and secure way. The exchange of OMA DM commands and status uses binary encoded XML (WBXML). The central management server **1502** is a device management server that sends DM commands to the client device **1010** and the client device **1010** answers back with a status message. The DM commands can be Add, Get, Replace, Delete, and so on, and the status is the result in form of a status code and eventual returned data (for example, with a Get command).

The OMA DM implementation in the client device **1010** consists of two main parts:

OMA DM Protocol

OMA DM User Agent

The OMA DM Protocol holds the state machine controlling establishment, management, and termination of the DM session. OMA DM User Agent takes care of executing the actual OMA DM commands and generates the relevant status messages.

All data to be managed is organized in a management tree. The management tree is an abstraction of the mobile device. The management tree contains various types of nodes including a root node, interior node, and a leaf node.

The leaf node holds the data. The data can be one single value or a structure or even a file including any kind of data. The interior nodes are used to structure the data and to address where in the tree the data is stored. The root is the placeholder for the complete management tree. The management tree is grouped into Management Objects. Each management object holds a well-defined group of leaf nodes each holding a certain parameter.

The malware protection system as disclosed herein uses a leaf node as defined by the OMA DM standard to hold the database **1006** of malware signatures or definitions for the malware protection system on a given mobile device. In addition to malware signatures, a leaf node can also be used to hold specific malware protection system settings, such as desired update and full-system scan parameters, and a variety of security settings and other relevant information. The update of the malware signatures or definitions is performed using the OMA DM protocol.

Under the OMA DM protocol, the OMA definition User Agent executes the OMA DM commands necessary to update the malware system files and other settings such as security parameters and information on a mobile client device **1010**. The User Agent also provides status information back to the central management server **1502** to indicate successful update, etc. Further, the User Agent can also be used to execute specific anti-virus commands, such as initiate a full system scan, etc.

The database **1006** connected to the OMA DM enabled central management server **1502** serves as a central repository for malware definitions, settings and other information. The OMA DM enabled central management server **1502** also coordinates the operation of specific anti-virus programs and security levels throughout the operator's network **1008**. For example, when malware is detected on the network **1008**, the OMA DM enabled central management server **1502** issues

commands to the mobile devices **1010** to update the relative malware scan levels relative to specific threat vectors, as well as, updated malware definition files to enable the mobile client device **1010** to handle the potential virus outbreak. The OMA DM enabled central management server **1502** is maintained as either an enterprise or carrier network-based system.

The individual enterprise or carrier network **1008** OMA DM enabled central management servers **1502** obtain malware update information and system security parameters and other information through a variety of means. In one embodiment, the malware signatures and updates are provided by a third-party server as part of a subscription service. The updated signatures and information are received by the OMA DM enabled central management server **1502** are then propagated using the OMA DM protocols to the mobile client devices **1010** associated with the OMA DM server. In a second embodiment, the carrier or enterprise central management server **1502** actively manages the security parameters and other settings as necessary based on the subject threat of a given malware on the managed enterprise or carrier network **1008** at a given time. In yet another embodiment, the malware signatures are actively identified by programs running on the enterprise or carrier network server **1008** that then identify specific signatures in the database **1006** for distribution to the mobile client devices **1010**.

The present malware protection system embeds the malware protection application at the firmware level of the client device **1010**, thereby reducing the need for customization of the client malware scanner **1012** for different platforms. The client malware scanners **1012** on the mobile client devices **1010** are managed by the DM server **1008** at the carrier or enterprise network level. The DM server **1008** in CoreStats **1000** thus manages all updating of the client devices' **1010** malware definitions using the OMA DM protocols.

Although the disclosed embodiment utilizes the OMA DM framework for updating anti-virus definitions and other system protocols and settings through a managed device network, other methodologies and frameworks are utilized in a similar manner using the methods disclosed herein by one of ordinary skill in the art.

Conclusion

The numerous embodiments described above are applicable to a number of different applications. One particular application where the system and method is particularly applicable is in detecting malware in mobile environments. The malware detection system and method also has many additional applications outside the mobile environment that would be apparent to one of ordinary skill in the art.

The embodiments of the invention shown in the drawings and described above are exemplary of numerous embodiments that may be made within the scope of the appended claims. It is contemplated that numerous other configurations of the disclosed system, process, and devices for detecting malware may be created taking advantage of the disclosed approaches. It is the applicant's intention that the scope of the patent issuing herefrom will be limited only by the scope of the appended claims.

What is claimed is:

1. A method of detecting malware, comprising:

selecting, by a mobile device, a first set of hash values hashed from prefixes of a set of malware signatures, each of the prefixes having a first-portion-size, wherein the malware signatures have lengths greater than the first-portion-size;

hashing, by the mobile device, a plurality of strings of a target application to create a plurality of second hash values, each of the strings having the first-portion-size, the target application comprising a downloaded application having a size greater than the first-portion size;

comparing, by the mobile device, the plurality of second hash values to the first hash values to determine if there is a match;

determining, by the mobile device, that the target application is malware-free when there is no match between the plurality of second hash values and the first hash values; and

when there is a match between one of the first set of hash values and one of the second set of hash values:

determining the malware signature of the set of malware signatures from which the one of the first set of hash values was hashed that matched the one of the second set of hash values;

comparing a hash of the entire determined malware signature to hashes of one or more strings of the target application, each of the strings having lengths equal to the length of the determined malware signature; and

determining that the target application is malware-infected when there is a match between the hash of the entire determined malware signature and at least one of the strings of the target application having the lengths equal to the length of the determined malware signature.

2. The method of claim **1**, wherein the first-portion-size is less than or equal to a shortest one of the malware signatures.

3. The method of claim **1**, wherein the first hash value is selected from the group consisting of: a 32-bit value, a 64-bit value, a 96-bit value, and a 128-bit value.

4. The method of claim **1**, further comprising, when there is a match between at least one of the plurality of second hash values and at least one of the first hash values:

selecting a first splatter set of blocks derived from a first-portion-sized string of one of the malware signatures;

deriving a second splatter set of blocks from the target application starting at a same location in the target application wherein the match occurred, wherein the first splatter set and the second splatter set are equally sized and equally patterned splatter sets of blocks; and,

comparing the first splatter set and the second splatter set to determine if there is a splatter set match, wherein if there is no splatter set match then the target application is malware-free.

5. The method of claim **4**, wherein deriving of the first splatter set and the second splatter set is performed using a pseudorandom function.

6. The method of claim **1**, wherein a set of search values is created at an operational support system, each of the search values selected from the group consisting of: a first hash value, a splatter set, and a rigorous hash value, the method further comprising:

distributing the set of search values to a mobile platform.

7. The method of claim **6**, wherein distributing comprises distributing the set of search values using an device independent secure management protocol.

8. The method of claim **6**, wherein the distributing is performed by an operational support system.

9. The method of claim **1**, further comprising:

reporting the target application to an operational support system when the target application is malware-infected.

10. A mobile device comprising a system for detecting malware, the system comprising:

a data store, the data store comprising a plurality of hash values hashed from prefixes of a set of malware signatures, each of the prefixes having a first-portion-size,

wherein at least one of the malware signatures has a length greater than the first-portion-size; and

one or more processors configured to:

select a first set of hash values from the plurality of hash values;

hash a plurality of strings of a target application to create a plurality of second hash values, each of the strings having the first-portion-size, the target application comprising a downloaded application having a size greater than the first-portion-size;

compare the plurality of second hash values to the first set of hash values to determine if there is a match;

determine that the target application is malware-free when there is no match;

when there is a match between one of the first set of hash values and one of the second set of hash values:

determine the malware signature of the set of malware signatures from which the one of the first set of hash values was hashed;

compare a hash of the entire determined malware signature to hashes of one or more strings of the target application, each of the strings having lengths equal to the length of the determined malware signature; and

determine that the target application is malware-infected when there is a match between the hash of the entire determined malware signature and at least one of the strings of the target application having the lengths equal to the length of the determined malware signature.

11. The mobile device of claim **10**, wherein the mobile device is selected from a group consisting of: a mobile telephone, a smart phone, a mobile computing device, a smart handheld device, and a network element.

12. The mobile device of claim **10**, wherein the data store further comprises a plurality of splatter sets computed from the first-portion-sized strings of the malware signatures, and further comprising:

a splatter set selecting means for selecting, when there is a match between the plurality of second hash values and the first set of hash values, a first splatter set from the plurality of splatter sets;

a computing means for computing a second splatter set from the target application; and,

a splatter set comparing means for comparing the second splatter set to the first splatter set to determine if there is a splatter set match, wherein if there is no splatter set match then the target application is malware-free.

13. The mobile device of claim **10**, further comprising:

a receiving means for allowing an operational support system to modify the data store.

14. The mobile device of claim **10**, wherein the receiving means supports a device independent secure management protocol.

15. The mobile device of claim **10**, further comprising:

a reporting means for reporting the target application to an operational support system when the target application is malware-infected.

16. A non-transitory computer-readable storage medium having stored thereon instructions that, when executed, cause a processor of a mobile device to:

select a first set of hash values hashed from prefixes of a set of malware signatures, each of the prefixes having a first-portion-size, wherein the malware signatures have lengths greater than the first-portion-size;

hash a plurality of strings of a target application to create a plurality of second hash values, each of the strings having the first-portion-size, the target application comprising a downloaded application having a size greater than the first-portion size;

compare the plurality of second hash values to the first hash values to determine if there is a match;

determine that the target application is malware-free when there is no match between the plurality of second hash values and the first hash values; and

when there is a match between one of the first set of hash values and one of the second set of hash values:

determine a malware signature of the set of malware signatures from which the one of the first set of hash values was hashed;

compare a hash of the entire determined malware signature to hashes of one or more strings of the target application, each of the strings having lengths equal to the length of the determined malware signature; and

determine that the target application is malware-infected when there is a match between the hash of the entire determined malware signature and at least one of the strings of the target application having the lengths equal to the length of the determined malware signature.

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