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RESEARCH ARTICLE

MalView: Interactive Visual Analytics for Comprehending Malware Behavior

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ABSTRACT Malicious applications are usually comprehended through two major techniques, namely static and dynamic analyses. Through static analysis, a given malicious program is parsed, and some representative artifacts (e.g., control-flow graphs) are produced without any execution; whereas, the given malicious application needs to be executed when conducting dynamic analysis. These two mainstream techniques for analyzing the given software are effective in detecting certain classes of malware. More specifically, through static analysis, the patterns and signature of the malware are exposed, helping in detecting any known malicious payload hidden in or injected into the code. On the other hand, behavioral and run-time execution patterns of software are explored through dynamic analysis. To ease the analysis process, a third analysis approach, known as the visual representation of the artifacts created by both static and dynamic analysis tools, would also be a supplementary asset for malware experts. This paper introduces *MalView*, an interactive visualization platform, for malware analysis by which pattern matching techniques on both signature-based and behavioral analysis artifacts can be utilized to 1) classify malware, 2) identify the intention and location of the malicious payload in the artifacts, 3) analyze unknown malware (i.e., zero-day malware) by recognizing any unusual signature or behavior, and 4) explore the time dependencies and thus the system components affected or tampered by the underlying malware. The results of several case studies conducted in this work show that *MalView* offers more features and information compared to some other visualization tools, facilitating the malware analysis process.

INDEX TERMS Malware analysis, dynamic analysis, malware visualization system, visual analytics.

I. INTRODUCTION

Malicious software applications, or malware, are the primary source of many security problems. These intentionally manipulative malicious applications intend to perform unauthorized activities on behalf of their originators on the host machines for various reasons such as stealing advanced technologies and intellectual properties, governmental acts of revenge, and tampering sensitive information, to name a few. Malware applications are complex software programs that are often obfuscated to disguise their main intentions and thus deceive network administrators and the underlying intrusion detection systems. Although such obfuscations can be captured, reported, and maintained in a repository as a reference for building better detection mechanisms, newer malware programs are constantly developed by professional hackers raising the challenging problem of zero-day malware detection [1]. As a result, in order to build an effective malware detection and defense system, it is crucial to understand each malware and comprehend its behavior through rigorous analysis.

There are two conventional approaches that are widely adopted for analyzing software programs: 1) *static* analysis by which the underlying software is parsed, and

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intermediate transformations of the underlying software are generated without actually executing the software program. For instance, a control-flow graph can be created to represent the execution control of the program under test; and 2) *dynamic* analysis by which the program under test is executed in a controlled environment (e.g., a sandbox) and the behavior of the program is observed under various environmental conditions for further analysis. For instance, a sandbox (e.g., Cuckoo [2]) can capture the processes that are created along with the files that are tampered with or modified during the execution of the program under test. These two conventional program analysis techniques (i.e., static and dynamic) are often complementary to each other, each targeting different types of faults or malicious activities in the program that is being analyzed. There is also a third "*hybrid*" approach that enables conducting both static and dynamic analysis of the program under test.

Although these conventional program analysis techniques are shown to be effective in comprehending static and dynamic features of the software under test, it is often time-consuming, labor-intensive, and technically challenging to build a customized analysis platform. Therefore, to ease performing such a complex analysis, some other analysis techniques with a smoother learning curve and faster comprehension of functionalities of the underlying software under test should be developed for analysis purposes. The visual analytics approach is one of those possible solutions to facilitate the analysis process and efficiently and effectively showcase the processes involved in malware analysis.

This paper introduces an interactive visualization platform, called *MalView*, for performing analytical reasoning of malware behaviors. *MalView*[1] is an analysis-oriented development to our previously created malware visualization tool [3]. *MalView* emphasizes comprehensive understanding from visual analytics with in-depth, multi-faceted explorations of malware behavior and scalability to multiple malware families. The result of malware triage and analysis is significantly enhanced if a provenance of software artifacts can be identified, especially when specific attributes of suspected malware are used to identify similarities to a set of known malware artifacts, as shown by Casey *et al.* [4]. In light of improving malware analysis utilizing malware artifacts, the current prototype provides a detailed graphical representation for malware analysis to identify: (1) indicators of compromise and malicious activities, (2) tampering, modification, and possible damages occurred on the system, (3) the mechanic of how malware functions and infect, (4) the primary target of the malware, (5) the suspicious events occurred on the network, (6) the impact on the host and its registry, and more notably (7) the time and process dependencies occurred while executing the malware, the key feature of *MalView*.

[1]The application and demonstration video of *MalView* can be accessed at: https://malview.netlify.app and https://malview.netlify.app/video.

Malware visualization systems can be categorized into three categories: Malware forensics, Malware Comparison, and Malware Summarization [5]. The work in *MalView* is under Malware Forensics and Malware Comparison categories: assisting the understanding of the behavior of an individual malware sample for forensics. By exploring the characteristics and relationships between the process and its dependencies and mapping them to visual features, *MalView* provides an interactive and intuitive platform to comprehend malware behavior towards the ultimate goal of generating rules and signatures for fully-automated malware detection systems. To demonstrate the effectiveness of *MalView* in identifying and interpreting malicious and suspicious activities of malware, the paper reports the analysis of different families of malware namely: Remote Access Trojans (RATs), Backdoor, Ransomware, Behavioral, Email Flooder, and Hacktool. The results show that using *MalView* it is possible to quickly understand the main functionalities of the underlying malware without delving into a complex analysis of the static and dynamic analysis reports.

While conducting the case studies and inspecting some malware families, the authors noticed the different behavior exhibited by the same malware on different operating system (OS) platforms. As a result, each malware was executed and inspected on three different Windows platforms: Windows XP, Windows 7, and Windows 10. Even though the execution of each malware was performed in a controlled environment, it was noticed that the newer platforms of Windows operating systems (e.g., Windows 10) were creating more system and kernel-level processes making it harder to thoroughly inspect and analyze the exact flow of each malware on these recent versions of platforms. As a remedy for such problem, it is suggested to apply additional filtering mechanisms in order to analyze each malware and its processes thoroughly. This paper makes the following key contributions:

1) It introduces *MalView*, a malware visualization tool to enable analytical reasoning of malware behaviors.
2) The *MalView* visualization tool visualizes the output of several dynamic and static analysis tools.
3) The tool also integrates the output of many anti-virus tools using their Application Programming Interface (API) to provide additional insights for each malware.
4) The paper demonstrates the efficiency and effectiveness of *MalView* through several case studies conducted on a set of the family of malware.
5) The paper also compares the behavior of each malware when executed on three different Windows platforms (i.e., XP, 7, and 10) in order to recognize the impact of environmental settings on malware comprehension and analysis.

A. ORGANIZATION OF THE PAPER

The rest of the paper is laid out as follows: Section II gives an overview of the data collected and feed into the visualization. Section III introduces the system and visualization tasks that guide the system design. Next, section IV elaborates on the visual components with interactivity and highlights the key features of *MalView*. Section V presents the analysis performed using *MalView* on a set of family of malware types. The influence of the running platforms on malware behavior is articulated in Section VI. A feature-based comparison of *MalView* and some other malware visualization tools is demonstrated in Section VII. The state-of-the-art of malware visualisation is presented in Section VIII. Section IX concludes the paper and highlights the future research work.

II. CAPTURING DYNAMIC BEHAVIOR USING ProcMon

Dynamic analysis aims at studying the behavior and actions of malware sample when it is executed. This technique analyzes malware and returns the collected information of such behavior and actions for further processing or analysis [5]. Assuming that the malicious sample does not employ any anti-forensics guards, in this paper, the Windows Sysinternals Process Monitor [6], or Procmon, is employed to capture the run time behavior of malware during execution. *MalView* visualizes the outputs and traces produced by Procmon rather than explicitly executing a given malware directly. During the dynamic analysis of malware execution, Procmon can capture five types of events that the Windows-based malware interacts with the host system: 1) file system, 2) registry, 3) network, 4) process and 5) profiling.

While capturing dynamic behavior of malware, it is important to use a proper Procmon filtering to avoid capturing unnecessary information from the normal execution of the system. Furthermore, even when the underlying system is idle, it has numerous background processes running that can be captured by the Procmon. As a result, the authors filtered out the activities by capturing suspicious processes only represented by functions commonly encountered by malware analysts [7], [8]. Furthermore, they excluded the default system operations such as Procmon, Autoruns, Sysmon from further visualization and analysis.

A. DATA ATTRIBUTES

Procmon provides records of Windows activities through the low-level system events, where thousands of events are generated every minute. The standard output in Comma Separated Value (CSV) format from Procmon is used as the primary input for visualization components in *MalView*. One row in the CSV log file demonstrates one specific event and comprises of these major attributes [9]:

- Time of Day: The timestamp of the day when the event occurred.
- Process Name: The name of the process – active executable, performing the operation.
- PID: Process identifier (ID).
- Operation: The name of the executing operation.
- Path: The path to the target object being operated on. This field can be empty, depending on the operation/process.
- Result: The result of the operation. The values for this field include success, denied, or access.
- Detail: The additional notes about the event.

B. EVENT CATEGORIES

The log file output from Procmon contains five major types of process activities, which are color-coded in our framework.

- Registry: Events of registry operations, such as querying and enumerating keys and values.
- File System: Events related to operations on local and remote storage and file systems.
- Network: Network activities, including TCP and UDP.
- Process: Events of process/thread, such as process creation, start, and exit.
- Profiling: Events for every process in the system in terms of memory used, kernel and user time charged, output as a log for the profile.

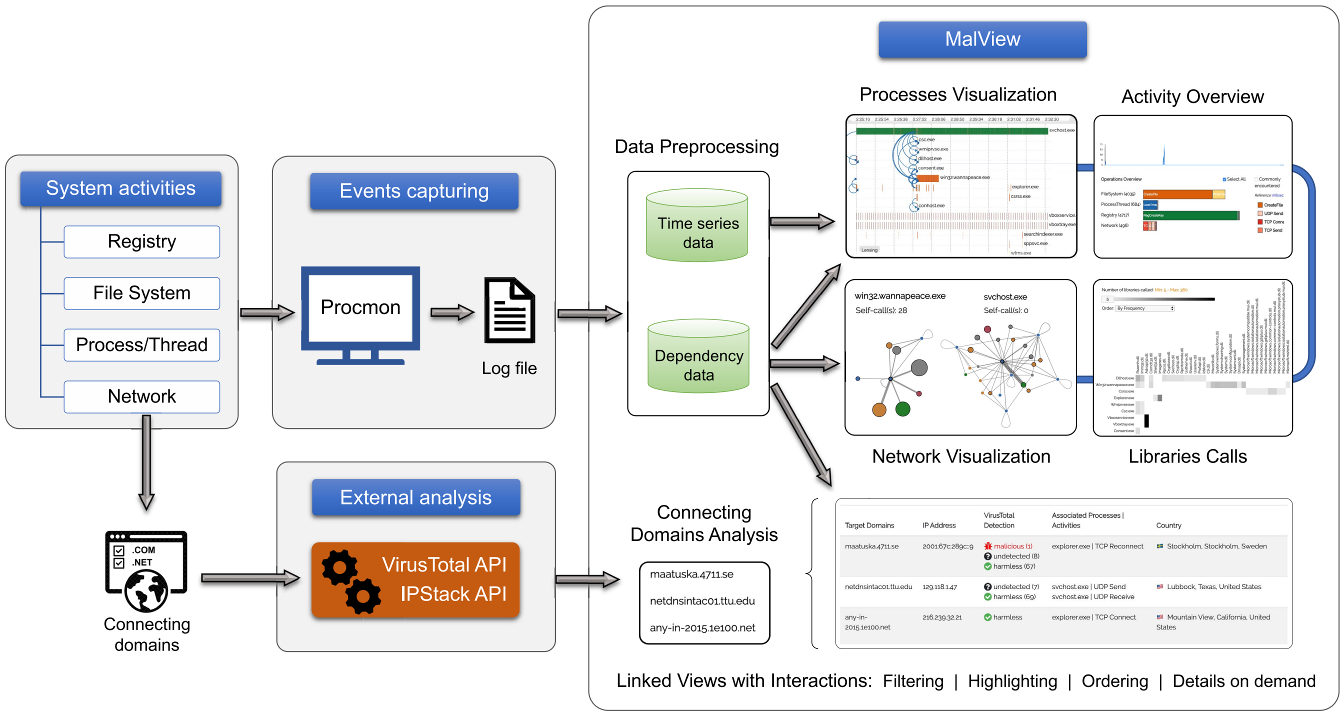
III. MalView: SYSTEM OVERVIEW

MalView is aimed at accelerating malware analysis and integrating visual analytics to enable interactive data exploration and malware behavior comprehension. Figure 1 depicts the architecture of *MalView*. The flow of information in *MalView* is as follows: 1) It uses a data provider in dynamic analysis, where the malware sample is executed on a host system, then the data provider logs relevant information into execution traces. 2) *MalView* takes in the raw data captured by the data provider, extracts the information, and maps them to visual features. 3) *MalView* explores the relationship between each process and its dependencies. To the best of our knowledge, this feature has not been taken into account in previous work, not only the malware as an individual but also its interactions with the system and the artifacts created.

The *MalView* prototype provides visual representations for system and malware activities captured by Procmon [6] utility. In the context of malware analysis, four important system-level activities are of utmost importance that need to be captured, namely registry, file system, processes and threads, and network activities. These are four major categories that are highlighted by InfoSec [7], [8] as an indication of malicious activities. The processes and events related to these four activities are captured by Procmon, filtered, and then fed to *MalView*.

MalView provides an analysis of linked views with interactions for users to gain comprehensive insights into malware behaviors within the system. Details of *MalView* visual components with their corresponding interactive features are described in the following section, *MalView*: Visual components.

The tool *MalView* is developed as a web-based application using JavaScript and D3.js library created by M. Bostock *et al.* [10]. The primary goal of *MalView* is to provide an interactive visualization platform that demonstrates the malware behaviors and interactions within the system. The captured events are presented in multiple



Target Domains	IP Address	VirusTotal Detection	Associated Processes | Activities	Country
maatuska.4711.se	2001:67c:289c::9	malicious (1) undetected (8) harmless (67)	explorer.exe | TCP Reconnect	Stockholm, Stockholm, Sweden
netdnsintac01.ttu.edu	129.118.1.47	undetected (7) harmless (69)	svchost.exe | UDP Send svchost.exe | UDP Receive	Lubbock, Texas, United States
any-in-2015.1e100.net	216.239.32.21	harmless	explorer.exe | TCP Connect	Mountain View, California, United States

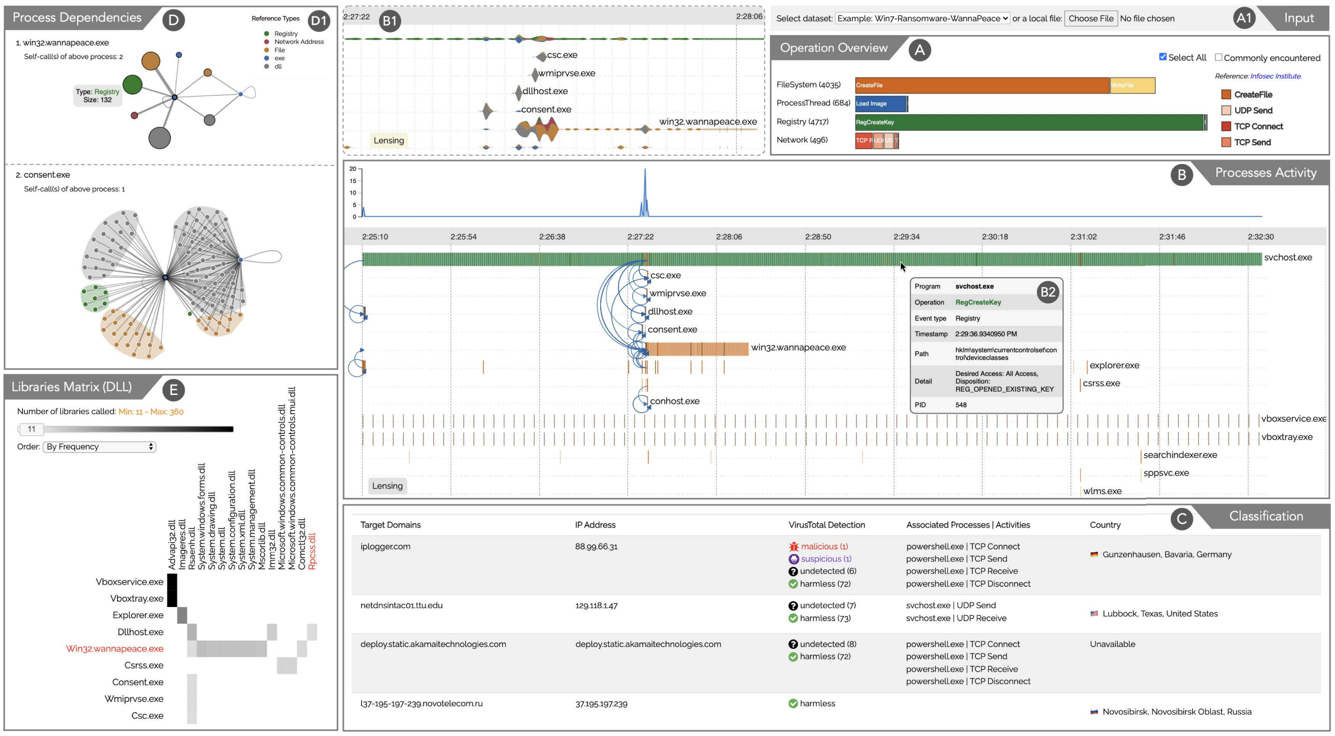
FIGURE 1. The schematic overview of *MalView* framework for analyzing the dynamic behavior of malware. The visualization provides linked views and supports interactive features, such as filtering, highlighting, ranking, and details-on-demand.

perspectives: in a temporal manner of processes and function calls between them, the dependency graph between a process and the objects it operates on, including registry, system files, network addresses, and dynamic-link libraries. The platform gives classification of malicious or benign connecting domains with further analysis. To meet the primary goal, *MalView* implements the analysis tasks below, based on the analysis task types for employing information visualization systems [11]:

- **T1 Provide a comprehensive overview of system activities.** The visual design should present the general distribution of activities chronologically to facilitate the initial summary based on the selected malware.
- **T2 Display details-on-demand for activities and interactions.** The user can get a close-up look at an entity or select an activity to view its event data. The system should show the information in a deeper level of supporting details that accompany the interactions among different processes.
- **T3 Characterize data distribution for processes and their dependencies.** In addition to displaying the detailed information of processes on demands, it is also important to show the distribution of temporal patterns of processes and simultaneously use that as the context to explore their dependencies. To this end, the system should show the groupings of operated objects (e.g., dynamic-link libraries) based on their similarities in features.
- **T4 Present the associations: relationships among processes and function calls between a process and its dependencies.** To characterize the complex associations between entities within the system, the system should show the relationships caused by interactions among processes and function calls from a process to its dependencies.
- **T5 Highlight critical activities in context.** Here, *critical* is defined in context: For the timeline as a whole, *MalView* should allow user to zoom into the time interval that captured the most active interactions of the malware. For malware activities in particular, the system should incorporate filter-based feature to highlight the commonly encountered malicious types, besides the original representation.
- **T6 Order the entities based on dependencies characteristics.** A specific ranking order along a data dimension be of tremendous help in the arrangement of visual components to convey important characteristics and allow the user to focus on the top essential entities.
- **T7 Classify malicious vs. benign activities.** Another key to understand malware forensics is the ability to show the malicious and benign activities. The system should be able to classify the level of malice that corresponds with the malware sample captured.

IV. MalView: VISUAL COMPONENTS

Taking into account the mapping to time, the associations between processes and dependencies, and guided by the designed tasks, we designed the user interfaces of *MalView*. Figure 2 depicts the main modules of *MalView* for



Program	svchost.exe
Operation	RegCreateKey
Event type	Registry
Timestamp	2:29:36.9340950 PM
Path	hklm\system\currentcontrolset\control\deviceclasses
Detail	Desired Access: All Access, Disposition: REG_OPENED_EXISTING_KEY
PID	548

Target Domains	IP Address	VirusTotal Detection	Associated Processes | Activities	Country
iplogger.com	88.99.66.31	malicious (1) suspicious (1) undetected (6) ✓ harmless (72)	powershell.exe | TCP Connect powershell.exe | TCP Send powershell.exe | TCP Receive powershell.exe | TCP Disconnect	Gunzenhausen, Bavaria, Germany
netdnsintac01.ttu.edu	129.118.1.47	undetected (7) ✓ harmless (73)	svchost.exe | UDP Send svchost.exe | UDP Receive	Lubbock, Texas, United States
deploy.static.akamaitechnologies.com	deploy.static.akamaitechnologies.com	undetected (8) ✓ harmless (72)	powershell.exe | TCP Connect powershell.exe | TCP Send powershell.exe | TCP Receive powershell.exe | TCP Disconnect	Unavailable
l37-195-197-239.novotelecom.ru	37.195.197.239	✓ harmless		Novosibirsk, Novosibirsk Oblast, Russia

FIGURE 2. **The *MalView* system contains the following main views: *Input and Operation Overview* (A), *Processes Activity* (B), *Classification* (C), *Process Dependencies* (D) and *Libraries Matrix* (E). The *Process Activity* view has another mode of showing the *referenced operated object* (B1), with feature of lensing for zooming in upon a particular interval in both viewing modes. Detail-on-demand is provided upon mouse interaction on selected item, as in the example in panel (B2).**

supporting users in comprehension and visual reasoning of malware activities and interactions.

A. INPUT AND OPERATION OVERVIEW

MalView provides the options for users to select input data from a default set of data samples or from their local machine, as depicted in Figure 2, panel (A1). The default dataset contains more than 60 samples of primary input data, helping users to familiarize themselves with the system and explore how the tool works. In addition to the default dataset, *MalView* allows users to use and analyze the output log file from running Procmon on their machine via the ''Choose file'' button for uploading the file for direct analysis.

After the input file is uploaded, the *operation overview* (A) shows how the operations are categorized and allows user to observe the the prevalence of event types (visualization task **T3**). Each event type is represented as a rectangle, stacked horizontally by its category in a bar chart visualization. There are four color hue representing four categories: yellow for File System, blue for Process and Thread, green for Registry, red for Network. We employ the color coding based on the category the event type belongs to and incorporated it with the statistics of the amount of total corresponding function calls during the monitored period. An individual event type is mounted with interactivity: it acts as a button providing filtering upon mouseclick, the result of which is shown directly on the below adjacent panel, *processes activity* (B)

A special group of existing critical operations, defined by ''Commonly encounter'' from InfoSec [7], [8], is shown on the right of panel A. All the available operations captured that match the commonly encounter criteria are presented. This list serves as a selection box for highlighting critical activities in both *operation overview* and *processes activity* (visualization task **T5**).

B. TEMPORAL PATTERNS

Building upon the visual information mantra by Shneiderman [12]: ''Overview first, zoom and filter, then details-on-demand,'' the *process activity* in Figure 2(B) is designed to explore the temporal patterns from the system's low-level events along with inter-process communications. The timeline is presented horizontally from left to right, while the processes are listed vertically. Besides the operations executed by a process itself, there are interactions between two processes, such as one creating the other with its primary thread, demonstrated by the arc connecting the two. On top of panel B is an area chart showing the arc distribution, providing the overview of the function call frequencies (visualization task **T1**).

Each process is associated with an aligned set of events executed by the process itself. An individual event is represented by a thin vertical bar, color coded by its event type, which is introduced in section II-B and presented in panel A. These small, thin bars are presented with 50%

transparency so that if multiple events appear at nearly the same time, the color will add up on display (visualization task **T3**); therefore, users can see that the calls are busy there and there is a chance for anomalies detection at these spots (visualization task **T7**).

The interaction arc starts from the parent process (the one that initializes the call, or the source) and ends at the child process (the destination, or the target of the call) (visualization task **T4**). The interactions here are the typical events of processes and thread, as specified in section II-B; hence they have the blue color of process and thread category. One of the most common events in this category is Process Create, in which a process creates a new process and its primary thread. Besides the source-target interactions, *MalView* also supports to visualize the call-to-self events (or the loops). In this case, the process is both the one that initializes and the target of the call.

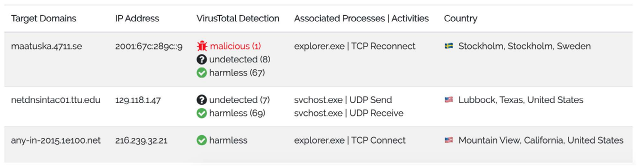
MalView supports details-on-demand in terms of process detail, event call detail, filtering calls related to one specific process, and zooming in a period (visualization task **T2**). The details of an event can be shown on the tooltip by mousing over the corresponding bar, including process name, operation, event type, timestamp, process ID, and additional operation-specific information about the event, as shown in Figure 2(B2). Similarly, the detail of process interaction is displayed on the tooltip by mousing over the arc, providing information on the source process, target process, and the event type of the call. For a particular process, users can choose to observe only the call originated from or to this process by a simple mouseclick on that process. The zooming feature for the arc distribution (visualization task **T5**) will be presented with a case study in section VI-D.

1) OPERATED OBJECTS

This *processes activity* panel supports the detail view by a magnification feature called "Lensing" (visualization task **T2**). When this feature is enabled, hovering along the timeline will expand the current window at that time step. For example, panel (B1) in Figure 2 presents the "Lensing" feature for the interval of 2:27:22 to 2:28:06. Here, the view shows another mode of presenting the referenced streamgraph rather than individual events. We utilize the event categorization that revolves around five key types: registry, file system, network, process, and profiling, to determine the operated objects. Since profiling operation can be less informative about process activity and more about kernel time and memory used, we exclude profiling from the scope of our operated objects. In addition, dynamic-link libraries that contain code and data that can be used by more than one program at once are also indispensable from the analysis process. These considerations lead to our final operated object list: *registry*, *network address*, *system file*, *exe* (executable file), and *dll*, as shown in panel (D1). That serves as a reference to both panel (B1) and, later, *process dependencies* in panel (D).

C. MALWARE AND CLASSIFICATION

Figure 2(C) presents the classification for malicious or benign activities of the captured log file produced by Procmon (visualization task **T7**). Aligning with the primary aim of providing a visual analytics tool and platform to demonstrate malware's static and dynamic behavior, *MalView* captures the results provided by the integrated APIs and visualizes them to the end-user. *MalView* incorporates a number of APIs such as VirusTotal API and inherently relies on the output produced by these APIs. We investigate the target domains that the network activities are connected to. The extracted information for each connected domain contains its Internet Protocol (IP) address, the detection classification results, the associated process and activities related to the domain, and lastly, the country to which the server is hosted.



Target Domains	IP Address	VirusTotal Detection	Associated Processes | Activities	Country
maatuska.4711.se	2001:67c:289c::9	malicious (1) undetected (8) ✓ harmless (67)	explorer.exe | TCP Reconnect	Stockholm, Stockholm, Sweden
netdnsintac01.ttu.edu	129.118.1.47	undetected (7) ✓ harmless (69)	svchost.exe | UDP Send svchost.exe | UDP Receive	Lubbock, Texas, United States
any-in-2015.1e100.net	216.239.32.21	✓ harmless	explorer.exe | TCP Connect	Mountain View, California, United States

FIGURE 3. ***MalView* analysis summary of TeeracB malware on Windows 7.**

The API automatically scans a given malware, and their patterns are automatically compared with more than 70 servers and databases. The classification result consists of four categories: malicious, suspicious, undetected, or harmless, each indicated by the number of detections found corresponding to the targeted domain. Spring *et al.* [13] discussed that the malicious domains are attempts to connect with a command and control server or dropbox and are expected to behave differently from a typical phishing or a drive-by-download malicious site. In *MalView*, this list of connecting domains is ordered by the variety of the outcomes of each domain (visualization task **T6**). Figure 3 demonstrates the analysis summary of *TeeracB* malware on Windows 7. One malicious domain is detected, named "maatuska.4711.se", connected by the "explorer.exe" process with "TCP Reconnect" activity.

D. PROCESS DEPENDENCIES

This *process dependencies* view (Figure 2(D)) presents an in-depth analysis of each process in the system, where one process can operate on many types of objects, as introduced in section IV-B1 and shown in panel (D1). The visualization task **T4** is actualized as presenting the one-to-many relationships between the process and its dependencies. In addition, as the number of dependencies increases in cases with complex activity, we need a way to handle visual clutters by reducing the number of visual elements while preserving the structure. For these reasons, we employ 1) the force-directed layout with node-link diagram to demonstrate the relationships and 2) the node bundling technique [14] incorporated into the force-directed layout to reduce visual clutter by node aggregation. Force-directed layout has been explored in many efforts, such as [15], [16], [17], to represent the even distribution of nodes and links and speed up spring force calculations.

The *process dependencies* panel contains multiple windows; each corresponds to one single process, ranked by the degree of that process node (visualization task **T6**). In each window, aside from the main process node (positioned in the center of the graph with thick, dark stroke), each node can be in one of the two states: individual or bundling. The individual state corresponds to each node representing one object operated on by the process. The bundling state leverage the node bundling/aggregation technique [14], as shown in the top panel of (D), where each node encompasses multiple objects with the same type and connection. The size of this bundled node is proportional to the number of the individual nodes it comprises (visualization task **T3**). Mouse-clicking on a bundled node transforms itself into a set of individual nodes bounded by a convex hull, as shown in the lower panel. These two states can be switched back and forth by a single mouse click on the bundled node or the convex hull surrounding the internal nodes. Besides the source-target type of connection, the graph also presents the available call-to-self events (the loops) of each process, in accordance with the *processes activity* panel in Figure 2(B).

E. LIBRARIES MATRIX

Figure 2(E) describes the dynamic-link library (DLL) calls by each process (visualization task **T4**), supporting users to detect the abnormal frequency patterns (visualization task **T7**). These are the Windows API calls to the libraries that are part of the Windows operating system, not to be confused with the one calling VirusTotal/IPStack API for scanning connected domains, as presented in Section IV-C. System activities may involve multiple library calls from one process or a common library providing resources for various processes. To represent vast number of relationships between processes and libraries, *MalView* utilizes an interactive heat-map matrix to prevent cluttering in contrast to conventional node-link graph visualization (visualization task **T3**). In the matrix, each cell value is color encoded by the gray color scale, in which darker presents frequent calls while lighter is rare calls. There are several criteria for ranking processes (rows)/libraries (columns): by similarity, frequency, or the number of different libraries called.

V. CASE STUDIES

In an effort to provide its users with a safe and productive experience, Microsoft provides information about malware and unwanted applications affecting its operating systems online [18] and details about these in its documentation platform [19]. Microsoft [19] classifies malware into 13 categories categories:1) Backdoor, 2) Downloader, 3) Dropper, 4) Exploit, 5) Hacktool, 6) Macro virus, 7) Obfuscator, 8) Password Stealer, 9) Ransomware, 10) Rogue security software, 11) Trojan, 12) Trojan clicker, and 13) Worm. Furthermore, Microsoft also provides a tool to search for current cyber threats, viruses, and malware in its online platform called Microsoft Security Intelligence (MSI) platform [20].

MalView can be utilized in different settings. 1) When the objective is to comprehend malware functionalities and not detection, 2) when a new malware application (zero-day malware) is developed and not detectable by any tool (due to lack of profiles and signatures), 3) when the objective is to classify a family of malware and then employ a set of generic solutions and remedies to address each class of malware, and 4) when new malware is developed, and we are interested in investigating whether it follows some existing known malicious patterns or not (i.e., labeling malware type). Accordingly, if there is an incident report about zero-day vulnerability where there is no clear patching solution developed, *MalView* can help us to analyze and comprehend the malware with zero-day vulnerability and thus enable us to identify patches or solutions better. To demonstrate the usability of *MalView* in analyzing malware software visually, we conducted a set of case studies in which the output and behavior of the selected malware were captured. Due to the space limit, we capture and present the processes involved in seven malware, namely 1) Backdoor, 2) RemoteAccess, 3) Behaviour, 4) Ransomware, 5) EmailFlooder, 6) Hacktool, and 7) Trojan (Info stealer). The following sections demonstrate the applications of *MalView* to several of these malware types.

A. EXPERIMENTAL SETUP

The malware experimentation setup needs an isolated and controlled environment so that the malicious code does not propagate or infect other entities in the network. This clean and isolated environment also helps to identify the changes and possible tampers in the system due to the malicious activities of the malware specimen. For this work, we installed three different Windows systems on an Oracle Virtual Box: Windows XP, Windows 7, and Windows 10. The windows defender services, windows security services, firewalls, and other automatic security updates were disabled on each of the virtual OSs to prevent any interruption during the malware sample's execution and capture all the traces of their dynamic behavior. To capture the interaction between the malware and each host system, Procmon was installed on all environments. More specifically, all the user applications on the virtual OS were closed, the malware process name was added to the monitor filter to capture only the events of the malware executable. Then the executable was run for two minutes before saving the time-ordered system activities from Procmon and fed to *MalView*.

Since *MalView* depends on the output of Procmon, the amount of information it visualizes depends on how long Procmon is executed. The execution time also shortens the amount of data captured by Procmon. According to our experience with *MalView*, a larger and more complex output and traces produced by Procmon makes *MalView* less effective since the visualization needs to capture a vast number of processes and events. However, a key feature of *MalView* is to offer different levels of abstraction and complexity. If we

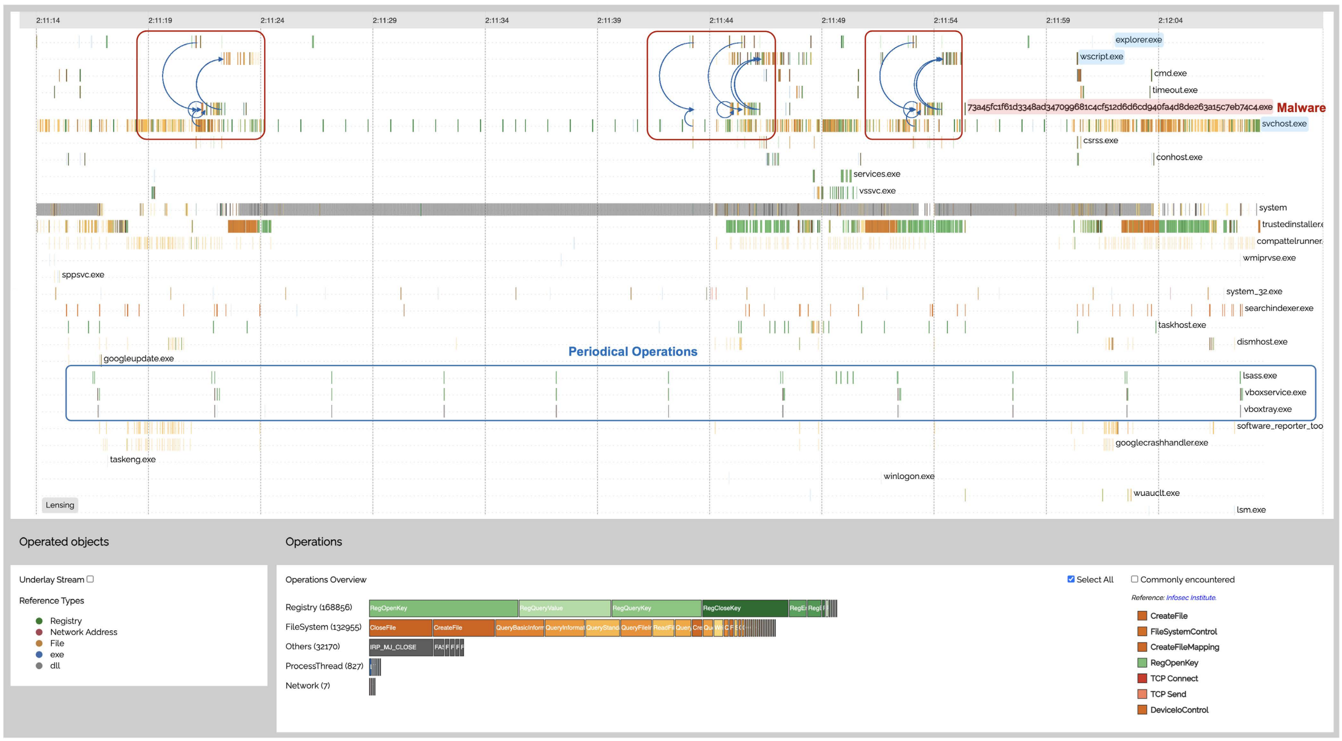


FIGURE 4. ***MalView* analysis summary on RAT, with the filter set on displaying the interactions with RAT only: There are multiple and repeated function calls between the process corresponding to the RAT and *explorer.exe*, *wscript.exe* and *svchost.exe*. Patterns of periodical operations are also presented, such as of Local Security Authority Subsystem Service *lsass.exe* or Virtual Box's *vboxservice.exe*.**

adjust the window width (interface size) and rerun the sample, the visual components would readjust to fit the new window size. More specifically, the execution time depends on how large the malware sample is, ranging from 0.3s to several seconds.

B. REMOTE ACCESS TROJAN (RAT)

Remote Access Tools are useful applications to provide administrative assistance to the end-users remotely. However, these pieces of software are increasingly abused by adversaries to gain control over the target systems and are referred to as Remote Access Trojans (RATs). RATs are distributed through email attachments or as a patch with pirated software to infect the target in order to gain administrative control. Once the target machines are infected, RATs have complete control over the victim system to perform malicious activities, such as password sniffing, keylogging, track file transfer information, webcam feed, control the system by issuing shell commands, or even propagate some other malwares/viruses. RATs are particularly hard to detect, as they execute legitimate operating system processes resembling the behavior of other commercial remote access tools, and they usually do not show up as running tasks. Besides, there are tools that enable performing obfuscation on a given application and produce obfuscated malicious applications. Using various obfuscation methods, along with managing resource utilization, RATs can remain undetected. According to the October 2018 Global Threat Index [21] published by Check Point, RATs are ranked among the top 10 ‘‘most wanted’’ malware.

We captured the run time behavior of RATs on different Windows and visualized the behavior using visualization tool *MalView*. The live malware sample was downloaded from public malware dataset *VirusShare* [22]. According to a multi-scan report from Virustotal [23], this sample has a community score of 66 out of 70, i.e., out of 70 detection engines, 66 could identify it as a malicious executable. Figure 4 shows the detail analysis performed on an RAT sample using *MalView*. The malicious indicators presented by *MalView* are as follows:

- Process: The malicious executable spawns processes like *explorer.exe*, *wscript.exe*, and *svchost.exe*. The execution of these processes indicates that the RAT program is trying to start a command prompt and then run some scripts to start a session to monitor the process remotely.
- Registry: The sample RAT performs a large number of registry operations, including the creation of registry keys as well as a query of the registry entries.
- Files: The malicious PE performs a large number of various file operations, including the creation of new files and mapping file systems.
- Network activity: The sample RAT does not demonstrate any significant number of TCP/UDP requests.

Besides the malware-associated events, *MalView* is also able to capture the recurrent pattern of periodical operations, such as the system process of Local Security Authority Subsystem Service *lsass.exe* or Virtual Box's *vboxservice.exe*.

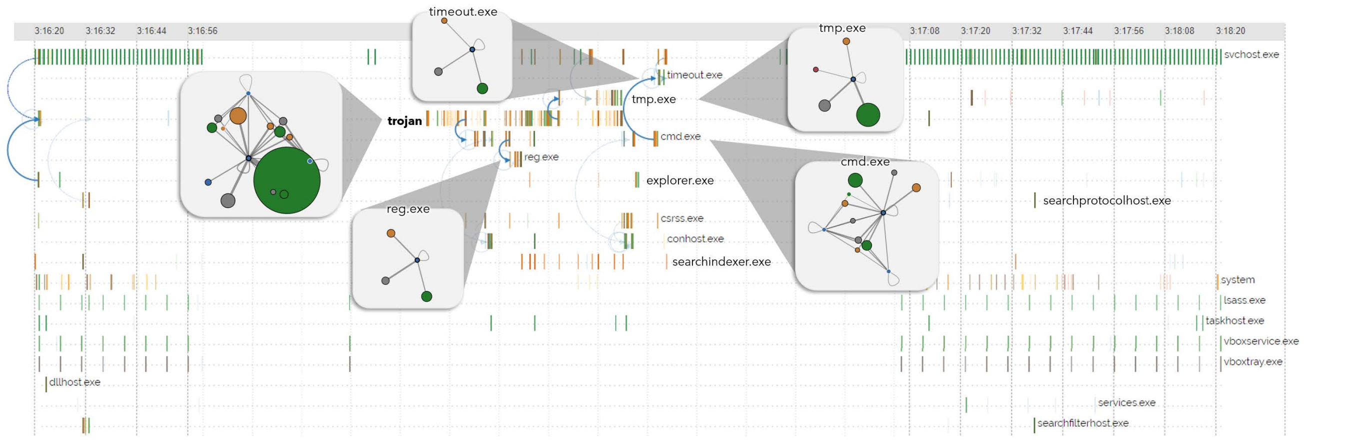


FIGURE 5. ***MalView* visualization for a sample Trojan. User can request to overlay the networks of suspicious processes (which contain the self calls).**

The influence of running platform will be discussed further in Section VI.

C. TROJANS

A Trojan is a type of malware that pretends to be a benign program, but after installation, it executes hidden code and then performs malicious activities such as deleting or tampering with data, stealing information, running some other scripts, and creating backdoors. In general, it enables the attacker to access the victim's system, and these types of malware are not able to replicate themselves [24].

1) SAMPLE TROJAN

A sample of Trojan[2] was obtained from VirusShare [22]. The output file containing all the processes was created after running the malware in a controlled environment using Windows 7 as its platform. Figure 5 shows the *MalView* output for this malware. We applied lensing on the critical period to view the activity details. We chose four important processes based on the dependencies, including *cmd.exe*, *tmp.exe*, *reg.exe*, and *timeout.exe*.

By clicking the name of this malware on *MalView* Process Activity window, we can observe that this executable file has created two processes: *cmd.exe* and *tmp.exe* (at the blue links). By further clicking on the child process, we can retrieve the list of processes created by *cmd.exe* and *tmp.exe*. Then, the *cmd.exe* process has created two child processes: *reg.exe* and *timeout.exe*. The *tmp.exe* process did not create any child process. The process networks of *cmd.exe*, *tmp.exe*, *reg.exe*, and *timeout.exe* are overlaid on top of the process timeline on request.

2) TROJAN MultiInjector

MultiInjector, under trojan classification, is a trojan that tries to inject code into other processes to hide or execute its payload and download and install other malware [25]. Figure 6(a) presents a sample of trojan MultiInjector under *MalView* analysis. *MalView* reveals the sequence of Process Create events generated by the malware and its interactions with other processes in the system, with multiple recurring patterns of function calls. Panel (b) shows the result of zooming into the most active/busy interval that was automatically detected by the tool, while panel (c) presents the outcome from filtering to highlight only interactions associated with the malware. The final result patterns are shown in panel (d).

By exploring details-on-demand via mousing over, as shown in panel (c), the first event in this sequence is Process Create from the malware to *cmd.exe* leading to the subsequent calls. Around 12:23:47, there are four consecutive Process Create calls from the malware to *net.exe*. The subsequent calls can be seen in panel (b) and panel (a) (for a broad view). Finally, the repeated event patterns associated with malware are clear in panel (d): one *Process Create* event from the malware to *cmd.exe*, followed by the four subsequences to *net.exe*. The behavior from this observation aligns with the characteristics of the malware of injecting code into other processes. The visualization helps to discern these low-level operations from the malware to other system processes.

D. BACKDOOR

A backdoor is a type of malware that provides unauthorized remote access to the compromised system by exploiting security vulnerabilities. The malware works in the background while hiding from the user. Meanwhile, it enables the attacker to have access to the victim's computer, such as databases and file servers, as well as running system-level commands. The process of injecting Backdoor is usually performed in two stages: First, a small file, called a dropper, is installed. Second, the dropper downloads the main malicious file from a remote location [26]. It is important to mention that Trojan and backdoor malwares are not the same: A Trojan might contain a backdoor, but a backdoor can execute as a stand-alone program without being a part of a Trojan.

[2]MD5:b3eebe51ccc4a95815ddef3ef55604d2

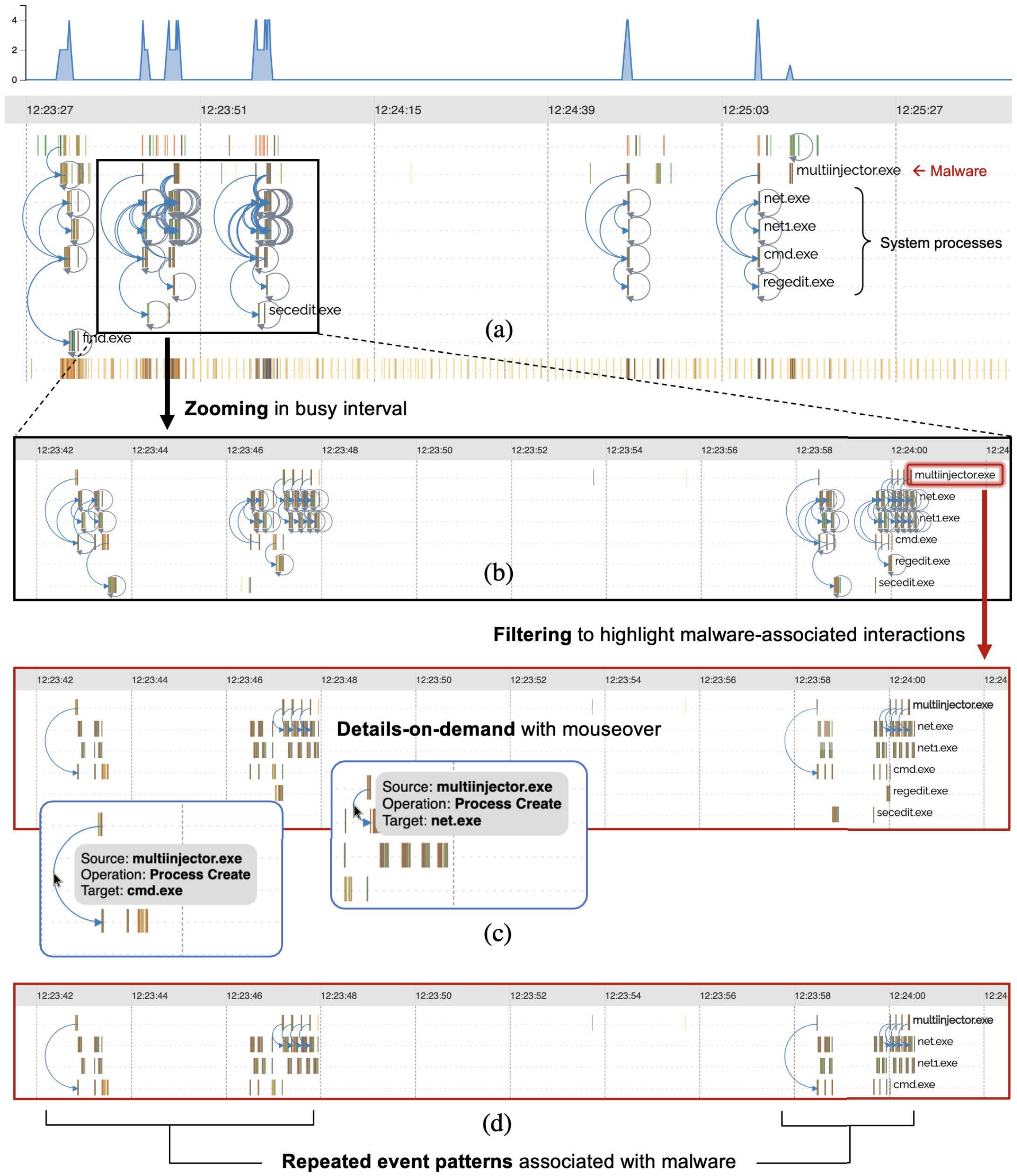

12:23:27
12:23:51
12:24:15
12:24:39
12:25:03
12:25:27
multiinjector.exe
Malware
net.exe
net1.exe
cmd.exe
regedit.exe
System processes
secedit.exe
find.exe
(a)
Zooming in busy interval
(b)
Filtering to highlight malware-associated interactions
Details-on-demand with mouseover
Source: multiinjector.exe
Operation: Process Create
Target: net.exe
Source: multiinjector.exe
Operation: Process Create
Target: cmd.exe
(c)
(d)
Repeated event patterns associated with malware

FIGURE 6. Trojan MultiInjector under *MalView* analysis: the sequence of Process Create events generated by the malware and its interactions with other processes in the system.

The *MalView* visualization of malware Backdoor Androm execution on Windows 7 is presented in Figure 7. The accumulation of interactions presented in the top area chart divides the observation into two phases. The first phase heavily involves activities associated with the malware and *svchost.exe*. The last function call from the malware is to *regasm.exe* (at the end of Box A), followed by an interesting recurring pattern in the second phase, as highlighted in Box B. This recurring pattern starts with a function call from *regasm.exe* itself to *schtasks.exe*, where the time between the two patterns is about two seconds. Here, process *regasm.exe* is the assembly registration tool, which reads metadata within an assembly and adds necessary entries to the registry.

The overlay dependency graphs in Figure 7 open up several interesting findings. First, although its activities end early during the observation, the malware operates on multiple registry files, as shown by the large size of the green registry nodes. Second, *svchost.exe* has a long sequence of

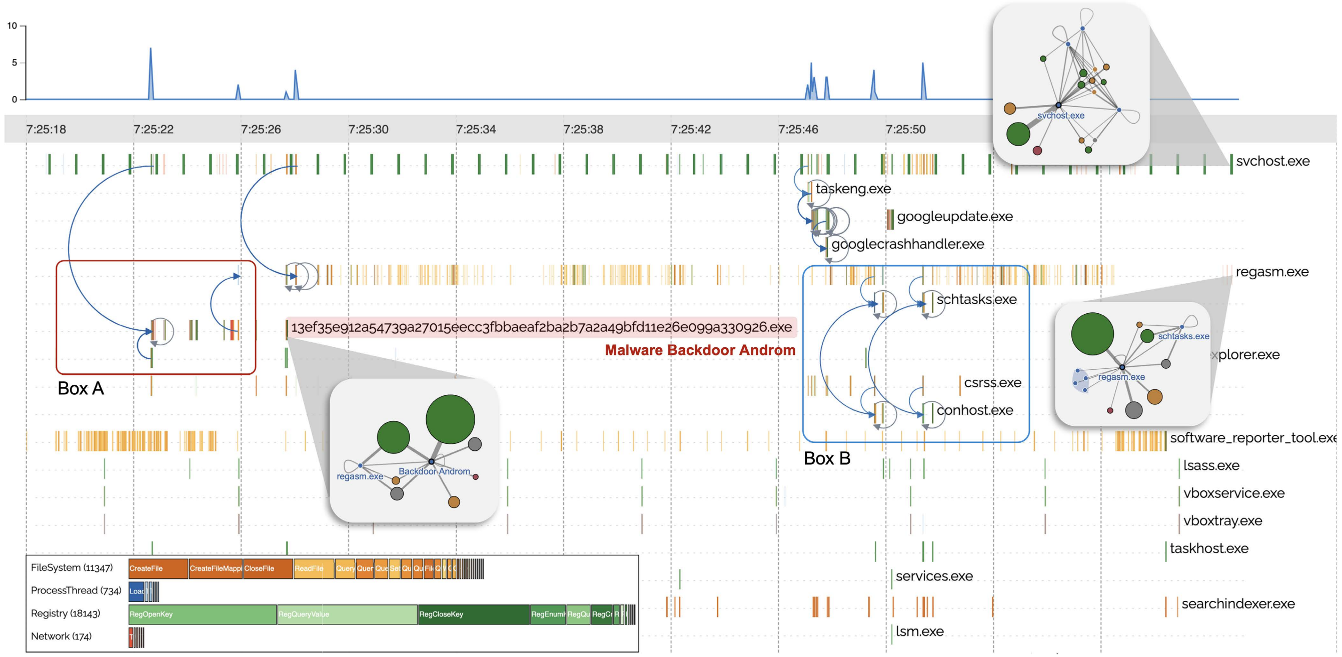


FIGURE 7. ***MalView* visualization of malware Backdoor Androm on Windows 7. The top area chart demonstrates two separate phases: the first one with malware activities, ending with a call to *regasm.exe* (Box A) and the second with recurring patterns involving *regasm.exe* itself (Box B).**

periodic operations on registry files and operates on numerous types of objects, as seen on the dependency graph. As the generic host process for Win32 services, it also makes function calls to the malware process twice, about five seconds apart. Finally, while *regasm.exe* interacts with five other processes, it only shares dependencies with *schtasks.exe*. The dependency graphs and process activity timeline are complementary and can effectively support the analytical reasoning of malware behaviors.

E. RANSOMWARE

A typical ransomware program encrypts the victims' computer files and demands a ransom to restore access to the data. A ransomware program locks a system utilizes some visual messages, imposing law enforcement to threaten the target. The ransomware scam has matured over time, utilizing different methods to impair a computer. According to a report published by Symantec [27], the latest advancement prevents the computer from functioning and dismisses the client from gaining any access. The system at such a stage displays a message that proclaims to be from a local law enforcement organization. The ransomware application asks for money in exchange for letting the users re-gain access to their systems. In recent news in July 2021 by Malwarebytes report [28], a severe ransomware attack was reportedly taking place against the popular Remote Monitoring and Management software tool Kaseya VSA. This attack has forced to immediately shut down the VSA servers, where Kaseya VSA was used to encrypt over 1,000 businesses. The attackers are asking for \$70M in exchange for a universal decryptor. Also reported by Malwarebytes [29], 35% of small and

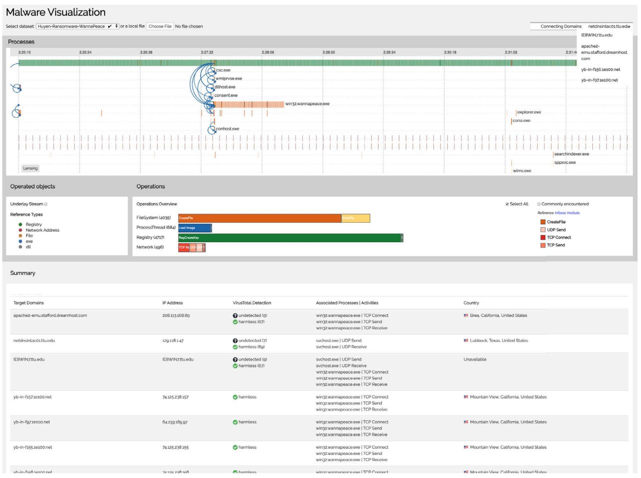


FIGURE 8. ***MalView* analysis summary of ransomware WannaPeace on Windows 7.**

medium-sized businesses were under attack of ransomware. A lot of times, these organizations end up paying for the ransom. According to a multi-scan report from Virustotal, the sample studied in this paper has a community score of 47 out of 72, i.e., out of 72 detection engines, 47 could identify it as a malicious executable.

Figure 8 shows the visualization for the dynamic activities of the ransomware *wannapeace.exe*.[3] The malicious indicators presented by the *MalView* are as follows:

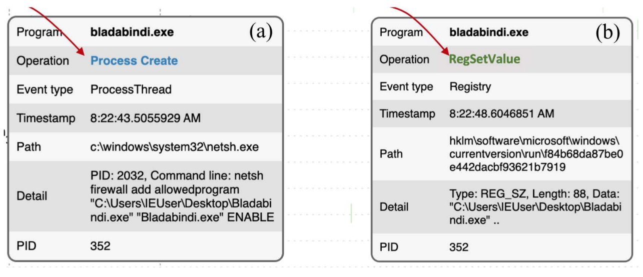
[3]MD5:eefa6f98681d78b63f15d7e58934c6cc

- Processes: The time window shows that the ransomware spawns: *conhost.exe* and *consent.exe*. The *conhost.exe* indicates that the ransomware is accessing the command line, whereas the *consent.exe* is an indicator that the program is trying to utilize the user access.
- Registry: It creates a registry key to make changes.
- Files: Malicious PE performs a lot of file operations. For instance, it performs 3434 times of *CreateFile* operations and 601 times of *WriteFile* operations.
- Network activity: The malware performs many TCP/UDP connection requests, sends, and receives.
- Domain Activity: It connects to seven different domains, as shown on the upper right corner of Figure 8.

F. BEHAVIORAL MALWARE

At the time of this writing, a search on Microsoft Security Intelligence threat search platform [20] returned 500 malware as Behavior type, in which the distribution of alert levels was as 400, 38, 3, and 16 for severe, high, moderate, and low, respectively. A behavior type of malware generally includes malware that exhibits suspicious activities, but it is not classified into a specific popular category of malware. This type of malware is difficult to detect because its activities can greatly vary depending on the intention of the underlying malware and the current user context. Our study of several malwares in "Behavior" type shows that these suspicious activities include 1) disabling system recovery, 2) deleting shadow copies, 3) hidden code executions, 4) creating files in the user's system, 5) changing the registry key to run itself, and 6) accessing to *netsh.exe* to modify firewall configuration that allows itself to run on system startup. Examples of such behavioral malware include *Bladabindi.gen* [30], *Vawtrak.A* [31], and *Teerac.B* [32]. Furthermore, some behavioral malware (e.g., *MultiInjector* [33]) involves accessing the command prompt (CMD).

For instance, Figure 9 shows suspicious activities from an example of the Behavior malware type called *Bladabindi*. Panel (a) shows that it starts *netsh.exe* to modify firewall configuration to add itself as a permissible program. Panel (b) provides a piece of evidence as it sets the registry value (*RegSetValue*) on the user system to runs itself at Windows Startup for the same malware.



Program	bladabindi.exe
Operation	Process Create
Event type	ProcessThread
Timestamp	8:22:43.5055929 AM
Path	c:\windows\system32\netsh.exe
Detail	PID: 2032, Command line: netsh firewall add allowedprogram "C:\Users\IEUser\Desktop\Bladabindi.exe" "Bladabindi.exe" ENABLE
PID	352

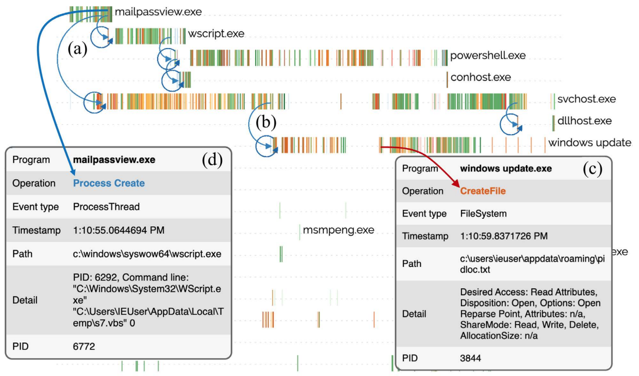
Program	bladabindi.exe
Operation	RegSetValue
Event type	Registry
Timestamp	8:22:48.6046851 AM
Path	hklm\software\microsoft\windows\currentversion\run\f84b68da87be0e442dacbf93621b7919
Detail	Type: REG_SZ, Length: 88, Data: "C:\Users\IEUser\Desktop\Bladabindi.exe" ..
PID	352

FIGURE 9. ***MalView* shows suspicious activities from a Behavior malware, named *Bladabindi*. Panel (a) shows that it starts *netsh.exe* to modify firewall configuration. Panel (b) depicts that it sets the registry values to run itself.**

G. HACKTOOL MALWARE

Hacktool is a piece of software that malicious attackers use to gain unauthorized access to user's devices [18]. As of the time of this writing, Microsoft lists 188 active entries as Hacktools, of which 93 are severe, 80 are high, and 15 are moderate in terms of alert levels [20]. The popular attacking channel for Hacktool is via insecure Universal Serial Bus (USB) communication design and Windows Autoplay features [34]. Malicious activities for Hacktool launched from USB include 1) changing registry settings, 2) installing a backdoor, 3) stealing confidential information, and 4) reading data encryption keys. Recently, besides Trojan, Hacktool is also the second most prevalent type of malware embedded in pirated software [35].

Figure 10 shows *MalView* view while analyzing a sample of Hacktool malware type named *Mailpassview* [36]. It first creates *svchost.exe* process (a). The *svchost.exe* process then creates *windows update.exe* (b). This process then creates several files like *holdermail.txt* (via using *vcb.exe*) to store "Browser Password Recovery Report," *pidloc.txt* to contain information of compromised computers (c). These are the pieces of evidence about the existence of Hawkeye Keylogger [37] to steal sensitive data (e.g., email password).

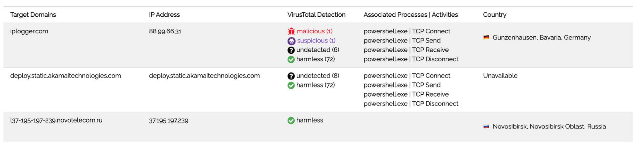


Program	mailpassview.exe
Operation	Process Create
Event type	ProcessThread
Timestamp	1:10:55.0644694 PM
Path	c:\windows\syswow64\wscript.exe
Detail	PID: 6292, Command line: "C:\Windows\System32\WScript.exe" "C:\Users\IEUser\AppData\Local\Temp\s7.vbs" 0
PID	6772

Program	windows update.exe
Operation	CreateFile
Event type	FileSystem
Timestamp	1:10:59.8371726 PM
Path	c:\users\ieuser\appdata\roaming\pidloc.txt
Detail	Desired Access: Read Attributes, Disposition: Open, Options: Open Reparse Point, Attributes: n/a, ShareMode: Read, Write, Delete, AllocationSize: n/a
PID	3844

FIGURE 10. ***MalView* view on a Hacktool malware type called *Mailpassview*. It first creates process *svchost.exe* (a), then *svchost.exe* starts *windows update.exe* (b), and then *windows update.exe* creates *pidloc.txt* (c).**

Determining whether the connecting domains from network activities are malicious or benign is important. The classification for malicious connecting domain for the malware *Mailpassview* is shown is Figure 11. Among the examined domains, *iplogger.com* is assessed as ***malicious*** and ***suspicious*** by VirusTotal, with the IP address 88.99.66.31 from Gunzenhausen, Bavaria, Germany. Recall from the chained calls shown in Figure 10: The process corresponding to the malware *mailpassview.exe* called and initiated *wscript.exe* with Process Create (panel "D" in Figure 10), then *wscript.exe* also called and initiated *powershell.exe* with Process Create. This chain continues with process *powershell.exe* connecting to malicious target domain *iplogger.com* with four different activities: *TCP Connect, TCP Send, TCP Receive* and *TCP Disconnect.* Here, *wscript.exe* is stored in C:\Windows\System32 and provides an environment in



Target Domains	IP Address	VirusTotal Detection	Associated Processes | Activities	Country
iplogger.com	88.99.66.31	malicious (1) suspicious (1) undetected (6) harmless (72)	powershell.exe | TCP Connect powershell.exe | TCP Send powershell.exe | TCP Receive powershell.exe | TCP Disconnect	Gunzenhausen, Bavaria, Germany
deploy.static.akamaitechnologies.com	deploy.static.akamaitechnologies.com	undetected (8) harmless (72)	powershell.exe | TCP Connect powershell.exe | TCP Send powershell.exe | TCP Receive powershell.exe | TCP Disconnect	Unavailable
l37-195-197-239.novotelecom.ru	37.195.197.239	harmless		Novosibirsk, Novosibirsk Oblast, Russia

FIGURE 11. The classification for malicious connecting domains from malware *Mailpassview*. The target domain *iplogger.com* is assessed as malicious and suspicious by VirusTotal. This domain is connected from *powershell.exe* via four activities: *TCP Connect, TCP Send, TCP Receive* and *TCP Disconnect*.

which users can execute scripts, which is different from the malicious programs that malware programmers or cyber criminals write and name it as *wscript.exe*.

VI. THE INFLUENCE OF RUNNING PLATFORMS ON MALWARE BEHAVIOR

To examine how malware behaves in different platforms, we also executed multiple malware on Microsoft's mainstream Windows OSs.

A. RANSOMWARE

The ransomware samples were collected under different Windows platforms and had their behaviors compared using *MalView*. Figure 12 captures the behavior of the ransomware on Windows XP, Windows 7, and Windows 10, respectively.

- The ransomware sample performs a large number of registry operations on both Windows 10 and 7; whereas, it accesses the registry just one time on Windows XP.
- On Windows 10, the ransomware did not perform any file operations; whereas, Windows 7 shows many file activities. The Windows XP platform shows traces of a few file operations.
- The DLL called by the ransomware remained almost unchanged for three platforms.
- The upper right panel of the tool shows a time interval sequence of process, file, registry operations performed by the ransomware. Both Windows 10 and Windows XP show that the malicious PE executes sparsely; whereas, on Windows 7, it shows more consecutive operations.
- The lower right panels show the statistics of commonly encountered and critical activities of the ransomware.

B. EMAIL FLOODER

We chose the ''email flooder'' malware to compare the visualization for this sample run in different platforms, including Windows XP, 7, and 10, as depicted in Figure 13. In particular, the output for Windows XP is simpler than the outputs produced by Windows 7 and 10. For example, the number of different processes for Windows XP is four vs. seven and nine for Windows 7 and 10, respectively. In addition, the total number of operations is much higher in Windows 10 than in Windows XP. It is observable that there is more information, including more processes, calls, dependencies, and activities in Windows 10 and 7 than XP. Since some of these pieces of information might be because of the Windows activities

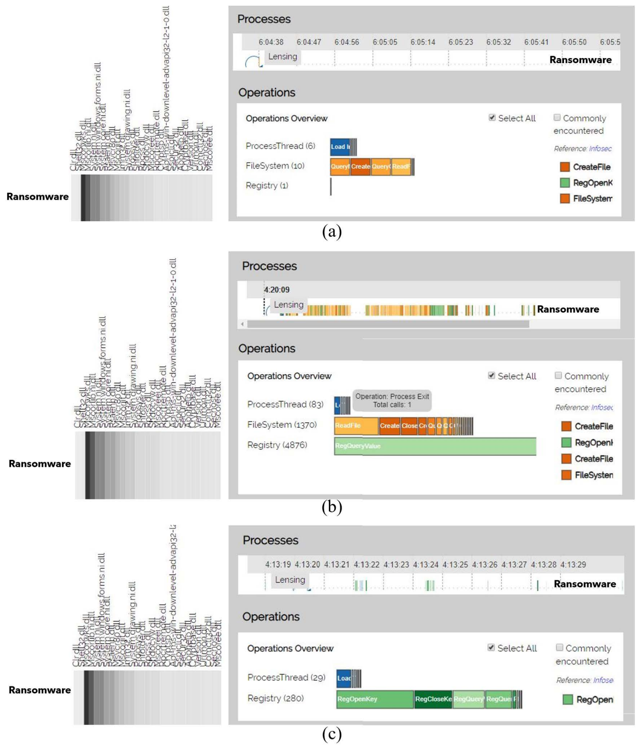


FIGURE 12. *MalView* visualizations of the sample ransomware on (a) Windows XP, (b) Windows 7, and (c) Windows 10.

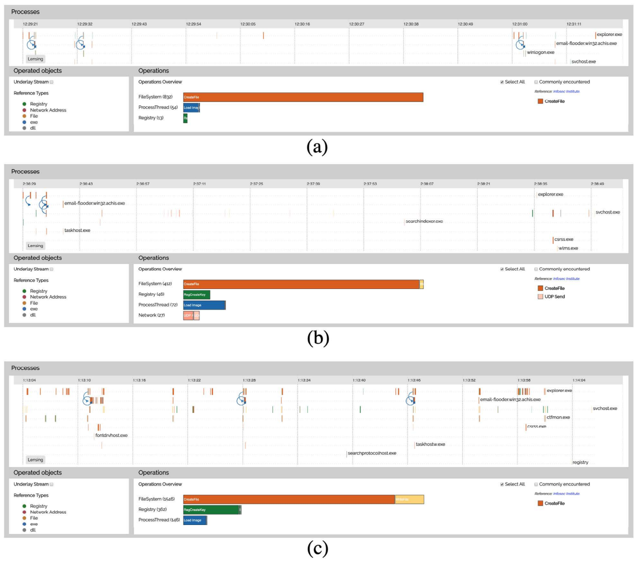


FIGURE 13. *MalView* visualizations of Email Flooder on (a) Windows XP, (b) Windows 7, and (c) Windows 10.

themselves and not the malware activities, tracking malware behavior in newer platforms might be more complicated.

C. BEHAVIORAL MALWARE

Figure 14 shows *MalView* views applied to *Bladabindi* malware executed on these three Windows operating systems in the top panel, middle panel, and bottom panel,

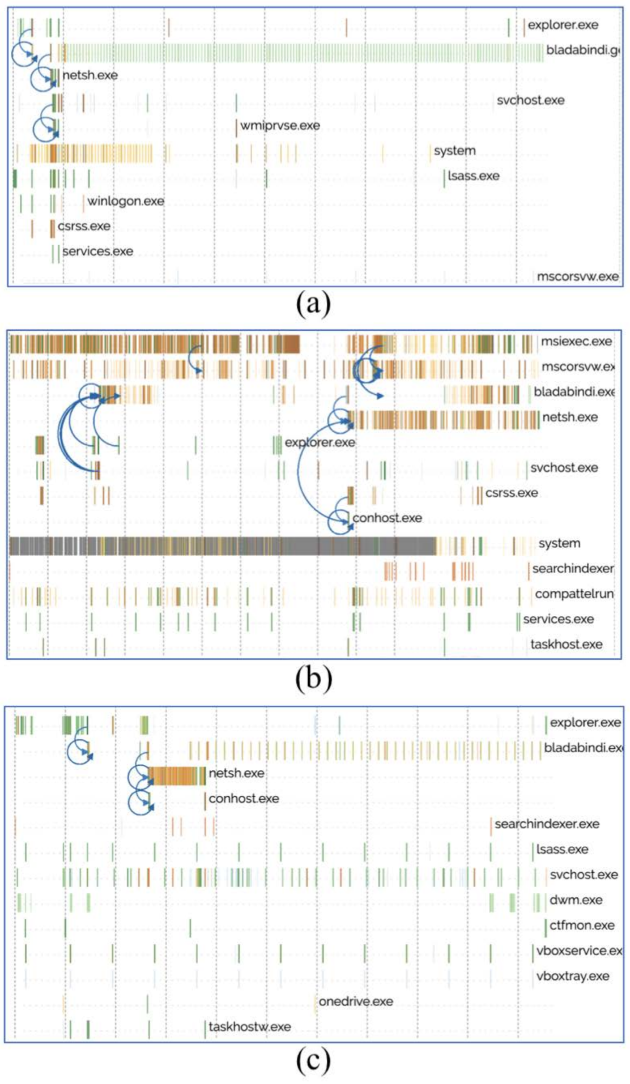


FIGURE 14. ***Bladabindi* malware executions on different platforms: Windows XP (a), Windows 7 (b) and Windows 10 (c).**

respectively. In general, more platform-related processes are being executed in the latter two operating systems in comparison to Windows XP. However, its suspicious activities remain the same. In all platforms, it first starts *netsh.exe* to modify firewall configuration and then sets the registry values to run itself.

D. PATTERNS ACROSS PLATFORMS

One of the key features and benefits of employing visualization tools is to perform pattern detection and classification visually prior to delving into analytical approaches. *MalView* captures key features that are indicators for profiling classes or families of malware.

More specifically, using *MalView* it is possible to capture features such as volume of processes, registry activities, files manipulation and accesses, and network activities. As described below, these features are able to detect any "*behavioral* patterns in the set of malware studied and thus enable us to classify them according to their dynamic behavior. Instead of trying to generate patterns of interest, in this study, we show how the analysis works based on malware behavior tracing, the kind of information it entails, and how the tool can enable analysts to quickly study the interaction of malware with system internals using selections, focus and context technique, and aggregations.

With *MalView*, we focus on the interactions of the malware program to other system internals processes. While Procmon, as the data provider, brings detailed information into each of the processes running in the system, the interval and log activity captured may be subjective to the person behind the capturing execution. To focus on the time interval in which we can witness the most significant amount of malware activity to other system internals processes, called *busy interval*, we applied focus and context visualization technique in *MalView* to support 1) close-up view for individual malware analysis and 2) standardization for malware comparison. To accommodate the context around the focal point, we select the interval that satisfies either ensuring the equal paddings to the first and last interaction to the boundary of the interval or equal paddings to the peak of the area chart - where there witness the highest amount of interactions.

Patterns of *Bladabindi* malware behavior across platforms: (a) Windows XP, (b) Windows 7, and (c) Windows 10, all under focus and context technique with busy interval length of 20 seconds, are shown Figure 15. By using mousing over an arc representing a function call, an user can observe the detailed information including type of operation, source and target processes. A recurring pattern observed from the *bladabindi* is the following sequence of calls: A *ProcessCreate* from *explorer.exe* to the malware, following by a *ProcessCreate* from the malware to *netsh.exe*. As shown in Figure 5 and Figure 7, different processes produce very different dependency connections in terms of topology, grouping and volume. However, as presented on the right of Figure 15, the dependencies of the three *bladabindi* malware processes across different platforms demonstrate many similarities: the three biggest nodes that have the degree of one are all from registry (green), file (sand color), and dll (grey). For nodes with a degree of two - having connections with both *bladabindi* and *netsh.exe*, their categories are the same regardless of the running platforms. For further analysis, these patterns can serve as indicators for such classes of malware.

VII. MALWARE VISUALIZATION TOOLS VS. MalView

This section compares the features offered by *MalView* with the ones offered by some other malware visualization tools, including Hybrid [38] and AnyRun [39]. First, we briefly review each visualization tool and then compare its features.

A. AnyRun: INTERACTIVE ONLINE MALWARE SANDBOX

Funded in 2016 by a Russian security researcher, Alexey Lapshin, AnyRun [39] offers a free "*interactive*" sandbox tool for dynamic analysis of malware. The tool enables uploading a suspicious file and, in the meantime, interacting with the

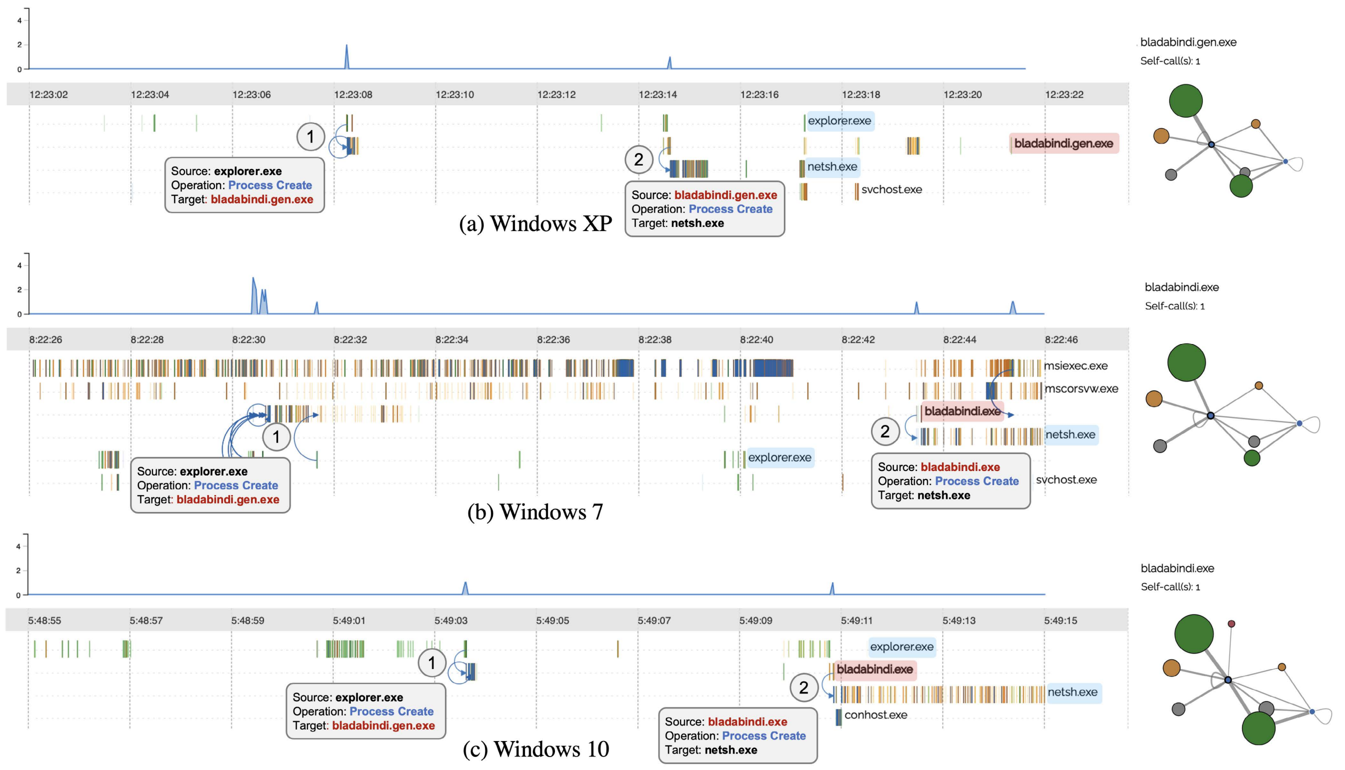


FIGURE 15. **Patterns of malware behavior across platforms: *Bladabindi* malware executions on (a) Windows XP, (b) Windows 7, and (c) Windows 10, all under focus and context technique with busy interval length of 20 seconds. On the right end are the corresponding dependency graphs of the malware process. While different processes express different dependency graphs, as shown in Figure 5 and Figure 7, the dependency graph of *Bladabindi* malware is relatively consistent across different platforms.**

sandbox and thus with malware to trigger some functionalities or execute macros embedded into the uploaded file. AnyRun offers several key features, as follows:

- The tool's main feature is the visualization of interactive graphs and tree structure for comprehending malware. The feature helps visually identify suspicious processes, determine the family of malicious activities and patterns, and highlight external files that are downloaded by the malware.
- It also enables content analysis of different types of suspicious and malware files, including PCAP files (i.e., network activity dump).
- The tool also performs network analysis with the goal of tagging suspicious events. It analyzes Hypertext Transfer Protocol (Secure) (HTTP(s)) requests and responses along with their headers
- The tool can be used as an educational and training tool to assist the security experts to understand the structure of attacks through Mitre Att&ck Mapping [40].
- It enables opening web addresses (URLs) in different browsers and therefore helps in URL analysis and, more importantly, phishing attacks using various mainstream and supported browsers.
- The tool generates a fine-format report for publication and sharing purposes. The professionally-looking report consists of supporting screenshots, Process Behavior Graphs, indicators of being malicious/suspicious, and many other components.

B. HYBRID: AUTOMATED MALWARE ANALYSIS SERVICE

Hybrid [38] is a free malware analysis tool that enables both static and dynamic analysis. It utilizes several analysis reports and sandbox tools, including Falcon Sandbox [41], a dynamic analysis framework. In addition to the dynamic analysis offered by Falcon Sandbox, Hybrid integrates some other anti-virus tools such as VirusTotal, OPSWAT Metadefender, SIEM systems, NSRL (i.e., white listing), TOR (e.g., avoiding external IP fingerprinting), Phantom, Thug Honey Client (e.g., URL exploit analysis), and Suricata (ETOpen/ETPro rules). The tool provides several useful analysis features such as:

- Risk summary and verdict of being malicious or benign.
- A good number of malicious/suspicious indicators
- A large set of network rules for intrusion detection and network analysis
- Integration with YARA [42] for rule-based pattern matching-based malware detection
- Analysis of a wide variety of files including binary samples and PCAP files
- Analysis of URLs for detection of phishing attacks

TABLE 1. **A feature-based comparison of Anyrun [39], Hybrid [38] and *MalView*.**

#	Features	AnyRun	Hybrid	*MalView*
	I) General Features			
1	Integrated with VirusTotal [23]	*	√	√
2	Integrated with MetaDefender [43]	*	√	
3	Integrated with CrowdStrike Falcon [41]		√	
4	Compliance with InfoSec Classification [7], [8]			√
5	Filtering (i.e., Simplification) Capabilities			√
6	Classification into Malicious/Benign	√	√	√
7	List of Imported DLLs	√	√	√
8	Statistics of Extracted Executable Files	√	√	√
9	Highlights Malicious Indicators (e.g., report from anti-viruses, installation activities, creation of a windows session/station, termination of a session, and spanning a lots of processes	√	√	√
10	Highlights Suspicious Indicators (e.g., inspection of PE files, suspicious API calls, locating of resource files, deleting executable files, creating files in Windows directory, importing suspicious APIs)	√	√	√
	II) Behavioral Activities and Dynamic Analysis			
11	Behavioral Graphs/Activities	√		√
12	Different Classes and details of Processes			√
13	Call graph and Number of Calls for each Process/category	√		√
14	Scalar representation of process calls			√
15	Dependencies among processes/executable files			√
16	Time Dependencies between processes/executable files			√
17	Lists dangerous/suspicious system level activities (creating/changing important files: registry, SVCHOST to execute hidden code, writes to start menu, etc.)	√	√	
18	Registry/File Activities	√	√	√
19	List of Registry/File changes and modifications and events	√	√	√
20	Statistics about events and registry activity including read/write/ delete events			√
21	Statistics about executable files	√	√	√
22	Provide Falcon Sandbox Report (Dynamic Execution)	√	√	
23	Basic Risk Assessment (e.g., access to clipboard, spanning processes, reading the computer name, and injecting into explorer)	√	√	
24	Extract memory strings and tokens	√	√	
25	The name of the extracted executable files	√	√	√
26	List the size of different Sections of PE files	√	√	Partially
	III) Network Level Analysis			
27	Domain Name System (DNS) Requests	√	√	√
28	Host Connections	√	√	√
29	HTTP Traffic/Requests	√	√	√
30	Network Threats	√		√
31	PCAP Download	√		
32	Registry Changes	√		
33	Details on GET/POST methods	√		

*: The feature is under development.

C. A FEATURE-BASED COMPARISON

This section aims to highlight the key features of AnyRun [39] and Hybrid [38] in comparison with the features offered by *MalView*. The comparison is performed through the classification of features into 1) general features, 2) behavioral activities and dynamic analysis, 3) structure-based and static analysis, and 4) network-level analysis. Table 1 lists the features classified into these four groups.

1) GENERAL FEATURES

MalView offers not only comparatively similar features but also additional features that are unique to *MalView*. More precisely, the tool offers features such as 1) compliance with InfoSec classification with respect to malicious processors and indicators (Feature #4), and 2) simplification of visualization through filtering and focusing only a subset of processes for the analysis (Feature #5).

2) BEHAVIORAL ACTIVITIES AND DYNAMIC ANALYSIS FEATURES

The features related to dynamic analysis are considerably diverse. As a result, each analysis tool offers its own set of unique features. Given the fact that *MalView* mostly visualizes the output of Procmon [6], it is primarily a dynamic analysis tool. Depending on how the underlying malware visualization tool is implemented, most of these tools are able to visualize the ''basic'' sets of dynamic data captured through Procmon or similar utilities. For instance, as Table 1 shows, most of the behavioral features are visualizable by these three tools.

The major and key feature that is unique to *MalView* is the exploration of *''time dependencies between processes''* (Features #15 and #16). The visualization of time and process dependencies are an important part of malware analysis in order to comprehend the nature of the underlying malware.

3) SIGNATURE-BASED AND STATIC ANALYSIS

As stated earlier, *MalView* is primarily a visual analytics tool based on the output of the dynamic analysis of the underlying application or malware. As a result, it is less focused on visualizing static features of executable files. However, *MalView* is integrated with several static analysis tools, including VirusTotal, and thus is capable of capturing this information and visualize them accordingly. VirusTotal is able to capture static information such as the size of header files, type of files, PE Specific, and other static and signature-based features. As a result, *MalView* can visualize all the information captured by VirusTotal and uses its API to retrieve this information and visualize them accordingly.

4) NETWORK LEVEL ANALYSIS

Similar to signature-based and static analysis features, *MalView* is less focused on visualizing purely network-level features. However, given the strength of Procmon in capturing all related processes and events, *MalView* is capable of visualizing the network-level events and processes captured by Procmon and thus provides a process-level view on this network-level information.

VIII. RELATED WORK

The malware analysis methods can be broadly categorized into static vs. dynamic analysis [44]. Many of these approaches utilize visual representation to enable the analysts to visually capture general activities related to malware from a large number of data files or logs which are infeasible to digest in text or binary format [45].

A. SIGNATURE-BASED FEATURES/STATIC ANALYSIS

Panas [46] visualized software binaries in order to demonstrate malware samples. In their approach, they first disassemble the file to obtain the Abstract Syntax Tree (AST) and then provided the intermediate representation of the file by using ROSE [47], an open-source compiler. Visualizing the signature of a set of different malware families, they were able to show the changes in different versions of a malware family. Also utilizing visualizations in dynamic malware analysis, Grégio *et al.* [45] proposed a solution with two interactive visualization tools. The two visualization prototypes are a timeline with a magnifier and a spiral view of the malicious activities. The first tool provides analysts with views of the malware activities over time. While the time selection for the x-axis is similar to ours (and many others), the uses of colors and what is to be presented in the y-axis are different. They used the y-axis to represent activities and colors to different processes or services involved by the malware execution. Each event (an activity at a timestamp of an involved process) is presented by a circle connected by a line, which represents changes over time. This presentation leads to the visual cluttering issue, especially when malware does many different activities in a short time interval [48].

Gove *et al.* [49] presented their tool Similarity Evidence Explorer for Malware (SEEM), which compares a focal sample of malware with other malicious samples in the database. The malware features are grouped into nine categories, and feature similarities are visually presented in three ways: 1) histogram, 2) Venn diagram list, and 3) a feature matrix. The histogram utilizes the Jaccard similarity of the features of the focal sample with the other samples. In contrast, the Venn diagram is more granular and shows information of overlap, strict subset, and disjoint features. The feature matrix highlights the specific features present in the analyzed sample. Long *et al.* [50] proposed a versatile and instinctive technique to identify a given malware file from its image sets. The authors argued that the desktop icons are one effective social engineering attempt employed by some malware developers. The victim clicks on the icon resulting in the execution of the malware. Hence, comparing a new malware based on its image with a previously known malware database results in effective malware identification. Extracted greyscale malware images are shown using a *force-directed graph* [15], [17], which is essentially a similarity network of sample malware images computed with the nearest neighbor index. The visualization tool shows hash values of the executable, and upon clicking on the values, it draws the similarity network graph, and it provides zooming functionalities for multiple hops of each node.

B. IMAGE-BASED AND DYNAMIC ANALYSIS

While static analysis is computationally efficient, its performance could be impaired by packed or encrypted malware. On the other hand, dynamic analysis analyzes actual behaviors from the malware while it is running, so it is more efficient [51]. In their work [52], Shaid and Maarof proposed a method to generate images representing malware API calls. First, the API calls are monitored in the malware behavior capturing step. These calls are then sorted from malicious to less malicious. Finally, each API call is assigned a color depending on its maliciousness level. Similarly, Kancherla *et al.* [51] proposed to convert the malware into a gray-scale image called byteplot. They then used machine learning (ML) methods (e.g., Support Vector Machines) to analyze the low-level features (e.g., intensity and textures) extracted from the resulted images. Regarding ML approaches, LeDoux and Lakhotia [53] presented that ML has a natural fit with malware analysis, where ML operates by rapidly learning, discovering inherent patterns and similarities in the corpus.

With image-based malware classification, O'Shaughnessy [54] utilized the space-filling curves approach to formalize a scalable solution for classification ambiguity among anti-virus programs. Donahue [55] proposed another idea of using Markov Byte Plot [56] to convert Portable Executable (PE) files into truecolor (defined by red, green, and blue (RGB) color components) images that help to highlight the differences between the packed and unpacked malware. Another common approach is to convert malware PE or binary files into images and analyze the resulted images. There are various ways to turn the malware into images and different methods to analyze the produced images. For instance, Han *et al.*, [57] proposed a three-step approach to analyze malware in this direction. First, the opcode sequences of the malware are extracted in Step 1. Step 2 generates an image with both width and height are of 2^n, where n is a user-defined number. Next, this step applies a hash function, such as SimHash [58], to each of the extracted opcode sequences to generate a pixel with corresponding x-y position and RGB color. Finally, similarities between the resulted images are calculated in Step 3. In their extended version of this approach [44], they also incorporated dynamic analysis to filter for essential opcode sequences.

Miles *et al.* [59] presented VirusBattle, a system equipped with intelligence navigation and visualization to mine and to discover interrelationships between malware instances automatically. This system provides two primary analyses: 1) a program's dynamic trace tree and 2) a scalable method of discovering shared Computed Semantics artifacts among instances of malware. VirusBattle analyzes the interrelationships over many types of malware artifacts, including the binary, code, code semantics, dynamic behaviors, malware metadata. Shaid and Marrof [60] proposed the method of presenting the behavioral pattern of malicious files using a Hot-to-Cold color ramp. As the malware runs, the user-mode API calls are captured, then ordered and grouped based on their maliciousness. This behavior-to-color map of the malware helps visualize when and in which order a malware sample performs malicious activities during execution.

Besides software systems, research in hardware advancement has introduced many approaches that facilitate malware analysis to build a transparent dynamic analysis system. In terms of hardware virtualization extensions, Dinaburg *et al.* [61] proposed Ether, an application that remained transparent and defeated a large percentage of obfuscation tools. Later, Lengyel *et al.* [62] built DRAKVUF on a similar virtualization extensions approach and provided greater insight into the execution of the system to trace system execution for malware analysis.

This visual analytics approach in *MalView* can benefit the branch prediction in dynamic environment analysis in GoldenEye by Xu *et al.* [63] and the analysis of sequences of API calls in VECG by Alaeiyan *et al.* [64]. The interactive visual representations can expedite the process of proactively detecting environment-sensitive and context-based behaviors, where "human-in-the-loop" can accelerate early stopping and quickly capture patterns that emerged from the API call sequences.

C. HYBRID (STATIC AND DYNAMIC) ANALYSIS

Most static approaches focus on comparing, clustering malware instances, or classifying if a new sample belongs to a known family of malware. For example, Paturi *et al.*, [65] used Pythagoras tree to represent the similarities in codes between malware. The similarity metrics might be "Cosine similarity" or "Normalized Compression Distance." The hierarchical structure of the Pythagoras tree is characterized as the distance between nodes at each lower depth of the tree is reduced by $\sqrt{2}/2$. Thus, the tree helps bring malware with higher similarities into clusters as leaf nodes with shorter distances stay close to one another.

Anderson *et al.* [66] presented a malware classification system that works based on the combination of static and dynamic features. For static feature extraction, they used three sources, including 1) the binary file, 2) the disassembled binary, and 3) the control flow graph of the disassembled binary file. For dynamic feature extraction, they used dynamic instruction sequence and the dynamic call sequence. They tested their system using a large malware dataset and achieved 98.07% accuracy with the combined static and dynamic features. They also achieved a 96.14% accuracy by using only static features. Yoo [67] designed the visualization based on the belief that malicious content in an executable file has a unique feature called SOM (Self-Organizing Map). By calculating the SOM and visualizing a specific executable file, the potential portion of the malicious content can be determined, and by checking the generated pattern, the malware family can be detected.

Saxe *et al.* [68] developed an interactive visualization system for comparing malware samples in a dataset using the extracted features. Based on the presence of the system call sequence, the similarity matrix for the malware dataset is generated. This system also provides a comparison view among malware samples based on their malicious activity. On mobile computing platforms such as Android devices, Jenkins and Cai [69], [70] explored Inter-Component Communications (ICC) via interactive visual explorations, showing thorough ICC comprehension and security vulnerability inspection, revealing the malicious behaviors that were normally hidden to users.

D. VISUALIZATION TOOLS AND ANALYSIS

Analyzing malware through visual behaviors has been studied with the aim to observe the overall flow of a program, discover malicious patterns, and quickly assess the nature of the malware sample [5], [71]. Wagner *et al.* [72] proposed KAMAS, a knowledge-assisted visualization system for behavior-based malware analysis, which visualizes API call sequences gathered during the execution of malicious software. Our approach aligns with this direction, but we shift the focus on the analysis side with different malware families and the influence of operating systems on malware behavior. In particular, the design decisions and techniques in *MalView* are applied in the malware analysis domain and derived from visualization principles for time-series data, which is the collection of observations through repeated measurements over time, including but not limited to numerical, geolocation, and text data [73], [74], [75]. Using Ether [61] as the monitoring platform, Quist and Liebrock [76] propose a directed graph structure of all the basic blocks of an executable with a navigable interface to explore the code structure. Treemaps and thread graphs are also visualization techniques that show usefulness in detecting maliciousness of software and in classifying malicious behavior [77]. The classification decisions can be supported by the visual analytics solution provided by Angelini *et al.* [78] to provide the user a better understanding of such decisions and the possibility of changing the classification results. Visual analytics approach, when combined with predictive analysis, can project potential threats or detect malicious attacks for securing efficient manufacturing automation [79].

Conti *et al.* [80] designed a system for file analysis with these features: 1) Analyze undocumented file format, 2) Audit files for vulnerabilities, 3) Compare files, 4) Crack, Cryptanalysis, and Forensic analysis, 5) Identify unknown file format, 6) Malware analysis and 7) Reporting. Their system is an extension to the hex editor and consists of both textual and graphical visualization. Quist and Liebrock [76] developed a tool called VERA (Visualization of Executables for Reversing and Analysis) that can be used for visualizing the structure and flow of an executable file, including memory reads and writes. Later, they extended their work [81] by adding more reverse engineering tools and providing more testing case studies in detail.

Trinius *et al.* [77] used two different approaches for malware visualization. They first generated an XML file containing dynamic analysis information of the malware sample using *CWSandbox* [82], including 1) loaded system libraries, 2) outgoing and incoming network connections, and 3) accessed or manipulated registry keys. Using the XML output, they visualized the key feature using two techniques: "*treemaps*" and "*thread graphs*". They argue that these two methods are complementary and, using these two visual representations, can effectively help detect the malicious behavior of the given malware and identify the malware family. They tested their proposed approach by executable and non-executable (PDF format) malware samples.

Gregio and Santos [83] developed an interactive timeline tool for visualizing dynamic malware behavior using various techniques [48]. They ran the given malware in a controlled environment and captured its behavior using a modified version of BehEMOT [84] (a malware behavior monitoring tool). They captured high-level activities such as file write and delete, process creation and termination, registry reads and writes, mutexes and network operations, and system calls using System Service Dispatch Table (SSDT) hooking, which operates at the kernel level. In addition, they used identification labels provided by VirusTotal [23].

An interactive visualization tool called MalwareVis is introduced by Zhou *et al.* [48] for malware dynamic analysis with a concentration on network traces including the total number of packets, size of the transmission, number of streams, and the packet trace's duration. They ran the malware in a controlled environment and captured these network traces by using packet sniffer software, where the output packet capture (PCAP) files were used for visualization. They used table views and shape views for representing the features that allow the user to browse, filter, and compare different types of malware. Cappers *et al.* [85] also utilize PCAP to discover the patterns in traffic to explore the intrusive behavior from malware activities.

IX. CONCLUSION AND FUTURE WORK

This paper introduces *MalView*, an interactive visualization platform for hybrid analysis and diagnosis of malware. Our approach first represents the behavioral properties of the major malware classes (such as Trojan or backdoor), aiming to capture the common visual signatures of these malicious applications. *MalView* implements a web-based prototype for demonstrating our approach to analyzing 60 malware samples from seven different classes. The behavior aspects of these malware files are captured using Process Monitor (i.e., Procmon [6] on three different platforms (Windows XP, Windows 7, and Windows 10). The functionality and features offered by *MalView* are designed and developed based on a thorough literature review and a comparison with the state-of-the-art malware analysis tools, including AnyRun and Hybrid. In order to have better insight regarding the features offered by *MalView*, a feature table is presented in which *MalView* is compared with AnyRun and Hybrid analysis tools. The feature comparison is performed based on four classes of features. The feature table demonstrates that *MalView* comparatively implements most of the features offered by the other two tools. In addition, the time and processed dependencies, the key features of *MalView*, are implemented in the prototype, making the analysis more thorough. Given the ability to process, visualize and analyze the system activities and put them into a comprehensive view, *MalView* can serve as an informative and potential interest to developers, engineers, and practitioners outside the laboratory.

There are several lines of research that can be explored through visual analytics when complemented by conventional static and dynamic analysis: The early detection of zero-day vulnerability and malware is a grand challenge. There are several machine learning-based approaches for addressing this problem [1], [53]. With the capability of visual analytics facilitating explainable machine learning [86], [87], applying visual analytics techniques to detecting and analyzing unknown and zero-day malware is an interesting research approach that can be explored using *MalView*. The key feature of *MalView* is its features in demonstrating time and process dependencies that occurred during static and dynamic analysis. A potential research direction is to model malware behavior through recurrent neural networks on the visual signatures and then predict malware behaviors or even classify suspicious programs into a particular class of malware. It would also be interesting to model malware samples through genome alignments and then model the malware classification or detection problem through deoxyribonucleic acid (DNA) or sequence matching approaches. The sequence matching might be useful in capturing the core malicious functionalities of obfuscated malware. The obfuscation techniques employed by the obfuscating tools often follow similar patterns, and thus we expect the control-flow graphs produced for all these obfuscated malicious applications share fully or partially the same core. *MalView* will offer a visual analytic approach to spot these similar patterns in the execution traces. Once a section of the underlying execution trace is identified as obfuscated, it can be ignored by the user of *MalView* and then enables the users to focus on other parts of the malware in order to comprehend it. A second approach would be to employ existing de-obfuscated tools to de-obfuscate the malware under investigation (MUI) and then let Procmon generates the de-obfuscated traces of execution and processes.

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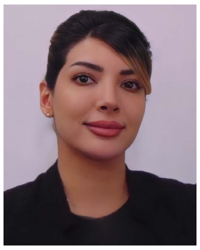

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