Examining Cloud Data Security Vulnerabilities During Usage

Daniel Amoah, DCS, CISSP, Azure Solutions Architect
dpamoah@hotmail.com, daamoah@micrsoft.com
Solutions Architect (Infrastructure and Cyber)
Microsoft Corporation
Denver, CO 80249

Samuel Sambasivam, PhD
Samuel.Sambasivam@Woodbury.edu
Computer Science Data Analytics
Woodbury University
Burbank, CA 91504

Abstract

Cloud computing is a popular computing paradigm with overwhelming benefits, yet there are complex and unresolved cloud data security vulnerabilities in the usage stage of a cloud data life cycle. The purpose of this design science study was to examine cloud data security vulnerabilities during usage by developing a forensic artifact capable of determining cloud data security vulnerabilities. In line with the research question, the study was based on three propositions: 1) that unencrypted data vulnerability is detectable during usage in the cloud, 2) that detectable vulnerable data in the cloud is recoverable using forensics means, and 3) recoverable data is discernable to the extent that it provides value to the data collector. A total of 9 forensics experiments were conducted in three phases using different configurations to collect and analyze the forensic artifacts required to validate or disprove the research propositions. The findings of this design science study showed that both encrypted and unencrypted cloud datasets in memory during cloud data usage are detectable. Detectable unencrypted cloud data during usage is vulnerable, recoverable, and discernable. Encrypted cloud data during usage is also recoverable but not discernable. However, the practicality of homomorphic encryption, which allows the computation of encrypted data, remains a challenge. Therefore, security practitioners must adopt a defense-in-depth strategy that encompasses administrative, physical, and technical controls to minimize the risk of adversary access to volatile memory.

Keywords: Cloud Data Security, Data Lifecycle Security, Data Usage Vulnerability, Cloud Forensics, Memory Forensics.

1. INTRODUCTION

Cloud computing is a new computing paradigm that is more appealing due to benefits such as ubiquitous network access, easy on-demand self-service, rapid resource elasticity, location independence, resource pooling, and usage-based pricing (Sun et al., 2014). The cloud ecosystem can offer better computing services and other benefits such as business agility, cost savings from management, maintenance, and operations than privately owned on-premises data centers (Alam et al., 2018). However, cloud computing has introduced new and complex data security concerns (Khan et al., 2017; Kumar & Goyal, 2019).

Studies have proposed various procedures to achieve the highest data security level for cloud data protection (Kumar & Goyal, 2019; Matloob, 2017; Mazonka et al., 2020; Singh & Chatterjee, 2017). Subramanian and Jeyaraj (2018)

emphasized a need for data protection in all data lifecycle stages in cloud computing. Kacha and Zitouni (2017) described a data lifecycle's usage stage as performing computational processing on cloud data, where risks of misuse or abuse are very high due to many customers in the cloud. According to Mazonka et al. (2020), unlike data in transit and data at rest, which could be protected using encryption, data in use, or performing computation on sensitive data in the cloud, is a single point of failure in computing platforms because current processors operate entirely on plaintexts. To compute on encrypted sensitive data, existing computer architectures must first decrypt, operate on the data, and then re-encrypt. Unencrypted computational data in memory is vulnerable to attack (Singh & Chatterjee, 2017).

Verifying or validating the vulnerability of unencrypted cloud data requires the use of cloud forensic tools and methods (Arshad et al., 2018). However, there are unique challenges in conducting forensics in a public cloud computing environment (Nasreldin et al., 2015). There are architectural, access, jurisdictional, and multi-tenancy challenges associated with a complete forensic analysis of cloud data (Chaudhary & Siddique, 2017). Amato et al. (2020) described a novel semantic approach for conducting digital forensic that enhances evidence discovery and correlation in cloud computing.

This design science research examined the development of a forensic artifact capable of determining cloud data security vulnerabilities during cloud usage. The artifact development consisted of a cloud forensic investigation in different configurations to identify the configurations that offered the most likely source of unencrypted data vulnerability during cloud usage.

Problem Statement

The problem to be addressed in the research study was that the strategies cybersecurity specialists use to mitigate cloud data security vulnerabilities during usage are lacking (Singh & Chatterjee, 2017). Data security and privacy protection concerns remain the most critical issues in cloud computing (Barnwal et al., 2017; ISC2, 2020). According to International Information System Security Certification Consortium (ISC2) 2020 Cloud Data Security report, 69% of organizations are concerned about cloud data loss or leakage (ISC2, 2020). Another report by CloudPassage for Amazon Webservices showed that 63% of organizations are worried about cloud data loss or leakage (CloudPassage, 2020).

Barona and Anita (2017), Kacha and Zitouni (2017), Subramanian and Jeyaraj (2018), and Sun (2020) discussed different types of cloud data security vulnerabilities inherent in the cloud data lifecycle. During the usage stage, when the data is unencrypted, insiders, or outsiders' adversaries with malicious intentions, can gain access to private data used on cloud platforms illegally (Khan, 2016).

Research Question

The research question that guided the study was: What cloud data security vulnerabilities exist during usage? In line with the research question of the study, the following propositions were made:

Prop 1. Unencrypted data vulnerability is detectable during usage in the cloud.

Prop 2. Detectable vulnerable data in the cloud is recoverable using forensics means.

Prop 3. Recoverable data is discernable to the extent that it provides value to the data collector.

2. REVIEW OF THE LITERATURE

This section examined the existing academic and professional literature on cloud data lifecycle security. Cloud computing is a popular computing paradigm with substantial research on multiple interrelated topics, including data security (Barona & Anita, 2017; Kacha & Zitouni, 2017; Subramanian & Jeyaraj, 2018; Sun, 2020). However, as the section illustrates, there are no definitive studies in the literature on cloud data security vulnerabilities in the usage stage (Singh & Chatterjee, 2017).

Security Concerns in Cloud Computing

Over the last ten years, the cloud risk spectrum has expanded due to an increasing growth for cloud-based prospects for business (Kumar & Goyal, 2019). Critical or sensitive cloud storage data can be remotely accessed by attackers who now have the aptitude to utilize users' login information for remote access (Mattoo, 2017; Vumo et al., 2019). Security concerns in the cloud are a significant issue for 94% of organizations (ISC2, 2020). Another cloud security report by CloudPassage showed that 95% of organizations are concerned about the security of their cloud workloads (CloudPassage, 2020).

Cloud Data Lifecycle Vulnerabilities

There is a need for data protection in all data lifecycle stages (Subramanian & Jeyaraj, 2018). The cloud data lifecycle describes the phases in data from creation to destruction (Kumar et al.,

2017). The data lifecycle stages are creation, transmission, storage, usage, sharing, archiving, and disposal (Lin et al., 2014). Creation is the generation of new digital content or updating existing content (Kumar et al., 2017). Storing is the act of committing the digital data to some sort of storage repository and typically occurs nearly simultaneously with creation (Subramanian & Jeyaraj, 2018).

The viewing, processing, or using data in some activity describes the data usage stage (Subramanian & Jeyaraj, 2018). Kacha and Zitouni (2017) described data-in-use as performing computational processing on the cloud data, with a very high risk of misuse or abuse due to many customers in the cloud. The share stage describes activities such as exchanging data between users, customers, and partners (Kumar et al., 2017). In the archive phase, data leaves active use and enters long-term storage (Kumar et al., 2017). The disposal phase describes data destruction using physical or digital means (Kumar et al., 2017). Data deleted from storage media is not entirely erased because file systems cannot remove data; therefore, attackers may use data scavenging techniques to recover deleted data (Khan, 2016).

Data in use and remanence are green pastures for research (Subramanian & Jeyaraj, 2018). There are security vulnerabilities within the SaaS, PaaS, and IaaS models and all the cloud data lifecycle stages (Kumar et al., 2017). It is impossible to process encrypted data either in the cloud environment or in on-premises environments (Kumar et al., 2017). Static data used in cloud applications are usually unencrypted because encrypted data prompts for keys during processing (Kumar et al., 2017).

Encryption

Matloob (2017), Mazonka et al. (2020), and Lo'ai and Saldamli (2019) described encryption as one of the well-known and best solutions for securing data in the cloud. Encryption encodes information into a coded structure and transforms it back to the original state (Matloob, 2017). However, it is impossible to protect data-in-use with encryption either in the cloud environment or in on-premises environments because existing computer architectures must first decrypt, operate on the data, and then re-encrypt (Gaidhani et al., 2017). Other solutions in the academic literature from Alaya et al. (2020), Farokhi et al. (2017), Li et al. (2020), Tran et al. (2020), and Xiong and Dong (2019) focused on using some form of homomorphic encryption schemes to solve the cloud computing data security problems in the usage stage. However, homomorphic encryption has practical implementation challenges for widespread deployment (Alabdulatif et al., 2020; Alloghani et al., 2019; Geng, 2019; Ullah et al., 2019).

Digital Forensics

Digital forensics is a practice that uses scientifically driven and verified methods toward the identification, preservation, acquisition, analysis, interpretation, and documentation of digital data and source analysis and presentation of evidence for reconstructing suspicious events (Palmer, 2001). Digital forensics focuses on forensic procedures, legal approaches, and evidence (Serketzis et al., 2019).

Conducting forensics in a cloud environment is problematic due to the highly distributed and complex cloud architecture (Arshad et al., 2018). Also, established digital forensics practices such as searching and collecting data are not feasible in the public cloud environment due to the lack of individual ownership of devices and the volatile nature of data stored in the cloud (Arshad et al., 2018).

Challenges in Cloud Forensics

There are many unique challenges for conducting digital forensics in a public cloud computing environment (Nasreldin et al., 2015). Some of the cloud forensic challenges include architecture, data collection, evidence analysis, incident first responder, legal, standards, and training (Chaudhary & Siddique, 2017). Other forensic challenges unique to cloud computing are jurisdiction, multi-tenancy, and CSP dependency (Chaudhary & Siddique, 2017).

Traditionally, the forensic investigator controls the evidence collection, but in cloud computing forensics, access to the evidence may not be physically available (Chaudhary & Siddique, 2017). The investigator also faces challenges in analyzing available logs and artifacts (Tak et al., 2018). The forensic investigation challenges in the cloud computing environment are also related to evidence control, collection, preservation, and validation (Tak et al., 2018). There are also unique digital forensics challenges within the IaaS, PaaS, and SaaS models (Chaudhary & Siddique, 2017).

Gaps in the Literature

Studies have proposed various procedures to achieve the highest data security level for cloud data protection (Kumar & Goyal, 2019; Matloob, 2017; Mazonka et al., 2020; Singh & Chatterjee, 2017). Mazonka et al. (2020) posited that unlike data in transit and data at rest, which could be

protected using encryption, data in use, or performing computation on sensitive data in the cloud is a single point of failure in computing platforms because current processors operate entirely on plaintexts. To compute on encrypted sensitive data, existing computer architectures must first decrypt, operate on the data, and then re-encrypt. Public cloud data usage security remains an unresolved concern affecting critical user information privacy and requires more research (Singh & Chatterjee, 2017).

3. METHOD

Design Science was the most appropriate research methodology for this forensic study. According to Edmondson and McManus (2007), implemented research is a mature theory because components used to create an artifact are meticulously studied and documented in the body of knowledge but lacks a developed artifact for the research purpose. Peffers et al. (2007) stated that design science methodology is used to create a knowledge discovery artifact for a research problem. The result of a design science research study is the purposeful creation of an artifact, which can be a product, process, technology, tool, methodology, technique, procedure, or any combination for achieving some purpose (Lapão et al., 2017; Peffers et al., 2007).

Research Design

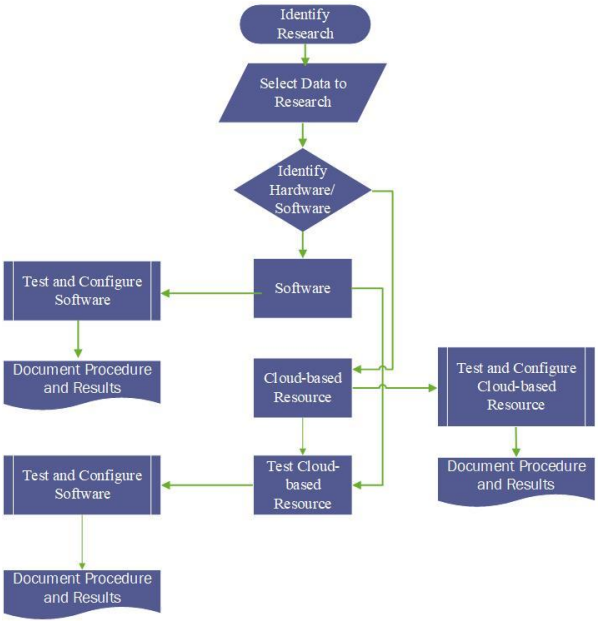
The research design was implemented in a standard public cloud operational environment using standard vendor installation instructions. The overall design consisted of two virtual machines (VM) servers hosted in a public cloud, two VM workstations hosted in the public cloud, and a physical workstation. Memory and other research data were collected from the cloud servers using forensics tools and procedures during data computation analysis. The setup of the design allowed for a repeatable process that was easily documented.

Artifact Design

Digital forensics is a practice that uses scientifically driven and verified methods toward the identification, preservation, acquisition, analysis, interpretation, and documentation of digital data and source analysis and presentation of evidence for reconstructing suspicious events (Palmer, 2001). Cloud forensic investigation involves five primary dimensions: data collection, evidence segregation, virtualized environment, preservation of evidence, and reporting and documentation (Chaudhary & Siddique, 2017). Dynamic digital forensics is a forensic data collection and analysis of a running state system or distributed across multiple locations (Arshad et al., 2018). Forensics includes specialized forensic software or hardware that enables a complete digital investigation (Alenezi et al., 2019).

Forensic methods were used to validate or disprove the research propositions through a rigorous process of data collection. Data collection approaches were tested to identify controlled data sets from the testing environment. The research was conducted in three phases. Phase I of the study involved installing hardware, software, and testing without external or internal manipulations. The VM servers and workstations were deployed in Microsoft Azure public cloud with default settings. Initial data were collected and analyzed to determine if there were identifiable data to document.

Figure 1
Methodology for Forensic Evaluation



Note. Methodology for forensic evaluation

In phase II, controlled use of client-server applications with encrypted cloud data was introduced to the same configuration in phase I. The encrypted data was downloaded to the VM server and opened through a client-server interaction via Simple Message Block (SMB), making the encrypted data available in memory (data-in-use). Data was collected using forensics tools from the Azure VM servers and analyzed. In phase III, the same default configuration settings from phase I was used but with controlled use of

client-server applications using unencrypted cloud data to determine data vulnerability in memory. Figure 1 illustrates the methodology used for the forensics evaluation using free and publicly available specialized forensics software (FireEye's Redline) and hardware for the research.

Figure 1 illustrates the basic flow of the methodology used for the forensic evaluation, from identifying the problem, selecting data, identifying hardware and software for testing and configuration, and documenting the procedures and results at each stage.

Collection of Running Memory

Data was collected from the VM servers in the public cloud and examined according to standard forensic guidelines to provide unaltered data supported by documented collection procedures used in each phase of the collection and analysis process. Data were categorized in each phase of the collection process according to data type, date and time collected, test case number, and test case descriptions. Forensics data collection and storage procedures were applied in all data collection for this study.

4. FINDINGS

Description of the Study Sample

The research used random samples of Indicators of Compromise (IOC) obtained from the following publicly available, accessible, and open-source projects: https://github.com/topics/ioc https://cyberwarzone.com/download-indicators-of-compromise/

IOCs are forensic artifacts observed in an operating system or on a network and utilized to indicate a computer intrusion and detect cyber-attacks in an early stage (Catakoglu et al., 2016). The sample IOC data and two non-IOC data were used in the study. Table 1 summarizes the sample data used to validate cloud data security vulnerabilities during usage.

Results

In phase I, the test environment (two VM servers and two VM workstations) was built on Microsoft Azure public cloud with default settings on Windows operating systems as described in Section Three. Various techniques and tools can be employed in digital forensics to analyze live memory (Al-Sharif et al., 2018). The VM servers and workstations were initially analyzed using Redline forensic software and manual hex searches of the file system to ensure the datasets were not present. Figure 2 shows Redline Command run to capture active memory of VM Server1 during interaction with VM Workstation1 with no dataset on the Server. Volatile memory analysis can be performed using four unique methods: file carving, process-object searching, string search, and file signature search (Thantilage & Jeyamohan, 2017). This study used string searches and process-object searches for the analysis of the collected memory artifacts.

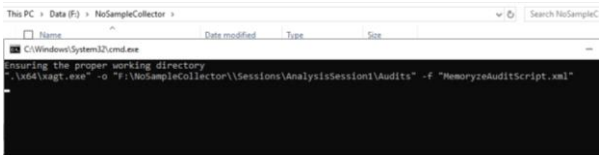
Table 1

Description of Sample Data Sets Used in Study

Dataset	Source	Deployment Method	Errors on Client	Operating System
www.apicola.cl	IOC	Notepad	None	Windows Server 2019
halkbankasi.cf	IOC	Word Document	None	Windows Server 2019
paypalll.ga	IOC	Word Document	None	Windows Server 2019
quiroga.cl	IOC	Notepad	None	Windows Server 2019
$Daniel&Amoah$	Non-IOC	Word Document	None	Windows Server 2019
COVID-19	Non-IOC	Word Document	None	Windows Server 2019

Figure 2

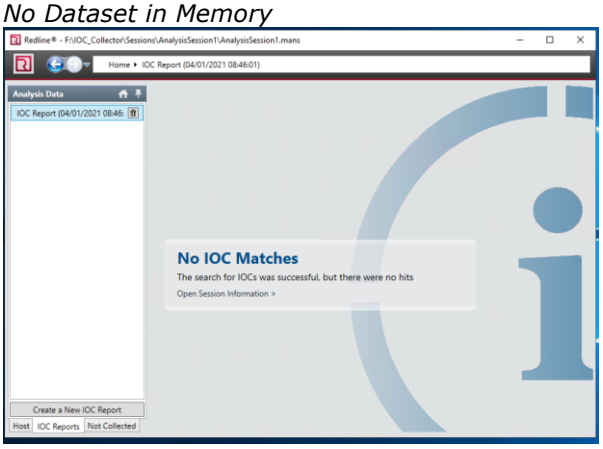
Commands run on VM Server1 to Capture Memory with No Dataset



The captured memory data from VM Server 1 was analyzed, as shown in Figure 3. The forensic analysis showed no indication of the presence of the research dataset in memory during the interaction between VM Workstation 1 and VM Server 1.

Figure 3

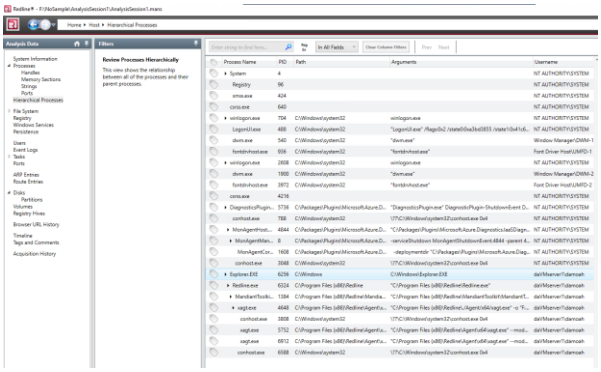
Forensics Analysis of VM Server1 Memory with No Dataset in Memory



Note. Figure 3 shows an initial view of the IOC search report for possible matches in the sample_ioc dataset in the collected memory.

Figure 3 shows that the captured memory has no elements of the sample_ioc dataset in the memory of VM Server1.

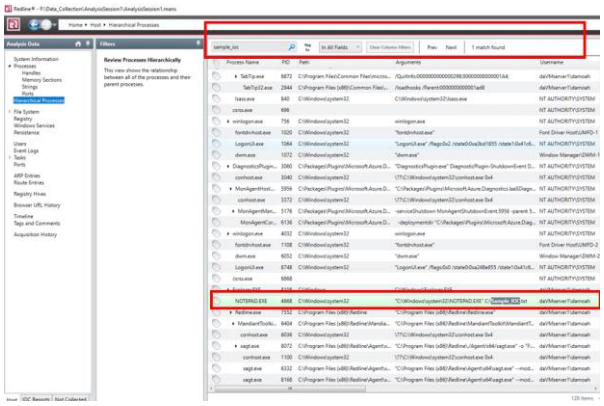
Figure 4
Forensics Analysis of VM Server1 with No Dataset



Note. Figure 4 shows that while no sample_ioc data was found in memory, other data elements not considered were available in memory.

In phase II, controlled use of a client-server application with encrypted cloud dataset was introduced to VM Server1 using methods described in Section Three. The encrypted data was accessed via VM Workstation1 but not decrypted. VM Server1's live memory was captured and analyzed during the client-server application interaction, as shown in Figure 5.

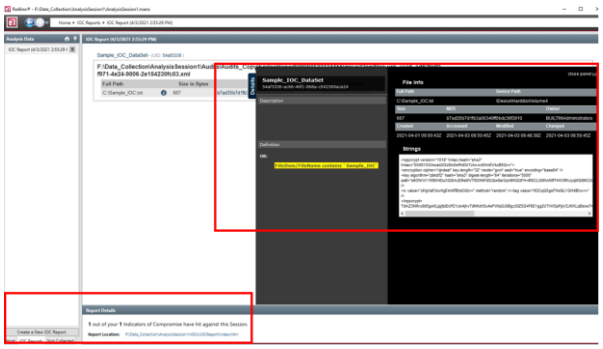
Figure 5
Forensics Analysis of VM Server1 Memory with Encrypted Dataset Match



Note. As shown in Figure 5, the forensics analysis showed the encrypted sample IOC dataset in memory.

A search for "sample_ioc" on hierarchical processes in memory returned one match, but the dataset file was encrypted and, therefore, not discernable. Encrypted dataset elements were detected in the memory analysis of VM Server1 during the client-server interaction.

Figure 6
Forensics Analysis of VM Server1 Memory with Encrypted Dataset Match Details



Note. In Figure 6, the memory analysis of VM Server1 with the encrypted dataset match was expanded to show the contents of the dataset file.

As shown in Figure 6, the contents of the sample_ioc encrypted dataset were not discernable.

Figure 7

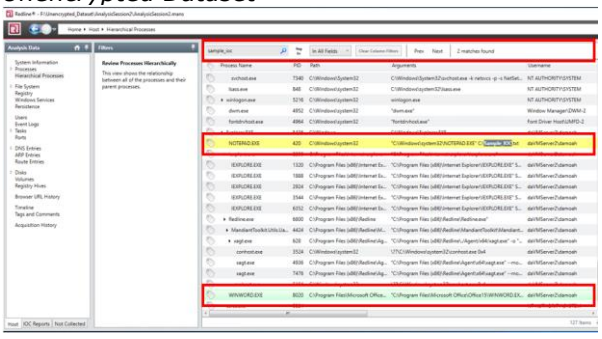
Forensics Analysis of VM Server1 with Search Terms for IOC Dataset Elements

Note. In Figure 7, the forensics analysis of VM Server1 Memory was further expanded with specific search terms for known IOC dataset elements in the sample_ioc dataset.

The dataset elements "COVID-19", "paypall.ga", "halkbankasi.cf", and "$Daniel&Amoah$" were used individually at different times as search criteria on the captured memory of VM Server1. Each of the searches resulted in "no matches found." The results clearly showed that an encrypted dataset in memory is not discernable. In phase III, the unencrypted sample dataset was introduced to VM Server2 with the same default configuration settings as in phases I and II. A client-server application interaction was initiated from VM Workstation2 to VM Server2 to access and use the unencrypted datasets. A live memory of VM Server2 was captured with the forensic tool and analyzed, as shown in Figure 9.

Figure 8

Forensics Analysis of VM Server2 Memory with Unencrypted Dataset

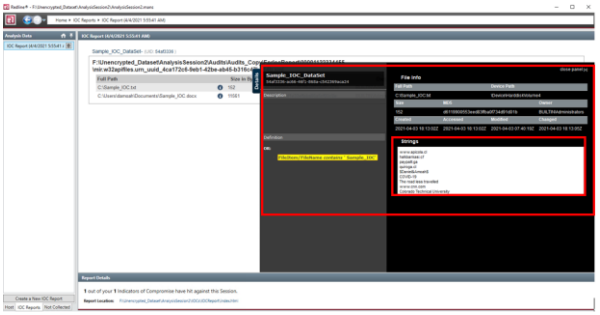


Note. As shown in Figure 8, the forensics analysis showed the unencrypted sample IOC dataset in memory with a search for "sample_ioc on hierarchical processes.

The search returned two matches for sample_ioc datasets in Notepad and Microsoft Word, representing a match for each deployment method for the sample_ioc dataset. However, further trace analysis of the sample_ioc on the captured memory showed all the unencrypted sample_ioc dataset in memory, as shown in Figure 9.

Figure 9

Forensics Analysis of VM Server2 Memory with Unencrypted Dataset Match Details

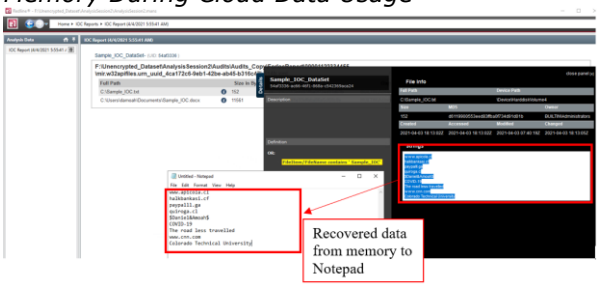


Note. In Figure 9, the complete unencrypted sample_ioc dataset was discernable and accessible in memory.

As shown in figure 9, the IOC search report on the captured memory image returned one match, but the dataset file was encrypted and not discernable. The unencrypted dataset elements were detected in the memory analysis of VM Server2 during the client-server interaction and usage of data.

Figure 10

Forensic Data Recovery from VM Server2 Memory During Cloud Data Usage



Note. Figure 10 shows a detectable and discernable sample_ioc dataset that was easy to highlight and copy into the Notepad application on a standalone forensic workstation. The copied dataset provides great value to the data collector because it reveals secret information.

The collected artifacts' examination and analysis reviewed three significant themes: data

detectability in memory, discernability of data in memory, and recoverability of data in memory.

Data is Detectable During Cloud Data Usage

The collected memory artifacts' analysis showed that both encrypted and unencrypted datasets were detectable in memory during cloud data usage. The artifacts in phases I, II, and III indicate that encrypted and unencrypted data is detectable in memory during usage in the cloud. In phase I, where no sample data was introduced in the examination, collection, and analysis, other non-sample data were observed in memory, as shown in the captured forensic memory analysis in Figure 4. In phase II, encrypted sample_ioc data was introduced to VM Server1, and the encrypted data was accessed via a client-server interaction. The collected live memory analysis showed the encrypted sample_ioc dataset, as shown in Figures 5 and 6. In phase III, the unencrypted sample_ioc dataset was also observed and captured in the analysis shown in Figures 8 and 9. The finding in the three phases addresses the first research proposition: that unencrypted data vulnerability is detectable during usage in the cloud.

Data is Recoverable During Cloud Data Usage

The collected artifacts' analysis showed that detected cloud data in memory could be recovered using forensic tools, as shown in Figure 10. The forensic examination and analysis also showed that both encrypted and unencrypted data could be recovered in memory. However, encrypted data in memory does not provide immediate value to the data collector because data confidentiality is not compromised. On the other hand, unencrypted data in memory is vulnerable and provides immediate value to the data collector because there is no data confidentiality, as shown in Figure 10. The forensic artifact in Figure 10 supports the second research proposition: detectable vulnerable data in the cloud is recoverable using forensic means.

Data is Discernable During Cloud Data Usage

Data discernability describes the ability to identify specific or unique datasets in memory valuable to the data collector. In phase II, the forensic analysis showed that encrypted data in memory is not discernable, as shown in Figure 6. Encrypted data does not reveal any specific data elements and, therefore, retains data confidentiality. Unencrypted cloud data during usage, on the other hand, is discernable in memory, as shown in the collected and analyzed artifacts in Figure 10. Unencrypted data in a file system can be viewed and recovered (Shashidhar & Novak, 2015). The collected forensic artifacts showed that unencrypted cloud data during usage is discernable and, therefore, vulnerable.

5. DISCUSSION

The purpose of the design science study was to examine cloud data security vulnerabilities during usage by developing a forensic artifact capable of determining cloud data security vulnerabilities. The study determined whether unencrypted data vulnerability was detectable, recoverable, and discernable during usage in the cloud.

Theme 1: Defense-in-Depth Strategy to Safeguard Data Detectability in Memory

As indicated by the collected memory artifacts, encrypted and unencrypted cloud datasets in memory during cloud data usage are detectable. The ability to detect datasets in memory during cloud data usage means data is vulnerable while in memory. Since data in memory is detectable, unencrypted data in memory is a serious threat to data security. There is, therefore, a need for cybersecurity specialists and practitioners to consider strategies and technologies to protect data in memory.

There are different strategies and approaches for safeguarding datasets in memory. According to Mazonka et al. (2020) and Lo'ai and Saldamli (2019), one of the well-known and best solutions for securing datasets in the cloud is encryption. Encryption is a process that converts plaintext data into cyphertext. However, it is currently impractical to protect data-in-use with encryption (Gaidhani et al., 2017; Kumar et al., 2017; Miyan, 2017). Homomorphic encryption is an encryption scheme that allows computation on encrypted data without first decrypting the data (Gaidhani et al., 2017). However, homomorphic encryption has practical implementation challenges for widespread deployment and adoption (Alabdulatif et al., 2020; Alloghani et al., 2019; Geng, 2019; Ullah et al., 2019).

A significant part of the data detectability in memory vulnerability is access to the volatile computer memory. It is, therefore, critical for cybersecurity specialists and practitioners to adopt comprehensive layers of different controls (defense-in-depth) to minimize the risk of access to the vulnerable memory (Mazonka et al., 2020; Rocha et al., 2013). Controls such as policies, identity and access management, personnel security, physical security, network security, host-based security, and application security, among other controls, effectively reduce the risk

(Jeganathan, 2018). Cybersecurity specialists can implement layers of technical and administrative controls to reduce the risk of vulnerabilities (Kumar & Goyal, 2019).

Theme 2: Use Available CSP Tools and Controls to Reduce Recoverability of Data in Memory

Recoverability of data in memory was the next theme from the findings of the collected and analyzed artifacts in phase III. The forensic examination and analysis showed that both encrypted and unencrypted data could be recovered in memory. The study artifacts showed that encryption provides data confidentiality because recovered encrypted datasets from memory remained encrypted and did not reveal any data secrets to the data collector. The study has shown that encrypted cloud data remained encrypted when accessed through client-server interaction. However, performing a computation or using encrypted data in computing platforms remains a challenge because current processors operate entirely on plaintexts (Mazonka et al., 2020).

The study also showed that unencrypted cloud data in use are vulnerable and recoverable. It is, therefore, critical for cybersecurity specialists and practitioners to adopt available cloud service provider (CSP) tools and strategies to secure cloud data during usage. For instance, within the Azure cloud platform, enabling Just-in-Time VM access restricts the VM's management ports and grants access on-demand for a limited time to only pre-approved IP addresses. Using a bastion service to connect the VMs also protects the VMs against exposing the public IP on the VM. Using conditional access policies to restrict access and auto-shutdown VMs also reduces the risk of data recoverability in memory. There are multiple administrative and technical controls and strategies to safeguard unencrypted data in memory to prevent unauthorized recoverability (Subramanian & Jeyaraj, 2018). There is no silver bullet when it comes to protecting unencrypted data in use. No single technology ultimately provides the required protection (CSA, 2017). However, using available CSP tools and controls to enforce administrative and technical controls reduces the risk of recovering unencrypted data from memory.

Theme 3: Device Management and Isolation to Reduce Discernability of Data in Memory

The study artifacts showed that collected encrypted cloud data usage in memory is not discernable, as demonstrated in phase II. It is impossible to identify unique data elements from encrypted cloud data collected from memory without decrypting the data, as shown in Figure 6. On the other hand, unencrypted cloud data in use is vulnerable, recoverable, and discernable without decrypting the collected data, as shown in Figure 10 in the study artifacts. Unencrypted discernable data in memory is vulnerable to bus snooping attacks (Tavana et al., 2017). The risk of volatile memory vulnerability depends on access to the cloud-based resources memory; therefore, cybersecurity specialists and practitioners should implement strong authentication mechanisms through identity and access control, device management, zero-trust security model principles, and device isolation as part of broader layers of controls to minimize the risk to unencrypted data in use.

6. CONCLUSIONS

The results of the design science study showed that data could be detected during cloud usage in memory. The results also indicated that cloud data detected during usage could be recovered from memory. Finally, the results showed that encrypted cloud data usage in memory was not discernable while unencrypted cloud data in use was vulnerable, recoverable, and discernable.

The findings of this study apply to all information technology settings that use sensitive data in public cloud computing. A quantitative or qualitative study on cloud data usage security would add to the body of knowledge a comprehensive list of practical approaches cybersecurity professionals can use to minimize the risk of cloud data usage vulnerability. The practicality of homomorphic encryption also requires more research.

7. ACKNOWLEDGEMENTS

I want to acknowledge the support, encouragement, and guidance I received from my research supervisor, Dr. Samuel Sambasivam. Thank you, Dr. Sambasivam. Your counsel made the path to success on the doctoral journey clearer.

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