

Digital Evidence Collection & Preservation Procedures ROLE OF METADATA (Hashing)

NULL - OWASP Coimbatore Chapter 6th July 2024

ASHOK KUMAR MOHAN

Founder & Director @ KRIYAVAN Cyber Forensic Service, Mdu, TN, IN



Metadata

"data about data" is Metadata

Exif - Exchangeable image file format (Modified Accessed Created times)





SRC: http://www.forensichandbook.com/catching-criminals-with-digital-photos/

VOLUME

Huge amount of data



VELOCITY High speed of

accumulation of data



from various sources

VALUE Extract useful data



💷 Exif Toolbox 💷 💷 🗾 📈 Properties Equip Make: Canon Equip Model: Canon EOS 450D Orientation: 1 X Resolution: 72/1 Y Resolution: 72/1 Resolution Unit: 2 Date Time: 2008:09:06 13:23:53 YCbCr Positioning: 2 Exposure Time: 0 F-Number: F/10 ISO Speed: ISO-400 Longitude: 36.165597 Latitude: 69.960251 DTOrig: 2008:09:06 13:23:53 DTDigitized: 2008:09:06 13:23:53 CompConfig: -Shutter Speed: 1/196,72 Aperture: F/9,92 Exposure Bias: 0/1 Metering Mode: Pattern Flash: reserved FocalLength: 30 Maker Note: -



Exif Info: IMG_20201015_191111_771.jpg



as DOC (WhatsApp) Around 30 Metadata Features

FILE added

EXIF File Filename Image Width IMG_20201015_191111_771.jpg 3303 File Size Image Height 468 kB 1840 File Type Light Source JPEG Unknown File Type Extension Orientation Unknown (0) jpg MIME Type GPS Latitude 10 deg 54' 9.00" image/jpeg Exif Byte Order GPS Latitude Ref Big-endian (Motorola, MM) North Image Width GPS Longitude Ref 3303 East -Image Height GPS Longitude 1840 76 deg 53' 49.00" Encoding Process Progressive DCT, Huffman coding Bits Per Sample 8 Color Components 3 Y Cb Cr Sub Sampling YCbCr4:2:0 (2 2)

JFIF JFIF Version 1.01 **Resolution Unit** None X Resolution 1 Y Resolution Composite Image Size 3303x1840 Megapixels 6.1 GPS Latitude 10 deg 54' 9.00" N GPS Longitude 76 deg 53' 49.00" E GPS Position 10 deg 54' 9.00" N, 76 deg 53' 49.00" E

Lif Info: WhatsApp Image 2020-10-15 at 11.03.11 PM.jpeg File



FILE added as IMAGE (WhatsApp)

Around 15 Metadata Features

Filename WhatsApp Image 2020-10-15 at 11.03.11 PM.jpeg File Size 103 kB File Type JPEG File Type Extension jpg MIME Type image/jpeg Image Width 1280 Image Height 712 Encoding Process Progressive DCT, Huffman coding



JFIF

1.01

None

1

JFIF Version

Resolution Unit

X Resolution

Y Resolution

Image Size

1280x712

Megapixels

0.911

Composite

Color Components 3

Bits Per Sample

8

Y Cb Cr Sub Sampling YCbCr4:2:0 (2 2)

Exit?

Exif Info: IMG_20201015_191111_771.jpg



FILE added as DOC (WhatsApp)

Around **30** Metadata Features

File

Filename IMG_20201015_191111_771.jpg

File Size 468 kB

File Type JPEG

File Type Extension jpg

MIME Type image/jpeg

Exif Byte Order Big-endian (Motorola, MM)

Image Width 3303

Image Height 1840

Encoding Process Progressive DCT, Huffman coding

Bits Per Sample 8

Color Components

Y Cb Cr Sub Sampling YCbCr4:2:0 (2 2)

EXIF

Image Width 3303

Image Height 1840

Light Source Unknown

Orientation Unknown (0)

GPS Latitude 10 deg 54' 9.00"

GPS Latitude Ref North

GPS Longitude Ref East

GPS Longitude 76 deg 53' 49.00"

JFIF

JFIF Version 1.01

Resolution Unit None

X Resolution

Y Resolution

Composite

Image Size 3303x1840

Megapixels 6.1

GPS Latitude 10 deg 54' 9.00" N

GPS Longitude 76 deg 53' 49.00" E

GPS Position 10 deg 54' 9.00" N, 76 deg 53' 49.00" E

Exif Info: WhatsApp Image 2020-10-15 at 11.03.11 PM.jpeg

YCbCr4:2:0 (2 2)



FILE added as IMAGE (WhatsApp)

Around **15** Metadata Features

File JFIF Filename JFIF Version WhatsApp Image 2020-10-15 at 11.03.11 1.01 PM.jpeg **Resolution Unit** File Size None 103 kB X Resolution File Type JPEG Y Resolution File Type Extension jpg Composite MIME Type image/jpeg Image Size 1280x712 Image Width 1280 Megapixels 0.911 Image Height 712 Encoding Process Progressive DCT, Huffman coding Bits Per Sample 8 Color Components 3 Y Cb Cr Sub Sampling

53' 49.00" E

Exif Info: IMG20201015073702.jpg



File

Filename IMG20201015073702.jpg

File Size 1198 kB

File Type JPEG

File Type Extension jpg

MIME Type image/jpeg

Exif Byte Order Little-endian (Intel, II)

Image Width 4000

Image Height 1840

Encoding Process Baseline DCT, Huffman coding

Bits Per Sample 8

Color Components

3

Y Cb Cr Sub Sampling YCbCr4:2:0 (2 2)

JFIF

EXIF

Image Width 4000

Image Height 1840

^{Make} realme

Camera Model Name realme 5 Pro

Orientation Horizontal (normal)

X Resolution 72

Y Resolution 72

Resolution Unit inches

Modify Date 2020:10:15 07:37:02

Y Cb Cr Positioning Centered

Interoperability Index Unknown ()

Interoperability Version

Exposure Time 1/661

F Number 1.8

Exposure Program Not Defined

ISO 180

ICC_Profile

Profile CMM Type Apple Computer Inc.

Profile Version 4.0.0

Profile Class Display Device Profile

Color Space Data RGB

Profile Connection Space XYZ

Profile Date Time 2018:06:24 13:22:32

Profile File Signature acsp

Primary Platform Apple Computer Inc.

CMM Flags Not Embedded, Independent

Device Manufacturer Unknown (OPPO)

Device Model

Device Attributes Reflective, Glossy, Positive, Color

Rendering Intent Perceptual

Connection Space Illuminant 0.9642 1 0.82491

Profile Creator Apple Computer Inc.

Profile ID 0

Y Cb Cr Sub Sampling YCbCr4:2:0 (2 2)

JFIF

JFIF Version 1.01

Resolution Unit None

X Resolution

Y Resolution

Not Defined

ISO 180

Exif Version 0210

Date/Time Original 2020:10:15 07:37:02

Create Date 2020:10:15 07:37:02

Components Configuration Y, Cb, Cr, -

Shutter Speed Value

Aperture Value 1.5

Brightness Value undef

Exposure Compensation 0

Max Aperture Value 1.0

Metering Mode Unknown

Flash Off, Did not fire

Focal Length 4.7 mm

User Comment oppo_0

Sub Sec Time 734000

Sub Sec Time Original 734000

Sub Sec Time Digitized 734000

FI 1 1 1 1 1 1

Apple Computer Inc.

Profile ID 0

Profile Description Display P3

Profile Copyright Copyright Apple Inc., 2017

Media White Point 0.95045 1 1.08905

Red Matrix Column 0.51512 0.2412 -0.00105

Green Matrix Column 0.29198 0.69225 0.04189

Blue Matrix Column 0.1571 0.06657 0.78407

Red Tone Reproduction Curve [binary data]

Chromatic Adaptation 1.04788 0.02292 -0.0502 0.02959 0.99048 -0.01706 -0.00923 0.01508 0.75168

Blue Tone Reproduction Curve [binary data]

Green Tone Reproduction Curve [binary data]

Composite

Aperture 1.8

Image Size 4000x1840

Megapixels 7.4

Shutter Speed 1/661

Create Date 2020:10:15 07:37:02.734000

User Comment oppo_0

Sub Sec Time 734000

Sub Sec Time Original 734000

Sub Sec Time Digitized 734000

Flashpix Version 0100

Color Space Uncalibrated

Exif Image Width 0

Exif Image Height 0

Sensing Method Unknown (0)

Scene Type Unknown (0) Original IMAGE from Mobile

> Around **90** Metadata Features

Image Size 4000x1840

Megapixels 7.4

Shutter Speed 1/661

Create Date 2020:10:15 07:37:02.734000

Date/Time Original 2020:10:15 07:37:02.734000

Modify Date 2020:10:15 07:37:02.734000

GPS Latitude

GPS Longitude

Focal Length 4.7 mm

Light Value 10.2





HASHING

A hash function is any function that can be used to **map data of arbitrary size to data of fixed size**

- Uses **Crypto**graphic Algorithms (MD5, SHA, ...)
- Variable length Input = Constant length Output
- Irreversible (only for checking the Integrity)





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SRC: http://www.pinpointlabs.com/wordpress/tag/hash-verification/ http://www.softpedia.com/get/Security/Security-Related/MD5-and-SHA-1-Checksum-Utility.shtml







releases.ubuntu.com/16.0 \times

releases.ubuntu.com/16.04/MD5SUMS (i)

c94d54942a2954cf852884d656224186 *ubuntu-16.04-desktop-amd64.iso 610c4a399df39a78866f9236b8c658da *ubuntu-16.04-desktop-i386.iso 23e97cd5d4145d4105fbf29878534049 *ubuntu-16.04-server-amd64.img 23e97cd5d4145d4105fbf29878534049 *ubuntu-16.04-server-amd64.iso 494c03028524dff2de5c41a800674692 *ubuntu-16.04-server-i386.img 494c03028524dff2de5c41a800674692 *ubuntu-16.04-server-i386.iso 9e4e30c37c99b4e029b4bfc2ee93eec2 *ubuntu-16.04.1-desktop-i386.iso d2d939ca0e65816790375f6826e4032f *ubuntu-16.04.1-server-amd64.img d2d939ca0e65816790375f6826e4032f *ubuntu-16.04.1-server-amd64.iso 455206c599c25d6a576ba23ca906741a *ubuntu-16.04.1-server-i386.img 455206c599c25d6a576ba23ca906741a *ubuntu-16.04.1-server-i386.iso

17643c29e3c4609818f26becf76d29a3 *ubuntu-16.04.1-desktop-amd64.iso

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0_0;





Seizure

Identify the probable Evidences
Acquire appropriate Warrant from Law Enforcement Agencies
Seizure:

- Mostly capturing forcefully
- Collection and preservation of evidence



Acquisition

Authentication

- write blockers
- hashing

Acquisition (owning)

• Creating duplicate/clone of evidence by "Imaging"



Analysis

• Verification (CoC)

• Validation (MD5)

Analysis = search and recover all. the hidden/deleted evidence



Reporting

• Documentation (CoC)

• **Preservation** (Disposal of Backups)

Reporting : document all the above process done on the evidence to prove in court

Presentation (Expert Witness)





Hash Collisions

- A collision is a condition whereby two different messages (evidences),
 - let say m1 (a.jpg) and m2 (b.jpg),
 - after applying the hash value, then H(m1) = H(m2).
- A collision can always be found using Brute Force algorithm,
 - however it is computationally difficult.

No.	Digital Formaic Tool	Hash Ponction	Fortunes
1	EsCor	1400	Report Formaic Capability
			Evidence Processor Manager
			Searchboac and Table support
			Case Analyses
			Enail Review
2	Sea Sub	MDS	Network Personalics
			Computer Forenas
			Clead Forenzics
			Memory Formation
3	Should Kit	MDG	Contains a collection of unit
			commends for volume analysis
			and file systems.
4	FTE longer	SHA1 and MD5	Arquire and Personne data from
			different media
			Ferrarian for computer and mobile
			Detect and validate suspects
			Makesons actorings
5	Bulk Estantor	MDS	Ferrarie Science
			Feature Extraction.
	1		Film, inserts and results

MD5

SHA-x

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 A collision can always be found using Brute Force algorithm,
 <u>however it is computationally difficult</u>.

	Table 1: List of most widely used Digital Forensic Tool						
No.	Digital Forensic Tool	Hash Function	Features				
1	EnCase	MD5	Remote Forensic Capability				
			Evidence Processor Manager				
			Smartphone and Table support				
			Case Analyzer				
	1		Email Review				
2	San Sift	MD5	Network Forensics				
	1		Computer Forensics				
		K.	Cloud Forensics				
		F.	Memory Forensics				
3	Sleuth Kit	MD57	Contains a collection of unix				
		1 No	commands for volume analysis				
			and file systems				
4	FTK Imager	SHA1 and MD5	Acquire and Preserve data from				
			different media				
			Forensics for computer and mobile				
			Detect and validate suspected				
			Malicious activities				
5	Bulk Extractor	MD5	Forensic Scanner				
			Feature Extraction				
			Files, images and emails				

The Impact of MD5 File Hash Collisions On Digital Forensic Imaging

Is there an example of two known strings which have the same MD5 hash value (representing a so-called "MD5 collision")?



One could create collisions using Marc Steven's HashClash on AWS and estimated the the cost of around \$0.65 per collision.

These 2 images have the same md5 hash: 253dd04e87492e4fc3471de5e776bc3d





https://crypto.stackexchange.com/questions/1434/are-there-twoknown-strings-which-have-the-same-md5-hash-value

Collisions On Digital Forensic Imaging

Is there an example of two known strings which have the same MD5 hash value (representing a so-called "MD5 collision")?

While the two files have the same 128-bit ID5 hash, it is worth noting that their 160it Secure Hash Algorithm (SHA-1) values iffer (Eastlake & Jones, 2001). This onfirms that the contents of the two files re actually different and that there is a ona fide MD5 hash collision:

ile: hash1.bin D5 9054025255FB1A26E4BC422AEF54EB4 HA..A34473CF767C6108A5751A20971F1FDFBA97690A One could create collisions using Marc Steven's HashClash on AWS and estimated the the cost of around

While the two files have the same 128-bit MD5 hash, it is worth noting that their 160bit Secure Hash Algorithm (SHA-1) values differ (Eastlake & Jones, 2001). This confirms that the contents of the two files are actually different and that there is a bona fide MD5 hash collision:

File: hash1.bin MD5 9054025255FB1A26E4BC422AEF54EB4 SHA..A34473CF767C6108A5751A20971F1FDFBA97690A

File: hash2.bin MD5 79054025255FB1A26E4BC422AEF54EB4 SHA 4283DD2D70AF1AD3C2D5FDC917330BF502035658

g a so-called MDS collision /

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MD5

SHA-x

Shattere

Broken SHA-1 in practice https://shattered.io/





This attack required over 9,223,372,036,854,775,808 SHA1

computations. This took the equivalent processing power as **6,500 years** of single-CPU computations and **110 years** of single-GPU computations. A collision is when two different documents have the same hash fingerprint



Normal behavior - different hashes

Collision - same hashes

SHAttered

The first concrete collision attack against SHA-1 https://shattered.io

SHAttered

The first concrete collision attack against SHA-1 https://shattered.io





, T	— sha1sum *.pdf			
3	8762cf7f55934b34d179ae6a4c80cadccbb7f0a	a 1.pdf		
3	8762cf7f55934b34d179ae6a4c80cadccbb7f0a	a 2.pdf		
ſ	<mark>— ⇔/tmp/sha1</mark>	· · · · · · · · · · · · · · · · · · ·	0.64G	B 8-11
l	- sha256sum *.pdf			
2	bb787a73e37352f92383abe7e2902936d1059ac	d9f1ba6daaa9c1e58ee6	970d0	1.pdf

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Hash Collisions

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MD5

SHA-x



How to ?

Use the latest hash Algorithms or multi-tier hashes



Defense

Use SHA-256 or SHA-3 as replacement

Use shattered.io to test your PDF

Google products are already protected

Use collision detection code



Future of Hashing !?! (ought to be collision free)

- Cuckoo Hashing
- Perfect Hash Function
- Minimal Perfect Hashing
- Fuzzy Hashing (SSDEEP)
- Modified Secure Hashing algorithm (MSHA-512)

MD5, once considered really safe, now it's completely compromised. Then there was **SHA-1**, which is now unsafe.

The same thing will surely happen to the widely used **SHA-2 & 3** someday in near

future.

Sharing is Security Modified Secure Hashing algorithm (MSHA-51

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What we've covered ?

Bird's Eye View of Metadata (Hashing)



Sh@rin9 !s S3cur!tY

h @ 9 9 y \$ |-| @ 4 ! N 9





This is a custom-made session which comprises of **my personal opinions**, **experiences and Bits 'n' Pieces** from all my mistakes accumulated over a decade in learning these stuffs. Every effort is made to keep the concepts authentic; but limited to ever changing information of the context used. Copyrights of the images used corresponds to the sources cited (SRC:) appropriately. All inferences discussed here are communicated at my discretion. By viewing/using this presentation i assume that you understand and will accept to share these concepts at your own risk of defending the same.

\\as(=)0K





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Sharing is Security



Volume 13 • Issue 5 • September-October 2021

Index	Artifact (Evidence)	Source	Field: subject	Field: tags	Field: category	Field: copyright	Field: title	Field: <sparse field></sparse
X1	pinkie.jpg	Ex1:C2M	pirated	stolen	<null></null>	<null></null>	<null></null>	<null></null>
X2	birds.jpg	Ex1:C2M	<null></null>	pirated	<null></null>	<null></null>	<null></null>	<null></null>
X3	DOC-S1As1.docx	Ex1:P2D	<null></null>	stolen	pirated	<null></null>	<null></null>	<null></null>
X4	pinkie.jpg	Ex1:L2P	<null></null>	<null></null>	<null></null>	stolen	<null></null>	<null></null>
X5	pinkie.jpg	Ex1:D2C	stolen	<null></null>	<null></null>	<null></null>	pirated	<null></null>
X6	Filename.vbe <random file="" type=""></random>	Ex2:*	<null></null>	stolen	<null></null>	<null></null>	<null></null>	amazon
X7	Filename.xlsm < unusual file type>	Ex3:*	<null></null>	<null></null>	<null></null>	pirated	<null></null>	fighter
X8	Filename.raw <corrupt file="" type=""></corrupt>	Ex4:*	<null></null>	<null></null>	<null></null>	<null></null>	<null></null>	rao

Table 2. Demonstration of Assorted and Sparse Metadata (Filed-Value) Combinations

in place. In existing similarity metadata matches, these sparse occurring file types are ignored totally and are addressed in the proposed unique association models. In the course of this article, the authors explain the unique mapping methodology to achieve the same. As a proof of concept the metadata field values namely amazon, fighter, pirated, rao, and stolen are embedded into the artifact metadata fields for demonstration.

The authors make use of Exiftool(a platform-agnostic CLI application) created and managed by Phil Harvey (2005) for interpretation, marking, and even restricting metadata over a variety of file types. It is powerful, speedy, customizable, and also provisionally processes files based on the value of any metadata taking numerous output formatting options. It also notes down every change in the file to creation, modification, and access date. Also, it's straightforward to create a text output file for each image file and the same can be extended to be stored in json, csv, and xls file formats.

With reference to the standard digital evidence analysis models by Agrawal, N., Bolosky, et al., (2007), the authors have categorized every digital artifacts (Origin O) into six major variety of families namely image (Family 1), file archiver (Family 2), executable (Family 3), document (Family 4), multimedia (Family 5) and forensic image (Family 6) as in Figure 1. The authors demonstrate the raw headers of one of the sample artifacts from the recently generated Amrita-TIFAC-Cyber/Digital-Forensics/UMAM-DF (Unique Metadata Association Model - Digital Forensics) datasets (2020). It shows the shift of metadata identifiers from the source (z) and the same artifact copied to





Artifact Mapping	ArtifactSame Family-Same Family-MappingSame Type-Difference		Different Family - Same Type	Different Family -Different Type
File (pair) Nature	File (pair)PurelyHabituallyNatureHomogeneousHomogeneous		Habitually Heterogeneous	Purely Heterogeneous
Example 1	G1: JPG - GIF	G1: JPG - EPS	G1: TIFF - PS1	G1: JPG - MP3
Example 2	G2: PNG - JPG	G2: TIFF - SVG	G2: BZ2 - 3GPP	G2: EXE - ISO
Example 3	G3: JPG - PNG	G3: PNG - PICT	G3: CAB - GFZIP	G3: TXT - E01

Table 3. Homogeneous and Heterogeneous Artifact Mapping

social media platform Facebook (z') illustrated around 90% of the actual metadata is modified or removed by the social media platform that possesses a nightmare for digital forensic investigators while proving their hypothesis before the jurisdiction.

(z) pinkie.jpg (S1As1-Mobile)

FF D8 FF E0 00 10 4A 46 49 46 00 01 01 01 0048 00 48 00 00 FF E1 13 EA 45 78 69 66 00 00 4D 4D 00 2A 00 00 00 08 00 0E 01 28 00 03

(z') pinkie.jpg (S1As6-Facebook)

FF D8 FF E0 00 10 4A 46 49 46 00 01 01 00 0001 00 01 00 00 FF ED 00 84 50 68 6F 74 6F 73 68 6F 70 20 33 2E 30 00 38 42 49 33 30 30

Metadata Association Models

The lemma based theorems on metadata similarity by Raghavan, S., & Raghavan, S. V. (2017) to identify the cause and effect of the relationship between metadata values to derive a grouping artifact on reducing the volume of metadata to be examined is a remarkable work. They gave details about the similarity between metadata in two hierarchies as similarity pockets and similarity groups. Afterward from these two association group is derived to find out the reduction factor and grouping efficiency by performing a lemma based analytics on metadata. Their future works were comprehensible on applying the theoretical proofs to existing datasets and to evaluate the difference between the forthcoming practical results of lemma implementation of their models. They also put forward to broaden the operational metadata association model to heterogeneous data sources and automating the same to be valid for digital evidence stored and processed during big data. This metadata association model is pretty good while handling any evidence with a distinct number of digital artifacts where a set of distinct extensions from a selected source is considered. The authors categorize artifacts into evidence types in various families and distinct file types with the example grouping shown in the following Table 3 with respect to Figure 1.

Determining Sparse Associations Between Metadata

With respect to the demonstration of assorted and sparse metadata (filed-value) combinations from Table 2, being motivated to generate and share the unique metadata-based dataset to the digital forensic research community. After comprehensive literature, on existing digital forensic datasets the authors have taken the following ten unique JPG images from dataset mobile source S1 and these acts as the reference (genesis) artifacts for the proposed unique mapping algorithm. The same set is synthetically recreated across all other sources as shown in Figure 2 keeping in mind each file holds the metadata created from their corresponding source file system and application for the visually similar images as stated by Buchholz, F., & Spafford, E. (2004). The ultimate purpose of this dataset is to recreate

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Figure 2. Real-World Images Obtained from S1: Mobile (S1As1) with Complete Metadata



visually similar evidence (images in this case) at all sources and monitor the change or degradation of metadata on each iteration as shown in Figures 5 and 6.

WIDESPREAD SIMILARITY ASSOCIATION(S)

Metadata associations have been discussed in handling the digital forensic investigation for a while and there exist a plethora of syntactical models that roughly match the metadata composition and are not as much of predominant in addressing the explicit semantic behavior of the metadata attributes and their corresponding parameters. Raghavan, S., Clark, A., et al., (2009, January) hypothetically explicate the handling of multiple sources of evidence in a single framework (FIA) classified based upon source, data semantics, and storage file formats with the help of Malcolm Corney case on car theft investigation at Queensland University of Technology. They also emphasize extending this framework to design a suitable contrivance for validating their prototype amid real-world digital forensic datasets.

Raghavan, S., & Raghavan, S. V. (2013b, November) plotted metadata associations to establish a relationship between the artifacts and group the associated artifacts. AssocGEN analysis engine determines the relationship stuck between artifacts from files, logs, and network packet source to group the interrelated artifacts with respect to the circumstance of a digital investigation. Raghavan, S., & Saran, H. (2013, November) put forward the Provenance Information Model (PIM) to deal with the challenges related to timestamp analysis transversely for manifold time zones to precisely take into custody, the time zone in sequence and authenticate time-related affirmation during metadata analysis named after UniTIME timelining tool. Raghavan, S. (2014) thesis on Metadata Association Model



Figure 4. Phase-wise Implementation and Data Flow of Unique Associations

The artifacts are categorized into three distinct classifications namely primary, secondary, and tertiary as shown in Figure 4 for a convincing artifact triaging. The author's scope on this cataloging is to collect each and every metadata from a primary category like images, documents, and multimedia files in a forensically sound manner. Then the necessary metadata is collected in a secondary category based on the combination of EXIF, ICC, IPTC, and XMP metadata standards and lastly, the universally obtainable file system metadata is collected in the tertiary category. Unique metadata mapping aims at collecting all metadata even from tertiary evidence like pcap or evtx that might have a sparse association with any of the primary or secondary evidences.

The building blocks for the metadata element for any artifact is represented by a regular 2-tuples notation by the authors throughout the article as <*field:value*> pair as in (3,4) for the publicly available metadata standards.

$$M_{f} - ID_{n} be the identifier for the 1st tuple \langle field : \rangle \forall f identifical notation \exists an fixed n \in [ASCII (num|char)] \}$$
(3)

$$M_{v} - ID_{n} be the identifier for the 2nd tuple \langle : value \rangle \forall videntifical notation \exists an viable n \in [ASCII (num|char)] \}$$
(4)

The combine notation of any metadata value corresponding to a metadata field that belongs to a unique artifact from a selected source is represented via (5) the below distinctive notation.

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Figure 5. Iterative and Sequential Mobility (of Artifacts) in UMAM-DF Dataset

considerations for dataset collection are unchanged as the first set of experiments and it results in ten unique datasets. It collects the metadata of the file before and after sharing them between source devices and social media to calculate the final Association Group (AG) and Unique Association(UA) matches are shown in Figure 6.

The authors labeled the following metadata archive as "UMAM-DF" (Unique Metadata Association Model - Digital Forensics) dataset and are made publicly available at Amrita-TIFAC-Cyber/Digital-Forensics/UMAM-DF (Unique Metadata Association Model - Digital Forensics) datasets (2020) for suggestions and recommendations to enhance the same in near future for upcoming research works.

PROTOTYPE IMPLEMENTATION ON UMAM-DF DATASET

The series of sequential experiments collected with UMAM-DF dataset is engaged in testing the availability of metadata field-value pair matches across the sources with the collected set of 36 evidence sets as shared in Amrita-TIFAC-Cyber/Digital-Forensics/UMAM-DF (Unique Metadata Association Model - Digital Forensics) datasets (2020). The statistics of the similarity model and unique model of unaltered datasets are depicted in Table 5 resulting in linear Unique Group (UG) matches and variable Unique Association (UA) matches to adhere with their mathematical proof and algorithmic sequences.

The authors post a disclaimer for the repetitive values in SG produced during the experiment, as it is purely caused due to the availability of multiple identical metadata $S_n : A_n - M_f - ID_n : M_v - ID_n$ field-value pairs. This coherence can be ignored to maintain the integrity of the dataset as it is shared across the forensic community for reproducing the results as expected to verify the proposed model. The extended version of the same with normalized features is tabulated in Table 6.

Experiment 1 as shown in Figure 5 reveals the metadata matches of SP increases from 23(S1AS1) to 26(C2M) concluding that the additional metadata field-value pairs to be 22.5 and shows for every



Figure 6. Social Media Mobility (of Artifacts) in UMAM-DF Dataset

copy/paste at an average ± 2 SP is achieved. The UP count reducing from 388 at S1AS1 in step 1 to 341 in step 6 reveals that around 47 unique pockets went missing when the files (namely01.betta-left.jpg to 10.sunset.jpg) went on to a complete round from mobile, back to mobile passing all other four sources as plotted in Figure 7. The experiment 2,3,4&5 expresses a similar shift over 47,21,62&62 unique pockets respectively in UP. The UG for all the experiments varies by \pm SP across all experiments.

Unique pockets count of 380, 396, 339, 319 & 319 from source S1As6 drastically got reduced to 95,210, 96, 66 & 66 after passing via Telegram, Whatsapp, Instagram, Twitter, and Facebook

UMAM-DF Dataset	Source	SP	UP	SG	UG	AG	UA
Experiment 1	S1As1	23	388	01	20	02	31
Experiment 2	S2As2	23	400	01	20	04	33
Experiment 3	S3As3	23	347	01	20	01	26
Experiment 4	S4As4	21	327	01	20	03	25
Experiment 5	S5As5	23	183	01	24	02	25
Experiment 6	S1As6	22	380	11	20	07	07
Experiment 7	S2As6	24	396	01	20	03	27
Experiment 8	S3As6	23	339	01	20	03	08
Experiment 9	S4As6	21	319	03	20	06	13
Experiment 10	S5As6	22	181	01	24	01	01
Overall Matches in S	225	3260	22	208	32	196	

Table 5. Results for UP, UG, UA with respect to SP, SG, AG. (Unaltered UMAM-DF dataset)