

SOURCE IDENTIFICATION OF HIGH DEFINITION VIDEOS: A FORENSIC
ANALYSIS OF DOWNLOADERS AND YOUTUBE VIDEO COMPRESSION
USING A GROUP OF ACTION CAMERAS.

By

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ABSTRACT

Video cameras are a large part of today's mainstream society, where many people feel the need to record and share their life's experiences. YouTube, created in 2007, has become the most popular host of Internet videos from around the world with an estimated 1 billion unique monthly users (Youtube.com). YouTube is localized in 61 countries and across 61 languages. Over 100 hours of video are uploaded every minute. These videos can contain important information about a crime, or event, that might have occurred. For example, in September of 2014, the terrorist group called ISIS released a set of videos on YouTube that portrayed the beheadings of American and British citizens. These videos were called into question, and their authenticity needed to be determined. It is the job of the forensic investigator to determine if a particular video, in question, is a complete and accurate representation of what it purports to be.

This research paper will address the effects of YouTube on source camera identification while seeking to quantify the amount of change that can occur during the conversion process. It is well understood that YouTube re-encodes all video uploaded to the site, which has several implications for forensic authentication analysis [1]. The testing material described in this paper was comprised of 11

different cameras and three different downloader tools. Chapter 1 describes a variety of established image authentication techniques used to determine the origin of a video. Chapter 2 describes the underlying framework of YouTube, how it works, and the effects it can have on video. Chapter 3 describes and compares three tools that can be used for downloading YouTube videos. Chapter 4 describes how the test data was acquired. Chapter 5 addresses structure and source identification techniques using the test results. Chapter 6 describes all conclusions reached during analysis. Chapter 7 ends with future research in the field.

The form and content of this abstract are approved. I recommend its publication.

Approved: Catalin Grigoras.

DEDICATION

I would like to dedicate this paper to my mother Chiara Giammarrusco. She dedicated her life to giving me every opportunity I could have asked for. Not a day goes by where I don't think about her and the hard work that sculpted the person I am today. I'm forever grateful and always striving to make her proud.

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CHAPTER I

INTRODUCTION

Recent advancements in digital imaging technology have allowed users to easily create video through the use of smartphones, tablets and other mobile devices. The desire for people to share their videos online has been supported by different online social media websites.

As these videos are shared on the Internet, it can become extremely difficult to determine the origin of a video in an event that a crime has been committed. Recorded video of any illegal activity has a unique ability to serve as evidence, if determined to be consistent with an authentic recording or, in piracy cases, the video itself can be illegal in its creation and possession.

Digital camera identification is the process of linking images to a source camera. A reliable method to identify a source camera from other possible cameras can help assist in the authentication process significantly in a case that involves piracy, child pornography, or espionage. Camera identification methods include, but are not limited to: defective pixel analysis, sensor dust analysis, photo response non uniformity (PRNU), file structure analysis, metadata analysis, and identification based on color filter array (CFA). The research in this study briefly discusses these methods then focuses on structure, metadata and PRNU for the study.

Defective Pixel Analysis

When an imaging sensor in a digital camera fails to sense the light levels of a scene correctly it is known as a defective pixel. A defective pixel can leave traces in

every image generated by a digital camera. Therefore, this technique can be used as a unique camera identifier [1]. Upon acquisition of the image, the location of a defective pixel will be identical in subsequent images. This method is very limited since a unique pixel defect can be corrected after image acquisition in the integrated post-processing stage. As advancements in technology continue to develop, this method has become less relevant in camera authentication as the chances of having a defective pixel in question are extremely rare.

Sensor Dust Analysis

The lenses on DSLR cameras are interchangeable and, upon the removal of the camera lens, the sensor is exposed to hazards such as dust and moisture. The particles are attracted to the imaging sensor by electrostatic fields. Once the dust settles onto the sensor it creates a pattern. Sensor dust patterns are displayed as artifacts on the captured images and they become largely visible at smaller aperture values [2]. Normally, this unique dust pattern is not changed unless the sensor surface is cleaned. Therefore, it can be used to match a given image to a source DSLR camera. This method is very limited, as with defective pixels, but should be noted as a possible source identification technique.

Color Filter Array Analysis

Another method in camera identification uses the color filter array. The CFA is a mosaic of tiny color filters placed over the matrix (pixel sensor) of an image sensor to capture color information. Most state-of-the-art digital cameras employ a single mosaic structured CFA to cut costs rather than having different filters for each color component. [3] As a consequence, each pixel in the image has only one color

component associated with it. In order to obtain the missing color, each digital camera employs a proprietary interpolation algorithm. This introduces a specific statistical periodic correlation between subsets of pixels, per color channel [4]. This can be estimated as a digital signature of a camera model. When a JPEG image is re-saved with an image editor, the original CFA correlation is changed as well. A CFA analysis can reveal inconsistencies with an original JPEG and/or indicate traces of image recompression.

Photo Response Non Uniformity Analysis

Photo-response non-uniformity (PRNU) is a tool that makes use of pixel identification and can be used as a unique tool in identifying the “fingerprint” of digital sensors. In theory, when uniform light falls on a camera sensor, each pixel should output exactly the same value, or an ideal uniform response. The differing sensitivity of individual pixels to the same amount of light is called PRNU [5]. This technique looks at the individual pixels that may report slightly lower or higher values than their neighbors, even when these pixels are illuminated uniformly.

By extracting invisible sensor pattern noise from images left behind by the image sensor, a device signature or camera’s sensor fingerprint can be determined. The ability to extract the signal is affected by the quality of the sensor, the amount of light interacting with the sensor, and the scene content. Cell phones and lower-priced cameras are more susceptible to the defects of the sensor components than higher end model cameras. Every sensor has its own unique pattern due to the manufacturing processes. Small variations in a sensor’s cell size and material result in slightly different output values per cell. When two patterns show a strong level of similarity,

it is an indication that the images might have come from the same camera. Extensive research has been done to establish the best type of filter and algorithm for effectively extracting the noise from the image in a timely manner. Currently, wavlet based de-noising is typically used for PRNU extraction [6].

Combinations of adaptive and median filtering strategies have also shown to be effective [7]. While the research continues to develop a more advanced PRNU extraction method this paper uses the median filtering extraction method, which has proven to be reliable. Median filtering is a nonlinear operation often used in image processing to reduce "salt and pepper" noise. A median filter is more effective than convolution when the goal is to simultaneously reduce noise and preserve edges (mathworks.com). Figure 1 displays the effects a median filter can have on a noisy image.

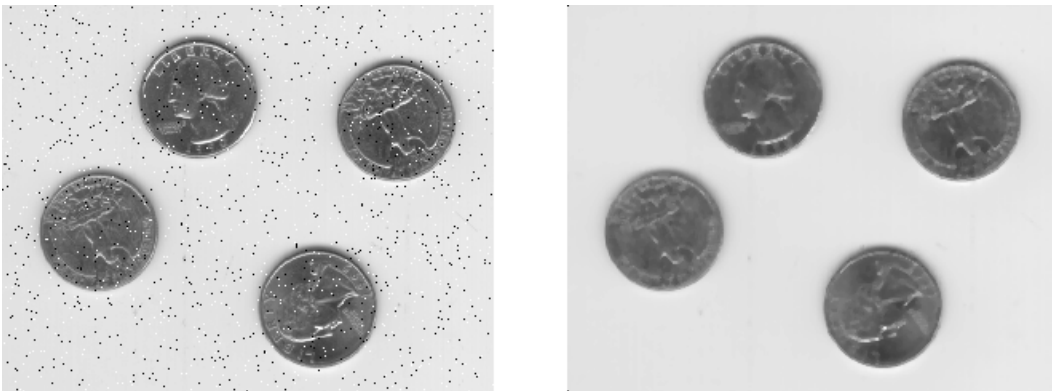


Figure 1 –Median filtering to reduce “salt and pepper noise.”

(mathworks.com)

De-noising algorithms generally have troubles discriminating between true noise and small details. It is important to select an appropriate filter that leaves the

image structure in tact, most notably around edges where the local variance is high.

Structure Analysis

All digital cameras create files in a particular way, each with its own unique structure. It is important to understand that when an image file is created, a huge surplus of information is carried along with it. This information is needed in order for computers and other devices to recognize and process the contents of the file.

Figure 2 shows some of the information that is stored within a video container file.

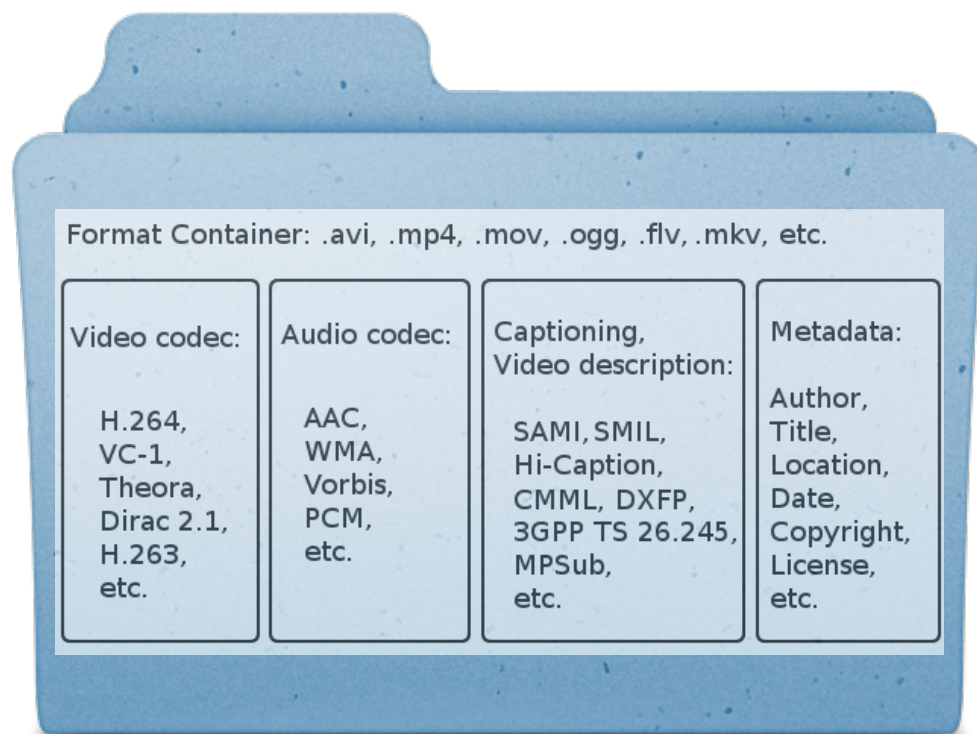


Figure 2- Container Structure

An image file typically contains: the digital information about the image, a list of contents within the file, the location of the contents within the file, instructions on how to decode, then reassemble the physical image, and information about the file or

container itself [8]. All this information is embedded into the image file and can be distinct between manufacturers and cameras. When computers, or image processing software interact with the file, this structure can be altered. While this type of alteration does not necessarily mean that image content itself has been altered, it can raise concern about the authenticity of the image

Metadata Analysis

Modern digital cameras may write EXIF (Exchangeable Image Format) or XMP (Extensible Metadata Platform) metadata to the image. The EXIF data is embedded with the image in the header of the digital file. This metadata can contain tags such as date and time, camera settings, geographical locations, or the serial number of the camera that produced the image. Although metadata can prove to be very useful in camera identification, it can easily be deleted or manipulated. Social media websites may remove or alter metadata information to decrease file size and maintain user privacy [9]. A framework of specific authentication techniques that should be used by forensic investigators can be found by (Anderson, Scott, 2001). It is very important to know the limits of your tools and combine techniques when providing camera identification analysis.

CHAPTER II

YOUTUBE FRAMEWORK

It is important to think of the files uploaded to YouTube as a master video that will be used as source material to generate various quality video streams at different resolutions. Simply stated, the better the quality of file that is uploaded, to YouTube, the better quality that will be received upon download. When uploading video to YouTube one of the following formats must be used in order for YouTube to recognize the video: .MOV, .MPEG4, .MP4, .AVI, .WMV, .MPEGPS, .FLV, .3GPP, .WebM.

Re-Encoding

YouTube re-encodes all video uploaded to the site, which has several implications. First, there's no value in trying to match YouTube's output to avoid re-encoding. The video will always re-encode regardless if the dimensions are identical upon upload and download [1]. This fact is significant and should not be overlooked when providing authentication analysis.

Secondly, YouTube uses dynamic adaptive streaming over HTTP (DASH) for delivering videos. DASH is an adaptive bitrate streaming technique that enables high quality streaming of media content over the Internet delivered from conventional HTTP web servers (MPEG.ORG). Once video is uploaded to YouTube the content is made available at a variety of different bit rates and resolutions to prevent re-buffering during playback. The DASH format serves audio and video in two separate streams for some resolutions/formats including 1080p and 480p.

Downloading

It is important to understand the legal ramifications of downloading video from YouTube. In general, downloading videos that other people have posted on YouTube is not allowed. YouTube only provides an option to download MP4s of the user's own videos. Consequently, this limits the extent of downloading capabilities by excluding other user's videos. However, in a real world application, the video in question would be coming from an unknown source and this research is based upon that principle.

Various YouTube downloading utilities were used in this study. These tools play an important role in acquiring the video used for authentication analysis. Fortunately, for the user, there are hundreds of freeware and software downloader tools available for Mac and PC. Most tools can easily download all available formats while others are restricted in downloading capabilities.

Available Formats

A list of available formats can be viewed using Exiftool. This tool works by reading the metadata from a source file on YouTube. The information is then printed out in a list form. This is one method to view the formats available upon download. Other tools, which are mentioned in the next chapter, work in a similar manner using metadata from the source file on YouTube. This research uses a 1080p resolution and an MP4 format for all videos upon uploading to the site. Figure 3 displays a list of the available downloading formats and resolutions that were available from the 1080p video.

m4a	audio only	DASH audio , audio@128k (worst)
mp4	144p	DASH video , video only
mp4	240p	DASH video , video only
mp4	360p	DASH video , video only
mp4	480p	DASH video , video only
mp4	720p	DASH video , video only
mp4	1080p	DASH video , video only
webm	360p	3D
mp4	360p	3D
mp4	720p	3D
3gp	176x144	
3gp	320x240	
flv	400x240	
webm	640x360	
mp4	640x360	
mp4	1280x720	(best)

Figure 3 YouTube Resolution options for a 1080p upload.

CHAPTER III

DOWNLOADER TOOLS

A downloader tool is any type of freeware, software, or command line script that allows the user to download video off the Internet. In this study, the tools must recognize the Dynamic Adaptive Streaming over HTTP (DASH) video hosted by YouTube's server.

It is not possible to acquire video from an unknown user on YouTube by simply clicking download from the host. Therefore, these tools are relevant and need to be validated and verified for accuracy and precision. A comprehensive list of validated downloading tools is currently unavailable and relatively unfeasible, considering the constant advancement of technology. It is not possible to verify and validate all the tools. That said, the focus of this study highlights the three most popular downloading tools at this time.

It is important to understand that each tool acts like a “black box” when downloading video information from the host website. The user is unable to observe the inner workings or alterations that are occurring until the video output is obtained. Some tools work in the same way and output identical videos.

It is understood that some type of recompression is occurring since the DASH format comes as two separate tracks, one for video and one for audio. However, it is difficult to determine what changes occur during this process due to the “black box” principle. It is crucial for an examiner to understand his or her tools as well as the effects they can have, during analysis, on a video that is being scrutinized.

It is recommended to avoid video capture programs that record a computers video display output (such as Cam Studio, Snag It, Video Capture, ect). These programs have poor analysis results due to the fact that what is played on the screen has the artifacts of the decoding and is not the original resolution.

Real Player One

Real player one (RPO) is a downloader tool developed by RealNetworks, Inc for Mac and PC. Recently, this program has changed to a cloud-based format. RPO works as an extension within an Internet browser. Once a video is recognized on the browser, RPO will provide the option to download the video displayed. Instead of providing the option of downloading different resolutions, it will download any resolution that is currently displayed at the time. In order to download a 1080p resolution video from YouTube, the user needs to display the video at 1080p under the quality settings on YouTube.

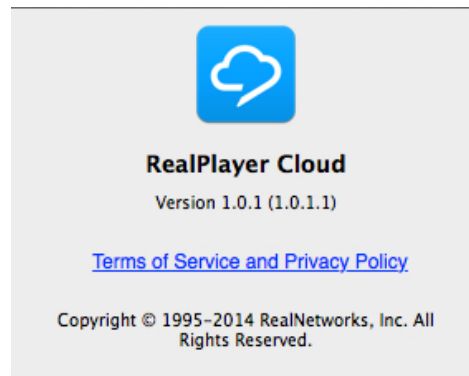


Figure 4- RPO Version information

YouTube Downloader

YouTube Downloader version 2.0 (YTD) is a downloader tool developed by GreenTree Applications for both PC and MAC. This tool uses FFmpeg licensed under

the LGPLv3 and its source code can be easily downloaded and viewed. The following formats were available for download once the URL is recognized by YTD: HD 1080, HD 720p, HQ 480p, HQ 360p (flv), HQ 360p (mp4), 240p, and 144p. No other settings are necessary or available within this tool. All research videos downloaded using YTD were 1080p.

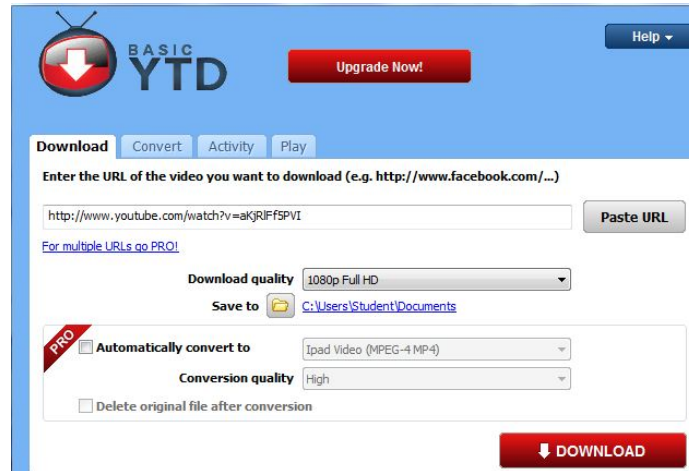


Figure 5- YTD User Interface

ATube Catcher

ATube Catcher version 3.8 is a freeware downloader tool developed by Diego Uscanga. This tool can be thought of as a small web browser that interprets the content and downloads the video in the directory selected. It then converts a video to the format requested. All formats created by YouTube were available for download within this tool. ATube catcher provides a large list of recompression options that should be avoided for research purposes. The “no recompression” option, displayed by figure 6, was used during this research.

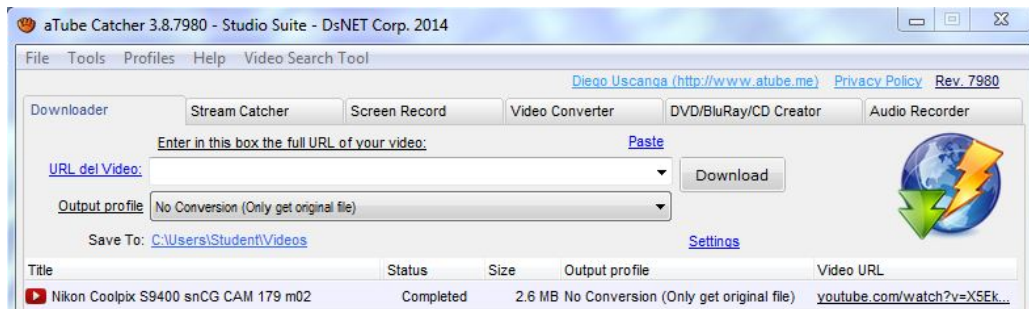


Figure 6- aTube Catcher User Interface

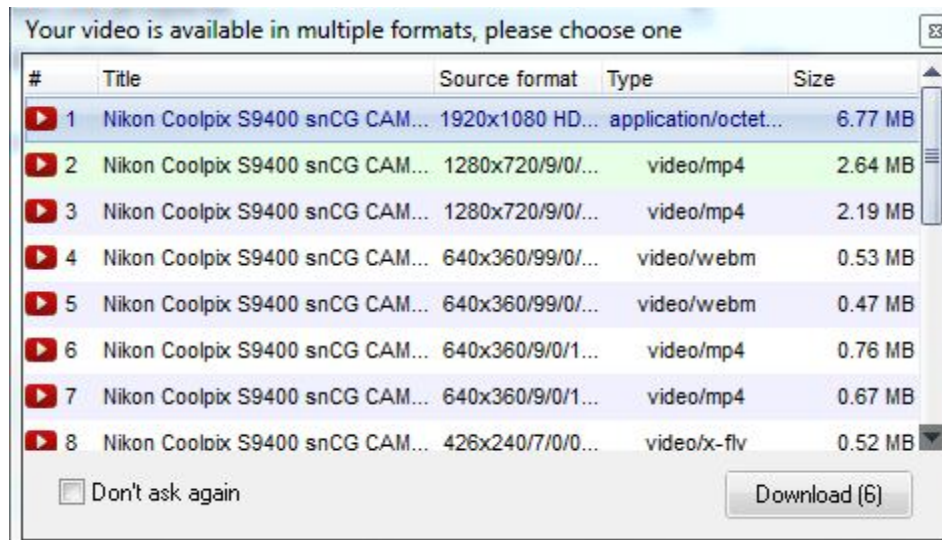


Figure 7- aTube Catcher Download Resolution Options

Very little research has been published on YouTube compression effects and no research has been published, so far, on the tools or cameras used in this paper. A fellow student at the National Center for Media Forensics has done research in this area looking at cell phone images in social media websites [9]. His focus was determining the changes social media websites, such as MySpace and Facebook, had on the cell phone images.

Other Tools

It was difficult to select three tools to implement during research due to the large population of tools widely available. Prior research was done to study the trends and ensure the tools selected were some of the most widely used. Over a dozen tools were tested before determining the best options. Some YouTube downloader tools may contain viruses upon download. This paper recommends having some form of anti virus software prior to downloading any tools to protect against a possible attack.

Some of the tools that were studied, but not used, include Clip grab, MacX, and a command line script tool called YouTube-dl. Unfortunately, Clip Grab encountered many consistent errors while trying to preform the download. Therefore, Clip Grab was not selected as one of the primary tools for research.

MacX is a tool designed for mac platforms. The PRNU results of the MacX downloader yielded identical results as YTD. Instead of repeating identical results, MacX was not used as one of the three primary tools. This tool should be noted, however, as a high-quality tool for downloading video from YouTube, and the results mirrored YTD.

A command line script, using brew called YouTube-dl, was also used in preliminary research. This script works well for some formats but would not allow a playable download of the 1080p resolution needed due to the DASH format used by YouTube. The youtube-dl script can be used as a tool for some YouTube videos but is not applicable in this research due to resolution limitations.

CHAPTER IV

MATERIAL AND METHODS

Data Base Acquisition

The video camera database was collected using 10 Go Pro Hero black Edition's and one Nikon Cool Pix S-9. Two videos were produced using each of the 11 cameras. Each video has a time frame of roughly 15-20 seconds. Ideally, a large number of frames should be used to calculate the Photo Response Non-Uniformity. All camera dimensions were set at 1920x1080p during recording. The codecs used to encode the videos were H.264, AAC. The color profile settings on all cameras used for research was HD (1-1-1). Figure 8 shows some of the cameras used for the experiment.



Figure 8- Go-Pro Cameras

The research videos were produced in a controlled setting on a wall illuminated by florescent lighting. The wall was uniformly lit and painted a neutral, flat cream color. The controlled lighting conditions selected were ideal for extracting uniform images. Extra attention was given to ensure no shadows were cast on the image during acquisition, as this would hinder results. Figure 9 shows the color and texture of the wall used for research.

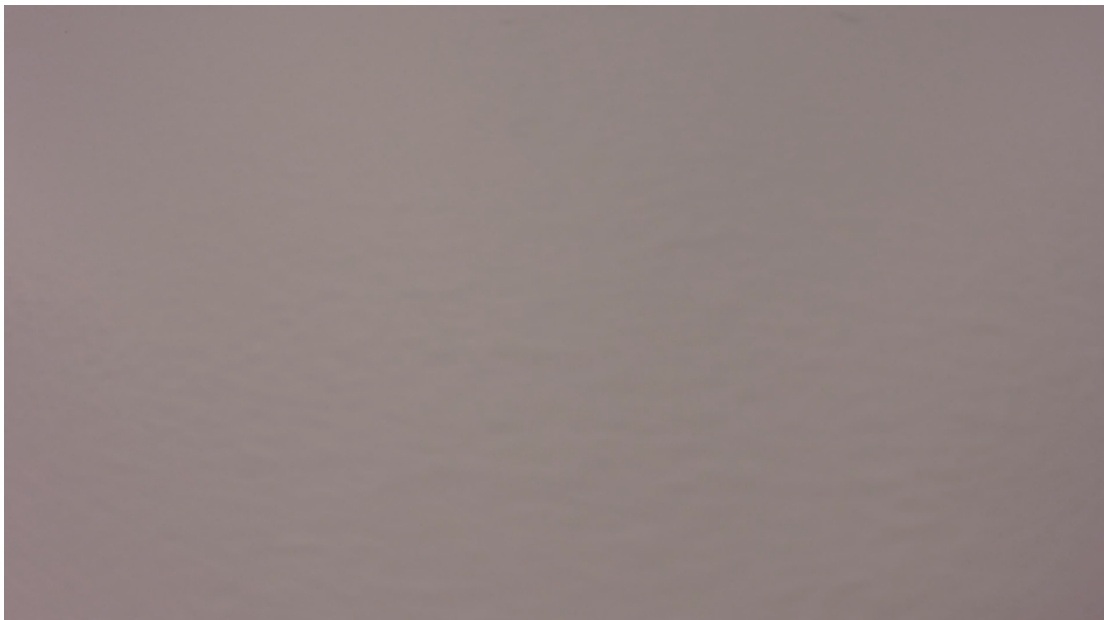


Figure 9- Wall Color and Texture

Database Upload and Download

After the video data was acquired and saved, the entire collection of videos was uploaded to YouTube. This process was done using the uploading manager on the YouTube website. At this time there is no other way to upload videos to YouTube. During the uploading process, no special settings or inadvertent changes were made. Attention to detail is important during this process to ensure the correct

video is uploaded and titled accurately for proper download.

By using three tools selected for analysis RPO, YTD and aTube Catcher, all 22 videos were downloaded from each tool and saved. It was now possible to begin the experiment with three video sets, one from each of the tools, and the original set that was not uploaded to YouTube.

Methods

Structure analysis, metadata analysis, and PRNU analysis, was used to determine how well a source camera can be identified from the other videos collected. First, the changes found after the downloading process, within the structure and metadata of the video file, are discussed. Next, the structural and metadata analysis section describes the consistencies and changes that occurred during the uploading and downloading process. The PRNU analysis, described last, looks to reach a conclusion for camera identification with the YouTube videos.

Structure

To analyze the structure of the files a program called MediaInfo v0.7.69 was used. This program provides easy access to technical information about video and audio files. Each of the video files were reviewed in order to determine if any changes in size, structure, or information loss were present.

During the structure analysis, a tool called Exiftool v9.72 was also used. This program is a command line application tool for reading, writing, and editing metadata information in a wide variety of files. This tool performs well at reading the information within the metadata and pulling it out in a cohesive and organized format. Exiftool provided the most detailed information about the file structure.

Photo Response Non Uniformity

A basic algorithm for linking a camera to an image can be described in a few simple steps. First, the camera reference patterns need to be calculated in order to develop a correlation between each of the patterns and the noise of an image [10]. The easiest way to calculate an approximation to the camera reference pattern is to average multiple images. Next, all frame averaging was done using a custom script in Matlab version 2012a. To speed up this process the scene content needs to be removed using a median filter de-noising algorithm. The noise residuals are then averaged. If a larger quantity of images is available to average, a greater suppression of random noise or scene content can be obtained. It has been suggested that a minimum of 50 images should be used for frame averaging [1].

After an established reference pattern has been created, a correlation can be determined with the noise of a particular image [10]. To find the random noise simply employ the same principal as before; Use the de-noising filter to approximate the noise-free image and subtract this from the original, leaving only the noise residual. To find the correlation between this noise n and a particular reference pattern r use the standard formula-

$$\text{corr}(n, r) = \frac{(n - \bar{n}) \cdot (r - \bar{r})}{\|n - \bar{n}\| \|r - \bar{r}\|}$$

Every video from every camera, 22 total, were compared against each other using correlation coefficients (CC) to ultimately determine a possible conclusion for a source camera. This research was focused at looking for an inter variability and intra variability comparison. An inter variability comparison in this research uses two

videos created by different cameras. For example, a video from camera one would be compared against a video from camera three. This inter variability comparison uses all videos and all cameras against each other. This comparison is against others cameras and does not compare one camera against itself. Figure 10 Shows an example of an inter variability using Go-pro Cameras.



Figure 10- Inter Variability

An intra variability comparison, in this research, uses two videos created by the same camera. For example, a video from camera one would be compared against another video from camera one. This comparison is against a single camera and does not compare one camera against another. Figure 11 shows an example of an Inter variability comparison using Go-Pro Cameras.



Figure 11- Intra Variability

These two terms will be used throughout the rest of this paper and are important to understand. This research compares the non-YouTube originals between themselves and against the others to study both the intra and inter variability before YouTube. The inter and intra variability was also tested for the downloaded videos that were acquired through each of the tools.

If a frame-averaged image were compared and calculated for correlation against itself, the value of the correlation would be 1.0 meaning the images are identical. This exact match means that out of the three possible color channels (red, green, and blue) a perfect correlation of identical pixel noise was reported. When an image is compared, in correlation, to other frame averaged videos, taken from a

different camera, the value of the correlation coefficients would begin to drop. This drop is expected due to the fact that two different source cameras are being used. The lowest possible correlation that could theoretically be calculated would be a -1. This result would indicate that out of all possible pixel noise in each of the red, blue, and green channels not a single pixel displayed any identical properties.

CHAPTER V

RESULTS

Structure and Metadata Analysis

The findings showed some very interesting differences between each of the downloader tools when given the exact same file to download off YouTube. Substantial differences in file size, file type, media duration, and movie data size, were present. A single randomly selected video from the data set was used during the structure analysis as an example to avoid redundancy. Video structure data for all the files can be found in the appendix (Section 1). The single video, randomly selected, gave an accurate representation of how the tools function when they encounter a video file regardless of length. Unique changes in video structure were also apparent between tools.

The Hex information within the video file was re-encoded when the video was downloaded from Youtube using each of the three downloader tools. The original video file that was not uploaded to YouTube contained valuable information including camera model, serial number, and encoder information. This hex data, upon download, was replaced with hex information from each of the tools. Figure 12 displays these changes:

impossible to understand. It is up to the examiner to learn the camera encoding structure and decipher the relevant data.

Consistencies

The results showed the file size and duration were consistent when YTD and RPO were compared against each other. These tools work in a very similar fashion since their results are nearly identical. The original video had a file size of 38MB before it was uploaded to YouTube. After the video was downloaded using RPO and YTD, the file size had changed to 4.8MB. ATube reported a file size of 6.8MB upon download. A large amount of data loss occurred after the download, which was anticipated due to the compression scheme that YouTube uses. However, it was unexpected and interesting to see the differences between file size and media duration between the various tools.

Other consistencies found included image dimensions and matrix structure. The file type was not converted to any other file format with one exception. RPO changed the file type in all videos to M4V. The M4V file format is an iTunes video format [11] and it is not understood why RPO changed specifically to this format.

The tools performed well at recognizing and downloading the correct 1080x1920 version from YouTube. This is a crucial first step that cannot be overlooked during analysis. The Results were consistent amongst all tools when reporting the correct size of the videos. The matrix structure was not changed and was confirmed as identical to the original file.

Inconsistencies

The structure results that deviated from the originals included media duration

and movie data size. The original duration of the movie, randomly selected for file analysis, as a sample for the entire collection, had a time of 15.25s. This media duration changed when the video was downloaded from YouTube. All of the tools seemed to be adding time to the original file. ATube reported a video duration of 15.33s which is .08s longer than the original. Both YTD and RPO displayed a duration time of 15.30s which is .05s longer than the original. Table 1 shows the data found within the selected sample video and the changes that occurred.

Table 1-Video 1-1 Exif Data acquired using Exiftool version 9.72
(Note-File Size, Data Size and Media Duration Inconsistencies)

Data Type	Original	YTD	RPO	aTube
<u>File Size</u>	38 MB	4.8MB	4.8MB	6.8MB
File Type	MP4	MP4	M4V	MP4
Image Width	1920	1920	1920	1920
Image Height	1080	1080	1080	1080
Video Frame Rate	29.97	29.97	29.971	29.97
Matrix Structure	1 0 0 0 1 0 0 0 1	1 0 0 0 1 0 0 0 1	1 0 0 0 1 0 0 0 1	1 0 0 0 1 0 0 0 1
<u>Media Duration</u>	15.25 s	15.30 s	15.30 s	15.33 s
<u>Movie Data Size</u>	39289830	5039051	5039051	7166451
Image Size	1920x1080	1920x1080	1920x1080	1920x1080

PRNU Analysis

From the research in this paper, it is clear that YouTube degraded the PRNU

noise that was used to determine a source camera. This degradation and loss of PRNU noise was expected due to the compression scheme that YouTube uses. It was also apparent that the C.C values of the original videos were higher than those of any of the YouTube videos.

Figure 2, 3, and 4 exhibit each of the tool's inter variability results when compared to the originals. Figure 5 shows all of the inter variability results located on one plot for a reference. The YouTube videos, within figure 5, scattered roughly around the .03 CC mark. The aTube tool shows the largest range in values with some of the highest and lowest C.C values. The results from the downloaded YouTube videos, were well below those of the original videos which were densely scattered above the .10 C.C mark. Table 6, 7, and 8 exhibit each of the tool's intra variability results when compared to the originals. Table 9 shows all of the intra variability results on one plot for a reference. Within Table 9 it is clear that the single Nikon camera used in the experiment has preformed very uniformly with all the other Go-Pro action cameras. The results from the aTube tool showed the highest level of correlation out of any of the tools. The correlation data from the group of tools populated dense results at the .5 mark. The original video correlation results populated heavily around the .3 mark. The highest value was determined to be the original GP-Camera 10 with a value of .53426. This was coincidentally the longest video which leads us to believe in future research a longer time frame, when acquiring video, could produce higher correlation values.

Table 2- Inter Variability (YTD Vs. Original)

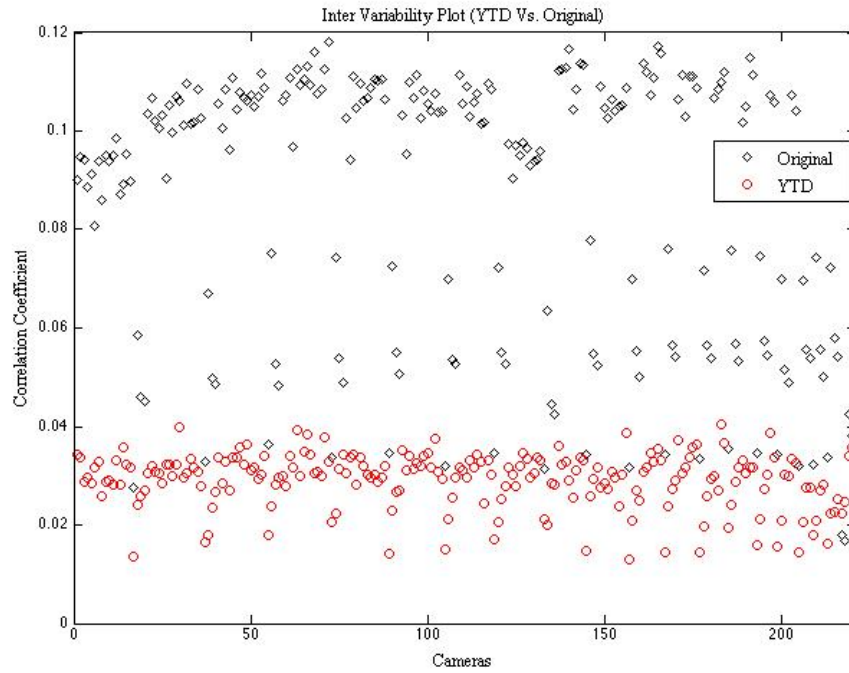


Table 3- Inter Variability (aTube Vs. Original)

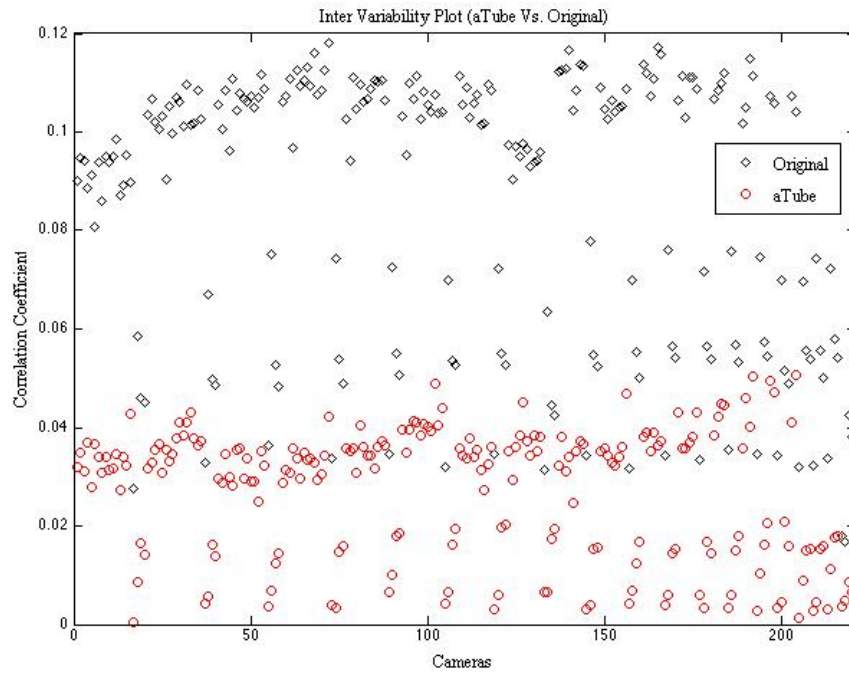


Table 4- Inter Variability (RPO Vs. Original)

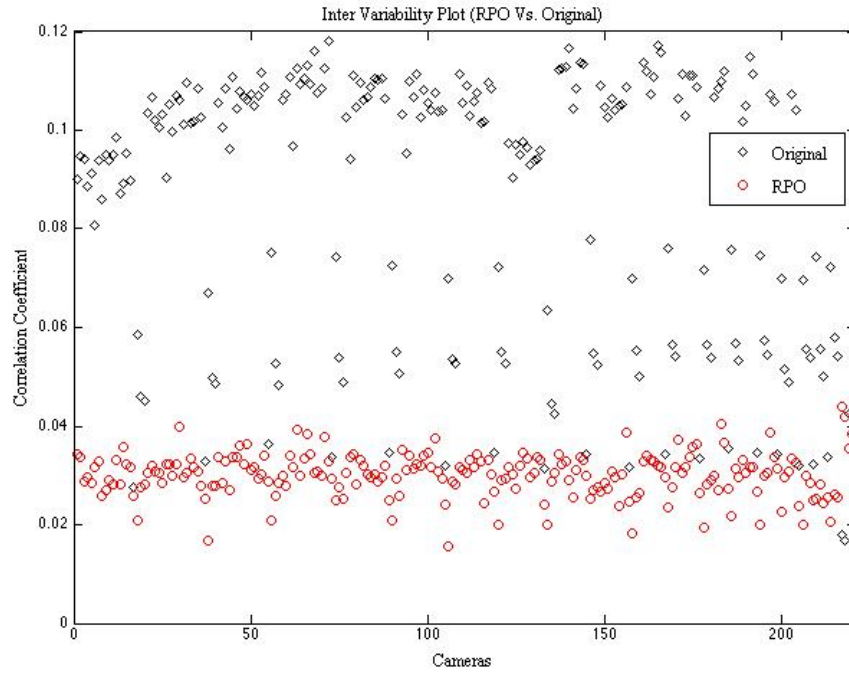


Table 5- Inter Variability (YTD, RPO, aTube, Vs. Original)

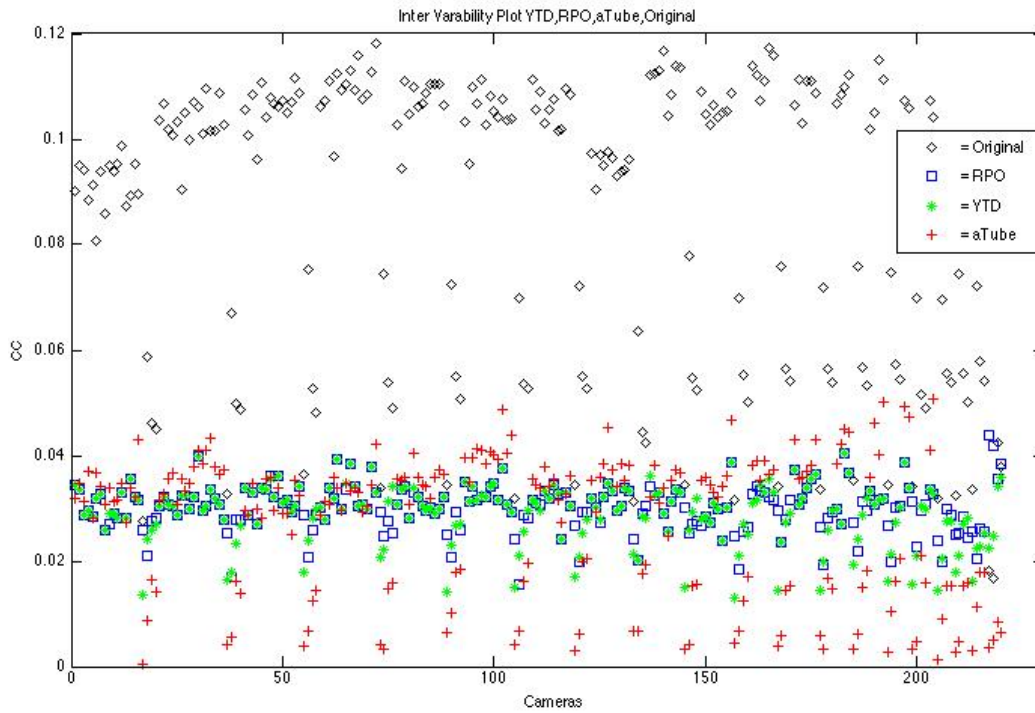


Table 6- Intra Variability Plot (RPO Vs. Original)

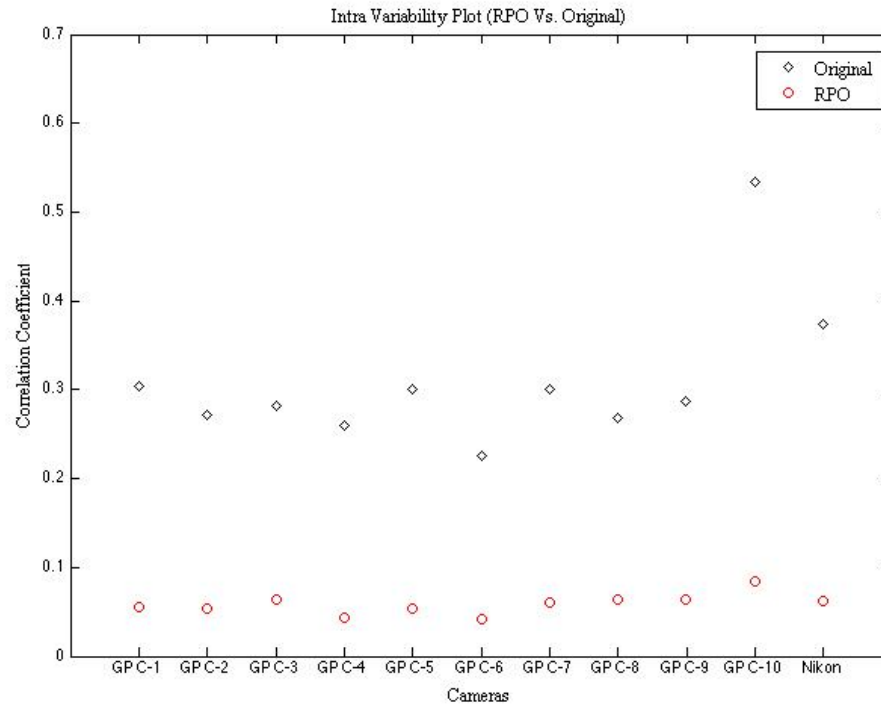


Table 7- Intra Variability Plot (aTube Vs. Original)

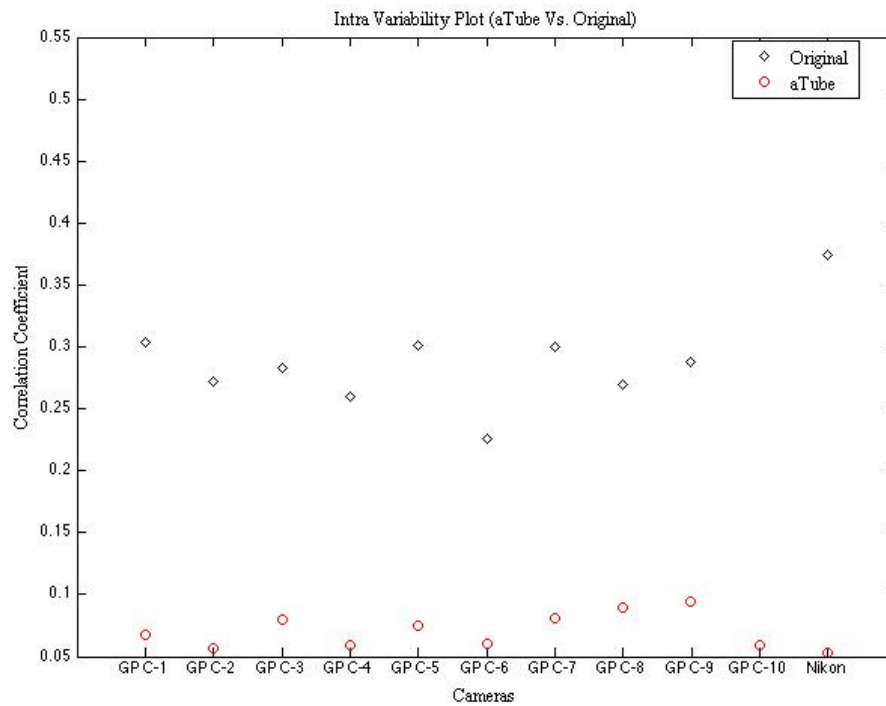


Table 8- Intra Variability (YTD Vs. Original)

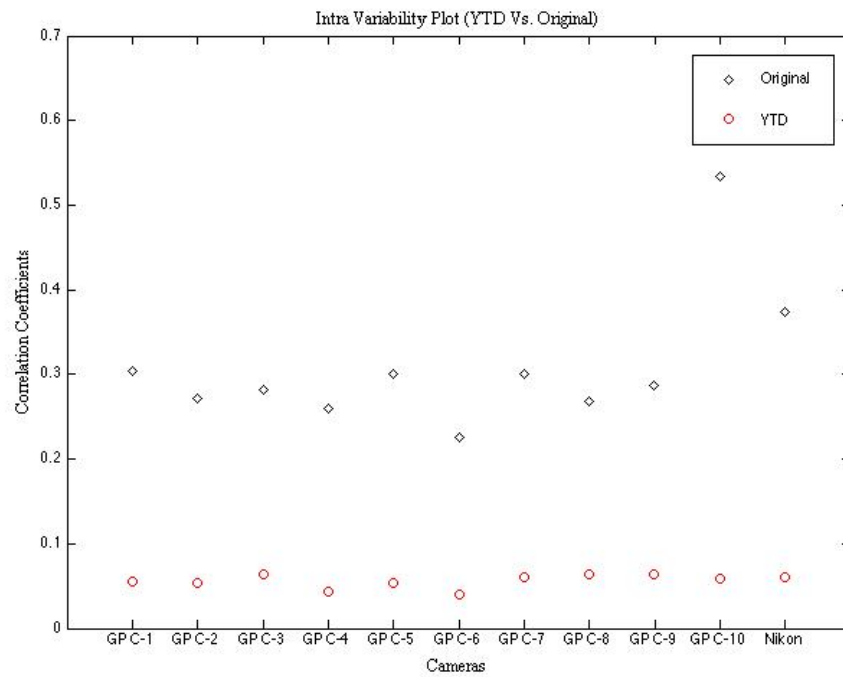
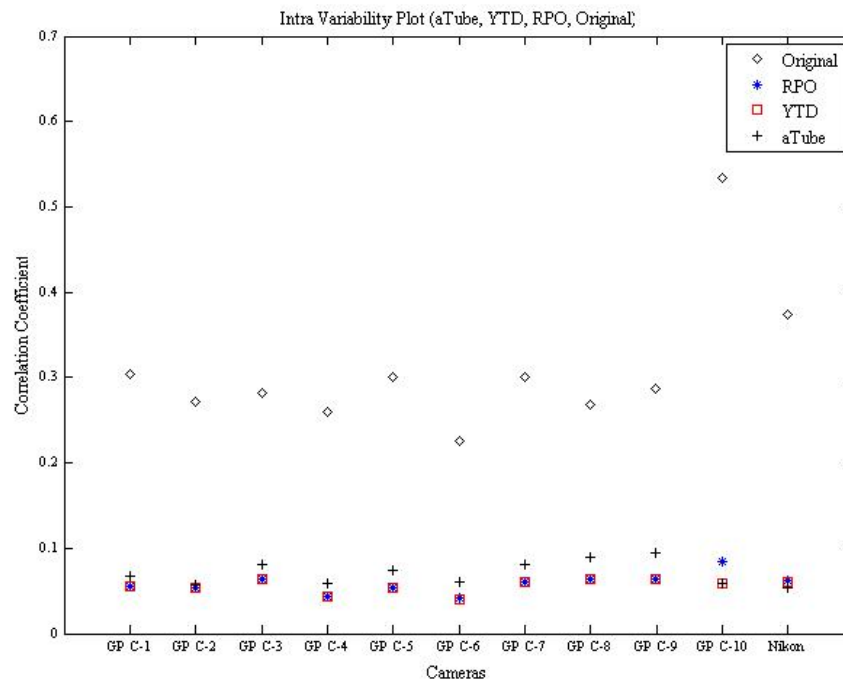
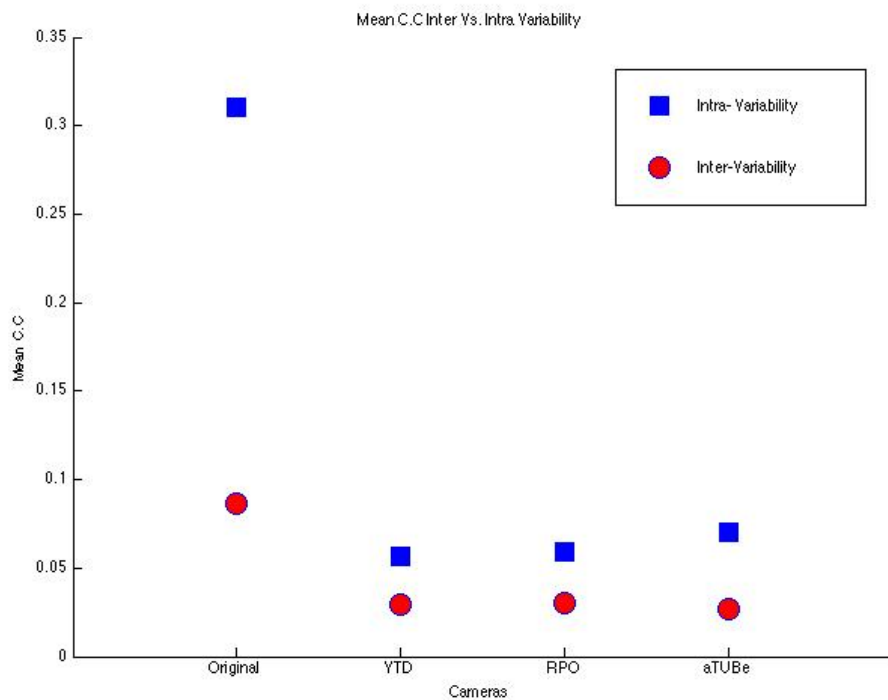


Table 9- Intra Variability (aTube, YTD, RPO, Vs. Original)



The mean correlation values of the original videos were determined to be higher than those of any of the tools. This was expected since a significant data loss after all YouTube downloads would cause degradation of quality and extractable noise. Table 10 shows a plot of the intra and inter variability when all correlation values were averaged for each of the three tools and the original.

Table 10- Mean Correlation Values



The intra variability PRNU results show a clear threshold of separation where a consistent video, an inconclusive video, and an inconsistent video can be determined using a histogram plot. The histogram plot demonstrates how to determine if an intra variability comparison of a camera in question is consistent, inconclusive, or inconsistent with an original or compressed video from YouTube. Histogram tables 11, 12, and 13 show an inconclusive area of separation using a black

circle. YTD, RPO and aTube each show a clear area of intra variability camera separation.

If a camera's correlation value were to fall within this black area of separation the result would be inconclusive. If the correlation value were to fall below the inconclusive area of separation, the result would be consistent with YouTube compression. Additionally, a video in question can be determined to be an original video, if the threshold of the correlation is above the inconclusive area of separation.

Table 11- Histogram (Intra Variability Original Vs. YTD)

Area of Separation (.063971 to .22584)

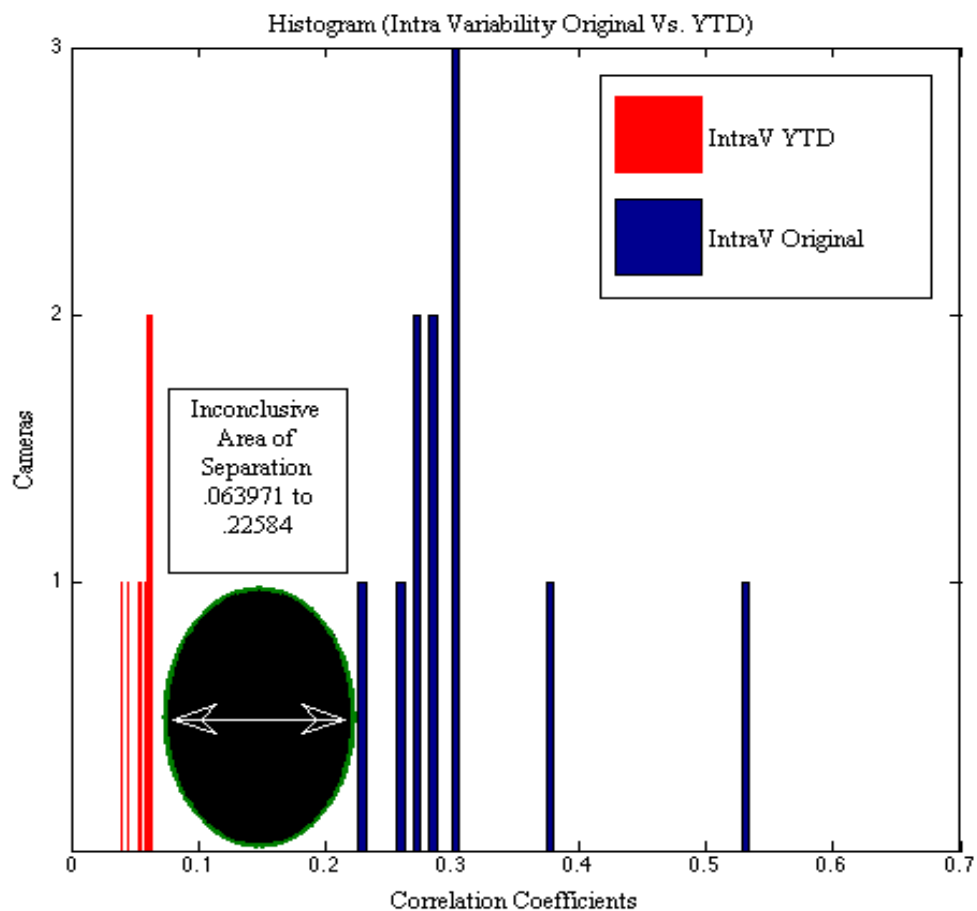


Table 12- Histogram (Intra Variability Original Vs. RPO)

Area of separation (.08466 to .22584)

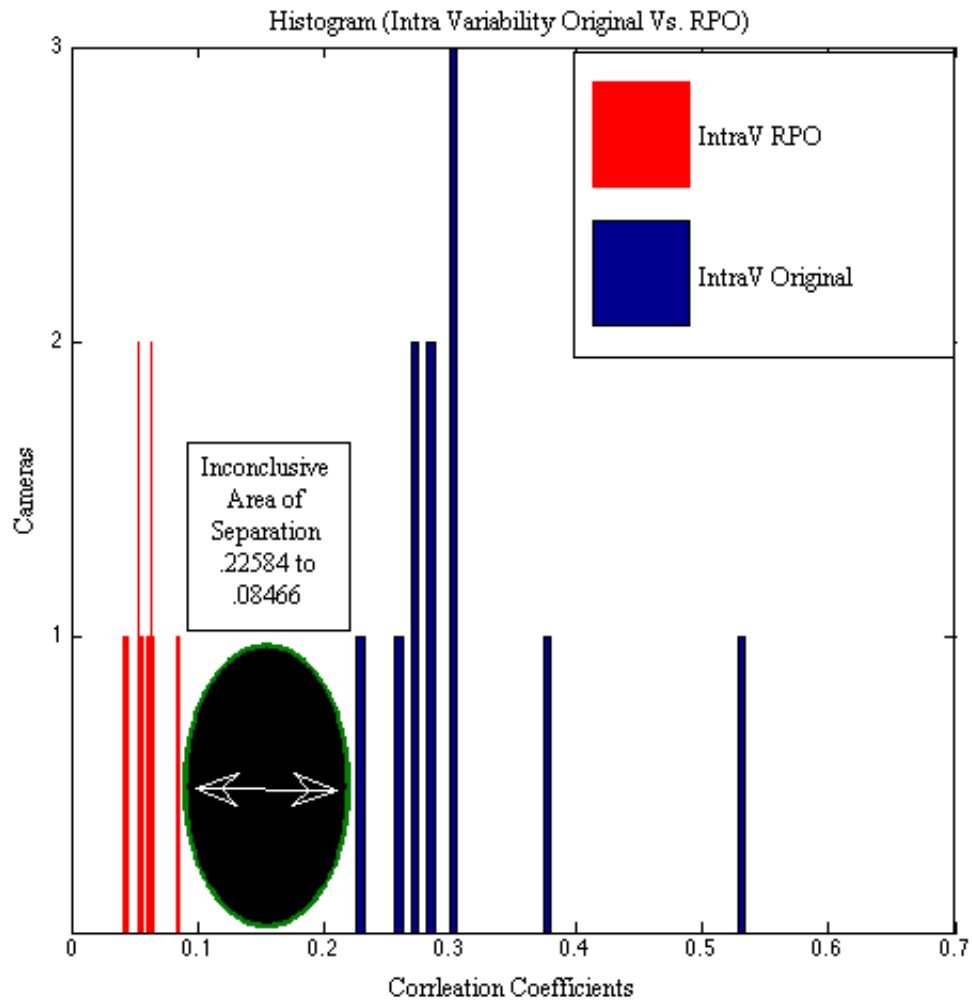
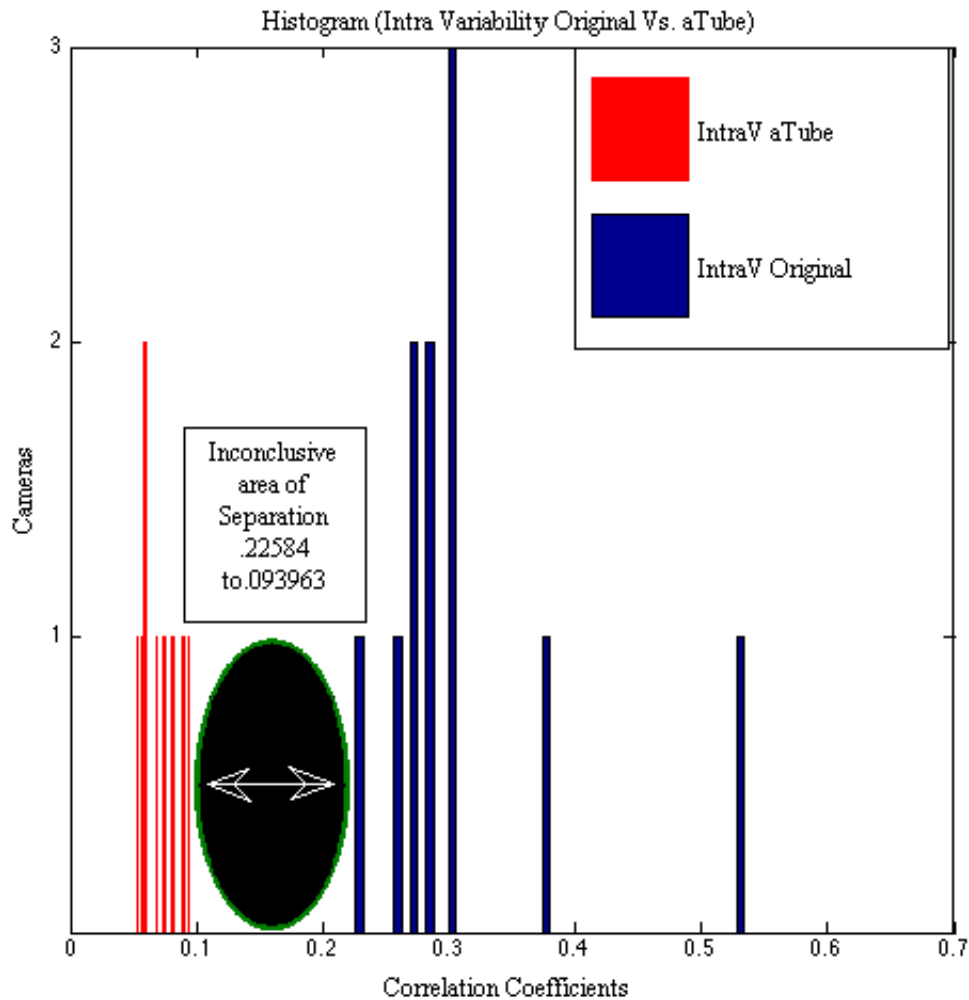


Table 13- Histogram (Intra Variability Original Vs. aTube)

Area of Separation (.093963 to .22584)



The inter variability PRNU results do not exhibit any clear threshold of separation where an inconclusive video would fall. The results were interlaced within each other and no threshold was apparent. For inter variability, if a camera's correlation value were to be significantly higher than the “grey” area, where the

correlations are interlaced, a verbal decision can be reached as being consistent with an original uncompressed, video.

On the other side of the histogram if a camera's correlation value were to be significantly lower than the "grey" area, where the correlations are interlaced, a verbal decision could be reached as being inconsistent with an original, uncompressed video.

Table 14-Histogram (Inter Variability Original Vs. YTD)

No clear separation is present

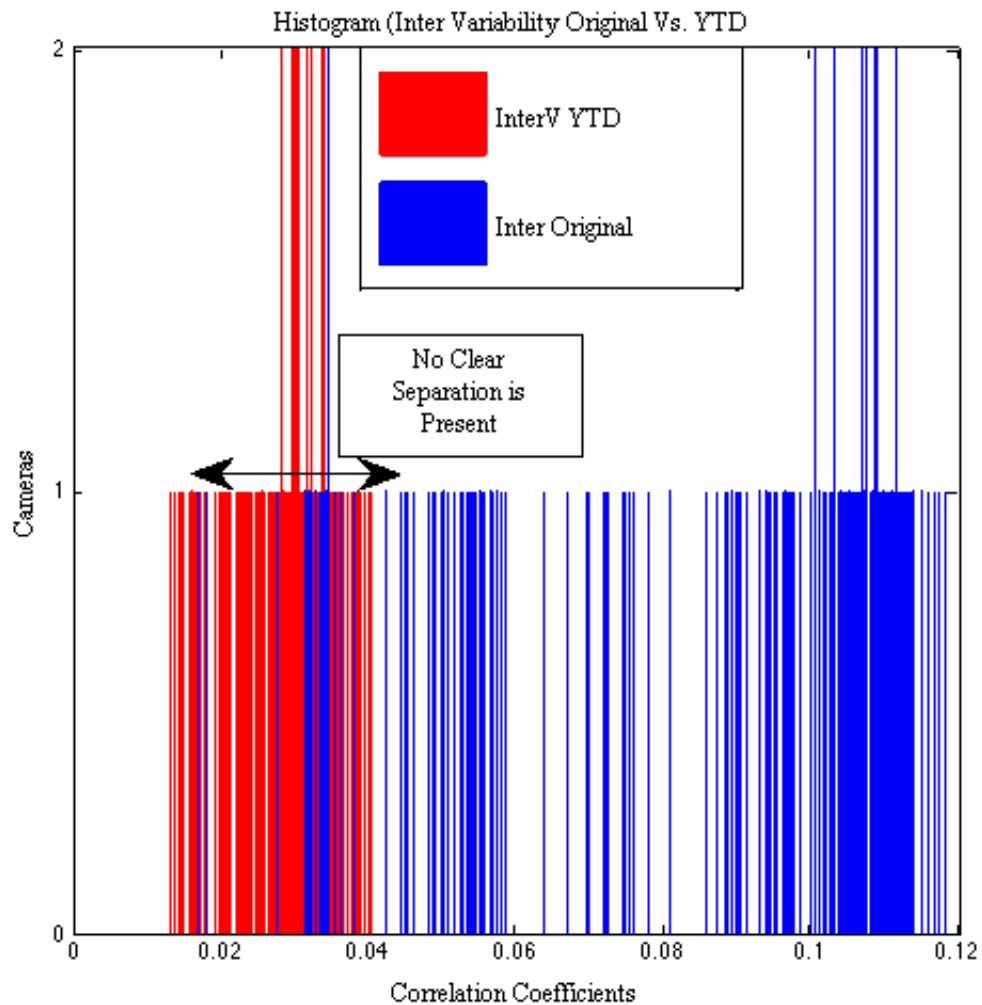


Table 15- Histogram (Inter Variability Original Vs. RPO)

(No clear separation is present)

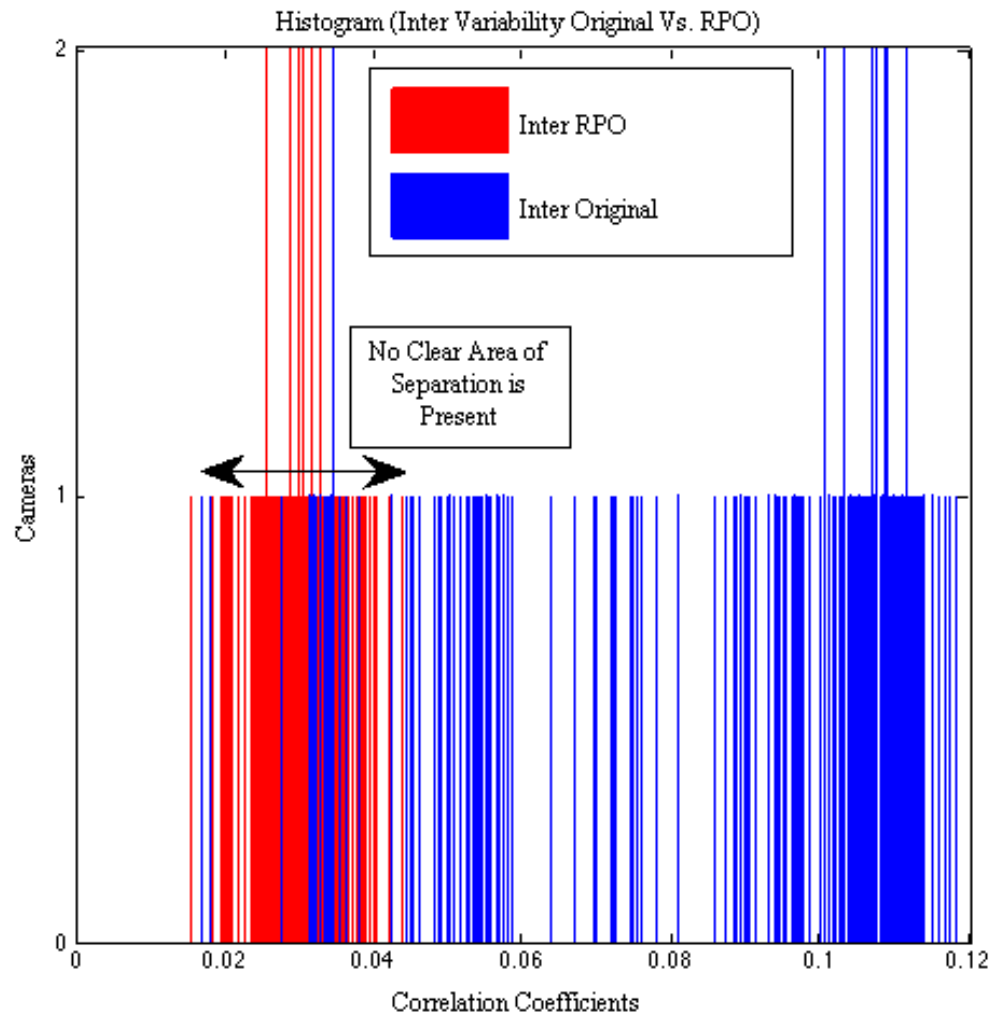
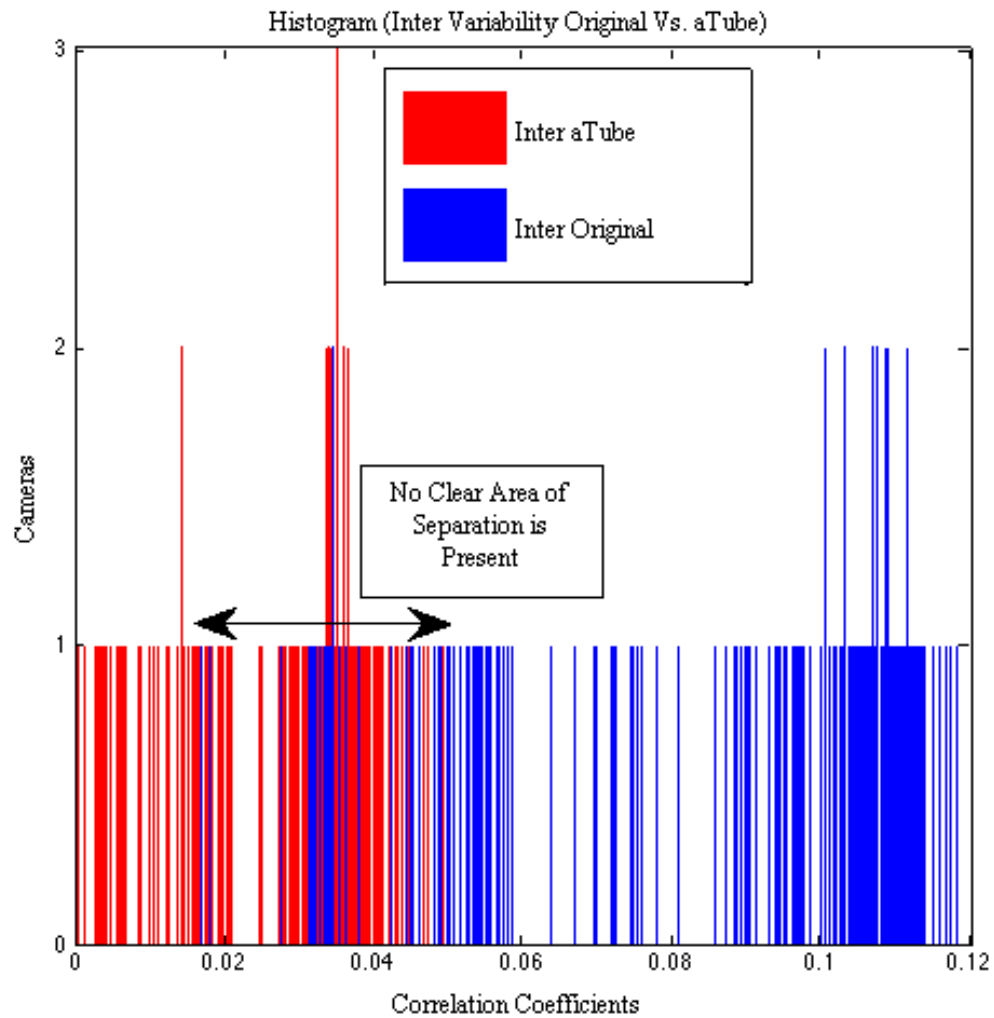


Table 16- Histogram (Inter Variability Original Vs. aTube)

(No clear separation is present)



CHAPTER VI

CONCLUSION

The first conclusion reached from analysis showed that the downloader tools affect the PRNU measurements. This conclusion is also supported by the file sizes from table 1. A higher compression ratio for YTD and RPO was present due to the fact that an identical number of frames per second reported a lower file size than aTube. The high frequency small details were lost when large compression ratios were present. This compression can degrade the PRNU data and the discrimination power of the analysis.

The research demonstrated that when downloading videos from YouTube for analysis, one should test their downloading tools and select the method which will incorporate the least amount of compression.

If a video is called into question, and a reference video database is available, the examiner can look for a match. In a forensic case, it is recommend to a build database collected over time, with thousands of cameras and videos, to help determine the origin of a video. Since a reference population was available in this research, a threshold and a conclusion can be determined. This is the same principle that should be applied in all forensic cases.

The results suggest that using a combination of techniques including format, structure, and PRNU will yield the most accurate results. PRNU can be relied upon when the structure analysis exhibits signs of change. In any video forensic case, an examiner should build a sample database, and calibrate all system's before forensic

analysis. It's very important to know the limits of your science and combine techniques when providing camera identification and authentication analysis.

The techniques discussed in this paper are limited in providing positive proof of camera identification since the number of possible combinations between cameras, their settings, and eventually digital edits and recompressions before uploading to YouTube or other video hosting services is almost impossible to compute. Due to the number of different variables, the following conclusions are proposed that can be used within a framework for forensic cases:

-Consistent with an authentic video...

-Inconclusive...

-Inconsistent with an authentic video...

A conclusion in a forensic case contains the forensic results obtained by the examiner. Reporting the results in a clear and concise manner is crucial in conveying the report during legal proceedings. Table 17 was created to show an example of a basic conceptual structure for video authentication. The table is divided into three main sections: file structure, global structure analysis, and source camera identification. Within each of these sections the authentication and identification techniques listed can be removed, replaced, or built upon. Using all analysis techniques, listed in table 17, might not be practical or even feasible for an examiner due to time constraints or financial resources. It is up to the judgment of the

examiner to determine what techniques are necessary to provide a logical and unbiased conclusion as to the authentication or source of the video in question.

Table 17- Proposed Structure

FILE STRUCTURE	Consistent	Inconclusive	Inconsistent
-File format			
-Hex Data			
GLOBAL ANALYSIS			
-Compression Level Analysis			
-Color Filter Array			
-Quantization Tables			
-DCT Coefficients			
SOURCE CAMERA IDENTIFICATION			
-Defective Pixels			
-Sensor Dust			
-PRNU			

CHAPTER VII

FURTHER RESEARCH

New action cameras are constantly being developed. Since the publication of this paper the developers at Go-Pro have come out with the newest line of action cameras. Further research into action camera identification, using YouTube, should include this line of cameras and others that become relevant.

New Video sharing hosts will inevitably be created for distributing video. Although YouTube is currently the most popular video sharing web service, other websites like Vimeo are gaining huge popularity. News organizations are also now sharing their video content over the Internet through their website.

New resolutions will become relevant as action cameras currently allow acquisition of 4k and 8k videos. A higher resolution video with would improve PRNU results given the same lighting conditions. The structure of the video files along with the principles of acquisition and saving should generally remain the same while resolution improves.

New downloader tools will be available in the future and will become relevant to acquire a video in question. These tools will work with new hosting websites to allow users the option to save higher resolution videos. YouTube has not created the option to download any video as of 2014.

Other algorithms to extract PRNU noise (e.g Wavelet) should be tested and used in further experimentation. Combinations of algorithms have proven to be effective and should be tested on action cameras [7]. New or updated algorithms will

be developed that will process data more efficiently and allow for even higher correlation values.

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APPENDIX

Section 1- File Structure for all Videos

		Camera 1-1		
Information	Original	YTD	RPO	aTube
File Size	38 MB	4.8 MB	4.8	6.8 MB
File Type	MP4	MP4	M4V	MP4
Image Width	1920	1920	1920	1920
Image Height	1080	1080	1080	1080
Frame Rate	29.97	29.97	29.97	29.97
Media Duration	15.25 s	15.30 s	15.30 s	15.33 s
Movie Data Size	39289830	5039051	5039051	7166451

		Camera 1-2		
Information	Original	YTD	RPO	aTube
File Size	42 MB	5.3 MB	5.3 MB	7.6 MB
File Type	MP4	MP4	M4V	MP4
Image Width	1920	1920	1920	1920
Image Height	1080	1080	1080	1080
Frame Rate	29.97	29.97	29.97	29.97
Media Duration	16.98 s	17.04 s	17.04 s	17.07 s
Movie Data Size	43717774	5554012	5554012	7972646

		Camera 2-1		
Information	Original	YTD	RPO	aTube
File Size	42 MB	4.8 MB	4.8 MB	6.9 MB
File Type	MP4	MP4	M4V	MP4
Image Width	1920	1920	1920	1920
Image Height	1080	1080	1080	1080
Frame Rate	29.97	29.97	29.97	29.97
Media Duration	15.42 s	15.46 s	15.46 s	15.49 s
Movie Data Size	39736173	4999733	4999733	7232631

		Camera 2-2		
Information	Original	YTD	RPO	aTube
File Size	37 MB	4.5 MB	4.5 MB	6.6 MB
File Type	MP4	MP4	M4V	MP4
Image Width	1920	1920	1920	1920
Image Height	1080	1080	1080	1080
Frame Rate	29.97	29.97	29.97	29.97
Media Duration	14.81 s	14.88 s	14.88 s	14.91 s
Movie Data Size	38255882	4747095	4747095	6947857

		Camera 3-1		
Information	Original	YTD	RPO	aTube
File Size	42MB	5.4MB	5.4MB	7.7 MB
File Type	MP4	MP4	M4V	MP4
Image Width	1920	1920	1920	1920
Image Height	1080	1080	1080	1080
Frame Rate	29.97	29.97	29.97	29.97
Media Duration	17.15 s	17.20 s	17.20 s	17.23 s
Movie Data Size	44062209	5687497	5687497	8070707

		Camera 3-2		
Information	Original	YTD	RPO	aTube
File Size	36 MB	4.4 MB	4.4 MB	6.5 MB
File Type	MP4	MP4	M4V	MP4
Image Width	1920	1920	1920	1920
Image Height	1080	1080	1080	1080
Frame Rate	29.97	29.97	29.97	29.97
Media Duration	14.45 s	14.51 s	14.51 s	14.54 s
Movie Data Size	37280960	4645405	4645405	6795142

		Camera 4-1		
Information	Original	YTD	RPO	aTube
File Size	27 MB	3.4 MB	3.4 MB	4.9 MB
File Type	MP4	MP4	M4V	MP4
Image Width	1920	1920	1920	1920
Image Height	1080	1080	1080	1080
Frame Rate	29.97	29.97	29.97	29.97
Media Duration	10.84 s	10.91 s	10.91 s	10.94 s
Movie Data Size	28240322	3559080	3559080	5121068

		Camera 4-2		
Information	Original	YTD	RPO	aTube
File Size	34 MB	4.5 MB	4.5 MB	6.2 MB
File Type	MP4	MP4	M4V	MP4
Image Width	1920	1920	1920	1920
Image Height	1080	1080	1080	1080
Frame Rate	29.97	29.97	29.97	29.97
Media Duration	13.95 s	14.00 s	14.00 s	14.02 s
Movie Data Size	36031905	4731901	4731901	6527835

		Camera 5-1		
Information	Original	YTD	RPO	aTube
File Size	47 MB	5.8 MB	5.8 MB	8.5 MB
File Type	MP4	MP4	M4V	MP4
Image Width	1920	1920	1920	1920
Image Height	1080	1080	1080	1080
Frame Rate	29.97	29.97	29.97	29.97
Media Duration	19.02 s	19.09 s	19.09 s	19.11 s
Movie Data Size	48811178	6108459	6108459	8935926

		Camera 5-2		
Information	Original	YTD	RPO	aTube
File Size	40 MB	5.2MB	5.2MB	7.4 MB
File Type	MP4	MP4	M4V	MP4
Image Width	1920	1920	1920	1920
Image Height	1080	1080	1080	1080
Frame Rate	29.97	29.97	29.97	29.97
Media Duration	16.45 s	16.51 s	16.51 s	16.53 s
Movie Data Size	42301985	5392419	5392419	7766282

		Camera 6-1		
Information	Original	YTD	RPO	aTube
File Size	42 MB	5.2 MB	5.2 MB	7.8 MB
File Type	MP4	MP4	M4V	MP4
Image Width	1920	1920	1920	1920
Image Height	1080	1080	1080	1080
Frame Rate	29.97	29.97	29.97	29.97
Media Duration	17.25 s	17.30 s	17.30 s	17.32 s
Movie Data Size	44276724	5487463	5487463	8116226

		Camera 6-2		
Information	Original	YTD	RPO	aTube
File Size	33 MB	4.1 MB	4.1 MB	6.1 MB
File Type	MP4	MP4	M4V	MP4
Image Width	1920	1920	1920	1920
Image Height	1080	1080	1080	1080
Frame Rate	29.97	29.97	29.97	29.97
Media Duration	13.45 s	13.51 s	13.51 s	13.54 s
Movie Data Size	34724321	4288379	4288379	6383676

		Camera 7-1		
Information	Original	YTD	RPO	aTube
File Size	32 MB	4.1 MB	4.1 MB	5.8 MB
File Type	MP4	MP4	M4V	MP4
Image Width	1920	1920	1920	1920
Image Height	1080	1080	1080	1080
Frame Rate	29.97	29.97	29.97	29.97
Media Duration	12.98 s	13.03 s	13.03 s	13.05 s
Movie Data Size	33603400	4292800	4292800	6119916

		Camera 7-2		
Information	Original	YTD	RPO	aTube
File Size	36 MB	4.5 MB	4.5 MB	6.6 MB
File Type	MP4	MP4	M4V	MP4
Image Width	1920	1920	1920	1920
Image Height	1080	1080	1080	1080
Frame Rate	29.97	29.97	29.97	29.97
Media Duration	14.61 s	14.67 s	14.67 s	14.70 s
Movie Data Size	37702498	4743947	4743947	6910318

		Camera 8-1		
Information	Original	YTD	RPO	aTube
File Size	36 MB	4.6 MB	4.6 MB	6.6 MB
File Type	MP4	MP4	M4V	MP4
Image Width	1920	1920	1920	1920
Image Height	1080	1080	1080	1080
Frame Rate	29.97	29.97	29.97	29.97
Media Duration	14.71 s	14.77 s	14.77 s	14.79 s
Movie Data Size	37897629	4781548	4781548	6909869

		Camera 8-2		
Information	Original	YTD	RPO	aTube
File Size	36 MB	4.6 MB	4.6 MB	6.6 MB
File Type	MP4	MP4	M4V	MP4
Image Width	1920	1920	1920	1920
Image Height	1080	1080	1080	1080
Frame Rate	29.97	29.97	29.97	29.97
Media Duration	14.75 s	14.81 s	14.81 s	14.84 s
Movie Data Size	37959174	4757307	4757307	6958366

		Camera 9-1		
Information	Original	YTD	RPO	aTube
File Size	37 MB	4.5 MB	4.5 MB	6.8 MB
File Type	MP4	MP4	M4V	MP4
Image Width	1920	1920	1920	1920
Image Height	1080	1080	1080	1080
Frame Rate	29.97	29.97	29.97	29.97
Media Duration	14.95 s	15.00 s	15.00 s	15.02 s
Movie Data Size	38598176	4688087	4688087	7070215

		Camera 9-2		
Information	Original	YTD	RPO	aTube
File Size	34 MB	4.3 MB	4.3 MB	6.3 MB
File Type	MP4	MP4	M4V	MP4
Image Width	1920	1920	1920	1920
Image Height	1080	1080	1080	1080
Frame Rate	29.97	29.97	29.97	29.97
Media Duration	13.88 s	13.93 s	13.93 s	13.96 s
Movie Data Size	35939341	4464201	4464201	6565152

		Camera 10-1		
Information	Original	YTD	RPO	aTube
File Size	90 MB	7.5 MB	7.5 MB	8.9 MB
File Type	MP4	MP4	M4V	MP4
Image Width	1920	1920	1920	1920
Image Height	1080	1080	1080	1080
Frame Rate	23.976	23.976	23.976	23.976
Media Duration	24.52 s	24.59 s	24.59 s	24.61 s
Movie Data Size	93709849	7890852	7890852	9316208

		Camera 10-2		
Information	Original	YTD	RPO	aTube
File Size	84 MB	6.8 MB	6.8 MB	9.4 MB
File Type	MP4	MP4	M4V	MP4
Image Width	1920	1920	1920	1920
Image Height	1080	1080	1080	1080
Frame Rate	23.976	23.976	23.976	23.976
Media Duration	22.98 s	23.03 s	23.03 s	23.06 s
Movie Data Size	87936948	7062568	7062568	9839232

		Camera nikon-1		
Information	Original	YTD	RPO	aTube
File Size	38 MB	6.4 MB	6.4 MB	8.4 MB
File Type	MOV	MP4	M4V	MP4
Image Width	1920	1920	1920	1920
Image Height	1080	1080	1080	1080
Frame Rate	29.97	29.97	29.97	29.97
Media Duration	21.01 s	21.08 s	21.08 s	21.11 s
Movie Data Size	40041284	6639946	6639946	8767773

		Camera nikon-2		
Information	Original	YTD	RPO	aTube
File Size	42 MB	7.1 MB	7.1 MB	9.2 MB
File Type	MOV	MP4	M4V	MP4
Image Width	1920	1920	1920	1920
Image Height	1080	1080	1080	1080
Frame Rate	29.97	29.97	29.97	29.97
Media Duration	23.02 s	23.08 s	23.08 s	23.10 s
Movie Data Size	43894492	7446439	7446439	9641933