# Forensic Behavior Analysis in Video Conferencing based on the Metadata of encrypted Audio and Video Streams - Considerations and Possibilities

Robert Altschaffel, Jonas Hielscher, Kevin Lamshöft, Christian Krätzer, Jana Dittmann

Email: Robert.Altschaffel@iti.cs.uni-magdeburg.de

Otto-von-Guericke University
Magdeburg, Germany

# Presenter: Robert Altschaffel

- Research Assistant in Research Group Multimedia and Security, Otto-von-Guericke-University of Magdeburg
- Research interests:
  - Computer Forensics
  - Automotive IT
  - ICS (Industrial Control Systems)
  - Network Analysis
  - Data Protection/Privacy
- Broad range of publications on these research subjects

# AMSL – Advanced Multimedia and Security Lab

- Research group at the Otto-von-Guericke University Magdeburg, Germany
- Research fields and interests
  - Computer security, privacy, data sovereignty
  - Security in Automotive IT and Industrial Control systems (ICS)
  - Forensics (Desktop IT, crime scene, Automotive IT, Industrial Control Systems)
  - Watermarking and Steganography
  - Biometrics
- https://omen.cs.uni-magdeburg.de/itiamsl/deutsch/home/index.html

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# Introduction

- Video Conferencing (VC) is of increased importance during these times of crisis
- Video Conferencing often includes
  - Video Channel
  - Audio Channel
  - Text Channel
- Communication is usually encrypted – but what can be observed despite the encryption?
- Paper focuses on VC relying on a central communication server

# State of the art: Activity and content identification in encrypted traffic

- Various work on identifying activities or content in encrypted network traffic
  - Activities which are transmitted ‘live’
  - Basic Idea: Different activities led to different communication behavior
- Examples:
  - Reconstruction of inputs during a SSH session based on packet sizes and inter-packet times [1]
  - Identification of activities during a TeamViewer session based on properties of the network traffic [2]
  - Reconstruction of conversation in encrypted Skype traffic based on the size of transmitted packets and timing information [3]
  - Identification of speakers in Skype session based packet size and timing [4]


[1] D. X. Song, D. Wagner, and X. Tian, “Timing analysis of keystrokes and timing attacks on ssh,” in Proceedings of the 10th Conference on USENIX Security Symposium - Volume 10, ser. SSYM’01. USA: USENIX Association, 2001.
[2] R. Altschaffel, R. Clausing, C. Kraetzer, T. Hoppe, S. Kiltz, and J. Dittmann, “Statistical pattern recognition based content analysis on encrypted network: Traffic for the teamviewer application,” 03 2013, pp. 113–121.
[3] M. Korczynski and A. Duda, “Classifying service flows in the encrypted skype traffic,” 06 2012, pp. 1064–1068.
[4] Y. Zhu and H. Fu, “Traffic analysis attacks on skype voip calls,” Computer Communications, vol. 34, pp. 1202–1212, 07 2011.

# State of the Art: Computer Forensics

- Forensics describes a scientific and systematic approach for the reconstruction of events
- Forensic Process Models support the forensic process
  - Structuring the process
  - Making the process easier to describe and compare
- In this paper we use the Forensic Process Model from [1]
  - Of benefit for this paper:
  - Structures the forensic process into
    - 6 Investigation Steps (phases of the process including a Strategic Preparation)
    - 8 Data Types (describing how certain data is handled during the forensic process)

➢ Aim: identify a structured and comparable approach for activity identification during VC

[1] S. Kiltz, J. Dittmann, and C. Vielhauer, “Supporting Forensic Design – A Course Profile to Teach Forensics,” in Proc. 9th Int. Conf. on IT Security Incident Management & IT Forensics (IMF 2015). IEEE, 2015.

# Usability of audio and video streams for activity analysis

- General approach:
  - Identify the various activities which might influence communication behavior
  - Identify which properties of the communication behavior are influence by different activities
  - Identify where these properties can be observed
  - Create an overall process

# Usability of audio and video streams for activity analysis: Activities

- Identifying activities which lead to differences in communication
- **Activities in Text**
  - $TE_1$ inactive / not typing
  - $TE_2$ typing
  - $TE_3$ sending text
- **Activities in Audio**
  - $A_1$ deactivated / muted
  - $A_2$ unmute and silent
  - $A_3$ unmute and speaking fluently
  - $A_4$ unmute and speaking chopped off
- **Activities in Video**
  - $V_1$ deactivated
  - $V_2$ black screen
  - $V_3$ one person in front
  - $V_4$ multiple persons in front

# Usability of audio and video streams for activity analysis: Properties

- Properties based on packet size and timing (a used in [1], [2], [3] and [4])
- Features are extracted from these properties by an feature extractor based on the work in [2]
- ➢ Window-based features using fixed time windows
  - Packet size (minimum, maximum, mean, deviation)

[1] D. X. Song, D. Wagner, and X. Tian, “Timing analysis of keystrokes and timing attacks on ssh,” in Proceedings of the 10th Conference on USENIX Security Symposium - Volume 10, ser. SSYM’01. USA: USENIX Association, 2001.
[2] R. Altschaffel, R. Clausing, C. Kraetzer, T. Hoppe, S. Kiltz, and J. Dittmann, “Statistical pattern recognition based content analysis on encrypted network: Traffic for the teamviewer application,” 03 2013, pp. 113–121.
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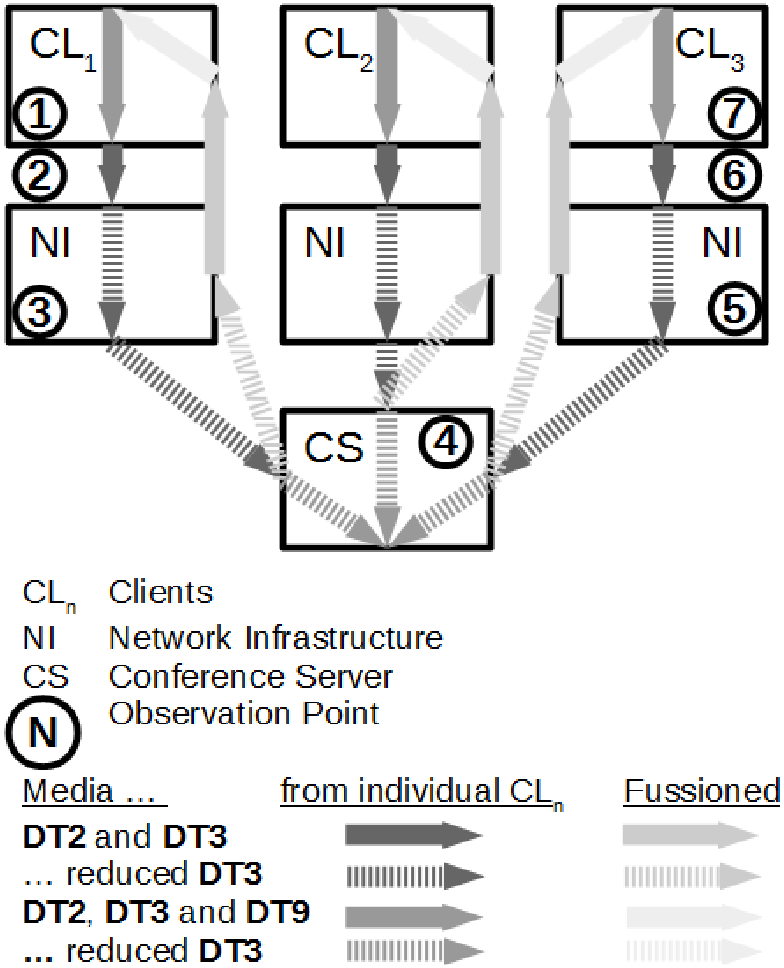
[4] Y. Zhu and H. Fu, “Traffic analysis attacks on skype voip calls,” Computer Communications, vol. 34, pp. 1202–1212, 07 2011.

# Usability of audio and video streams for activity analysis: Availability within infrastructure

- Different systems take part in enabling VC
  - Various clients ($CL_{1\text{-}3}$)
  - A central server (CS)
  - Network Infrastructure (NI)
- Observable Communication differs at various points
  - Also in terms of accessible data (Data Types from [1] in the extension from [2])
  - DT2 = raw, not interpreted data
  - DT3 = meta data
  - DT9 = interpreted audio/video stream



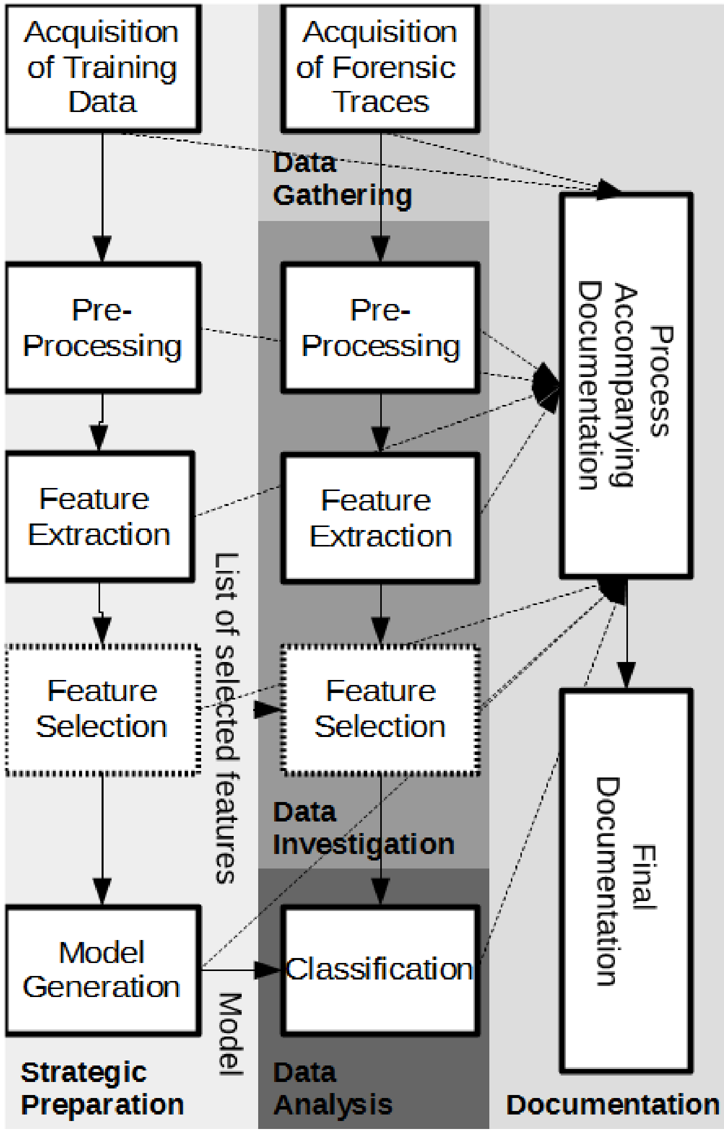


[1] S. Kiltz, J. Dittmann, and C. Vielhauer, "Supporting Forensic Design – A Course Profile to Teach Forensics," in Proc. 9th Int. Conf. on IT Security Incident Management & IT Forensics (IMF 2015). IEEE, 2015.

[2] R. Altschaffel, M. Hildebrandt, S. Kiltz, and J. Dittmann, "Digital Forensics in Industrial Control Systems," in Proceedings of 38th International Conference of Computer Safety, Reliability, and Security (Safecomp2019). Springer Nature Switzerland, 2019, pp. 128–136.

# Usability of audio and video streams for activity analysis: Process

- Pattern Recognition is used to identify various activities which can be mapped to the Investigation Steps from [1]
  - Training of a decision model before the classification takes place (= Strategic Preparation)
  - Model can then be used to classify gathered data (=Data Analysis/Data Investigation)
  - This data has to be gathered before (=Data Gathering)
  - The entire process is documented (=Documentation)




[1] S. Kiltz, J. Dittmann, and C. Vielhauer, "Supporting Forensic Design – A Course Profile to Teach Forensics," in Proc. 9th Int. Conf. on IT Security Incident Management & IT Forensics (IMF 2015). IEEE, 2015.

# Exemplary implementation and preliminary results

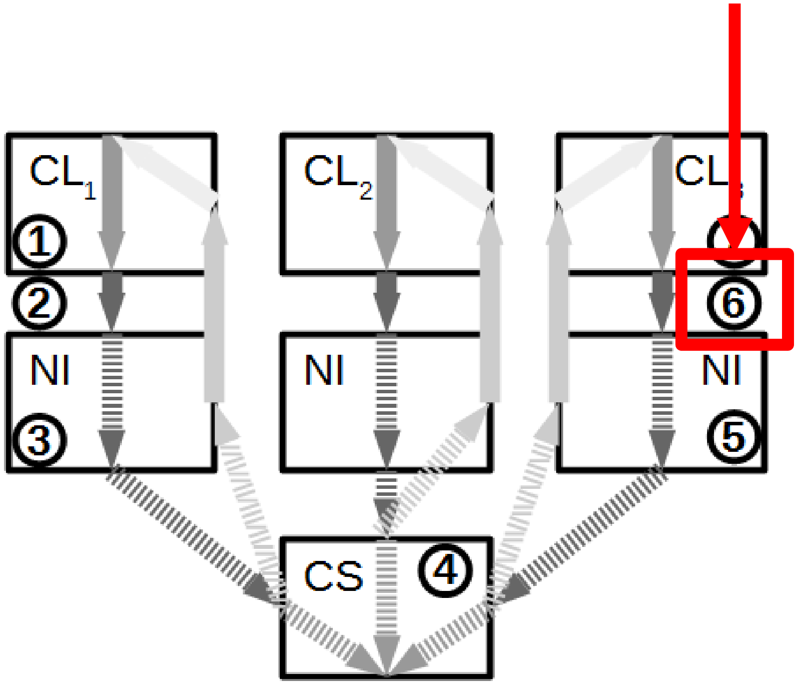
- Tests with Zoom [1] and BBB [2]
- Data Acquisition by test setup
- Pre-Processing and Feature Extraction based on [3]
- Model Generation and Classification done using WEKA [4]
- Visual confirmation of Pattern Recognition results


[1] Zoom Video Communications, Inc., “Zoom - Video Conferencing, WebConferencing, Webinars,” 2020, https://zoom.us [September 20. 2020].
[2] BigBlueButton, “BigBlueButton - Open Source Web Conferencing,”2020, https://bigbluebutton.org/ [September 20. 2020].
[3] R. Altschaffel, R. Clausing, C. Kraetzer, T. Hoppe, S. Kiltz, and J. Dittmann, “Statistical pattern recognition based content analysis on encrypted network: Traffic for the teamviewer application,” 03 2013, pp. 113–121.
[4] C. Jennings, H. Bostr ̈om, and J.-I. Bruaroey, “WebRTC 1.0: Real-Time Communication Between Browsers,” 2020, https://www.w3.org/TR/webrtc/ [September 20. 2020].[17] University of Waikato, “WEKA - The workbench for machine learning,”2020, https://www.cs.waikato.ac.nz/ml/weka/ [September 20. 2020]

# Exemplary implementation and preliminary results

- Test of three different solutions
  - BBB [1]
  - Zoom-App [2]
  - Zoom-Web [2]
- Data Acquisition at $\boldsymbol{O_6}$
  - Capturing only incoming traffic at a passive observer
- Test of activities
  - In Text
  - In Audio
  - In Video
- Goal: Distinguish user behavior
  - Visual verification
  - Classifier (Pattern Recognition)

*Observation point in our setup*




Only one extraction point at a passive observer is used in our test setup.


[1] BigBlueButton, "BigBlueButton - Open Source Web Conferencing,"2020, https://bigbluebutton.org/ [September 20. 2020].
[2] Zoom Video Communications, Inc., "Zoom - Video Conferencing, WebConferencing, Webinars," 2020, https://zoom.us [September 20. 2020].

## Exemplary implementation and preliminary results – Test cases

- [T1] - Audio
  - CL1 is using the microphone to send audio
  - Different levels of audio usage are compared
    - A1 microphone is muted in the conference client and on the hardware
    - A2 microphone is activated in the conference client but deactivated on the hardware
    - A3 microphone is fully activated and a monotone voice is recorded
    - A4 microphone is fully activated and a voice which varies in vocal pitch and volume is recorded
- [T2] - Video:
  - CL1 is using the built-in webcam to send video data
  - Different levels of video usage are compared
    - V1 The webcam is deactivated in the client
    - V2 The webcam is activated and a black image is recorded
    - V3 The webcam is activated and a static video (without visible movement) is recorded
    - V4 The webcam is activated and a moving video (movement of a person) is recorded
- [T3] - Video2x
  - CL1 and CL2 are using the built-in camera and both perform tests like in [T2] (V5)
  - test whether an observer can identify the number of active participants or not
- [T4] - Video-Audio
  - CL1is using different audio- and video features like described in [T1] and [T2]
  - aim is to test whether the stream of audio and video data can be separated on network level in order to evaluate them separately

# Exemplary implementation and preliminary results – Pattern Recognition

- Training of classifier with WEKA [1] with J48 algorithm
  - Success in 9 out of twelve performed tests

| Test | Zoom-Web | Zoom-App | BBB |
|---|---|---|---|
| [T1] | 0.9989 | 0.9947 | 1 |
| [T2] | 0.9993 | 0.9953 | 1 |
| [T3] | NA | NA | 1 |
| [T4] | 0.9993 | 0.9947 | NA |

Kappa statistics (in the range [0,1] with a value of 1 indicating optimal classification) for the different test cases

| Classified as | $V_1$ deactivated | $V_2$ black screen | $V_3$ one person in front |
|---|---|---|---|
| $V_1$ deactivated | 44 | 0 | 0 |
| $V_2$ black screen | 1 | 1221 | 0 |
| $V_3$ one person in front | 1 | 0 | 2898 |

Confusion matrix for [T2] using Zoom-Web.

[1] University of Waikato, “WEKA - The workbench for machine learning,”2020, https://www.cs.waikato.ac.nz/ml/weka/ [September 20. 2020]

# Exemplary implementation and preliminary results – Visual Verification

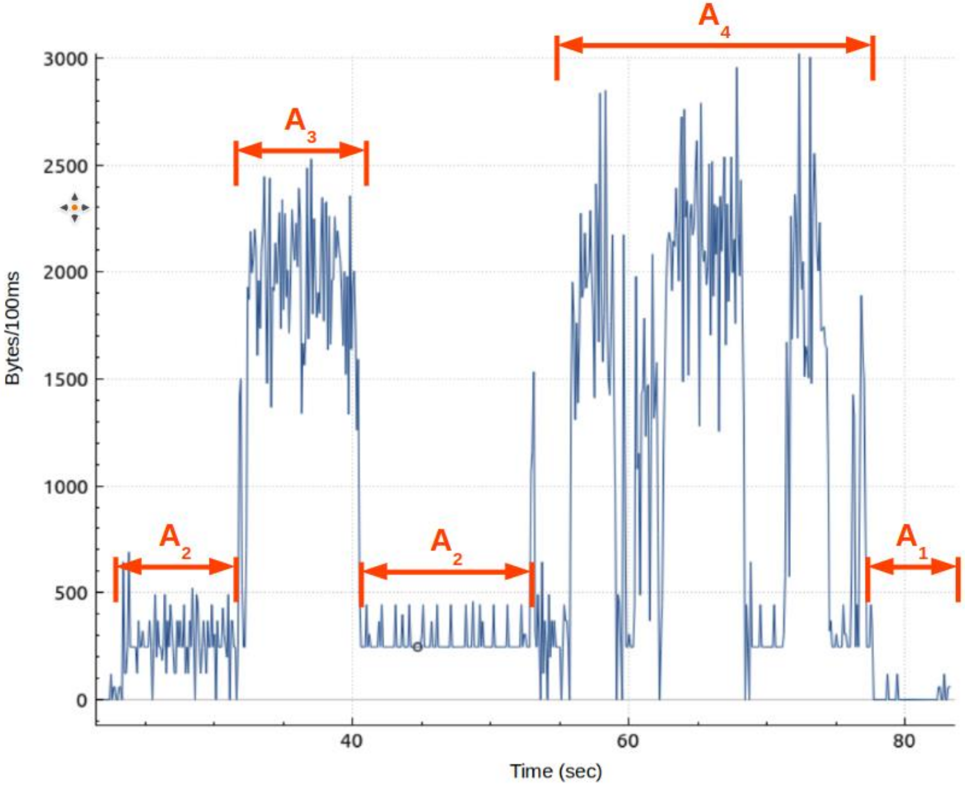
- Visual verification
  - Succeeded in most cases

**Activities in Audio**

| | |
|---|---|
| $A_1$ | deactivated / muted |
| $A_2$ | unmute and silent |
| $A_3$ | unmute and speaking fluently |
| $A_4$ | unmute and speaking chopped off |

**Activities in Video**

| | |
|---|---|
| $V_1$ | deactivated |
| $V_2$ | black screen |
| $V_3$ | one person in front |
| $V_4$ | multiple persons in front |




In case of the zoom app, different audio usage can be clearly distinguished by the amount of incoming (UDP) traffic at the passive observation point.

# Exemplary implementation and preliminary results

- Visual verification
  - Succeeded in most cases
- [T1]: Audio
- [T2]: Video
- [T3]: Video2x
- [T4]: Video-Audio

| Test | Zoom-Web | Zoom-App | BBB |
|---|---|---|---|
| [T1] | $A_1$ / $A_2$ / $A_3$ / $A_4$ | $A_1$ / $A_2$ / $A_3$ / $A_4$ | $(A_1 \wedge A_2)$ / $(A_3 \wedge A_4)$ |
| [T2] | $V_1$ / $V_2$ / $V_3$ | $V_1$ / $V_2$ / $V_3$ | $V_1$ / $(V_2 \wedge V_3)$ |
| [T3] | $V_1$ / $V_2$ / $V_3$ / $A_1$ / $A_2$ / $A_3$ / $A_4$ | $V_1$ / $V_2$ / $V_3$ / $A_1$ / $A_2$ / $A_3$ / $A_4$ | $X$ |
| [T4] | $X$ | $V_1$ / $V_2$ / $V_3$ / $V_4$ | $(V_1 \wedge V_2 \wedge V_3)$ / $V_4$ |

In the twelve tests, different usage of audio and video data can be distinguished from each other by simple visual verification of the I/O graph.

# Summary

- Identification of various activities within encrypted audio/video streams during Video Conferencing seems feasible
- Systematic approach based on Pattern Recognition and forensic principles
- Clear definition of the various possible points to observe VC communication and their impact on forensic investigations

- Future aspects
  - Extend training data set (in terms of used systems, number of users, observation points, etc.)
  - Potential use of biometrics to identify persons within these encrypted audio/video streams

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