VoiceGuard: Secure and Private Speech Processing

Hochschule Rosenheim
University of Applied Sciences

TECHNISCHE UNIVERSITÄT DARMSTADT

Ferdinand Brasser[1], Tommaso Frassetto[1], Korbinian Riedhammer[2], Ahmad-Reza Sadeghi[1], Thomas Schneider[1], Christian Weinert[1]

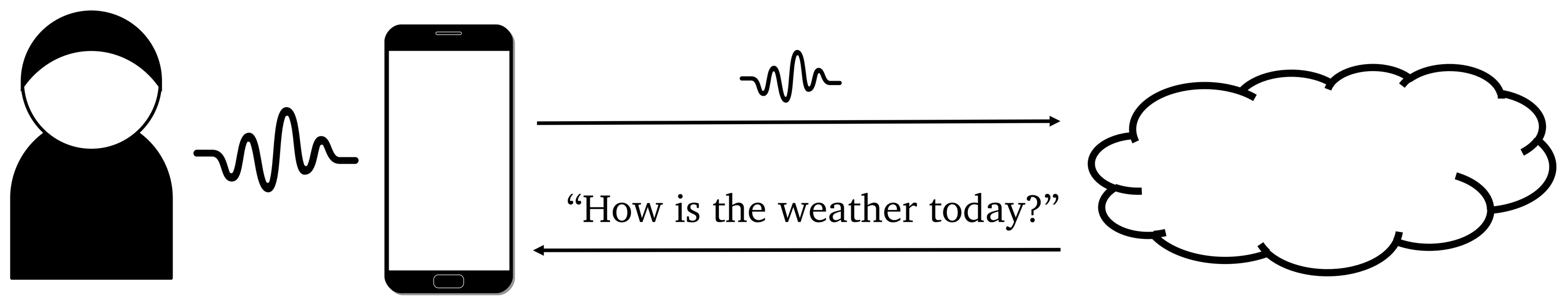
[1] *TU Darmstadt, Germany* [2] *University of Applied Sciences Rosenheim, Germany*

{ferdinand.brasser, tommaso.frassetto, ahmad.sadeghi}@trust.tu-darmstadt.de, korbinian@ieee.org, {schneider, weinert}@encrypto.cs.tu-darmstadt.de

1. Motivation & Contribution

Current Situation: Devices Providing Voice-based Interfaces are Omnipresent

- > 2B smartphone users (Amazon Alexa, Apple Siri, Google Assistant, Microsoft Cortana)
- Increasing number of smart-home devices (Amazon Echo, Apple Home-Pod, Google Home)



Risks: Voice Data Contains Sensitive Biometric Information as well as Spoken Words

➢ Impersonation attacks, fake recordings, extracting intimate / secret content, …

Problem Statement: Naïve Solution of Performing Speech Processing on Client-side fails

- Low-end devices are incapable of performing computationally demanding tasks
- Shipping the required machine learning model parameters to the clients contradicts the business interests of vendors

Contribution: Secure and Private Speech Processing Architecture dubbed "VoiceGuard"

- Efficiently protects speech processing tasks using *Intel Software Guard Extensions (SGX)*
- Supports user-specific models and generalizes to *on-premises* solutions

2. Related Work

Privacy-Preserving Machine Learning

- Via *Secure Multi-Party Computation*
  - Multiple parties jointly compute a publicly known function without revealing private inputs to each other by executing an interactive cryptographic protocol
  - × Orders of magnitude higher computation time and communication cost
  - × Impractical for on-the-fly processing due to repeated initialization costs
- Via *Homomorphic Encryption*
  - Operations are performed on encrypted data s.t. the decryption of the computation result equals the outcome when performing the same operations on plaintext data
  - × Currently far from suitable for speech recognition in real time due to high overhead

Privacy-Preserving Speech Processing (Pathak et al., *IEEE Signal Processing Magazine'13*)

- Speech recognition and speaker verification via homomorphic encryption
  - × > 3 hours to encrypt 1s of audio & to recognize a word out of a 10 word vocabulary
- Speaker verification via *secure string matching*
  - × Approach cannot be transferred to some processing tasks like speech recognition

Privacy-Preserving Encrypted Phonetic Search of Speech Data (Glackin et al., *ICASSP'17*)

- × Requires the vendor to give the acoustic model to the user in the clear

3. Background on Intel SGX

Intel Software Guard Extensions (SGX)

- Enables processing of confidential data on *untrusted* systems via so-called enclaves
- Enclave: program that is executed in isolation from *all* other software, including privileged software (e.g., OS or a hypervisor)
- Confidential data (e.g., user input) is provisioned to an enclave over a secure channel

Remote Attestation (RA)

- Allows an external party to verify whether an enclave was created correctly
- Cryptographic hash of the initial memory state (memory measurement M) of the enclave is digitally signed by the platform signing key PK which is built into the CPU

Sealing

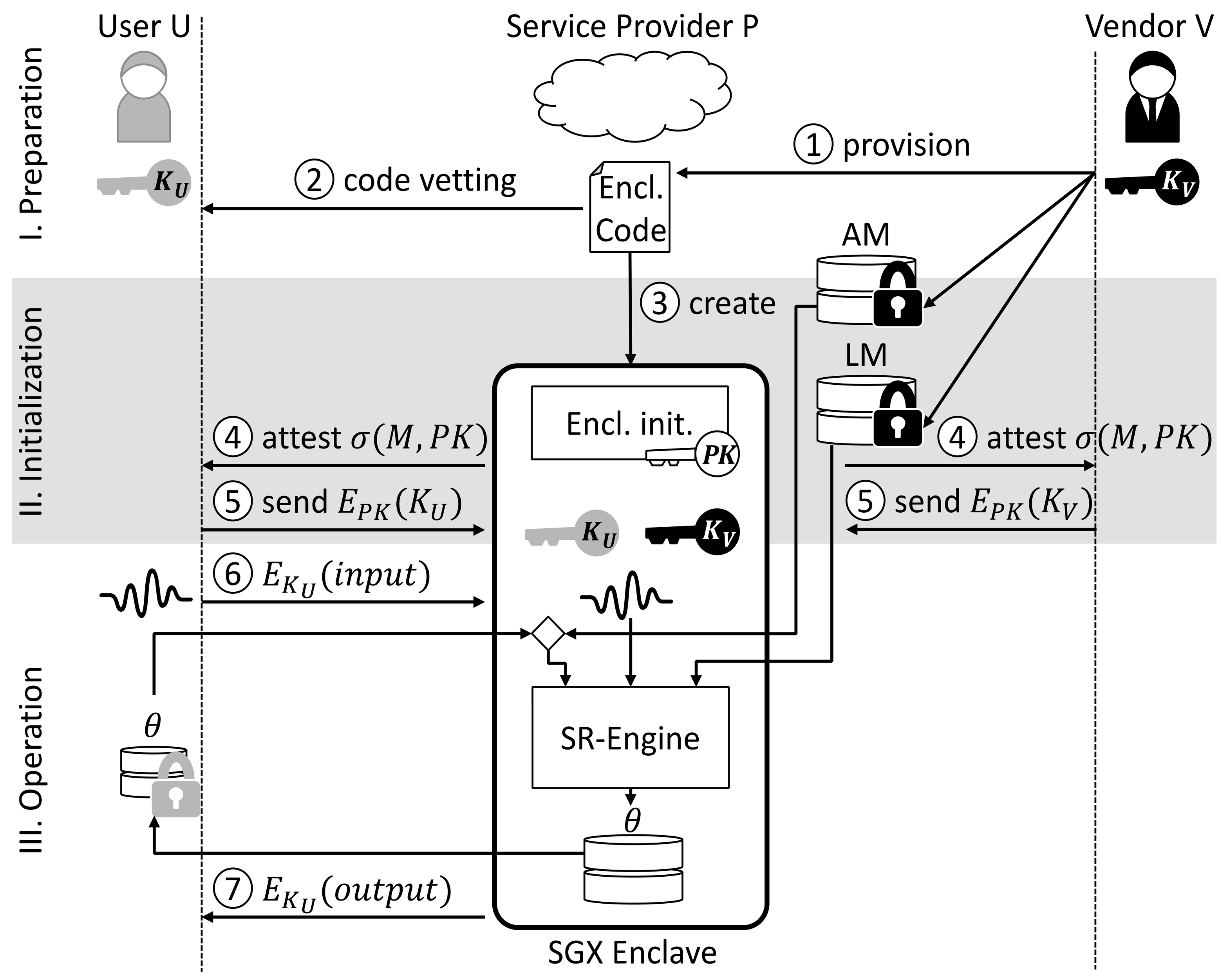
- Encrypt confidential data using an enclave-specific key and write to external storage

➢ Allows an enclave to use confidential data (e.g., acoustic model AM, language model LM, user-specific adaptation data θ) across multiple instantiations

Pros & Cons

- ✓ Widely available in recent Intel CPUs (≥ 6th Core-i generation)
- ✓ Almost native execution speed
- × Enclave code must incorporate defense mechanism to protect against side-channel attacks

4. VoiceGuard Architecture

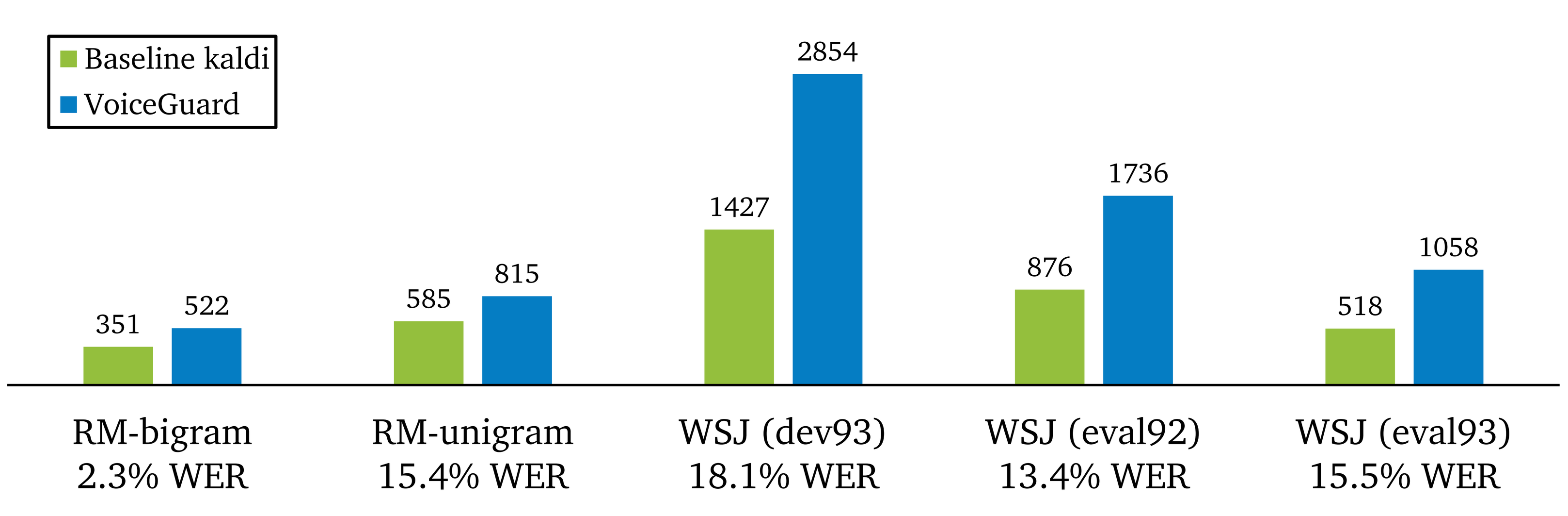


5. Evaluation

Evaluation of Prototype Implementation (based on the kaldi toolkit)

- DARPA Resource Management (RM)
  - Training on ≈ 4000 utterances
  - 3MB DNN (750k parameters); 0.5MB / 2MB (uni- / bigram) decoding graphs
  - Test on joint set of six test runs with ≈ 1500 utterances
- Wall Street Journal (WSJ)
  - Training on the ≈ 60h SI284 set & training of *nnet2_online* system with i-vectors
  - 14MB DNN (3.6M parameters), 641MB pruned trigram decoding graph

Baseline kaldi vs. VoiceGuard (Run-Time in s) on Core i7-7700 @ 3.60GHz



6. Conclusion & Future Work

VoiceGuard: Novel Architecture for Privacy-Preserving and Efficient Speech Processing

- ✓ Protects the user's sensitive voice data & the vendor's IP (i.e., model parameters)
- ✓ Supports user-specific models, such as feature transformations (e.g., fMLLR), i-vectors, or model transformations (e.g., custom output layers)
- ✓ Deployment either in the cloud or on-premises
- ✓ Prototype implementation demonstrates applicability for speech recognition in real time
- ✓ Generic ⇒ also works for related tasks (speaker verification or voice biometrics, including emotion recognition and medical speech processing)

Open Problems & Future Work

- SGX enclave memory is limited to 96MB memory ⇒ secure swapping is costly
  - × Typical high-accuracy ASR systems use larger models than evaluated here
  - ➢ Possible solution: distributing the processing across multiple SGX-enabled nodes
- Prototype code does not employ protection mechanisms against side-channel attacks
  - × Curious service providers could exploit micro-architectural effects to extract secret data
  - ➢ Possible solution: use enclave hardening frameworks & measure performance impact

CYSEC Cybersecurity TU Darmstadt

CRISP Center for Research in Security and Privacy

CROSSING

intel | Research Institute for Collaborative Autonomous and Resilient Systems