Maintaining Requirements for Long-Living Software Systems by Incorporating Security Knowledge

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International Requirements Engineering Conference (RE) 2014
Overview

• Motivation and Research Questions

• Our Approach and its Components

• iTrust Case Study

• Conclusion and Future Work

“Not bad kid, but you’d vulnerable to attacks here and here.”
Motivation

• Security is an important quality facet of software systems.

• Identifying vulnerabilities in requirements is important to elicit new security requirements as well as to make reasonable design decisions.

• Manual assessment approaches (e.g. reviews, inspections) are time-consuming and security expertise is required.

• Security assessments have to be repeated if environmental knowledge changes.
**Motivation**

Assumptions about Environment and Knowledge of Attacker

“It is difficult to spy information from a secure chip.”

Use of internal and secure chips prevents the leakage of PINs

**Change in Knowledge**

“Open APIs (display+keyboard) can be used to fake dialogs, phish info.”

**Time**

Attacks using additional dialogs, so that the customer enters PIN in an insecure mode

No changes in System

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Research Questions

**RQ1:** How to organize security knowledge in a way that it can be used for assessing requirements of a long-living software system?

**RQ2:** How can requirements engineers identify security-critical issues in natural language requirements semiautomatically?

**RQ3:** How can requirements engineers be supported to extract proper security knowledge from identified security-critical issues in requirements?
Overview of our Approach

Security Assessment

Specification -> RQ2

Security-related Specification Items

Security Context Knowledge Extraction

Security Knowledge

RQ1

Heuristics

Requirements Engineer

RQ2

Requirements

Additional Knowledge

Security Requirements

RQ3
Security Knowledge

- Modeling security knowledge must be flexible enough to cope with *Unknown Unknows*

- Knowledge can rapidly change or become invalid

- Continuously adapting knowledge is necessary

### Table: View, Structure Model, Content Model

<table>
<thead>
<tr>
<th>View</th>
<th>Structure Model</th>
<th>Content Model</th>
<th>Integrated Modelling Theory</th>
</tr>
</thead>
<tbody>
<tr>
<td>Exemplary Representation</td>
<td>Taxonomies</td>
<td>Generic Content Model</td>
<td>Mathematical Models</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Narrative Description</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>Guidelines</td>
<td></td>
</tr>
<tr>
<td>Characteristic</td>
<td>Flexibility</td>
<td>Concept Models</td>
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<td>Concept Models with Conformance Constraints</td>
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</tbody>
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[Fernandez2010]
Security Concepts ans Relationships

• SLR to find a suitable security concepts and their relationships (attack-centric security knowledge)

• Reviewed 16 publications from following areas:
  – Threat modeling
  – Risk analysis
  – Computer and network security
  – Software vulnerabilities
  – Information security management

• Focused on information systems, cyber-physical systems, distributed systems, and agenda-based systems
Improper neutralization of input

GM: Maintaining Requirements by Incorporating Security Knowledge

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Overview of our Approach
**Definition**: A heuristic is an analytical method based on hypotheses to assess requirements with respect to security.

**Remarks**:
- Heuristics are able to cope with incomplete and uncertain knowledge.
- Heuristic findings are suboptimal (false positives).
- Hypotheses may evolve for long-living software systems.
To decrease effort and support evolution of environmental knowledge, natural language requirements need to be assessed automatically.
Step 1: Creating Analysis Model

1. The user enters an email address.
2. The user enters her PIN.
3. If successful the user is logged in. Otherwise, the system displays a message to inform the user whether the email address or the PIN are incorrect.

1. Extract relevant nouns

1. The user enters an email address.
2. The user enters her PIN.
3. If successful the user is logged in. Otherwise, the system displays a message to inform the user whether the email address or the PIN are incorrect.
Step 1: Creating Analysis Model (cont.)

2. Label nouns according to the security knowledge

1. The user enters an email address.
2. The user enters her PIN.
3. If successful the user is logged in. Otherwise, the system displays a message to inform the user whether the email address or the PIN are incorrect.

3. Transform to analysis model
Step 2: Extract Hypotheses from Knowledge

1. The attacker selects an user identifier and attempts to login with a random password.
2. If the systems displays a message that the identifier is incorrect, the attacker knows that a corresponding account exists.
3. The attacker tries to guess the password systematically.

Transform to analysis model
Step 3: Vulnerability Analysis

- Analysis models are semantically matched using WordNet (taxonomy-based semantic similarity)

Trust Level: user
Asset: email address, PIN

SC: system
Entry Point: message
Asset: email address

SC: system
Entry Point: message
Asset: PIN

Trust Level: attacker
Asset: identifier

→ Suspectious sequence has been detected (potential vulnerability)
Overview of our Approach

- Security Assessment
  - Specification
  - Heuristics

- Security Context Knowledge Extraction
  - Security-related Specification Items
  - Requirements Engineer

- Security Knowledge
  - RQ1
  - Additional Knowledge
  - Security Requirements

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Security Context Knowledge Extraction

- To support manual knowledge extraction, the requirements engineering is guided by the heuristic findings.

- Acquiring new knowledge by leveraging linguistic structure of sentences.

The user is requested to enter her **email address** {Asset}, **PIN** {Asset}, and a secure transaction number {Asset?}.

- Modify, reinforce, and refine existing knowledge.

The **IP address** {→ email address?} of the user is logged after an error occurs.
iTrust Case Study

- Medical information system iTrust: Management of health records for patients and work schedule for staff
- Specified in 55 use cases written in natural language
- Implemented as web application by Realsearch Research Group (North Carolina State University)
To setup security knowledge and misuse cases, 10 UCs have been selected randomly.

Misuse Cases (MUC) have been obtained manually.

- **MUC1**: Interception of the registration email which contains sensitive information (threatens UC1).
- **MUC2**: Address field in the patient view contains a cross-site scripting vulnerability (threatens UC6).

Our approach is compared to Naive Bayes (NB), Support Vector Machine (SVM), and k Nearest Neighbor (k-NN).
iTrust Case Study - Results

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<th></th>
<th>ACC</th>
<th>FPR</th>
<th>FNR</th>
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<tbody>
<tr>
<td><strong>1st Iteration (n=44)</strong></td>
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<tr>
<td>Our Approach</td>
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<tr>
<td>MUC 1</td>
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<tr>
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<td>MUC 1/2</td>
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<tr>
<td>MUC 1</td>
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<td>0.00</td>
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<tr>
<td>MUC 2</td>
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<td>0.17</td>
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<tr>
<td>Naive Bayes</td>
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</tr>
<tr>
<td>MUC 1/2</td>
<td>0.71</td>
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<tr>
<td>k-NN</td>
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<tr>
<td>MUC 1/2</td>
<td>0.76</td>
<td>0.00</td>
<td>0.68</td>
</tr>
</tbody>
</table>
iTrust Case Study - Discussion

• Results indicate that the proposed concepts and their relationships are sufficient (RQ1)

• Vulnerable UCs could be identified automatically and results are better than NB, SVM, and k-NN (RQ2)

• After knowledge refinement (2nd iteration), false positive were reduced (RQ3)

• MUCs have been setup by the project team → more empirical studies are needed (e.g. industrial case study)
Conclusion and Future Work

• Heuristic security assessment and knowledge extraction approach to identify vulnerable requirements

• Our approach support established assessment approaches

• Case study shows that the proposed approach basically works

• Leverage structural dependencies between UCs to consider attacks that affect more than one UC

• Further studies to evaluate the proposed approach
Thank you for your attention!

Do you have any questions?