Stream Data Access Control Model: The Need for Data Semantics

Theppatorn Rhujittawiwat[1], Ahmed Saaudi[2] and Csilla Farkas[1]
[1]*University of South Carolina, Columbia, South Carolina, U.S.A.*
[2]*University of Al-Muthanna, Samawh, Iraq*

Keywords: Stream Data, Ontologies, Dynamic Access Control, Semantics-based Authorization.

Abstract: In this paper, we propose a semantics-based authorization model for stream data. We demonstrate that current authorization models are insufficient to provide dynamic access control for emerging technologies, such as the Internet of Things. We propose an authorization model using ontologies and rules to express security requirements for stream data. Our model supports secure interoperation and it is independent from the data syntax. We propose security object patterns to express access control needs. These patterns are associated with ontological concepts. Data instances inherit the security protection needs via stream pattern mapping. Security object patterns can incorporate domain, context, and temporal security restrictions. We show that our model is resistant to attacks that aim to bypass security restrictions by reconstructing stream data.

1 INTRODUCTION

Stream data management is an important requirement for emerging computing environments, such as the Internet of Things (IoT). Initiatives, such as IoT-Lite (Bermudez-Edo et al., 2015)(Bermudez-Edo et al., 2016) and Stream Annotation Ontology (SOA) (Kolozali et al., 2014), aim to support intelligent interoperation. Along with the development of IoT applications, concerns about cybersecurity threats emerged. In this paper, we address the specific cybersecurity needs of stream data in the IoT environment. We argue that current stream data security models do not support dynamic security, thus, insufficient to support IoT applications.

During the last decade, several researchers addressed the need to provide data security for stream data. Most of these models address confidentiality protection for stream data. The proposed solutions range from encryption-based end-to-end communication security (Penrig et al., 2000)(Puthal et al., 2015)(Puthal et al., 2017)(Veltri et al., 2013)(Zhu et al., 2006) to proposing generic security models (Carminati et al., 2015)(Manogaran et al., 2017)(Mengke et al., 2016)(Nehme et al., 2008). Communication security for stream data is widely provided by end-to-end encryption during transmission. To further improve the performance of this method, many researchers introduced efficient end-to-end encryption techniques such as the dynamic key length based approach (Puthal et al., 2015) and approaches for grouping and sharing keys (Penrig et al., 2000)(Puthal et al., 2017)(Veltri et al., 2013)(Zhu et al., 2006). However, end-to-end encryption techniques provide confidentiality over the entire data stream and are unable to provide fine granularity authorization. These techniques are cumbersome to enforce advanced security requirements, such as role-based access control, context-aware security, and dynamic security policies.

Several researchers proposed access control policy models for stream data (Cao et al., 2009)(Carminati et al., 2010)(Carminati et al., 2007a)(Carminati et al., 2007b)(Thoma et al., 2019). These approaches adopt access control concepts of traditional database management systems (DBMSs) to stream data. However, these efforts do not sufficiently address the specific needs of data stream management systems (DSMSs). For example, a DSMS can access only incoming data while a DBMS can access the complete data. The operator scheduling in a DSMS significantly impacts system performance. Operator scheduling strategies have been proposed by Carmiati et al. (Carminati et al., 2010) and by Thoma et al. (Thoma et al., 2019).

An enforcement of security requirements over the stream data instance has been proposed by Nehme et al. (Nehme et al., 2008). The security requirements are assigned to each attribute by their positions in the stream tuple. Their technique, called security punctuation, provides efficient access control for stream data. However, since the security punctuation is based on the syntax of the stream data, this approach provides limited interoperability. Moreover, modifica-

Rhujittawiwat, T., Saaudi, A. and Farkas, C.
Stream Data Access Control Model: The Need for Data Semantics.
DOI: 10.5220/0011528600003335
In *Proceedings of the 14th International Joint Conference on Knowledge Discovery, Knowledge Engineering and Knowledge Management (IC3K 2022) - Volume 3: KMIS*, pages 19-30
ISBN: 978-989-758-614-9; ISSN: 2184-3228

tion of the stream syntax may allow the attacker to bypass the access control restrictions.

Malicious corruption of the integrity of stream data was addressed by Guo et al. (Guo et al., 2007). The authors proposed a watermarking method to detect malicious modification of the stream data. The authors introduced the concept of data stream completeness. While their methods are able to detect modification of the data stream, they do not provide a model to express protection requirements.

In this paper, we present a security model to express security needs for stream data. Our work is based on the intersection of stream data semantics modeling and semantics-based authorization models. Data semantics is widely used to support stream data integration and data analytics (Le-Phuoc et al., 2011)(Whitehouse et al., 2006). Our solution was also influenced by work to support semantics-based authorization models (Sabelfeld and Myers, 2003)(Choi et al., 2014) and context-based decision support (Celdrán et al., 2014)(Chen et al., 2003)(Montanari et al., 2005).

The main contributions of our work are to 1) express security requirements via stream data semantics and 2) support dynamic and flexible policy management. Our focus is on the concept of protected object patterns. These patterns represent (partial) stream tuples and their combinations. Values for the tuple attributes may be variables or constants, thus allowing for the expression of security needs over varying levels of granularity. We model the mapping from the protection objects to the data instances via the corresponding ontologies. A protection object may be applicable to multiple ontology concepts and a concept may have multiple protection objects mapped to it. Stream data instances inherit the security requirements from the security object patterns. We show that our security label assignment provides strong confidentiality protection. Syntactically different but semantically same data items will have the same security protection assignment. In this paper, we present our functional model. We also give proof of formal properties of our security label assignment.

The organization of the paper is as follows: Section 3.2 discusses the motivating situations and problems which drive the direction of the solution. Section 4 defines the stream data model and security assignment. Section 5.1 describes the concept of stream data ontology. Section 5.2 illustrates logical reasoning and how to incorporate it into security policy. Section 6 presents an example of security policy implementation using ontology. We conclude in Section 7.

2 RELATED WORK

In this section, we give an overview of current research on stream data security, dynamic access control, and the limitations of these works.

2.1 Stream Data Security

Current work on stream data security focuses on confidentiality (Carminati et al., 2015)(Manogaran et al., 2017)(Mengke et al., 2016). The first priority of stream data design is performance. To provide security capabilities with the least effect on performance, the major methods of providing confidentiality are based on end-to-end cryptography (Penrig et al., 2000)(Puthal et al., 2015)(Puthal et al., 2017)(Veltri et al., 2013)(Zhu et al., 2006). However, end-to-end encryption techniques provide confidentiality over only the whole package. They are unable to provide fine granularity authorization, and cannot enforce advanced security requirements, such as role-based, lattice-based access control, or dynamic security policies. Therefore, such requirements must be enforced by the receiving applications. Many researchers introduce syntax-based security techniques for streaming data. The security requirements are assigned to each attribute by their positions in the stream tuple. Nehme et al. (Nehme et al., 2008) proposed a technique called security punctuation to provide efficient access control for stream data. A security punctuation technique focuses on providing privacy control for the data source side. The current security policy is sent from the data source and specifies the security labels of attributes in the data tuple. This approach allows the data source side to decide the security needs which are suitable for privacy sensitive data domains such as medical information.

The growing field of IoT has led to increasing number of stream data applications. Many of these applications also collect sensitive user data. To protect confidentiality and privacy of users, researchers propose access control for IoT stream data in different context. For example, Shafagh et al. (Shafagh et al., 2020) proposed a decentralized access control based on blockchain technology. Their approach provides an extra layer of anonymity for users but has a limited security granularity. Nambiar et al. (Nambiar et al., 2020) extended Apache Storm to protect privacy of the data in distributed systems. Their approach supports a variety of access control models, such as Discretionary Access Control (DAC), Mandatory Access Control (MAC), and Role-Based Access Control (RBAC).

Semantic approaches have been used in stream data since the field was established. However, their main focus is on how to interpret data and use it for data analytics (Le-Phuoc et al., 2011)(Whitehouse et al., 2006)(Sejdiu et al., 2021). The security community has demonstrated the benefit of semantics-based security, such as Sabelfeld et al. (Sabelfeld and Myers, 2003)(Choi et al., 2014)(Celdrán et al., 2014)(Chen et al., 2003)(Montanari et al., 2005). However, the potential of these approaches for supporting stream data security and privacy has not been fully investigated.

Moreover, stream data requires dynamic security policies because it is time sensitive. The same attribute in stream data may require different security levels at different times such as healthcare information in emergencies. Lu et al. (Lu et al., 2012) proposed a framework to provide privacy on mobile health monitoring devices. This approach uses mathematical models on monitored information to detect emergency situations and to release information to qualified helpers. Other mathematical models to express emergency situations were also proposed by many researchers (Jeong et al., 2014)(Lee et al., 2013)(Yu et al., 2017).

2.2 Dynamic Security Policy

Privacy is the major security concern related to commercial IoT devices. Recent research shows that current IoT devices focus on having secure connections between devices and the server (Alharbi and Aspinall, 2018)(Janes et al., 2020)(Ren et al., 2019). However, they lack a good access control policy to protect sensitive information. The information can be exposed to the third-party that operates the service such as Amazon Web Services (AWS) (Ren et al., 2019). End users, such as smart home users, are often left with little or no control over device security. Moreover, security policies may be dependent on the context. Semantics-based approaches can be used to express the context and situations, and adjust the security policy accordingly.

Carmiati at al. (Carminati et al., 2015) propose an approach to provide privacy while working around the current static model, such as using statistic models to detect anomalies in data and granting access to all data if they are requested during the presence of an anomaly. Semantics-based security policies can provide needed dynamic capabilities to protect privacy without hindering emergency management. An architecture that incorporates semantics-based security policy into a stream data model has the potential to provide a dynamic security policy that provides functionalities in emergencies without sacrificing privacy.

2.3 Vulnerabilities of Stream Access Control Enforcement via Syntactic Policy Enforcement

Nehme et al. (Nehme et al., 2013)(Nehme et al., 2008) proposed a security policy for stream data called security punctuation (sp). The security punctuations are inserted by the source of the stream to indicate the protection needs of the stream data. A security punctuation contains the following: punctuation type (pt), data description part (ddp), security restriction part(srp), sign, timestamp (ts), and enforcement (et). The security punctuation technique focuses on providing privacy control for the data source side. The current security policy is sent from the data source and specifies the security labels of attributes in the data tuple. This approach allows the data source side to decide the security needs which are suitable for privacy sensitive data domains, such as medical information.

Example 1: Security Punctuation Policy Examples.

1. Data Security Punctuation
$< dsp|S_1|R_1|+|1:00:00PM|I >$
Only queries registered by role R_1 can query the stream S_1.
$< dsp|A_1,A_2|R_2|+|1:00:00PM|D >$
Only queries registered by role R_2 can query the attributes A_1 and A_2 after 1PM.

2. Query Security Punctuation
$< qsp|null|R_3|+|1:00:00PM|I >$
Query acquires a role R_3.
$< qsp|S_2|R_4|+|1:00:00PM|D >$
Query acquires a role R_4 after 1PM and the role R_4 is permitted to only access stream S_2.

The security punctuation is subject to attacks that can destroy or delay the sp. This is a common vulnerability of syntax-based security policies. Malicious attackers can potentially disclose unauthorized data by changing the position of the target tuple or attribute, thus making the system interpret the security level incorrectly. For example, due to the nature of DSMS, the data can be accessed without authorization if the security policy is not updated with the correct time. The new sp can apply to only tuples which are still in the sliding window and tuples which arrive after sp. However, it cannot apply to tuples which are finished querying and not in the sliding window anymore. In the case that sp is destroyed during transmission, the policy will not be updated. This gives opportunities for attackers to access the unauthorized data with the outdated policy. In the case that sp is delayed during transmission, attackers can access the unauthorized data with the outdated policy until sp arrives. Moreover, if the data items are shuffled, the security punctuation that refers to the data

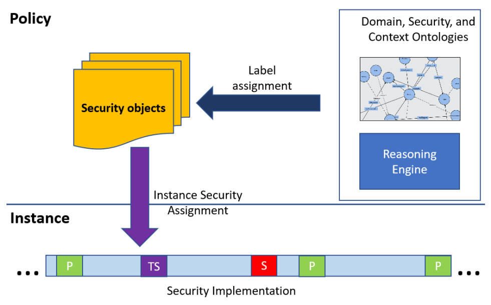


Figure 1: Architecture.

position in the tuple, may indicate the incorrect security requirements. Our work, that describes security for stream tuples based on data semantics, is independent of the actual stream syntax and can avoid these attacks. Moreover, our approach can be used with the security punctuation-based implementation to verify that the security has not been compromised.

3 ACCESS CONTROL ARCHITECTURE AND MOTIVATING EXAMPLE

The main focus of this work is to represent syntax-independent access control requirement for stream data. In this section, we present the system architecture for our stream data access control and a motivating example demonstrating the need for a semantics-based security model.

3.1 Architecture

We propose the use of ontologies to model domain and context semantics. Security requirements are expressed over the ontologies and dynamically updated according to context changes. Figure 1 shows the overview of our system architecture. The policy part of architecture contains domain and context ontologies, the reasoning engine, and the list of security objects. The policies will be applied on data instances of the stream. The reasoning engine will derive security labels from ontologies and assign them to security objects. The instances matching the security object descriptions will be assigned by security labels of those security objects.

3.2 Motivating Example

In this section, we present motivating examples to demonstrate the shortcomings of current stream data authorization models.

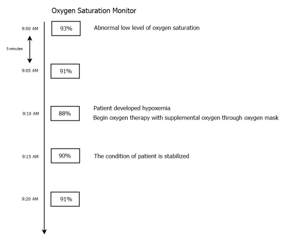

Oxygen Saturation Monitor
9:00 AM
93%
Abnormal low level of oxygen saturation
5 minutes
9:05 AM
91%
9:10 AM
88%
Patient developed hypoxemia
Begin oxygen therapy with supplemental oxygen through oxygen mask
9:15 AM
90%
The condition of patient is stabilized
9:20 AM
91%

Figure 2: Oxygen saturation monitoring results on a patient in an emergency ward.

In stream data, only a part of the data can be processed at any given time via continuous queries. The data will be processed with the same queries over and over again. A different order of the same stream tuples may result in different computational results. Similarly, missing tuples will impact the results of the continuous queries. Incorrect ordering can be detected in case the timestamps are correct. However, malicious users may modify the timestamp to achieve a desired evaluation schedule. Moreover, the completeness of the stream may be difficult to detect if there is no predetermined schedule for the arrival of the stream tuples. Next, we present a hypothetical scenario that may occur in the presence of malicious users.

Incorrect Oxygen Saturation Measurement. Health monitoring sensors broadcast vital signs, such as body temperature, pulse rate, respiration rate, blood pressure, and pulse oximetry. These vital signs are frequently observed by medical staffs during hospital admission. The frequency can vary depending on the condition of patients. For example, pulse oximetry measures the oxygen saturation in the blood. The normal value is between 95-100%. An oxygen saturation value below 90% is referred to as hypoxemia. Patients generally show signs of mental impairment at oxygen saturation below 85% and completely lose consciousness at below 75%(Powell et al., 1996). The presence of hypoxemia is generally caused by underlying conditions of the heart or lungs, which may require emergency care. The lack of oxygen from hypoxemia can lead to a wide range of complications from minor headaches to respiratory failure, which can lead to death or permanent brain damage in a matter of minutes without an immediate response. The oxygen saturation level is generally observed every 4 hours in admitted patient care but constantly observed in critically ill patient cases.

Figure 2 shows an example of oxygen saturation monitoring results. In this example, as soon as hypoxemia was detected, treatment was initiated. The timely treatment prevented long-term complications for the patient.

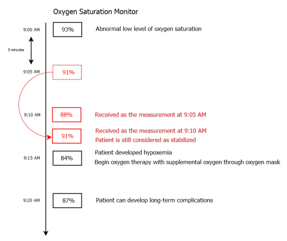

Oxygen Saturation Monitor
9:00 AM
93%
Abnormal low level of oxygen saturation
5 minutes
9:05 AM
91%
9:10 AM
88%
Received as the measurement at 9:05 AM
91%
Received as the measurement at 9:10 AM
Patient is still considered as stabilized
9:15 AM
84%
Patient developed hypoxemia
Begin oxygen therapy with supplemental oxygen through oxygen mask
9:20 AM
87%
Patient can develop long-term complications

Figure 3: Incorrect order of monitoring results.

Figure 3 shows an example of the same situation as Figure 2 with an incorrect ordering. The medical staff missed the early low oxygen saturation sign at 9:10 AM and didn't initiate the emergency procedure. To avoid penalty, they switched the timestamp of the measurements, claiming that the readings were inconclusive. The patient did not receive appropriate treatment in time which lead to long-term complications.

4 STREAM DATA MODEL

In addition to traditional data security requirements, stream data requires security capabilities to provide semantics-based dynamic security policy. Incomplete data and incorrect order may affect the integrity and security of the stream data. They also cannot be addressed with relational database security approaches. A semantics-based dynamic security policy is needed to provide fast and situation-responsive availability. It can also counter attribute shuffle attacks which are unique to the stream data model due to the lack of metadata in tuples.

In this section, we present our framework to address the above requirements.

Definition 1. *Data Schema*
A data schema D is a set of attribute names denoted by $D(A_1,...,A_n)$, where D is the name of the data schema and $A_i | i \in \{1,...,n\}$ is an attribute name.

Definition 2. *Data Instance on Data Schema D*
A data instance d on data schema $D(A_1,...,A_n)$ is denoted as $d =< a_1,...,a_n >$, where $a_i | i \in \{1,...,n\}$ is the value of attribute A_i such that a_i is in the domain of attribute A_i, i.e., $a_i \in Dom(A_i)$.
We also denote data instance d as $d =< A_1 = a_1,...,A_n = a_n >$ to explicitly identify the attribute values.

Definition 3. *Stream Tuple*
A stream tuple t from source l is denoted as $t = (l,d,ts)$, where ts is a timestamp representing the time when t was generated.

Example 2: A stream tuple t_1 from source $sensor_1$ at 1:00AM

t_1 = ($sensor_1$, $< A_1 = 10, A_2 = 20, A_1 = 30 >$, 1:00:00AM)

The above stream tuple t_1 was generated by source $sensor_1$ at 1:00:00AM. It contains a data instance $d =< A_1 = 10, A_2 = 20, A_1 = 30 >$ which specify the value of attribute A_1 is 10, the value of attribute A_2 is 20, and the value of attribute A_3 is 30.

Definition 4. *Data Stream*
A data stream S from source l during a time period from ts_j to ts_k is denoted as $S_l =< t_j,...,t_k >$, where $t_i = (l_i, d_i, ts_i)$ such that $l_i = l$ and $< ts_j,...,ts_k >$ is a sequence of timestamps during a time period from ts_j to ts_k.
We also denote a data stream S from source l during time interval from ts_j to ts_k as $S_l[ts_j,ts_k] =< t_j,...,t_k >$ or $S_l[ts_j,ts_k] =< (l,d_j,ts_j),...,(l,d_k,ts_k) >$.

Definition 5. *Stream Bundle*
Let ts denotes a timestamp and $l_1,...,l_n$ denote stream data sources. A stream bundle at the time ts, denoted as
$B_{ts} = \{(l_1,d_1,ts),...,(l_n,d_n,ts)\}$, is the set of stream tuples generated by the sources $l_1,...,l_n$ at time ts.
Note, at this point we do not address the issue of incompatible time stamps due to different levels of precision of the sources or due to the lack of synchronization.

Definition 6. *Atomic Protected Object Pattern*
An atomic protected object pattern, also referred to as an atomic protected object, is a triple consisting of 3 elements; a source description, a data description, and a timestamp description. A protected object o is denoted as
$o = ((l,exp_l),(d,exp_d),(ts,exp_{ts}))$
where each element is as follows. Let v denotes a variable, c denotes a constant, A_i an attribute name in d, and op denotes the operation $=$ or $<$. Note, we require that all attributes of the expressions are bounded, i.e., they must appear in the corresponding element l,d or ts.

1. A source description (l,exp_l) where
   (a) l is a data source c, such that c is a valid source, or v;
   (b) exp_l is a Boolean expression of the form $Component_1$ AND ... AND $Component_n$, where $Component_i$ $(i = 1,\ldots,n)$ is $TRUE$ or $(v\ op\ c)$.

   We also denote a source description $(v,TRUE)$, representing any source, as $(*)$.

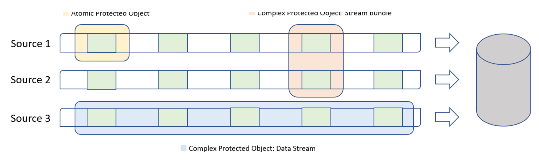

Atomic Protected Object
Complex Protected Object: Stream Bundle
Source 1
Source 2
Source 3
Complex Protected Object: Data Stream

Figure 4: Examples of different kinds of protected objects; 1. Atomic Protected Object:A tuple, 2. Stream Bundle: Tuples from multiple sources which arrive at the same time period, 3. Data Stream: Multiple tuples which continuous arrive from a single source

2. *A data description* (d, exp_d) *where*
   (a) *d is a data instance on data schema D, denoted as $d = < A_1 = k_1, ..., A_n = k_n >$, where k_i $(i = 1, \dots, n)$ is c, such that $c \in Dom(A_i)$ or v;*
   (b) *exp_d is a Boolean expression of the form $Component_1$ AND ... AND $Component_n$, where $Component_i$ $(i = 1, \dots, n)$ is $TRUE$, $(v_i\ op\ c)$, $(v_i\ op\ v_j)$, $(A_i\ op\ c)$, $(A_i\ op\ v_i)$, or $(A_i\ op\ A_j)$.*

   We also denote a data description $(< A_1 = v_1, ..., A_n = v_n >, TRUE)$, representing any data instance on data schema D, as $(*)$.
3. *A timestamp description* (ts, exp_{ts}) *where*
   (a) *ts is a timestamp, such that ts is c or v;*
   (b) *exp_{ts} is a Boolean expression of the form $Component_1$ AND ... AND $Component_n$, where $Component_i$ is $TRUE$ or $(v\ op\ c)$.*

   We also denote a timestamp description $(v, TRUE)$, representing any timestamp, as $(*)$.

Definition 7. *Simple Object Valuation*
Let ν be a symbol mapping, such that;

1. *ν maps a constant c to itself, i.e., $\nu : c \longrightarrow c$.*
2. *ν preserves equality of variables, i.e., $\nu : v \longrightarrow c_1$ and $\nu : v \longrightarrow c_2$ then $c_1 = c_2$.*
3. *ν maps special symbols to themselves, i.e., $\nu : = \longrightarrow =$, $\nu : < \longrightarrow <$.*
4. *ν maps an expression $\nu(x\ op\ y) = \nu(x)\ op\ \nu(y)$, where x, y are any of the symbols above.*

Definition 8. *Stream Pattern Mapping*
*Let $o = ((l, exp_l), (d = < A_1 = k_1, ..., A_n = k_n >, exp_d),$
$(ts, exp_{ts}))$ be an atomic protection object, and ν a symbol mapping. A stream pattern mapping N is defined as;*

1. *$N(l, exp_l)$ is defined as*
   $N(l, exp_l) = (\nu(l), \nu(exp_l))$.
2. *$N(< A_1 = k_1, ..., A_n = k_n >, exp_d)$ is defined as*
   $N(< A_1 = k_1, ..., A_n = k_n >, exp_d)) = (< \nu(A_1) = \nu(k_1), ..., \nu(A_n) = \nu(k_n) >, \nu(exp_d))$
   and $N(A_i) = N(k_i) = \nu(k_i)$.
3. *$N(ts, exp_{ts})$ is defined as*
   $N(ts, exp_{ts}) = (\nu(ts), \nu(exp_{ts}))$.

Definition 9. *Stream Pattern Mapping Satisfiability*
Let o be an atomic protected object. We say that the stream tuple t satisfies o iff there is a pattern mapping N from o to t denoted as $N(o) = t$, such that $N(exp_l)$ = $TRUE$, $N(exp_d)$ = $TRUE$, and $N(exp_{ts})$ = $TRUE$. Note, from now on, we only consider satisfied mapping when we use the phrase "pattern mapping".

Example 3: Protected Object Mapping.

Given protected object o_1 and tuples t_1, t_2
o_1 = (($sensor_1$,TRUE),(< $A_1 = v_1, A_2 = 20$ >, $v_1 < 20$
  AND $10 < v_1$),(v_2,TRUE))

t_1 = ($sensor_1$,< $A_1 = 15, A_2 = 20$ >,2:00:00AM)
t_2 = ($sensor_1$,< $A_1 = 10, A_2 = 20$ >,2:05:00AM)

Mapping o_1 to tuple t_1
1. The valuation from source description (l, exp_l)
  to source l_k
    $\nu(sensor_1)$ = $sensor_1$
    $\nu(exp_l)$ = TRUE
    Conditions in 1. are satisfied.
2. The valuation from data description (d, exp_d) to
  data instance d_k
    $\nu(v_1)$ = 15
    $\nu(20)$ = 20
    $\nu(exp_d)$ = $\nu(v_1)$<20 AND 10<$\nu(v_1)$ → 15<20 AND 10<15
    $\nu(exp_d)$ = TRUE
    Conditions in 2. are satisfied.
3. The valuation from tuple description
  (ts, exp_{ts}) to timestamp ts_k
    $\nu(v_2)$ = 2:00:00AM
    $\nu(exp_{ts})$ = TRUE
    Conditions in 3. are satisfied.
All valuations are satisfied. t_1 is a member of o_1.

Mapping o_1 to tuple t_2
1. The valuation from source description (l, exp_l)
  to source l_k
    $\nu(sensor_1)$ = $sensor_1$
    $\nu(exp_l)$ = TRUE
    Conditions in 1. are satisfied.
2. The valuation from data description (d, exp_d) to
  data instance d_k
    $\nu(v_1)$ = 10
    $\nu(20)$ = 20
    $\nu(exp_d)$ = $\nu(v_1)$<20 AND 10<$\nu(v_1)$ → 10<20 AND 10<10
    $\nu(exp_d)$ = FALSE
    Condition in 2. is not satisfied.
3. The valuation from tuple description
  (ts, exp_{ts}) to timestamp ts_k
    $\nu(v_2)$ = 2:05:00AM
    $\nu(exp_{ts})$ = TRUE
    Conditions in 3. are satisfied.
Valuation 2. is not satisfied. t_2 is not a member of o_1.

Definition 10. *Object Dominance*
Let o_1 and o_2 protected objects. We say that o_1 dominates o_2 if for every tuple t, there is a valuation $\nu(o_2) = t$, there must be a valuation $\nu(o_1)$ such that $\nu(o_1) = t$. We denote o_1 dominates o_2 as $o_1 \supseteq_d o_2$. Object dominance is reflective, transitive, and asymmetric, i.e., if $o_1 \supseteq_d o_2$ and $o_2 \supseteq_d o_3$ then $o_1 \supseteq_d o_3$.

5 SECURITY MODEL

We assign the default security labels for each entity on ontologies. Those default security labels represent

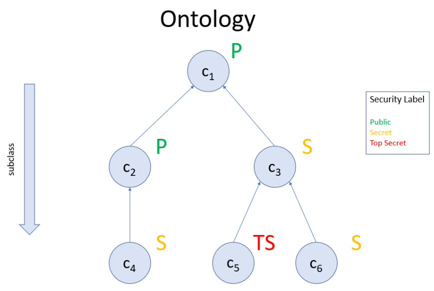


Figure 5: Ontology with Security Labels.

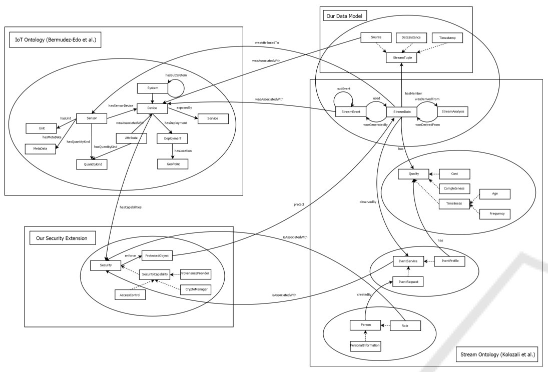

IoT Ontology (Bermudez-Edo et al.)
Our Data Model
Our Security Extension
Stream Ontology (Kolozali et al.)

Figure 6: Stream Ontology.

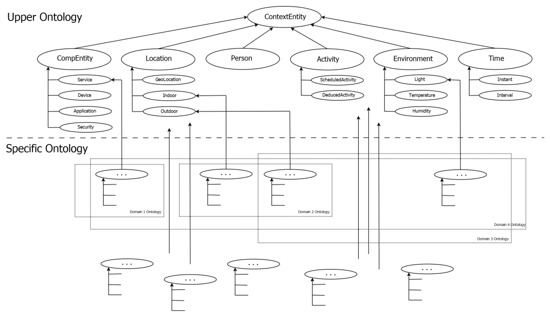


Figure 7: Context Ontology (Preuveneers et al., 2004) (Qin et al., 2007) (Wang et al., 2004).

security labels in the normal situation. We use a context reasoner to decide what is the current situation and assign an appropriate security label according to that situation. In this section, we give a brief overview of the ontologies and context reasoner.

5.1 Stream Data and Security Ontology

We expand the stream data ontology introduced by Kolozali et al. (Kolozali et al., 2014), adding data security. Traditional access control models consider security to be a passive property of data quality. However, security is a complex entity associated with many parts of the stream data, e.g., security capabilities that devices can provide, security associated role of users, and security property of data. We built an ontology containing six main modules: Stream Data, Device, Quality, User, Event, and Security.

Stream ontology is generalized so it can represent the stream data environment. We extend the stream ontology to represent the context of the stream data. The transmitted data may have different meanings in different contexts. We develop additional specific context ontologies for the data domain of each individual system. We further extend the stream ontology with the context ontology.

We present an extensible context ontology for modeling context in stream data environments. We follow the context model from CONON (Wang et al., 2004) and divide our context ontology into upper ontology and specific ontology. Our upper ontology contains all basic contextual entities from CONON with additional entities from CoDAMoS (Preuveneers et al., 2004) and Smart Space (Qin et al., 2007). The upper ontology describes 6 basic concepts: CompEntity, Location, Person, Activity, Environment, and Time. The specific ontology represents the details of general concepts in each sub-domain.

5.2 Context Reasoning

To illustrate the logical reasoning mechanism, we present a scenario in which the data generated from sensors can have different levels of security policies depending on the current situation. For example, when people are sleeping, their oxygen saturation levels will naturally decrease because their body needs less oxygen. Their bodies will reduce the respiration rate and heart rate during sleep. While the oxygen saturation will also decrease during exercise, this happens due to the body consuming more oxygen. Despite having low oxygen saturation, the respiration rate and heart rate will increase during exercise. An oxygen saturation value during rest that is below 90% is considered a medical condition called hypoxemia. However, an oxygen saturation value of 88% can be considered normal during intense exercise. In this case, the oxygen saturation alone cannot determine the condition of hypoxemia; the respiration rate and heart rate must also be considered. We want to provide a dynamic security policy to protect patient A's privacy by limiting access during normal situations but allowing access during emergencies. By using the context and ontology rules, we can derive that the current oxygen saturation is normal or is indicating an emergency situation. The security label assignments can be defined as $\lambda(o_1) = TopSecret$ and $\lambda(o_2) = Public$ where o_1 is an oxygen saturation during a normal situation and o_2 is an oxygen saturation during an emergency situation. The protected objects can be separated into 2 cases; rest and exercise and be defined as the following example;

Example 4: Protected Objects in Different Situations.

A protected object o_{1a} representing a normal situation during resting

o_{1a} = ((source=$patient_A$,TRUE), ($<oxygenSaturation = v_1$, $respirationRate = v_2$, $heartRate = v_3>$, $90 < v_1$), $*$)

A protected object o_{1b} representing a normal situation during exercising

o_{1b} = ((source=$patient_A$,TRUE), ($<oxygenSaturation = v_1$, $respirationRate = v_2$, $heartRate = v_3>$, $88 < v_1$ AND $40 < v_2$ AND $150 < v_3$), $*$)

A protected object o_{2a} representing an emergency situation during resting

o_{2a} = ((source=$patient_A$,TRUE), ($<oxygenSaturation = v_1$, $respirationRate = v_2$, $heartRate = v_3>$, $v_1 < 90$ AND $v_2 < 40$ AND $v_3 < 150$), $*$)

A protected object o_{2b} representing an emergency situation during exercising

o_{2b} = ((source=$patient_A$,TRUE), ($<oxygenSaturation = v_1$, $respirationRate = v_2$, $heartRate = v_3>$, $v_1 < 88$ AND $40 < v_2$ AND $150 < v_3$), $*$)

Definition 11. *Ontology Mapping*
Let O denote the ontology entity, and $o = ((l, exp_l), (d, exp_d), (ts, exp_{ts}))$ be an atomic protection object, and ν a symbol mapping. An ontology mapping N is defined as;

1. *If O is a CompEntity concept entity, $N(O) = o = ((l, exp_l), (d, TRUE), (ts, TRUE)$ where (l, exp_l) is the source corresponding to compEntity O with its associated location concept, and both $(d, TRUE)$, $(ts, TRUE)$ can be any given data description and timestamp description.*
2. *If O is either person, activity, or environment concept entity, $N(O) = o = ((l, TRUE), (d, exp_d), (ts, TRUE)$ where (d, exp_d) is the attributes corresponding to either person, activity, or environment concept associated with O, and both $(l, TRUE)$, $(ts, TRUE)$ can be any given source description and data description.*
3. *If O is a time concept entity, $N(O) = o = ((l, TRUE), (d, TRUE), (ts, exp_{ts}))$ where (ts, exp_{ts}) is the timestamp corresponding to time concept O, and both $(l, TRUE)$, $(d, TRUE)$ can be any given source description and data description.*
4. *If O is an ontology entity associated with more than one concept, $N(O) = o = ((l, exp_l), (d, exp_d), (ts, exp_{ts}))$ where (l, exp_l), (d, exp_d), (ts, exp_{ts}) are the source, attributes, and timestamp corresponding to ontology entity O.*

Definition 12. *Protection Object Security Label Assignment*
Let O_{Dom} denote the domain ontology, and Λ the mapping of security labels to the concepts in O_{Dom}. We denote $\Lambda(O_{Dom})$ the assignment of security labels to all the concepts in the ontology, and $\lambda(ct_i)$ to denote the security label of the concept ct_i. We require that $\lambda(ct_i) \geq \lambda(ct_j)$ if ct_i is a descendent of ct_j). The set of Core Security Objects (CSO) is the set of all object patterns corresponding to the ontological concepts. That is, for $CSO = (ct_s, TRUE), (ct_d, TRUE), (ct_{ts}, TRUE)$, $\Lambda(CSO) = LUB(\lambda(ct_s), \lambda(ct_d), \lambda(ct_{ts}))$.

Additional security restrictions due to context-aware or temporal needs, may be expressed over more specific protection objects. Let $o_1 \supseteq_d o_2$, then $\Lambda(o_1) \leq \Lambda(o_2)$.

Note, that emergency scenarios may require modification of core security object classifications and, in our current model, can only be handled by reassigning labels to the ontological concepts.

Definition 13. *Instance Label Assignment*
Let t be a data stream tuple and $N(o_1), \ldots, N(o_k)$ be satisfiable pattern mapping from protected objects $o_1, \ldots, o_k$ to t, where
$\lambda(o_1), \ldots, \lambda(o_k)$ are the security labels of $o_i | i \in \{1, \ldots, k\}$. We say that the security label of t is $LUB(\lambda(o_i)) | i \in \{1, \ldots, k\}$ where $LUB(\lambda(o_i))$ is the lowest upper bound of the security labels $\lambda(o_1), \ldots, \lambda(o_k)$.

Algorithm 1: Assign security label to stream tuple.

```
Require: Stream tuple $t$, and security labels of all protected objects $\lambda(o_1), \ldots, \lambda(o_n)$
Ensure: Label assignment to a stream tuple
1: Initialization
2: Find all pattern mappings $N_1, \ldots, N_k$ from $O$ (all protected objects) that are satisfied by $t$
3: Let $\{o_i, \ldots, o_k\} \in O$ be the protected objects that can be mapped by $N_1, \ldots, N_k$ to $t$
4: Let $\lambda(t) = LUB(\lambda(o_i), \ldots, \lambda(o_k))$
```

Example 5: Security Label Assignment to Stream Tuple.

Security Labels: TopSecret(TS) $>$ Secret(S) $>$ Public(P)
t_1 = (($sensor_1$, TRUE), $<A_1 = 20, A_2 = 20>$, 2:00:00AM)

CASE 1:
o_1 = (($sensor_1$,TRUE), ($<A_1 = v_1, A_2 = 20>$, $v_1 < 50$), (v_2,TRUE))
o_2 = (($sensor_1$,TRUE), ($<A_1 = v_1, A_2 = 20>$, $v_1 < 10$), (v_2,TRUE))
$\lambda(o_1) = Secret$
$\lambda(o_2) = TopSecret$

Assign security label to t_1

```
 $t_1$ is mapped to $o_1$.
 Label of $t_1$ = $\lambda(o_1)$ = Secret.

 CASE 2:
 $o_1$ = (($sensor_1$,TRUE),($< A_1 = v_1, A_2 = 20 >$,$v_1 < 50$),
        ($v_2$,TRUE))
 $o_2$ = (($sensor_1$,TRUE),($< A_1 = v_1, A_2 = 20 >$,$v_1 < 30$),
        ($v_2$,TRUE))
 $\lambda(o_1) = Secret$
 $\lambda(o_2) = TopSecret$

 Assign security label to $t_1$
 $t_1$ is mapped to both $o_1$ and $o_2$.
 $LUB(\lambda(o_1), \lambda(o_2)) = \lambda(o_2)$
 Label of $t_1$ = $\lambda(o_2)$ = Top Secret.
```

Next, we propose the concept of a complex protected object. This allows to express protection needs over aggregates of stream tuples, while allowing maximum availability of the individual tuples.

Definition 14. *Complex Protected Object*
Let $o_1, ..., o_n$ be the atomic protected objects. We say that data stream $S = < o_1, ..., o_n >$ or stream bundle $B = \{o_1, ..., o_n\}$ is a complex protected object O_c iff $\lambda(O_c) = \lambda(S) > LUB(\lambda(o_i)) | i \in \{1, ..., n\}$ or $\lambda(O_c) = \lambda(B) > LUB(\lambda(o_i)) | i \in \{1, ..., n\}$.
O_c is minimal, that is for any o_i, $\bar{O}_c = O_c - o_i$ then $\lambda(\bar{O}_c) \not> LUB(\lambda(o_j)) | j \in (\{1, ..., n\} - \{i\})$. And there are no two objects o_i and o_j such that $o_i \supseteq_d o_j$

Theorem 1. *Given a stream tuple t and security labels of all protected objects $\lambda(o_1), ..., \lambda(o_n)$. Algorithm 1 correctly assigns a security label to a stream tuple t such that the assigned label l is the LUB of all labels of security objects that can be mapped to t.*

Proof. By contradiction;
Let $\lambda(o_k)$ be a security label assigned to a stream tuple t. Assume that $\lambda(o_k)$ does not satisfy the security requirement of t.
Case 1: o_k cannot be mapped to t

1. From algorithm 1, o_k must be a protected object that can be mapped to t.
2. So t must be a member of o_k. This contradicts the supposition that t is not a member of o_k.

Case 2: Security label $\lambda(o_k)$ is lower than the security requirement of t

1. There must exist a o_t such that $\nu(o_t) > \nu(o_k)$ and there is a pattern mapping from o_t to t, $\nu(o_t) = t$.
2. But the algorithm 1, $\lambda(t)$ is assigned by $LUB(\lambda(o_i), ..., \lambda(o_t), ..., \lambda(o_j))$ where $\{o_i, ..., o_j\}$ be the protected objects that can be mapped to t.
3. So $\lambda(o_k)$ must be $LUB(\lambda(o_i), ..., \lambda(o_j))$ which is the highest security labels of protected objects mapped to t. This contradicts the supposition that $\lambda(o_k)$ is lower than the security requirement of t

Case 3: Security label $\lambda(o_k)$ is higher than the security requirements of t

1. From algorithm 1, $\lambda(t)$ is assigned by $LUB(\lambda(o_i), ..., \lambda(o_j))$ where $\{o_i, ..., o_j\}$ be the protected objects that can be mapped to t.
2. So $\lambda(o_k)$ must be $LUB(\lambda(o_i), ..., \lambda(o_j))$ which is the highest security labels of protected objects mapped to t. This contradicts the supposition that $\lambda(o_k)$ is higher than the security requirement of t

□

6 IMPLEMENTATION

In our previous work (Rhujittawiwat et al., 2021), we implemented our context-aware security policy engine. We implemented our framework using Protégé (Stanford, 2022) and Semantic Web Rule Language (SWRL) on an open-source home automation called Home Assistant (Home Assistant, 2021). Figure 8 shows a simplified ontology containing StreamTuple and ProtectedObject and figure 9 shows a protected object with simple elements describing the source, data instance, timestamp, and security label. SWRL allows us to write reasoning rules to assign security labels where protected object $o = ((source = l, exp_l), (d, exp_d), (timestamp = ts, exp_{ts}))$ with label assignment $\lambda(o) = Label$ in the form as following;

$$\begin{aligned} & StreamTuple(?t) \\ & \quad \wedge hasSource(?t, N(source = l, exp_l)) \\ & \quad \wedge hasDataInstance(?t, N(d, exp_d)) \\ & \qquad \wedge hasTimestamp(?t, N(timestamp = ts, exp_{ts})) \\ & \qquad \rightarrow hasLabel(?t, Label) \end{aligned} \tag{1}$$

Where $N(source = l, exp_l)$, $N(d, exp_d)$, and $N(timestamp = ts, exp_{ts})$ can be derived from;

$$\begin{aligned} & ProtectedObject(?o) \\ & \quad \wedge source(?o, ?source) \\ & \quad \wedge dataInstance(?o, ?data) \\ & \quad \wedge timestamp(?o, ?timestamp) \\ & \quad \wedge StreamTuple(?t) \\ & \quad \wedge hasSource(?t, ?source) \\ & \quad \wedge hasDataInstance(?t, ?data) \\ & \quad \wedge hasTimestamp(?t, ?timestamp) \end{aligned} \tag{2}$$

We show the SWRL rule to assign a security label in figure 10 and the result where the label is assigned to a stream tuple in figure 11

We use XML to facilitate data exchange between Home Assistant and Protégé. This approach makes it possible to extend data sharing for future applications. Figure 12 outlines how the data is extracted

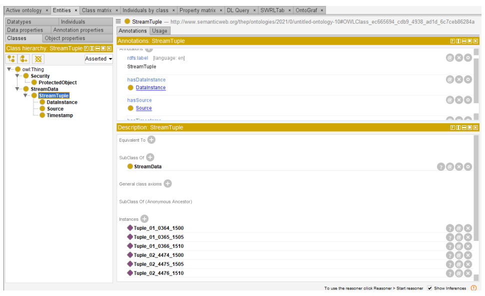


Figure 8: The Stream Ontology in the Protégé.

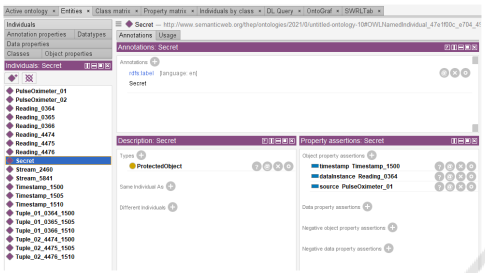
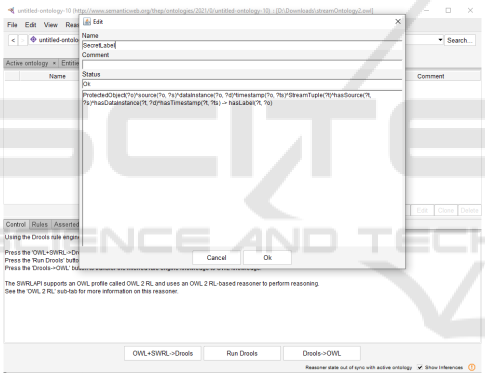


Figure 9: The Protected Object in the Protégé.


Edit

Name: SecretLabel

Comment:

Status: Ok

```
ProtectedObject(?o)^source(?o, ?s)^dataInstance(?o, ?d)^timestamp(?o, ?ts)^StreamTuple(?t)^hasSource(?t,
?s)^hasDataInstance(?t, ?d)^hasTimestamp(?t, ?ts) -> hasLabel(?t, ?o)
```

The SWRLAPI supports an OWL profile called OWL 2 RL and uses an OWL 2 RL-based reasoner to perform reasoning.
See the 'OWL 2 RL' sub-tab for more information on this reasoner.

Figure 10: Label assignment with SWRL in the Protégé.

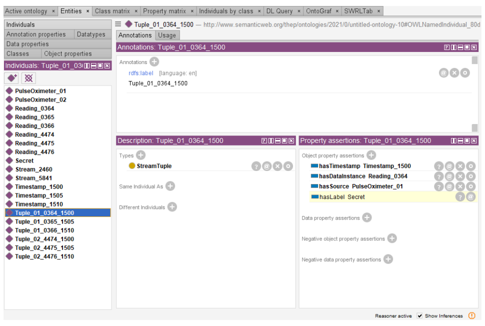

Individuals: Tuple_01_0364_1500
Description: Tuple_01_0364_1500
Types
StreamTuple
Property assertions: Tuple_01_0364_1500
hasTimestamp Timestamp_1500
hasDataInstance Reading_0364
hasSource PulseOximeter_01
hasLabel Secret

Figure 11: Reasoning result from label assignment.

from the Home Assistant database, converted to the XML schema, and shared with Protégé. Similarly, the decision reached by Protégé is converted to the XML format, and incorporated into the Home Assistant database.

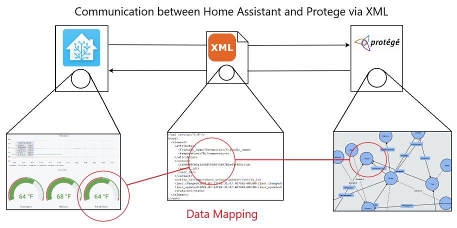


Figure 12: Communication between Home Assistant and Protégé via XML (Rhujittawiwat et al., 2021)

To get data from Protégé into Home Assistant, we converted the CSV file that was exported from Protégé. We created bash scripts to convert data from each side to XML and convert XML to respective data formats for each sides. Our ongoing work addresses the security label enforcement using security punctuation.

7 CONCLUSION

In this paper, we proposed a semantics-based access control model for stream data. Our solution eliminates the dependency on stream syntax and provides 1) syntax independent expression of security requirements, 2) high assurance of security compliance over the IoT network, and 3) dynamic and adaptable security policy representation. We proposed the concept of a stream data protection object that allows a user-friendly and inter-operable expression of the protected data. We developed techniques so stream data instances can inherit security requirements from the protection object. In our model, we support strong security by enforcing the most restrictive security requirement that an instance inherits. We also coupled our security model with context-based security. The security restrictions of the protection objects may change based on the current context. Our work provides an approach to support data security for the rapidly evolving IoT environment. We applied technologies that are widely used for IoT applications to support data integration and intelligent analysis, thus our model is compliant with the technologies already used by the industry.

REFERENCES

Alharbi, R. and Aspinall, D. (2018). An iot analysis framework: An investigation of iot smart cameras' vulnerabilities. In *Living in the Internet of Things: Cybersecurity of the IoT - 2018*. IET.

Bermudez-Edo, M., Elsaleh, T., Barnaghi, P., and Taylor, K. (2015). Iot-lite ontology.

Bermudez-Edo, M., Elsaleh, T., Barnaghi, P., and Taylor, K. (2016). Iot-lite: a lightweight semantic model for the internet of things. In *2016 INTL IEEE conferences on ubiquitous intelligence & computing, advanced and trusted computing, scalable computing and communications, cloud and big data computing, internet of people, and smart world congress (uic/atc/scalcom/cbdcom/iop/smartworld)*, pages 90–97. IEEE.

Cao, J., Carminati, B., Ferrari, E., and Tan, K.-L. (2009). Acstream: Enforcing access control over data streams. In *2009 IEEE 25th International Conference on Data Engineering*, pages 1495–1498. IEEE.

Carminati, B., Ferrari, E., Cao, J., and Tan, K. L. (2010). A framework to enforce access control over data streams. *ACM Transactions on Information and System Security (TISSEC)*, 13(3):1–31.

Carminati, B., Ferrari, E., and Guglielmi, M. (2015). Detection of unspecified emergencies for controlled information sharing. *IEEE Transactions on Dependable and Secure Computing*, 13(6):630–643.

Carminati, B., Ferrari, E., and Tan, K. L. (2007a). Enforcing access control over data streams. In *Proceedings of the 12th ACM symposium on Access control models and technologies*, pages 21–30.

Carminati, B., Ferrari, E., and Tan, K. L. (2007b). Specifying access control policies on data streams. In *International Conference on Database Systems for Advanced Applications*, pages 410–421. Springer.

Celdrán, A. H., Clemente, F. J. G., Pérez, M. G., and Pérez, G. M. (2014). Secoman: A semantic-aware policy framework for developing privacy-preserving and context-aware smart applications. *IEEE Systems Journal*, 10(3):1111–1124.

Chen, H., Finin, T., and Joshi, A. (2003). An ontology for context-aware pervasive computing environments. *The knowledge engineering review*, 18(3):197–207.

Choi, C., Choi, J., and Kim, P. (2014). Ontology-based access control model for security policy reasoning in cloud computing. *The Journal of Supercomputing*, 67(3):711–722.

Guo, H., Li, Y., and Jajodia, S. (2007). Chaining watermarks for detecting malicious modifications to streaming data. *Inf. Sci.*, 177(1):281–298.

Home Assistant (2021). Open source home automation. http://www.home-assistant.io/.

Janes, B., Crawford, H., and OConnor, T. (2020). Never ending story: Authentication and access control design flaws in shared iot devices. In *2020 IEEE Security and Privacy Workshops (SPW)*, pages 104–109. IEEE.

Jeong, Y.-S., Lee, S.-H., and Shin, S.-S. (2014). Access control protocol based on privacy property of patient in m-healthcare emergency. *Wireless personal communications*, 79(4):2565–2578.

Kolozali, S., Bermudez-Edo, M., Puschmann, D., Ganz, F., and Barnaghi, P. (2014). A knowledge-based approach for real-time iot data stream annotation and processing. In *2014 IEEE International Conference on Internet of Things (iThings), and IEEE Green Computing and Communications (GreenCom) and IEEE Cyber, Physical and Social Computing (CPSCom)*, pages 215–222. IEEE.

Le-Phuoc, D., Dao-Tran, M., Parreira, J. X., and Hauswirth, M. (2011). A native and adaptive approach for unified processing of linked streams and linked data. In *International Semantic Web Conference*, pages 370–388. Springer.

Lee, C.-C., Hsu, C.-W., Lai, Y.-M., and Vasilakos, A. (2013). An enhanced mobile-healthcare emergency system based on extended chaotic maps. *Journal of medical systems*, 37(5):9973.

Lu, R., Lin, X., and Shen, X. (2012). Spoc: A secure and privacy-preserving opportunistic computing framework for mobile-healthcare emergency. *IEEE transactions on parallel and distributed systems*, 24(3):614–624.

Manogaran, G., Thota, C., Lopez, D., and Sundarasekar, R. (2017). Big data security intelligence for healthcare industry 4.0. In *Cybersecurity for Industry 4.0*, pages 103–126. Springer.

Mengke, Y., Xiaoguang, Z., Jianqiu, Z., and Jianjian, X. (2016). Challenges and solutions of information security issues in the age of big data. *China Communications*, 13(3):193–202.

Montanari, R., Toninelli, A., and Bradshaw, J. M. (2005). Context-based security management for multi-agent systems. In *IEEE 2nd Symposium on Multi-Agent Security and Survivability, 2005.*, pages 75–84. IEEE.

Nambiar, S., Kalambur, S., and Sitaram, D. (2020). Modeling access control on streaming data in apache storm. *Procedia Computer Science*, 171:2734–2739.

Nehme, R. V., Lim, H.-S., and Bertino, E. (2013). Fence: Continuous access control enforcement in dynamic data stream environments. In *Proceedings of the third ACM conference on Data and application security and privacy*, pages 243–254.

Nehme, R. V., Rundensteiner, E. A., and Bertino, E. (2008). A security punctuation framework for enforcing access control on streaming data. In *2008 IEEE 24th International Conference on Data Engineering*, pages 406–415. IEEE.

Penrig, A., Song, D., and Tygar, D. (2000). Elk, a new protocol for efficient large-group key distribution. In *Proceedings 2001 IEEE Symposium on Security and Privacy. S&P 2001*, pages 247–262. IEEE.

Powell, J., Menon, D., and Jones, J. (1996). The effects of hypoxaemia and recommendations for postoperative oxygen therapy. *Anaesthesia*, 51(8):769–772.

Preuveneers, D., Van den Bergh, J., Wagelaar, D., Georges, A., Rigole, P., Clerckx, T., Berbers, Y., Coninx, K., Jonckers, V., and De Bosschere, K. (2004). Towards an extensible context ontology for ambient intelligence. In *European Symposium on Ambient Intelligence*, pages 148–159. Springer.

Puthal, D., Nepal, S., Ranjan, R., and Chen, J. (2015). A dynamic key length based approach for real-time security verification of big sensing data stream. In *Inter-*

national conference on web information systems engineering, pages 93–108. Springer.

Puthal, D., Wu, X., Nepal, S., Ranjan, R., and Chen, J. (2017). Seen: A selective encryption method to ensure confidentiality for big sensing data streams. *IEEE Transactions on Big Data*.

Qin, W., Shi, Y., and Suo, Y. (2007). Ontology-based context-aware middleware for smart spaces. *Tsinghua Science and Technology*, 12(6):707–713.

Ren, J., Dubois, D. J., Choffnes, D., Mandalari, A. M., Kolcun, R., and Haddadi, H. (2019). Information exposure from consumer iot devices: A multidimensional, network-informed measurement approach. In *Proceedings of the Internet Measurement Conference*, pages 267–279.

Rhujittawiwat, T., Anderson, C., Keen, D., Miles, C., Farkas, C., Smiles, S., Wells, N., Roginski, J., Frederick, S., and Banik, S. (2021). Making smart platforms smarter: adding third party applications to home automation platforms. *Journal of Computing Sciences in Colleges*, 37(5):43–53.

Sabelfeld, A. and Myers, A. C. (2003). Language-based information-flow security. *IEEE Journal on selected areas in communications*, 21(1):5–19.

Sejdiu, B., Ismaili, F., and Ahmedi, L. (2021). Iotsas: an integrated system for real-time semantic annotation and interpretation of iot sensor stream data. *Computers*, 10(10):127.

Shafagh, H., Burkhalter, L., Ratnasamy, S., and Hithnawi, A. (2020). Droplet: Decentralized authorization and access control for encrypted data streams. In *29th USENIX Security Symposium (USENIX Security 20)*, pages 2469–2486.

Stanford (2022). Protégé.

Thoma, C., Labrinidis, A., and Lee, A. J. (2019). Shoal: Query optimization and operator placement for access controlled stream processing systems. In *IFIP Annual Conference on Data and Applications Security and Privacy*, pages 261–280. Springer.

Veltri, L., Cirani, S., Busanelli, S., and Ferrari, G. (2013). A novel batch-based group key management protocol applied to the internet of things. *Ad Hoc Networks*, 11(8):2724–2737.

Wang, X. H., Zhang, D. Q., Gu, T., and Pung, H. K. (2004). Ontology based context modeling and reasoning using owl. In *IEEE annual conference on pervasive computing and communications workshops, 2004. Proceedings of the second*, pages 18–22. Ieee.

Whitehouse, K., Zhao, F., and Liu, J. (2006). Semantic streams: A framework for composable semantic interpretation of sensor data. In *European Workshop on Wireless Sensor Networks*, pages 5–20. Springer.

Yu, W., Liu, Z., Chen, C., Yang, B., and Guan, X. (2017). Privacy-preserving design for emergency response scheduling system in medical social networks. *Peer-to-Peer Networking and Applications*, 10(2):340–356.

Zhu, S., Setia, S., and Jajodia, S. (2006). Leap+ efficient security mechanisms for large-scale distributed sensor networks. *ACM Transactions on Sensor Networks (TOSN)*, 2(4):500–528.