Multidimensional Report Analysis in Urban Incident Management

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Abstract—In urban incidents and crises, accurate and timely information can be crucial to manage critical situations. The exponential growth of crowd sourced data has given means to access vast amounts of information on a real-time basis. However, this has complicated the task of analyzing ongoing events as the effort needed to filter relevant from irrelevant information has exponentially grown. This paper proposes a multidimensional analysis method of processing high influx of crowd sourced incident reports and creating processable pieces of information by filtering what's irrelevant and clustering what belongs together in a highly efficient way. Spatial, temporal, and semantic dimensions of an incident report constitute a basis which is taken advantage of in this work to ease the tasks which are undertaken manually in operation centers and alike.

I. Introduction

During the 2009 Winneden school shooting and 2016 Munich shooting, people fell victim to seemingly random rampage of two school students. It was not the 7 years and ca. 175 kilometers between the incidents making a difference on how these incidents were handled, but in particular also the communication means and information at disposal. During the former incident, authorities were limited to gathered intelligence and hints from citizens, and conventional telecommunication media (i.e. radio, television) for information dissemination. In less than a decade later, during the latter incident, the sources of information (both for authorities and citizens) were exponentially increased and spread, mainly over the Internet. The massive flow of – at times contrary – information on social media, however, turned out to be more puzzling than beneficial in managing the crisis. The importance of "information validity and timeliness" in managing crisis has already been pinpointed among others by Turoff, Chumer, Walle, et al. and the "key obstacle to effective crisis response [is considered to be] the communication needed to access relevant data" [1]. In recent years, it has been proven that social media can be considered as legitimate sources of real-time data during the crisis. The potential of social media in handling crises has been leveraged in many aspects but at the same time, due to open nature of such platforms and the fact that postings are not supervised, the question of information validity is yet to be addressed. In the age of information overflow it has become evident that the price of meaningful and reliable information is much higher than mere access to data.

With a focus on urban incidents, this work introduces a multidimensional analysis method to filter, classify, correlate and eventually cluster crowd sourced reports of possibly critical incidents under soft real-time constraints. The goal is twofold: to separate valid from invalid reports and to merge related reports together. A valid report in this context is to be understood as a piece of incident related data, that provides information useful for better understanding or the mitigation of the incident. Report merging refers to semantic and spatio-temporal clustering of reports into logical manageable units which provide a comprehensive overview of an incident.

This paper is structured as follows: after this introduction, related work is discussed (section II). In section III requirements are presented which were derived from field studies in several urban areas. The concept of the multidimensional analysis method to filter, classify, correlate and eventually cluster incident reports as well as the architecture to fulfill the non-functional requirements is given in section IV. A brief overview about implementation aspects is given in section V and the implementation is summarized in section VI. The paper concludes in section VII.

II. Related work

Incident management generally refers to the "notion of coordinating the actions necessary to manage disasters and emergencies" [2]. This, as previously mentioned, presupposes access to information describing the situation and related matters. Many actively use social media during catastrophes and crises and generate high amounts of information, which can be valuable for incident management by involved organizations and forces. Analyzing such crowd sourced information can take place manually, for example, by organizations such as Digital Humanitarian Network DHN (http://digitalhumanitarians.com/) or Virtual Operations Support Group (http://vosg.us/) requiring adequate organizational resources and professional knowledge; or it can succeed automatically. The focus of this work lies on automatic information briefing by clustering related incident reports together using spatio-temporal and semantic dimensions.

Nagarajan, Gomadam, Sheth, et al. present a system which analyzes tweets on three dimensions of theme, time, and space [3]. Similarly, Avvenuti, Cresci, Marchetti, et al. provide a framework, which uses temporal reasoning (in terms of burst detection) and semantic analysis to assist real-time decision-making for earthquake crisis management [4]. In either case, however, spatio-temporal analysis is limited to the time and location of the report and not the incident to which the report refers. Ghahremanlou, Sherchan, and Thom solve this shortcoming by introducing a geotagger based on semantical analysis to extract an incident's location from tweets' contents during crisis [5]. General approaches with a mere focus on spatio-temporal clustering are given in [6], [7]. Contrary to aforementioned approaches to spatio-temporal analysis, this work differentiates between the spatio-temporal attributes attached to an incident report with those of the actual incident: an experimental method is introduced to estimate incident's actual location from reporter's location.

Advantages of semantic technologies regarding incident reports is leveraged by Li and Li in an ontology based method for "multi-document summarization in disaster management" to extract most important (i.e. relevant) sentences out of given documents [8]. Other approaches in context of incident/crisis management are utilized in integration of heterogeneous information [9]–[11], response planing [12], resource management [13], [14], or even in meta and holistic ontologies that conceptualize the process of incident management as a whole [15], [16]. The scope of these approaches is mainly limited to conceptualizing circumstances of incident/crisis management in terms of an ontology, potentially to benefit from semantic reasoning (e.g., in automatic planing). This work employs a special incident ontology to initially classify incident reports and eventually correlate them.

III. Requirements

As part of the European Union research project CityRisks (project.cityrisks.eu), the proposed system at hand is result of extensive research and discussion with criminologists, local police forces, urban safety and security professionals, governmental organizations, and researchers of related fields. The conceived functional and non-functional requirements are aligned with a rather generic use case of a crime-related urban incident with citizens and authorities as actors, where the former reports about an ongoing incident to the latter and receives respective alerts, updates, and critical information in return. The data provided by citizens is expected to be semi-structured, i.e. containing both structured (e.g., timestamp, geo-location) and unstructured (e.g., text, image) data. Within the system, reports are filtered, classified, correlated and those referring to the same incident are merged together. The results are accessible both for authorities and involved organizations, and (partially) for citizens. Accordingly, the functional requirements are as follows:

TABLE I
Excerpt of concepts from the incident ontology

Anti-social behavior	Public disorder	Theft	Property damage
Bullying	Affray	Pickpocketing	Vandalism
Harassment	Gangs	Burglary	Arson
Social disorder	Protest	Robbery	Graffiti

1) Content analysis
2) Semantic processing
3) Spatio-temporal reasoning
4) Automatic coordination
5) Adaptive decision support

Requirement 1 comprises extracting structured data from textual (e.g., description in natural language) and visual (e.g., image) content of an incident report. Semantic processing (2) contextualizes data in terms of incident management and spatio-temporal reasoning (3) is required to merge related reports and dispatch targeted alerts. Requirement 4 postulates that the coordination between components should be done without human interference. Finally, it should be possible to correct automatic decisions through feedback (5). Additionally, following non-functional requirements are formulated:

- (Close to) Real-timeliness
- Scalability
- Availability
- Fault tolerance
- Extendibility

The non-functional requirements are constraints required in coping with urban incidents where timely response to high influx of data is of critical importance. Scalability has been foreseen as basis for availability, fault tolerance, and soft real-time analysis and processing. Extendibility is guaranteed through well-defined interfaces and protocols.

IV. Concept

The subject of investigation in this work are urban incident reports. An incident refers to an out-of-ordinary event affecting the public life and a report is a time-space-bounded piece of information about an incident.

A. Urban Incidents

The definition of an urban incident given above might struck as being too broad, thus not suitable for practical use. The system at hand makes use of an incident ontology – inspired by crime taxonomies used by law enforcement – to describe urban incidents. The incident ontology, however, puts the emphasis on representing concepts that

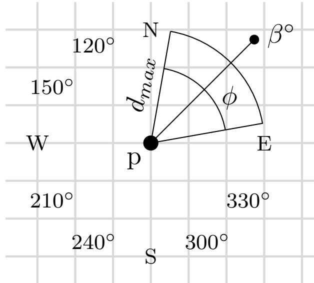


Fig. 1. Conceptual frame of view (FOV)

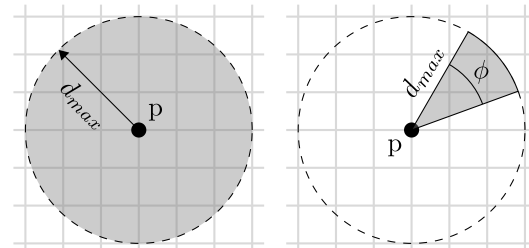
might affect citizens' safety and security and does not include every concept which might legally be categorized as a crime. Whereas a crime (as defined by the law) is of interest for police forces, it does not necessarily pose a safety/security danger for citizens: Berlin's Görlitzer Park is famous as a site of soft-drug dealing (considered a criminal act by the German law) and at the same time a spare time spot for families and tourists. Consequently, the incident ontology is strictly not a taxonomy of what is verboten by the law. It is also noteworthy, that such an ontology is not sensitive to cultural differences. For example, in countries where prostitution is considered as a criminal offense, the chances are higher that the neighborhood, in which prostitution is taking part, exhibits higher (violent) crime rates (see [17]), though it might not be the case for countries (e.g., Germany) where prostitution is legalized. An excerpt of the incident ontology's concepts is given in Table I.

B. Incident reports

In the course of this work, it is assumed that urban incidents are reported by people. Due to the existence of obstacles like trees or buildings in an urban setup, a reporter's field of view (FOV) heavily depends on position p and direction of observation β. For the following discussion we assume as first approximation, that the FOV for all positions and directions is limited only by an observation reach of maximum d_{max}. The field of view can then be imagined as a circular sector centered at the reporters position with an opening arc of ϕ and a radius of d_{max} as of Fig.1.

Since a report only contains the position of the reporter, p_r, and not the actual incident p_i, it is required to develop a method to infer or at least estimate an incident's actual location from its corresponding report. This is required in future calculations to find out if two reports originating from the vicinity of each other refer to the same incident or not. If the observer's orientation, β, is not known, the incident is estimated to be within a radius d_{max} of the reporter as depicted in Fig.2a, so if the position of the reporter is considered to be the reference point of a polar coordinate system, the following holds:

$$(r_i, \theta_i) \in \{(r, \theta) : r \leq d_{max}\}$$



(a) w/o observer's orientation (b) w/ observer's orientation

Fig. 2. Possible incident location inferred from an incident report

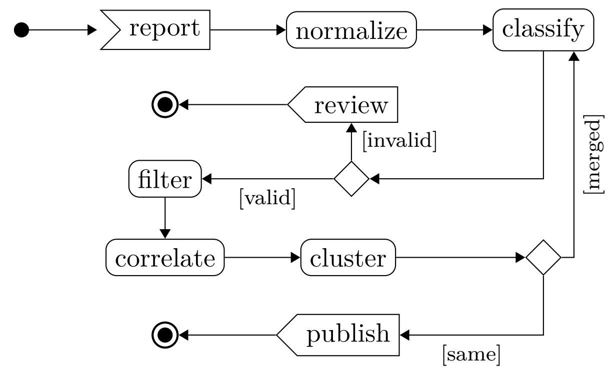


Fig. 3. Actions upon receiving an incident report

(r_i, θ_i) being the corresponding polar coordinate of the incident with (Cartesian) coordinates (x_i, y_i).

Analogous, if the orientation of the observer, β, is known the incident is assumed to be within the circular sector centered around the reporter with an arc of ϕ degrees, where ϕ is an arbitrary angle defining the observer's field of view (FOV) as shown in Fig.2b, so that the following holds:

$$(r_i, \theta_i) \in \{(r, \theta) : r \leq d_{max} \wedge \beta - \frac{1}{2}\phi \leq \theta \leq \beta + \frac{1}{2}\phi\}$$

It should be noted that since an incident does not happen in a single point $p_i = (x_i, y_i)$ and to account for uncertainties, the region centered around p_i with a diameter of d_i (effective incident plane) is accepted as location of the incident instead of the single point p_i. In this sense, the shaded areas of Fig.2 denote the region in which FOV of a reporter might overlap with the effective incident plane.

C. Workflow

Fig.3 depicts a simplified version of the workflow initiated upon receiving an incident report. First, its textual content is translated and the visual content is tagged (normalization), the report is then classified using a special incident ontology. If it does not match any concepts from the incident ontology, it is forwarded for manual review (e.g., by an operator). Otherwise, it is forwarded for filtering. Using a collection of ontologies (multi-ontology approach), the report is analyzed for concepts which might not be of relevance in context of urban incidents. The result of filtering is used as a weighing function to determine priority of otherwise coequal incident reports. New reports are correlated with existing ones and related ones are merged together (clustering). Eventually the enhanced incident information are published.

In this approach incident reports are analyzed on three dimensions: 1) semantic, 2) temporal, and 3) spatial. Incoming incident reports are considered as events which are processed and enhanced within an ecosystem of complex event processing (CEP). The idea behind CEP is to manage a stream of events by analyzing event patterns[18] using predefined rules to enrich data in a near real-time manner. In the context of this work, CEP was extended from temporal event processing to spatio-temporal event processing using a toolkit developed at Fraunhofer FOKUS in the context of EU project IMSK and refined continuously. The building blocks of the ecosystem are called Knowledge Processing Components (KPC)[19] and can be considered as nodes within a distributed system communicating only by asynchronous message passing[20] through a communication layer (requirements 4 and 5). For each activity (in Fig.3) a one-request/multiple-response paradigm is foreseen, where a single request is processed by multiple entities resulting in multiple responses with different (correctness) probability values. Under the assumption that results with lower probabilities require less processing time, one-request/multiple-response allows preliminary processing with results of lower quality until data of better quality is available. Take the normalization task where an arbitrary text is to be translated (request), for example, into English. An automatic translation (response 1) with lower quality would accelerate the whole report processing procedure until an operator, for example, would provide a more accurate translation (response 2). As soon as a more qualified response is present the procedure begins from the top.

The distributed architecture of the framework enables seamless horizontal scaling that also caters for availability and fault tolerance. A thorough discussion on KPCs conceptualized and realized in this work is given in sequel.

D. Incident report reasoning

Semantic reasoning: Semantic reasoning refers to classifying and correlating incident reports based on their content (i.e. body). To digest textual content, methods of information retrieval [21] and semantic technologies are used and for visual content, artificial intelligent classifiers (see [22]) are leveraged to assign terms to a picture/video. This corresponds to requirements 1 and 2.

First step of semantic analysis is term extraction as of bag-of-words model. In this sense, an incident report is represented by a collection of terms. Natural language processing in context of information retrieval is leveraged here to extract terms from textual content of a report. Analogous, the visual content is processed through convolutional networks and matching concepts are assigned. Extracted terms from textual content of a reports and assigned concepts of its visual content together form the basis of semantic analysis. The result is referred in sequel as normalized report.

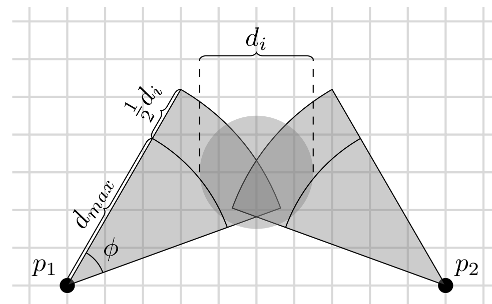


Fig. 4. Two reports of same incident

The special incident ontology used in this works maps a number of authentic incident reports (basis reports) to each incident concept within the ontology. The basis reports build an inverted index which can be used to classify incoming reports: each new normalized report is compared to basis reports of the incident ontology on the basis of a modified tf-idf measurement. If the similarity measure between a new report and a basis report passes a given threshold and is at highest, the corresponding incident type is assigned to that report, otherwise the report is marked for manual review. The same approach can be used to measure similarity between two reports to see if they refer to the same incident. Analogous, multiple blacklist ontologies are utilized to filter out reports which are not relevant to urban safety. These ontologies represent concepts that can safely be considered as immaterial to our goal.

Spatio-temporal reasoning: An incident report can be subject to spatial and temporal matching with regard to other incident reports (requirement 3). The case for temporal matching is trivial: if the beginning of an incident's validity window exceeds the end time of another (or vice versa), these reports do not refer to the same incident, thus they do not match. Otherwise, it could be said that they temporally match. Allen's interval algebra [23] can be used for this.

Spatial matching, however, pose a genuine challenge. Correlating two reports r_1 and r_2 is at most precise when both contain observers' orientation. In this case, if the circular sectors around p_1 and p_2 with a radius of $d_{max} + d_i/2$ and a predefined angle of ϕ overlap, it can be said that both reports refer to the same incident. This is depicted in Fig.4. Now, consider neither or only one of observers' orientation is given. Even if assumed FOV of both reports fully overlap, it cannot reliably be

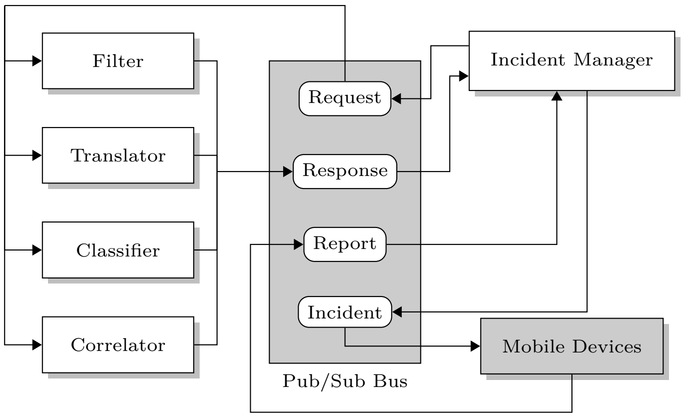


Fig. 5. System architecture

determined if both reports refer to the same incident or not. In such case the probability of reports referring to the same incident can be estimated using the following heuristic: in most circumstances it is fairly improbable that two reports originating from the vicinity of each other in an urban setup refer to different incidents as the probability of two different incidents in immediate vicinity is practically minuscule. Keeping in mind, that the position of an observer, e.g., measured with its smart phone, is not exactly known but normally distributed, error propagation methods have to be taken into account to estimate the probability of two reports r_1, r_2 for which $\|p_1 - p_2\| < 2d_{max} + d_i$ holds, to refer to the same incident. The details are subject of current investigations and will be published separately.

On the other hand if the circles around the observers with a radius of $d_{max} + d_i/2$ (taking effective incident plane into account) do not overlap, it can certainly be asserted, that the reports refer to different incidents. The same argument applies if one or both of the reports contain observer's orientation (circular sector FOV is then considered instead of a circular FOV).

V. System Architecture

The concepts of previous section and the activities depicted in Fig.3 are fulfilled through a number of worker KPCs (requirements 1 – 3). Additionally, a coordinator KPC is designated to regulate the workflow and task assignment among other KPCs (requirements 4, 5). With regard to their tasks, KPCs can logically be divided in the following five groups:

Content normalization: Normalization refers to the task of extracting structured data from unstructured data and to adapt them to a common format. This applies on both textual and visual content. The designated KPC for this task, the Translator, translates textual content to the main language of the incident ontology and leverages approaches of information retrieval for linguistic analysis (e.g., tokenization, stemming, lemmatization, etc.). Visual content is classified using artificial intelligence. This KPC takes an incident report and enhances it with a list of terms extracted from its body.

Classification: A normalized report must be first subsumed within the incident ontology before it can semantically be related to other incident reports. A special incident ontology has been designed and developed for classification. The Classifier KPC assigns concepts from the incident ontology to normalized incident reports. The result of classification is used for semantic reasoning and can also be used, for example, as input of a priority weight function: a report about an ongoing armed bank robbery must have a higher priority than a car theft.

Filtering: Filtering, similar to classification, refers to the task of positioning incident reports within concepts deemed as irrelevant for urban incident management. This KPC takes a normalized report and decides according to a set of predefined rules, whether the report is to be included in the processing pipeline or not. For example, reports containing visual content not safe for work are regarded as disposable.

Correlation and clustering: Relating new incident reports with existing logical incidents is referred to as correlation and clustering. As previously mentioned, this is done by correlating reports on their temporal, spatial, and semantic dimensions. This task is carried out by the Correlator KPC, which also can take an arbitrary location and correlate it with ongoing incidents (required for targeted alerting).

Task coordination: A special KPC is dedicated to coordinating tasks among other KPCs. For each activity, the Incident Manager takes results of a KPC and decides what do next. The decisions are made using predefined rules. The Incident Manager is also the first KPC to receive an incoming incident report.

To fulfill non-functional requirements, a distributed architecture as depicted in Fig.5 is proposed. Incident reports are provided by citizens using smartphones and can be complemented with pictures or videos. The communication among components succeeds solely over a message broker asynchronously. Multiple instances of the same KPC can transparently exist at the same time to provide availability and fault tolerance. The components are loosely coupled[24] and a global state is not shared among components. The lack of interdependence among KPCs enables parallel computing.

It is evident that the Incident manager plays a central role in coordinating tasks among KPCs. Depending on the current state of an incident report, Incident Manager decides the next operation for that report. Task requests are, however, not targeted for a specific component, rather are published under a specific topic so that any KPC capable of processing the request can do so without being actively triggered. This provides seamless extendibility and enables the single-request/multiple-response paradigm previously mentioned.

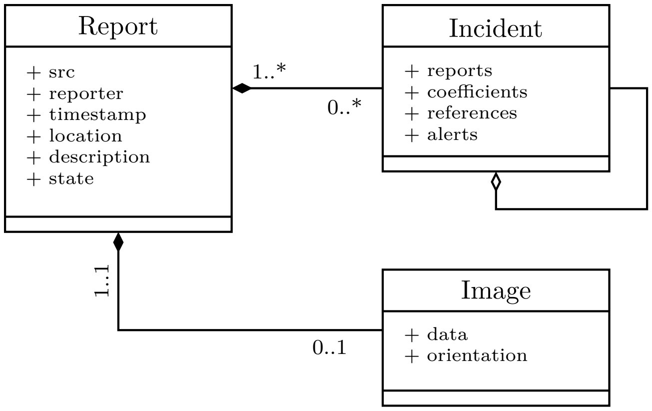


Fig. 6. Data models of incident and incident reports

The data models for reports and logical incidents as a collection of related reports are depicted in Fig.6. The unit of information is a report which contains a free text describing the incident, spatio-temporal information (i.e. location, timestamp), and can have media (e.g., a picture) attached. The main source of reports are smartphones, where the GPS sensor is used to capture reporter's location p, the compass sensor to determine his orientation β, and the camera to record images/videos. It should be noted, that the orientation β is considered as reliable only if an image or a video is recorded and attached as it is only under such condition, that a reporter's orientation might be pointing to the incident itself. An incident is composed of at least one report and can be merged with other related incidents to form a new incident.

VI. Implementation

The conceptualized system alongside a number of additional modules have been implemented and are to be in service in pilot projects across Europe in fall 2017 in London, Rome, and Sofia. The pilot phase for each city is one month during which participants can submit new incident reports and review existing ones using an Andoird application (Fig.7). Processed reports are published on the message bus and are accessible to operation centers through an interface developed by one of project partners enabling report review, modification and update.

Multiple frameworks and tools has been utilized in implementation: for the communication layer among KPCs, MQTT has been chosen as a lightweight message bus. For semantic reasoning and IR-related tasks, Apache Jena and Apache Lucene are integrated. JBoss Drools is used for temporal reasoning and rule based decision-making. MongoDB (document based DB) is used for long term and redis (Key-value DB) for short term (caching) persistence. Two external services are also used: Yandex for text translations and Clarifai Image and Video Recognition API for visual content tagging.

Filter, Classifier, Correlator, and Incident Manager are implemented as Vert.x verticles written in Java. Translator and it's subcomponents (Yandex and Clarifi clients) are written in Node.js. HTTP gateways for mobile devices are implemented using restify, a web service framework, also in Node.JS and are behind an NGINX reverse proxy. The standard serialization format both for the gateways and message exchange over the bus is JSON. All components are containerized using Docker and are orchestrated using Docker Compose.

VII. Conclusion

The necessity of timely access to information pose a constant challenge in mitigating urban incidents and crisis. This paper proposes a multidimensional method to classify, filter, correlate, and cluster user generated incident report to tackle the information overflow inherent to urban emergency events. An experimental novel approach has been conceptualized to estimate an incident's actual location from the location of its reporter for spatial reasoning. Concepts and methods from information retrieval and artificial intelligence have been utilized for classification and semantic reasoning of incident reports. It has been shown how temporal, semantic, and spatial reasoning can provide a basis for incident report digestion and briefing. The distributed microservice-based architecture foresees potential bottlenecks of a monolithic system and counters them with seamless horizontal scaling and redundancy, and addresses fault-tolerance and availability. Within the framework, the one-request/multiple-response paradigm, where multiple components process the same request and provide multiple responses, enables preliminary data processing with responses of lower quality until responses of higher quality are provided so that soft real-time constraints are enforced and retrospective data correction is achievable.

The planned pilot projects across European cities provide a basis for a thorough evaluation of the system in terms of accuracy and precision. In a further step the system resilience is to be tested under high loads to check how well realtime constraints are satisfied.

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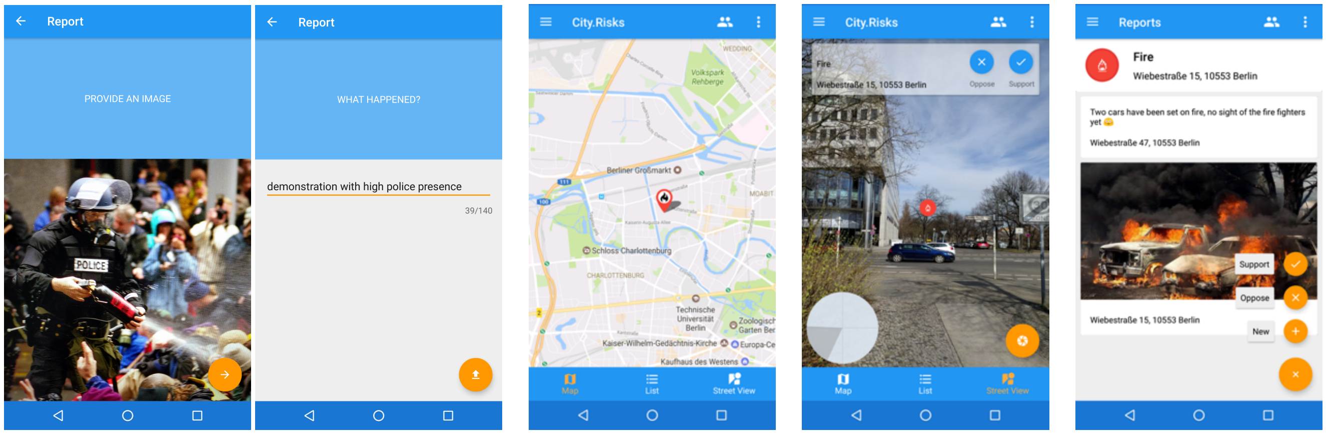

(a) Report Submission (b) Map view (c) AR view (d) List view

Fig. 7. Mobile application for report review and submission

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