# SmartRescue: Architecture for Fire Crisis Assessment and Prediction

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### ABSTRACT

In case of indoor fire hazards, firefighters face difficulties at assessing the fire situation and evacuating trapped victim inside the building, especially when the fire is big, and the building is unknown to them. On the other hand, modern sensor technologies in smartphone are becoming more advanced, widespread, and can be exploited for helping the firefighting operation. This paper proposes using smartphones as a distributed sensing and computing platform, for supporting firefighters to conduct their mission. The developed solution is based on collecting sensor data from smartphones. A Bayesian network then uses this data to generate a picture of the fire and predict its development. The additional indoor positioning feature make this proposed solution a promising tool to make the firefighter intervention more efficient and fast in order to save more lives.

### Keywords

Bayesian Network, Fire Prediction, Smartphone App, Indoor Positioning.

### INTRODUCTION

In fire situation, once the firefighters arrive on the scene, they waste a lot of time trying to assess the fire situation before starting to extinguish it. They need, for example, to know where the fire started, if there are people trapped inside, and how to get inside the building. Moreover, if the fire occurs in a large building, the firefighters have to wait for a briefing from a responsible person in the building to show them where the fire is and how to access that location. They also have to check every room in the building for potential trapped person or victims. This is a time costly process that can lead to fatalities in some cases.

Around the world, 23.7 thousand persons died in a fire incident in 2012 (Stephenson 2000). In Norway, 54 persons died in 2014 for the same reason (DSB 2014). Although this number is in decline from year to year due to better prevention techniques and imposed fire safety standards, it could have been even lower if the firefighter had in their disposal tools that help making their intervention faster and more efficient.

In this research, we investigate the potential use of data collected from smartphone sensors and artificial intelligence techniques to facilitate firefighters' operation in indoor fire. This paper proposes SmartRescue as a distributed sensing and computing platform for fire assessment and prediction. The fire assessment and prediction feature is intended to help the firefighters locate the origin of the fire and track the fire spread. The proposed platform also introduces an indoor localization system that helps spotting and rescuing trapped victims. A smartphone-based platform to support firefighters with fire prediction and indoor localization features is considered as the main contribution of this research.

The paper is organized as follow: First, it describes the overall building block of the SmartRescue architecture. Second, it briefly reviews relevant literature. Third, it details the underlying technologies used in the fire assessment and forecasting. Fourth, it presents an indoor positioning System based on K nearest neighbor Algorithm. Fifth, it describes a use case where Smart Rescue can be useful. Finally, in the concluding part, the contribution and future direction of this research are revealed.

## RELATED WORKS

A comprehensive review on automated fire assessment shows that this topic has extensively been studied (Mahdipour and Dadkhah 2014). In their review, they showed that automated fire assessment techniques focus on detecting fires and reducing false alarm. Various methods have been applied for that purpose, ranging from image and video processing, wireless sensor networks to intelligent techniques. However, the method we propose not only detect the fire, but also follows its progress until it reaches a fully developed stage. The review also shows that wireless sensor network has been used in some researches alongside genetic algorithm, expert knowledge, rule-based systems, and artificial neural networks for fire prediction. Nonetheless, none of these studies have used Bayesian network for fire assessment and prediction. Fire prediction using a Bayesian Network technique has been done (Cheng and Hadjisophocleous 2009, Cheng and Hadjisophocleous 2011), but these works only model the dynamics of the fire development based on the previous state of the fire and do not incorporate sensor data in their model.

Our fire assessment and prediction approach aims to provide, on one hand, a complement to work done in the automated fire assessment research field which did not investigate the use of Bayesian networks. On the other hand, it extends the work done to model fire dynamics by mean of Bayesian network with the uses of collected sensor data from the smartphones located in the fire zone and then feeding them to the Bayesian network.

The indoor localization has also been scrutinized, especially by exploiting the Wi-Fi signal strength, wearable sensors such as gyroscope or accelerometer in combination with smartphone (Biczok, Diez Martinez, et al. 2014, Cypriani, Delisle, et al. 2013, Gutierrez, Belmonte, et al. 2014, Hardegger, Mazilu, et al. 2013, Lan and Shih 2013, Noh, Yamaguchi, et al. 2013). However, the detection of indoor positioning by processing the Wi-Fi signal strength directly on smartphone so that one can locate people inside the building layout are not done in those studies.

## OVERALL ARCHITECTURE

The architecture mainly comprises two parts (Figure 1).

- The data transfer system: a local area wireless transmission technology (Wi-Fi, Wi-Fi Direct) responsible for transferring the sensors' data between devices in the fire area and a publish/subscribe system responsible for routing the message between different kinds of devices inside the network.
- The intelligent system: uses the gathered data to assess the fire situation, predict its development and localize victims inside or close to the fire zone.

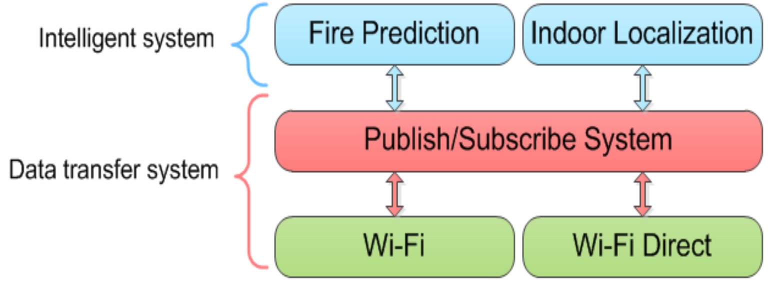


**Figure 1: Overall Architecture of SmartRescue**

## DATA TRANSFER SYSTEM

The publish/subscribe system consists of two entities: client and an event notification system (ENS)(Eugster, Felber, et al. 2003). The client can be a subscriber or a publisher. Subscribers are at the receiving end of the messages produced by the publishers. The data within the network is propagated from publishers to subscribers through the ENS. The difference between publish/subscribe system, and any other data transfer system is that the subscribers can choose the type of data they want to receive by defining a filter within the ENS. This filter can be based on a key word in the data, the content of the data, the location of the publisher. It is the task of the ENS to forward only the relevant events to the subscribers. For this, it administrates a routing table, which contains not only the next hop, but also the filter of the subscriber. A device can be a publisher, a subscriber, an ENS or any combination of those.

SmartRescue uses Phoenix to share sensor data between devices in the crisis area (Figure 2) (Salvador, Larrea, et al. 2012). Phoenix is a content-based publish/ subscribe system that support client's mobility in which the ENS is called a broker. Phoenix has two characteristics:

- It is a content-based: The subscriber can choose which kind of message it wants to receive based on the content of the message regardless of the publisher how generated it.
- It supports client mobility: In a mobile environment, the client (publisher or subscriber) can lose connection with the broker or migrate from a broker to another. The broker is responsible for forwarding the preferences of the subscriber to the new broker upon this.

The advantages of using publish-subscribe system in this context are: first, it gives the participants in the network a degree of freedom and privacy so that they can share the type of sensors' data they want to share and only receive the date they are interested in. In addition, it reduces the load over the network since it only propagates the necessary date for the client. This capability is even more of a valuable feature in a crisis situation where the resources are limited. Finally, Phoenix provides a high degree of decoupling between the components of a network that is precious to a local mobile network where the topology frequently changes.

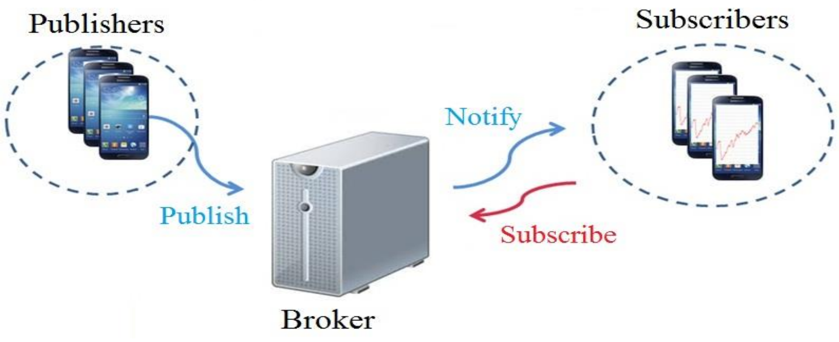


**Figure 2: Phoenix publishes/subscribe system**

## INTELLIGENT SYSTEM

### Fire prediction

Our approach is to model the building as a Bayesian network (BN) (Stephenson 2000). A BN merges the two concepts: that of graph theory and that of probability theory. The approach helps to capture the conditional dependencies between random variables by the mean of a direct acyclic graph (DAG). Each node in the DAG represents an event that can happen with a certain probability, and each directed edge represents a cause-effect relation between the nodes.

A fire is a dynamic process that evolves through time. Its status at a present time *t* depends on that at a previous time step. One might then think of using a dynamic Bayesian network (DBN) to capture the fire dynamic. However, a DBN is more complicated and consequently more process consuming. Since we intend to run the application on mobile devices with limited power and battery life, the application of a simple BN is preferable. Nonetheless, we added a node that represents the statue of the fire in a room at previous time step. In each time step, the probability distribution of a node at a time t will be passed to the node that represents its former state. The state of the node representing the previous time step will then change. This, in turn, will affect the state of the fire in the current time step and so on. By this mean, the network becomes able to model the dynamic aspect of the fire. Let $S$ be a set representing the fire state in a room.

$$S = \{\text{dormant}, \text{growing}, \text{developed}\}$$

Further, let $R$ be a room in the building, the BN infers the fire state in $R$ at a time $t$ based on the fire state in $R$ at *(t-1)* the fire state in the neighboring room $N$ and the value of temperature, humidity, visibility and pressure collected by the phone sensors placed in $R$ (Figure 3).

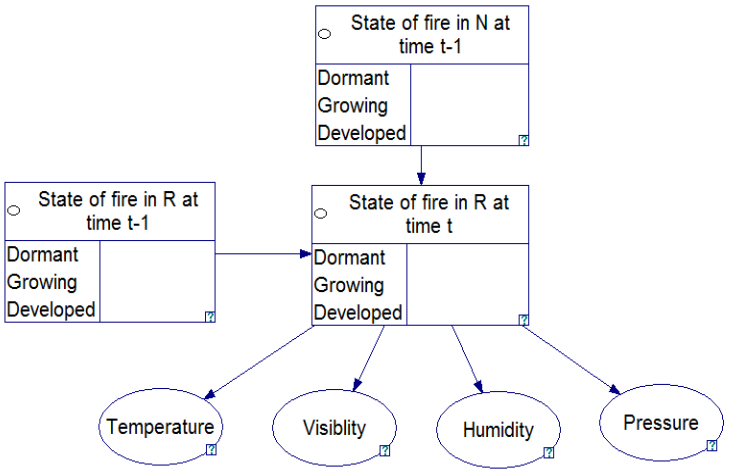


**Figure 3: BN for real-time fire assessment**

Note that the graph in Figure 3 only represented one neighboring room for simplicity. In reality, $R$ can have multiple neighbors. In that case nodes, links are added between those each neighbor and $R$. Let $R(t)$ be the random variable representing the state of the fire in $R$ and $N(t)$ that of the neighboring room at a time $t$. Further, let $O$ be the set of observed sensor data in $R$:

$$O = \{\text{temperature}, \text{humidity}, \text{visibility}, \text{pressure}\}$$

This allows the joint probability distribution of the random variable in the network to be expressed as follows:

$$P(R(t), R(t-1), N(t-1), O) = P\big(R(t-1)\big) * P\big(N(t-1)\big)$$

$$* P\big(R(t)\backslash R(t-1), N(t-1)\big) * \frac{P(R(t)\backslash 0) * P(O)}{P\big(R(t)\big)} \qquad (1)$$

In addition, the BN should be able to forecast the state of the fire at a future time *(t+n)*. For this, we designed a BN illustrated in Figure 4. The BN in Figure 4 is similar to the one in Figure 3. The only difference is the absence of nodes representing the observed sensor data $O$. This is due to the fact that sensor data is only known at the present time. The state of the fire in $R$ at future time step is inferred based on the state of the fire in $R$ and N at the previous time step *(t+n-1)*.

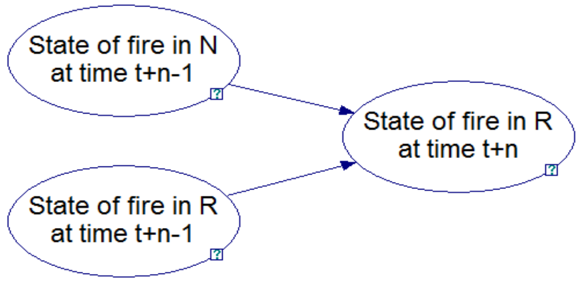


**Figure 4: BN for fire forecasting**

The joint probability distribution would be as follows:

$$P\big(R(t+n), R(t+n-1), N(t+n-1)\big) = P(R(t+n-1))$$

$$* P\big(N(t+n-1)\big) * P\big(R(t+n)\backslash R(t+n-1), N(t+n-1)\big) \quad (2)$$

At each time step, the probability distribution of the state of the fire at time *(t+n)* will be passed to the previous time step as virtual evidence. This simple network allows us to avoid using a DBN while modeling the fire dynamics.

Equation 1 and 2 cannot be solved directly to obtain the probability distribution of the fire state due to high computational complexity. However, different algorithms have been developed to approximate a solution to those equations. One of the fastest and more most precise is the Estimated Posterior Importance Sampling algorithm for Bayesian Network (EPIS-BN) (Murphy, Weiss, et al. 1999) which we used in our case.

The network is trained on the data obtained from several fire simulations done in fire dynamics simulator (FDS). The FDS permits the imitation of the geometry of a building and its material properties, defining fuel that triggers fire, and placing devices such as heat and temperature sensors in the simulated environment in such a way that fire parameter data can be measured and collected.

We used the third floor of the University of Agder building as the scenario for our model. The floor contains 5 classrooms, 30 offices, 7 group rooms, 4 computer labs, 2 meeting rooms and 3 stairways used as escape routes from the fire. The building is an interesting case study since it is large enough to be a challenge for firefighters in the event of a fire. Each room in the building will be represented by a BN as described in Figure 4 and 5.

We have implemented a SmartRescue application that uses google maps and JSMILE a Java interface of SMILE (Structural Modeling, Inference, and Learning Engine) (Druzdzel 1999) to implement the Bayesian network. SMILE applies probabilistic and decision-theoretic models such as Bayesian network. It allows the creation, editing and use of Bayesian network for probabilistic reasoning and decision making under uncertainty.

The application presents an interface with a map of the building with a heat map illustrating the state of the fire in each room (Figure 5). The heat map is updated every second to take into account the latest development of the fire. Its colors go from green to red depending on the intensity of the fire. The Bayesian network governs this change of color as described earlier. Furthermore, the application presents a “fast forward” button (inside the red circles red in Figure 5) that triggers the process of forecasting the fire status. When pressed the Bayesian network runs the inference and returns an estimate of the fire status in each future time step. Based on these results the heat map is then updated every quarter of a second instead of every second. This will allow the user to see what will happen in the next minute in just 15 seconds.

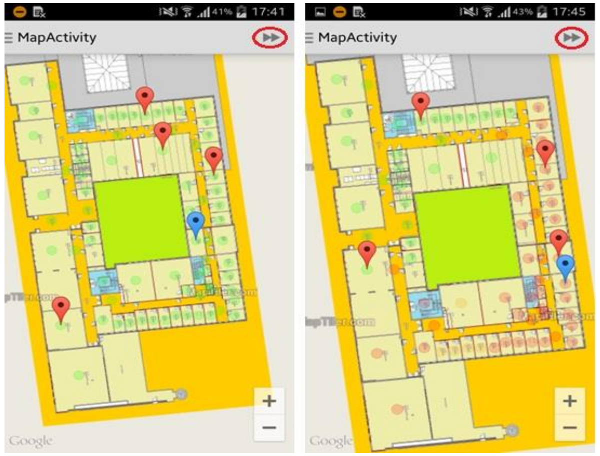


**Figure 5: SmartRescue application**

### Indoor localization

GPS are generally not suitable for indoor localization because the satellite signal gets attenuated by the roof (Schon and Bielenberg 2008). Thus, the location becomes largely inaccurate for a room level localization. Our approach tries to overcome this by using the Wi-Fi signal strength collected from different Wi-Fi access point inside the building. The method comprises two phases:

- Training phase: at this stage, the user registers the Wi-Fi signal strength from each access point every time the mobile device is in an unregistered room. At the end of this step, we end up with a mapping between the rooms and a set of signals strength.
- Learning phase: This the ordinary use phase. Every time a new set of signal strength is registered, the application uses three nearest neighbor algorithm to decide in which room the user is (Altman 1992). The algorithm measures the

Euclidian distance between the new set of signal strength and the sets registered in the first phase. These latest have a room assigned to them. After that, three closest set are picked, and a majority vote is taken among the rooms assigned to these sets. If the three sets have three different assigned rooms, the closest one is picked.

The indoor positioning method is simple, however, efficient: during our testing moving around the building, the algorithm was able to localize the smartphone with a room level accuracy in 87% of the cases. The reason is that the walls between the rooms relatively attenuate the Wi-Fi signals, thus the measured value differ enough for the algorithm to detect which they are from. Nonetheless, the method relies on the presence of a Wi-Fi access point infrastructure inside the building that may hinder its scalability.

## USE CASE SCENARIO

Consider a fire disaster case where the fire begins to spread in a building. Even though most of the persons occupied the building can escape, some people may trap and are unable to evacuate by themselves. Here, the SmartRescue app can be useful. They can turn on their SmartRescue apps. The apps start sending sensor data and their locations. As the firefighters arrive at the building, and activate the same apps, they immediately can observe the map in Figure 5 with the location of the victims and the fire status in each room. They can press the fast forward button to see how the fire is going to develop in the next minute. Thus, they can decide which one is the best and fastest way to reach and save the victims. If the firefighters go inside the building with their app, at any time they can check the development of the fire and change their rescue path. Once they reach the spotted victim location on the map, they can help evacuating the victim. .

The previous scenario has been implemented in a game at the University of Agder building with nine students acting as firefighters and thirteen students as victims trapped inside the building. The game was divided into two sessions. In the first session the firefighters did not use the apps while in the second session, they used the apps. The rescue process took 15 minutes in the first scenario and 13 minutes in the second one. This confirms the claim that Smart Rescue helps fasten the firefighters' intervention.

## CONCLUSION

This paper proposes a platform that uses smartphone sensors along with Bayesian network to assess fire situation and predict its development, as well as an indoor positioning system. The data is shared between smartphones using a wireless network and a publish/subscribe system. The Bayesian network models the fire dynamics and provides an overview of the fire situation along with forecasting its development. The indoor localization base on Wi-Fi signal strength helps finding trapped victims and avoids the firefighter the trouble of checking every room in the building. This solution helps facilitate and speed up the work of firefighters in order the save more lives. The future direction of this work would be to use smoke and temperature sensors in the building alongside the smartphones. Moreover, a navigation system can be introduced to guide people safely out of a burning building.

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