S^3H: A Symptom Surveillance System in High Spatial Resolution using Smartphones

Hui Huang, Ye Sun*, *IEEE Member*
Department of Mechanical Engineering-Engineering Mechanics,
Michigan Technological University, Houghton, MI 49931
*Email: yes@mtu.edu

***Abstract*—The pandemic outbreaks including seasonal influenza demonstrate the continuous threat from multi-level pandemics and underline the need for robust preparedness and response. The goal of this paper is to develop a symptom surveillance system (S^3H), providing supplementary data with public health data for long-term pandemic monitoring and prediction in large population. The system targets at high spatiotemporal monitoring of symptoms in public area including fever and cough distribution. Our preliminary study was conducted in the university library. Thermal imager and sound sensors based on smartphones were used to acquire the raw data. Image processing algorithms were used to calculate the temperature distribution in the certain population. For cough sound recognition, we take the Mel-frequency cepstral (MFC) as the feature of cough sound and kNN algorithm was performed for automatically recognizing the cough sound in a continuous recording.**

***Index Terms*—symptom surveillance system, pandemic monitoring, public health, smartphone-based, cough**

I. Introduction

The pandemic outbreaks are biological disasters. Emerging and re-emerging pandemic diseases pose an on-going threat to global health security, leading to 14 million deaths every year worldwide [1]. The world has experienced four major crises due to pandemic outbreak in this century: 2003 SARS outbreak [2], the spread of the H5N1 Highly Pathogenic Avian Influenza virus (HPAI) [3], 2009 H1N1 pandemic [4], and 2014 Ebola outbreak [5]. Comparing with the 1918 Spanish Flu which caused 50 million deaths in the world [6], the preparedness and recovery strategies have made tremendous progress. However, these recent crises still demonstrate the continuous threat from multi-level pandemics and underline the need for robust preparedness and response.

In order to provide efficient and effective responses in the early stage, multiple strategies have been developed for pandemic preparation and control in public health system. A great number of studies has focused on modeling, simulation, and visualization of pandemics in order to evaluate the dynamic transmission and the effectiveness of the proposed mitigation strategies. Various methodological approaches have been used including statistical analysis [14]-[16], simulation [17], [18], mathematical modeling and differential equations [7]-[9] for modelling and simulation. Also, different control measures were adopted and proved to be effective by public health agency including quarantine, isolation, social distance, vaccine, face masks. Regarding the recent pandemic outbreaks, early decision and response is always challenging due to *limited accessible data* [10] and self-contained models unavailable to health care officials. The previous experience also created high demand to increase the spatiotemporal resolution of epidemic spread monitoring higher than state and country level, especially in densely populated areas.

Due to the limited accessibility and low spatial resolution of available data for pandemic monitoring, we developed a symptom surveillance system (S3H) that can acquire the distribution of early symptoms (signs) of pandemics in a public area based on smartphones. The system was capable of extracting the physical symptom data, fever and cough distribution in a population, from raw data and is possible for long-term monitoring and statistical analysis. Our preliminary study was conducted in the university library with the smartphone based sensors capturing thermal distribution and sound in scheduled daily time. The smartphone based data collection enables wide application of S3H, targeting at symptom monitoring in scalable spatiotemporal resolution. The time-varying data can be stored and compared, providing supplementary data for further analysis and decision making in case that a pandemic including flu is in outbreak. The system can be used in public locations, which is possible to significantly increase the spatial resolution of pandemic monitoring from county or state level.

II. System Design

A. Pandemic Symptoms of Population

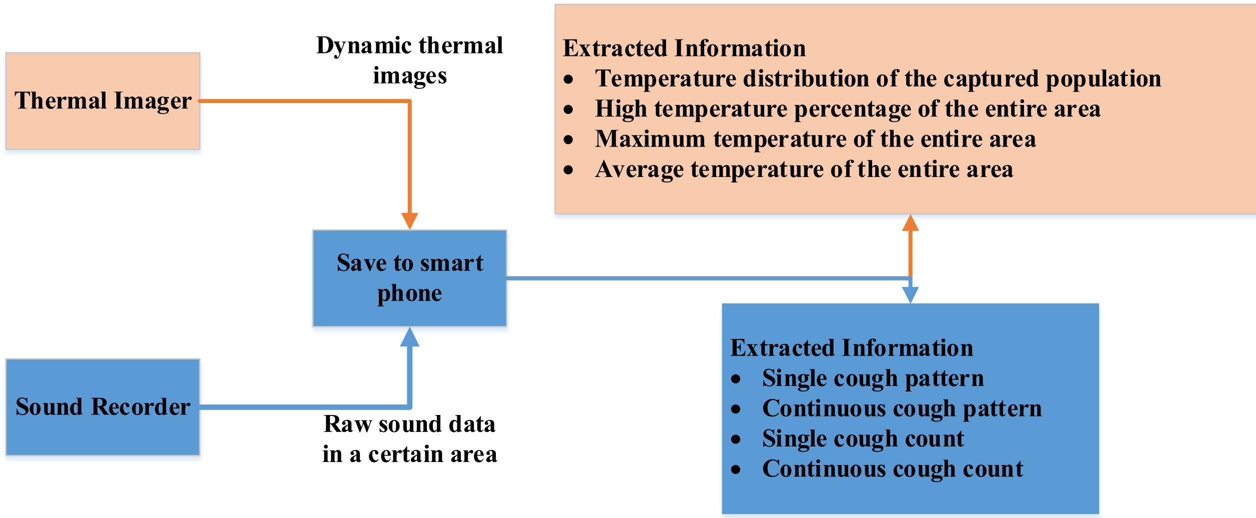
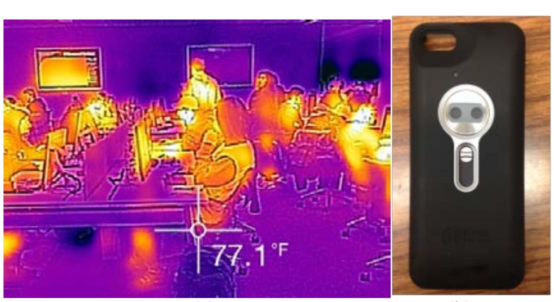


Fig. 1 System Architecture

First of all, we conducted a brief literature review of pandemic symptoms, which provided the evidence for system design of symptom surveillance. The physical symptoms of pandemics on individual, although not the same, still have some common ground. Among the four severe well-known pandemics-SARS, HPAI, H1N1, Ebola, and regular influenza (flu), one of the most common symptoms is fever. For SARS, fever was found in 100 percent of the patients; cough and headache were also reported in more than 50 percent of the patients [2]. In the outbreak of SARS, a number of airports used fever screening as effective surveillance and proved it to be an effective method [2], [13].

Fever and cough are also used as the diagnostic standards for Ebola and influenza (flu) [4]. A detailed early list of symptoms, often used as signs for self-diagnosis provided by Mayo Clinic [19], are summarized in Table 1. Therefore, the following sensing techniques were selected as the detection tools for the new series of supplemental data: 1) Fever screening by infrared thermal imagers. The thermal distribution pattern were recorded by thermal video cameras. Hot points then could be identified in the population. 2) Cough counter by sound sensors with pattern recognition. The system detects and analyzes the apparent external physical change of population based on these two external symptoms which can be acquired at critical locations.



(a) (b)

Fig. 2 Raw data of thermal distribution

TABLE I SYMPTOMS OF PANDEMICS

Pandemics	Early Symptoms (Signs)[1]
SARS	Fever of 100.5 F (38°C) or higher; Dry cough; Shortness of breath
HPAI	Similar to flu but highlight: Cough; Fever; Sore throat; Muscle aches Headache; Shortness of breath
H1N1	Similar to flu
Ebola	Fever; Severe headache; Joint and muscle aches; Chills; Weakness
flu	Fever; Cough; Sore throat; Runny or stuffy nose; Watery, red eyes; Body aches; Headache; Fatigue; Diarrhea; Nausea and vomiting

[1]From Mayo Clinic [19].

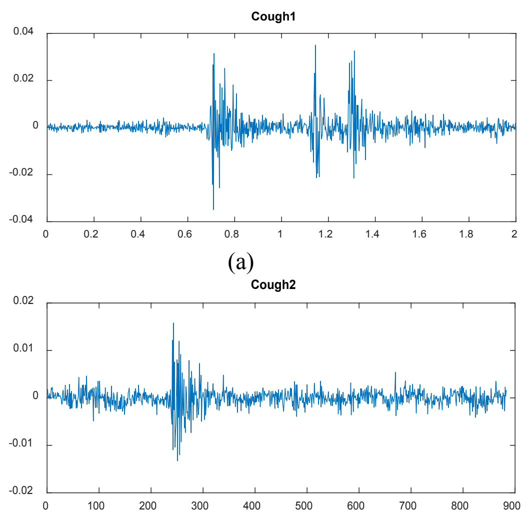
B. System Architecture

To summarize the design requirements based on the literature and guidance from medical experts, S^3H should be able to:

- Collect temperature distribution of a population in a public area for fever detection;
- Count single and continuous cough of a population in a certain time period, e.g. 5 minutes.
- Create baseline data of thermal distribution and cough counting for certain locations through a period of time
- Compare new data with baseline data
- Capture all the data easily for high spatial resolution
- Be inexpensive and capable of wide application

According to the design requirements, the surveillance system has two major components: 1) thermal distribution and temperature extraction; 2) cough recognition/counting in a population. The block diagram of system architecture is shown in Fig. 1.

The thermal imager and microphone of smartphones collect the temperature distribution data and sound data, respectively. All the data are saved to smartphones first. The image and sound are detected at the same time in the same location. The thermal image are taken three times to avoid large errors. The sound of the population is recorded for around 5 minutes.



(a)

(b)

Fig. 3 (a) double cough sound (b) single cough sound

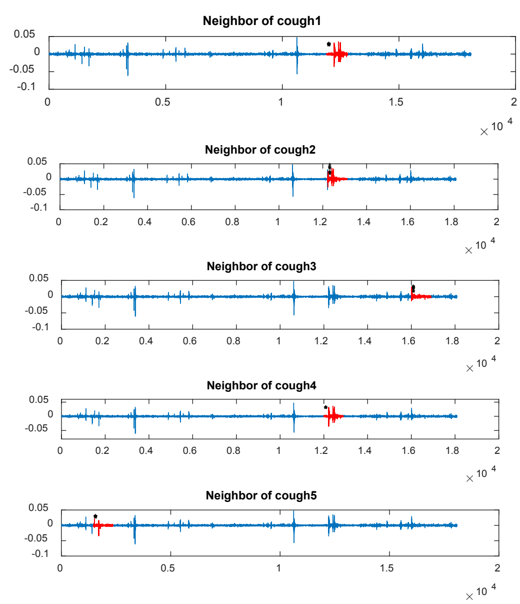


Fig. 4 The recognized cough sound using the five cough sound sample.

III. SYMPTOM DETECTION

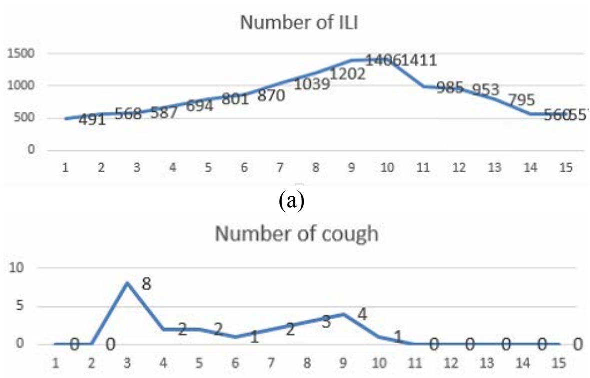
A. Temperature Distribution

The temperature distribution of the monitored population is obtained by image processing from raw thermal distribution images. A statistical analysis is then applied to extract basic variables of the monitored area, hoping to provide long-term monitoring data. In these captured images, there are often some areas without meaningful information. These areas cause large deviations of variables, such as temperature of the entire captured area. For example, the roof and floor area with no people in Fig. 2 (a). Also, there are some areas close to the window changing significantly as the result of ambient temperature such as Fig. 2 (b). The monitoring area should be relatively densely populated and far from doors and windows. Significant physical features was extracted from thermal images and recorded, including average temperature, maximum temperature, as well as high temperature percentage.

B. Cough Detection

The cough detection is based on digital sound recording of the same location as thermal distribution capture. First of all, the analysis of sound types is provided for cough pattern recognition. Based on our observation, there are some major types of sound in the library where we conducted experiments: typing on the computer, whispering, laughing, book dropping on the floor, walking, single cough and continuous cough (more than two).

For this common scenario, we can extract cough including both single and continuous ones based by applying pattern recognition algorithms. First, the audio recording is preprocessed for reducing noise and decreasing the huge amount of samples by filtering and down-sampling. The next step is to create the training sample of cough sound which we use to recognize the cough sound in the audio recording. Figure 3 is the typical waveform of cough sound. Typically, it is hard to distinguish the cough sound from other sound such as throat clearing, laughter and impulsive noise only by waveform or frequency. Thus we use the Mel frequency cepstral coefficients as the feature for recognizing cough sound. In sound processing, the MFC is a description of a sound's short-term power spectrum, which is derived from linear cosine transform of a log power spectrum on a nonlinear mel scale of frequency and thus approximates the human auditory system's response more closely than the linearly-spaced frequency bands used in the normal cepstrum. Numerically we can use the coefficients of MFC which is also called MFCC, to make up a MFC. To get the MFC we have to calculate the complex cepstrum which is defined as the Fourier transform of the logarithm of the signal spectrum and the cepstral coefficients $c(n)$ is calculated by the Fourier series coefficients of the logarithm of $S(w)$ [20].



(a)

(b)

Fig. 5 (a) Number of ILI from CDC by week. (b) Number of cough from our work by week

$$\log(S(w)) = \sum_{k=-\infty}^{\infty} c(n) \cdot \exp(-jnw) \quad (1)$$

The mel frequency scale S_k is obtained by mapping the powers of spectrum using K channel triangular overlapping filter. Then take the discrete cosine transform of the mel log powers and we are able to finally calculate the MFCC [20]:

$$c(n) = \sum_{k=1}^{K} \log(S_k) \cdot \cos(\frac{n\pi}{K}(k-0.5)),\ n = 1, 2, \ldots N \quad (2)$$

Where N is the number of cepstral coefficients to calculate. In the algorithm, a total of 7 MFCC are used to represent the feature of an episode of audio.

Then the k nearest neighbor (kNN) classification algorithm is used to perform automatic recognition of cough sound. In this algorithm, the training examples are vectors in a multidimensional feature space with a class label. An unlabeled vector is classified by calculating the Euclidean distance and choose the nearest samples to the labeled one. Thus, specific class could be recognized by this method. Suppose the training cough sound is $T(x_1, x_2, \ldots x_n)$, the sampling data is $S(y_1, y_2, \ldots y_n)$. For simple explanation, only one class x_1 cough sound is used. We can calculate the Euclidean distance between the sampling data and the training data x_1 to find the nearest neighbor:

$$\arg\min_{y_i} \| y_i - x_1 \|^2$$

TABLE II RESULTS OF RECOGNITION RATE

Date	Max temperature °C	Average temperature °C	Temperature over 30°C	Number of people	Outdoor temperature °C
20160111	34.83	15.15	5.47%	12	-12
20160112	34.91	16.33	3.82%	4	-12
20160113	34.86	14.85	5.08%	6	-12
20160114	34.92	13.51	3.90%	8	-6
20160115	34.87	17.42	4.72%	6	-3

This neighbor is the most similar sound to the cough sound and finally we recognized the cough sounds.

IV. FEASIBILITY AND VALIDATION

A. Experiment

The experiment is conduct in Michigan Tech University Library for 3 months and an iphone 5s is used as the digital sound recorder with 44 kHz sampling frequency as well as the thermal imager which is realized by collaborating with a FLIR ONE Thermal Imaging Camera. The thermal image and sound recording is acquired three times per day in the same location in the library, 10:00 am, 1:00 pm, and 5:00 pm when students were possible to have high attendance in the location in calendar months. The subject area is the studying zone where contains 18 seats with 18 workstations. The recording device is placed in front of this area for recording the thermal image and the sound of it. The sound is recorded for 5 minutes. The thermal image camera is first be calibrated using the hand surface temperature and then four thermal images are taken for the entire area.

The sound recorder was used to detect the broad sound in the library hall. When a person was coughing, the pattern was recognized and counted as one. The single and continuous cough were counted separately. The data was plotted in time series display to show the time variant fluctuation in different time scale. The spatial information was recorded with the location. If there is a large peak or singularity in the plotting, the stored data can be tracked to identify problems. These regular data can serve as the baseline and reference. As the recording is incremental, we are able to analyze the acquired dataset at any time, use statistical method (e.g. time series, spectrum analysis, spatial autocorrelation, etc.) for further analysis, and visualize the results. The real time detection provides strong support for fast response in early stage of pandemic outbreak if large difference is found in the data pattern.

B. Data processing

The thermal image includes the temperature information which is represented by color. Red color means high temperature and blue means low temperature. Each pixel in the thermal image includes red, green and blue colors from which we can calculate the temperature of each pixel in the thermal image. In our experiment, only the average temperature, the highest temperature and the percentage of high temperature over 30°C are used as the factors for symptom surveillance. Table 2 is a typical record for this parameters.

The number of cough sound is another parameter of symptom surveillance. The KNN algorithm is used in our experiment. There are five training cough samples cough 1 to cough 5 which represent five kinds of cough pattern. Cough 1, 2, 4 is double cough sound and cough 3 and 5 is single cough sound. The target audio recording includes cough 1. We'll use these cough sounds to recognize the cough in the target audio recording. Figure 4 shows the results of the five training samples, from which we can see that cough 1, 2, 4 have recognized the correct position of cough sound. However, if we use the single cough pattern to recognize the cough sound, the recognition rate will decrease.

C. Validation and Discussion

Actually, the real-time symptom surveillance system (S^3H) based on smartphones may open the door for public participation to increase the spatial resolution. In our work, we used local data as an example to show the feasibility of the proposed symptom surveillance system. The validation was achieved by comparing with the public flu data from Centers for Disease Control and Prevention (CDC). The results indeed detected some signs with the outbreak of flu from the cough sound counting though the temperature monitoring didn't detect any abnormal high temperature on people as flu symptom. Figure 5 shows the comparison between the cough sound monitoring by our S^3H system and the statistics from which it provides the number of influenza like illness (ILI) from CDC by week [21]. It is noticed that there is a peak in Week 9 in the cough counting data, which aligns with the data from ILI. However, another peak which was recorded in cough counting on week 3 did not align with the public data. This might be because that our recordings are limited within 5 mins and three times a day which can be expressed as the resolution of time. It is possible to be lack of most of the cough count. The future work including more public participation to increase the recording time or time resolution to acquire more accurate symptom monitoring.

V. Conclusion

The current version of S^3H was designed to be applied in library which is a limited scenario. More public environments need to be investigated to provide more data sources. Accordingly, the data processing algorithms also need to be improved and adjusted for different application scenarios. This monitoring is not a short-time work. In order to acquire enough baseline data for comparison and further analysis to find similarity and differences, more than two years are still needed to set up the database.

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