CATS: Crowd-based Alert and Tracing Services for building a Safe Community Cluster against COVID-19

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***Abstract*—COVID-19 has been causing several pandemic waves worldwide due to its long incubation period and hostile asymptomatic transmission. Society should continue to practice social distancing and masking in public despite aggressive vaccinations until achieving population immunity. However, the existing technology solutions, such as contact tracing apps and social-distancing devices, have been faced with suspicion due to privacy and accuracy concerns and have not been widely adopted.**

This paper proposes a novel infection management system named Crowd-based Alert and Tracing Services (CATS) to build a safe community cluster. CATS applies social distancing and masking principles to small, focused communities to provide higher privacy protection, efficient penetration of technology, and greater accuracy. We have designed a smart tag for managing social distancing. We also implemented a Machine Learning (ML)-based face mask tracking system to build non-binary Safety Impact Values (SIV).

***Index Terms*—COVID-19, Social Distancing, Mask-wearing, Machine Learning**

I. Introduction

Fighting against the global pandemic caused by COVID-19, many countries make a mask-wearing and social distancing in public areas compulsory in parallel with aggressive testings and vaccinations to achieve herd immunity. Many scientists support that they are the most effective health measures to break the coronavirus transmission chain. However, the technologies ensuring those health measures have not been broadly adopted due to privacy and accuracy concerns. Without gaining a critical mass of individual users, these personal technologies have been rendered useless. Although large-scale policy efforts have been made aggressively, the technologies cannot effectively support federal, state, and local governments' coordination and regulation enforcement logistics.

In this paper, we propose **Crowd-based Alert and Tracing Services (CATS) to build a safe community cluster,** which provides higher privacy protection, efficient penetration of technology, greater accuracy, and effective practical policy assistance. As illustrated in Figure 1, CATS enhances the technology-based tracing capacity by transforming the task from personal tracking to community gatekeeping and from binary to multi-context of contact information and policy assistance. First, as society gradually reopens, each community, such as schools, churches, businesses, and events, needs to be evaluated for appropriate gatekeeping methods such as masks and sanitization requirements, and temperature checks to ensure the members' safety. It is critical to deploy tracing and social distancing methods among the members. CATS facilitates tracing at a community or a facility level using multiple form-factors (i.e., a smartphone app, plug-in, or a smart tag) rather than an individual level to bear the characteristics of contacts according to the adoption choices of specific communities. Second, CATS enables public authorities to efficiently and dynamically assess their social distancing policies using the area-based safety value maps (opt-in data), various duration and distance alerts, and actively informing others via direct covert communication non-binary Safety Impact Values (SIV). As of the first step, we have designed and developed a Machine Learning (ML)-based face mask tracking method to find SIV of the community by measuring the % of mask-wearing and the % of no or wrong mask-wearing people. It can adequately educate policymakers about the pandemic's meaningful status at the broader level and assist in effective policy decisions and relief plans. Community-based safety spectrum data such as SIV from the masking status (crowdsourcing data from each community) will become a novel dataset that would augment existing biological COVID-19 data with sociological data.

The remainder of this paper is organized as follows. Section II describes the related work. We present the CATS technologies and architecture in Section III. Section IV provides the experimental setup, assumptions, and detecting results for each technical approaches, and Section V concludes the paper.

II. Related Work

In this section, we examine the existing solutions. We are well aware of the recent project activities of contact tracing in the U.S. (e.g., Apple and Google's contract tracing API [16], PACT [13] [4], PrivateKit [17], etc.) as well as the effective practices in countries in East Asia in combating this pandemic such as South Korea, Taiwan and Singapore [19]. While the success of contact tracing in East Asian countries is attributed to extensive testing and strong government coordination, the compromise of personal privacy was main weakness [5]. In contrast, US society highly values privacy and is distrustful of mass government surveillance. Policy decisions in the US are much more complex due to federal and state power divisions and the diverse populace. According to the recent

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polls [22], 71% of respondents said they have no plans to download and use a contact tracing app. Additionally, 44% expressed concern over digital privacy, 39% said the app gave a false sense of security, 37% believed the apps would not slow the spread of COVID-19, and 35% cited their distrust of the app providers. However, another survey shows 70 - 80% of Americans are willing to install an app if they are perfectly private and accurate, which is a significant increase. Many of RTLS companies, including Pozyx [14], Tsingoal [20], Localino [9], Iterate Labs [8], Arin [3], and RightCrowd [18], have already commenced COVID-19 contact tracing and social distancing application systems. Start-ups, enterprise/commercial GPS companies, and carriers are drawn to this space with wearables and the Internet of things apps. Several commercial devices available for tracking such as Filip Technologies Inc. [6], Location Based Technologies, Inc. [10], Amber Alert GPS [2], Wonder Technology Solutions [21], hereO [7], Quattro [11], and Masternaut [12]. More examples include [23], [25], [27], [28], [30], [33]–[35], [37]. However, most of them are expensive and fundamentally rely on GPS that is not available in-doors, nor is it energy-inefficient. Furthermore, these devices use cellular communication for one-to-one communication. Thus, they incur high monthly charges, and the efficacy of monitoring is limited. Most of all, none of them addresses the issue of privacy that significantly impacts the crowd participation. According to ABI Research, the significant barriers of personal location devices and applications market have been expensive devices, cellular subscriptions, indoor locations, and severe regionalization and fragmentation of coverage [1].

In summary, the existing approaches have the following significant limitations.

- Privacy/Technology adoption: Many individuals in the US do not have smartphones or will avoid any kind of contact tracing such as children, people with disabilities, people who are undocumented or have family members who've been in trouble with the law, will deteriorate the value of the system.
- Accuracy/False positives: It is known that signal alone cannot clearly distinguish the existence of walls or barriers between contacts.
- Binary tracing information: Different types of contacts (thus different potential impacts of contacts) are ignored. Thus, it only acts as a less effective backtracking mechanism after a potentially long asymptomatic incubation period.

Likewise, once the technical issues such as privacy and accuracy on the contact tracing and social distancing are resolved effectively, the community's adaptation will be dramatically increased. The core of our idea is to efficiently utilize crowds/communities to protect people from pandemic outbreaks using innovative technologies.

III. Crowd-based Alert and Tracing Services (CATS)

As shown in Figure 2, during the pandemic, almost all the communities are gatekeeping by putting up signs to wear masks and keep social distancing. However, putting up

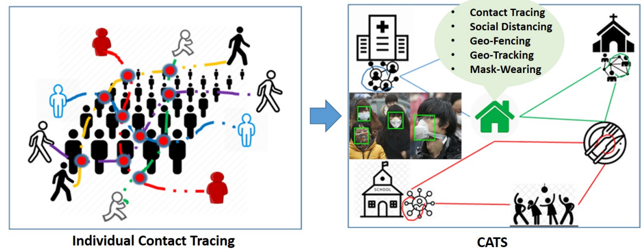

Fig. 1. CATS system concept

Fig. 2. Typical signs for pandemic rules

posters is not practical since some may intentionally challenge those rules, and others neglect them. Also, students who stay extended hours in school may not follow the social distancing and mask-wearing rules unintentionally. A more effective and less invasive nudge is required. However, surveys show that many people hesitate to adopt those technologies due to privacy and accuracy concerns.

A. Social Distancing Measurement

As illustrated in Figure 3, we have implemented a proof-of-concept tag with WiFi and BLE beacon stuffing and RSSI-based distance measurement functionalities using ESP 32 chipset. An Android smartphone app is developed to control the tag, and Google Cloud Messaging (GCM) is used for server communication. Both WiFi and BLE beacons should work in real-world environments, which may have hundreds of tags. When the beacon signal becomes prevalent in a crowded intersection, there could be a chance of beacon collision among the tags. Although WiFi and BLE beacons support spatiotemporal frequency isolation methods for mitigating the potential interference, it happens due to hidden nodes, periodic delivery, and broadcast. Hence, we look for an efficient beacon technology that can control and mitigate the beacon collision. A few theoretical studies show that periodic beacon's collision probability in practice is high. CATS tag uses relative location (distance) to measure social distancing. The length of two BLE tags can be calculated using the RSSI power using a simplified formula in Eq. (1) [26]. The RSSI signal strength depends on distance and broadcasting power value. BLE works with broadcasting power value (N) around 2–4 dBm, which depends on the environmental factor. The signal RSSI strength will be around -26 (a few inches) to -100 (40–50 m distance). The Measured Power is a factory-calibrated constant of expected RSSI at a distance of 1 meter.

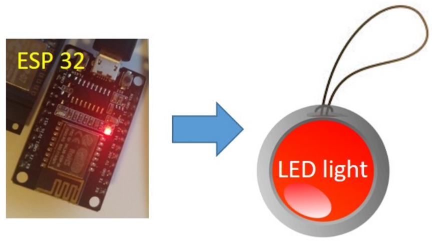

Fig. 3. Conceptual Smart Tag form-factor illustration

$$Distance = 10^{(MeasuredPower-RSSI)/(10*N)} \tag{1}$$

The RSSI value would be less accurate and not stable for distance measurement in a densely populated area such as shopping malls, grocery stores, and office buildings. However, considering the nature of social distancing problems, the environment is less populated, and sub-meter distance accuracy is not significant. The Ultra Wide Band (UWB) can measure distance and location to an accuracy of 5 to 10 cm with minimal noise interference due to the short pulse width, unlike WiFi, Bluetooth, and other narrowband radio systems that only reach several meters. UWB also consumes less power than WiFi, although Bluetooth 4.0 also uses significantly low power. However, UWB is not as pervasive as Bluetooth and WiFi. None of the current smartphones and mobile devices support UWB except the recent Apple's iPhone 11. As we choose to use both BLE and WiFi beacons, we have conducted various ways to enhance the accuracy, including contextual information, characterization of occlusion materials for different signals, and investigate device positions (height and movement) accurate distance analysis. CATS supports different configuration and operation options to cope with social distancing's various privacy and security requirements, which differ among communities such as schools, churches, industries, and government facilities. As monitoring and reporting are contained within an organization, any public system (server or other tags) does not read personal data, including personal identification and SIV inputs. They are kept in private within the personal smartphone app. The SIV scores are shared only after the ID anonymization. Any log data only stays within the community server and will be removed within a couple of weeks without any reviews.

B. Mask-Wearing Detection (MWD) for SIV

To reduce the spread of COVID-19, CDC urges individuals to cover their mouths and noses with a mask when they around others. Wearing a mask is meant to protect other people in case someone in the group is infected. Many people do not wear masks, even in public areas, and when social distancing measures are challenging to maintain. Such cases can be seen when crowds walk on the street, in airports, and schools. As presented in Figure 4, MWD system collects data, detects face masks, classifies the masking condition in a crowd, and counts people. To serve this purpose, MWD consists of data training and feature extraction modules. Eventually, we will deploy the model into the CCTVs. MWD can report SIV for each community and provide a sense of which area is safe from the spread of COVID-19. The system only creates SIV of the community and eliminates any personal identities to ensure privacy.

- **Data Training** module is in charge of annotating and augmenting crowd masking images to create datasets and trains the collected datasets to enable various ML procedures. First, we create and train new **MWD Datasets** for the crowded environment. Mask images were collected from Google images by running web search scripts with various keywords, including "mask." The dataset contains 526 images with either a mask or no mask in a crowd. As illustrated in Figure 4, the images have various crowd density, unlike the existing mask datasets [15], [36], which only contain images with a small number of faces for surveillance purposes. We divided our datasets into three categories, training set (70%), validation set (20%), and test set (10%). Second, the VGG Image Annotator (VIA) software [24] is used for **data annotation**. It manually draws bounding boxes on the images and assigns each labeled object to *Mask* that includes all people wearing a mask, and *No-Mask* that refers to all people without any mask. We also generate the ground-truth density map. All fully or partially front-facing human faces are labeled *Mask* and *No-Mask*. Every labeled object and the information are exported to a .json file for training. We converted the .json file information to the .txt format. Third, **data augmentation** techniques, including scaling, flipping, rotation, and converting images color scale to black and white scale, are applied to increase the training set. We use these techniques to grow the dataset to 1262 images. It improves model performance by reducing the chance of model overfitting. Finally, for **training configuration**, Adam optimizer [29] is used as an optimization method for the training of Mosaic by configuring a learning rate (1e-4), and a momentum (0.9). Performing multiple experiments starting from 1e-3 to 1e-9, we found that 1e-4 is the most optimal learning rate. Other recommended training hyper-parameters are adopted, including a batch of 16 and an epoch number of 100. It is implemented using the Pytorch framework [31]. All of the experiments were conducted on an NVIDIA GeForce GTX 1080 Ti.
- **Feature Extraction** module uses a YOLO v3 [32] to extract features. It continuously passes the extracted features to a masking check function, which detects and evaluates the masking status in various aspects, including mask, no-mask (incorrect masking). We have changed the hyperparameters of Yolo, such as batch size, learning rate, and epochs number. The Super-Resolution (SRCNN) technique reconstructs a High-Resolution (HR) image from the Lower-Resolution (LR) images before applying the YOLO. After the feature extraction, we have added a classification layer at the end of

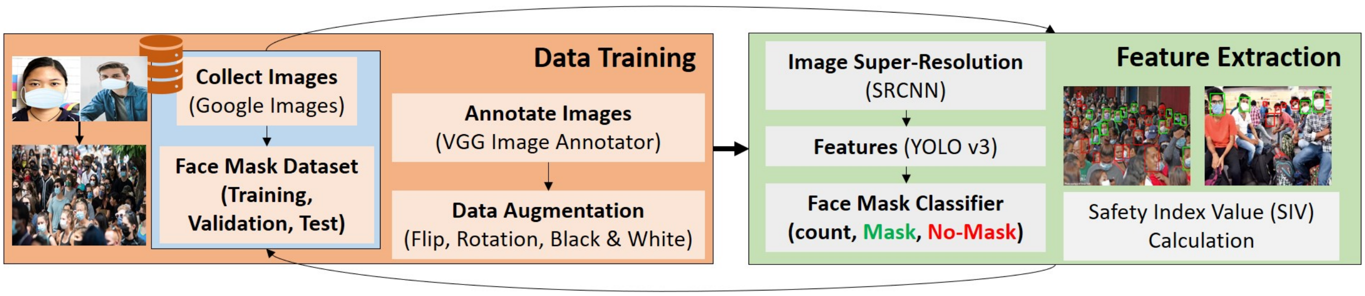

Fig. 4. MWD system architecture

YOLOv3. It classifies the masking features like a red box for *No-Mask* and a green box for *Mask*. It also counts the total number of people with *Mask* and *No-Mask*. Eventually, SIV is calculated for each image by applying the mask ratio, which is $SIV = Total_{mask}/Total_{people}$.

IV. Evaluations

We conducted an ML-based MWD experiment using the trained MWD prototype with the testing dataset.

Figure 5 presents the detection results of incorrect masking (e.g., the neckbeard, the sniffer, the stache, and the nose plug) and various face mask styles and colors. For example, the mask should cover the nose and mouth to stop the spread of infection. The red box detects both *No-Mask* and *incorrect mask*.

Figure 6 shows the calculated SIV in % from a target image. While the target image is going through the MWD model, it identifies the number of detected people ($Total_{people}$), total number with *Mask* ($Total_{mask}$), the number with *No-Mask* ($Total_{no-mask}$), and the original count of people in an image. SIV is calculated for each image by applying the mask ratio, which is $SIV = Total_{mask}/Total_{people}$. For example, the leaft image of Figure 6 has 82 of $Total_{people}$ and 9 of $Total_{mask}$ that results 11% of SIV (very unsafe as only 11% is masking).

The recall rate and precision metrics defined by Eq. (2) with true-positive (TP), false-negative (FN), and false-positive (FP) are used to evaluate the classification detection performance. A mean Average Precision (mAP) in object classification tasks is also calculated. mAP is in a range from 0% to 100%, and the higher value means better accuracy. As presented in Table I, mask recall of 82%, mask precision of 79%, no mask recall of 65%, no mask precision of 63%, and mAP (average) of 71% are pretty accurate for detection tasks in a crowd. Both recall and precision results in *No Mask* are relatively low because most of the labeled objects in the dataset are with *Mask*.

TABLE I
Classification Performance

Mask Recall	Mask Precision	No Mask (Face) Recall	No Mask (Face) Precision	mAP
82%	79%	65%	63%	71%

Fig. 5. Detection of various masks and incorrect masking

Fig. 6. SIV calculations

$$Recall = \frac{TP}{TP + FN}, \; Precision = \frac{TP}{TP + FP} \tag{2}$$

V. Conclusions

In this paper, we designed and developed a novel tracing strategy and system named Crowd-based Alert and Tracing Services (CATS) to build a safe community cluster. CATS applies social distancing and mask-wearing principles to small, focused communities to provide higher privacy protection, efficient penetration of technology, greater accuracy, and effective practical policy assistance. We have implemented a smart tag to support social distancing. We also implemented an ML-based mask tracking system to build non-binary Safety Impact Values (SIV).

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