A Participant Contribution Trust Scheme for Crisis Response Systems

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***Abstract*— When a crisis occurs, an immediate response by rescue personnel is crucial. Decisions for a rescue plan are based solely on data about the crisis from the location. It stands to reason that increasing the amount of such data will result in a faster, efficient rescue response. To make this possible, a crisis response system accepts inputs from people near the crisis via their handheld sensor devices such as smartphones and tablets through a participatory sensing system. However, receiving data from the public could potentially result in corrupted and inaccurate data that will negatively impact the rescue plans. Given that risk, assessing the accuracy of the participant's data contribution becomes essential. In this paper, we present a Participant Contribution Trust (PCT) scheme. PCT aims to provide the crisis response system only with the trusted accurate contributions. The steps involved in filtering the contributions include splitting the crisis area into sectors, comparing the contributions with other *intra-* and *inter-sector* contributions and confirming the accuracy of the sensed data. Our experimental results show that PCT has a high detection rate for eliminating inaccurate contributions resulting in the delivery of the most accurate data to the crisis response system.**

***Index Terms*— Trust; data quality; crisis response system; participatory sensing; reputation system.**

I. Introduction

A crisis, by definition, is a situation that has reached an unpredictable critical phase, and an urgent action needs to be taken to disrupt or decrease difficulties [1]. Accidents, fires, earthquakes and floods are examples of crises. They threaten people's lives and must be dealt with in a timely manner.

A Crisis Response System (CRS) consists of a group of authorities who are trained to deal with such situations [2]. The authorities need accurate data to be able to make appropriate rescue plans and act to resolve the situation. When a crisis happens, some of the data needed pre-exist with the authorities such as the location of forests, lakes, mountains, municipal facilities and routes into and out of the crisis site. However, additional data directly related to the crisis would be beneficial to make rescue plans. This data could be generated by individuals who are within close proximity to the crisis and gathered by a system that can deliver this data to the CRS.

A participatory sensing system consists of participants, an application server and end-users [3]. Participants sense their surrounding environment using their handheld sensor devices, such as smartphones, tablets and phablets. Next, participants send the sensor data to an application server. The server analyzes the received data and shares the final result with end-users [4].

CRS, on the one hand, requires all available data to reach its optimal performance. On the other hand, the participatory sensing system usually accepts sensor data from the public which raises the challenge of participant contributions trust; what data is accurate and what data is not. Therefore, the participatory sensing system needs to verify the accuracy of contributions before sending the data to the CRS.

To overcome this challenge, we propose a Participant Contribution Trust scheme (PCT). PCT aims to provide trusted sensed data by filtering the inaccurate contributions out from the accurate contributions. PCT compares contributions from different locations at the crisis site to confirm the accuracy of one another. It also computes participant reputation values to be used in selecting the highly reputed participants.

PCT consists of three major stages: (1) dividing the affected crisis area into multiple sectors, (2) filtering participant contributions and (3) updating participant reputation values. As well PCT is a viable CRS solution for various environmental conditions such as fire disaster, radiation measurement, wind speed, humidity and air quality.

In this work, we implement the proposed PCT on a fire crisis dataset. Around the crisis, multiple participants use their handheld sensor devices to sense the air temperature in degrees during different periods of time and from several locations. The data follows a certain trend. Thus, different locations will have different temperature readings indicating the direction of the fire and its intensity. Then, participants send the collected data to PCT. In addition to the temperature, the collected data includes metadata such as the participant's location, date and time. The CRS uses the output of PCT to measure the severity of the disaster and with that information authorities make an efficient rescue plan.

We perform experimental evaluations to assess the accuracy of the proposed PCT, and compare PCT to our previous work, the Reputation System to Evaluate Participant (RSEP) scheme [5]. We show the results of the comparison between the PCT and RSEP schemes.

The remainder of this paper is organized as follows. In Section II, we discuss several related works. Section III details our proposed participant contribution trust scheme and its related algorithms. In Section IV, we describe the experimental

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evaluation and setup, and discuss the evaluation results. Section V concludes our work.

II. Related work

Contribution trust is essential for participatory sensing systems to provide better services. Trust can be verified by measuring the accuracy of a participant's contributions using reputation systems and contributions confirmation by comparing theirs with the contributions made by other participants. In this section, we discuss the related work in the field of the CRS and participatory sensing systems.

Contribution trust has been studied in the CRS [6, 7, 8]. Tundjungsari and Yugaswara [6] proposed a scheme to collect data and distribute information among CRS authorities. The scheme distinguishes the good sensor data by applying a reputation system on their participants. The scheme distributes the information of the reputed participants to minimize the time wasted downloading the poor quality information. Tan et al. [7] proposed a trust model to evaluate participants in emergency communication. By using a filtering algorithm, the trust model avoids the untrusted participants by rejecting their contributions to improve the service performance. Conrado et al. [8] produced a data quality measurement framework that is compatible with social networks. This framework manages the uncertainty collected data by participants. It aims to support the CRS authorities with the best available contributions for the rescue plan decision-making process.

Contribution trust has been studied in the participatory sensing systems [9, 10, 5]. Restuccia and Das [9] proposed a trusted-based framework to measure contributions accuracy. It maintains a list of participants who are assumed to be trusted and protected from external attacks. Those trusted participants always sense accurate data. When other participants contribute in a task, the trust-based framework evaluates them by comparing their contributions with the contribution of the neighboring trusted participants. Manzoor et al. [10] built a trust system that evaluates participants' contributions based on their reputation values. The reputation values computation relies on the participants' previous contributions that have been evaluated based on the sensor data quality. In [5], we proposed the RSEP scheme. It validates participant contributions using their reputation values. It starts by clustering participants together based on the similarities of the contribution values. Then, the system evaluates each group of the participants based on their reputation weights using their members' reputation values. The highest group weight is the winner, and its participant contributions are the most accurate. At the end of the process, RSEP rewards the winner participants and penalizes the losers. RSEP has similarities to and differences from PCT, which we discuss in Section IV.

All of the systems described work on satisfying application requirements to maintain high-quality contributions. These systems, however, propose assumptions that may not be feasible in every environment. Our PCT scheme is designed to cover a wider range of environments and conditions than the schemes reviewed.

III. The PCT Scheme

In this section, we overview the proposed PCT scheme in Section III.A. Section III.B details the PCT algorithm. In Section III.C, we discuss the algorithm of participant reputation value computation. Then, we end this section by explaining how to divide the crisis area into sectors in Section III.D.

A. The PCT Scheme Overview

PCT aims to provide trusted contributions by selecting the most accurate sensed data. Then, it sends the accurate data to the CRS. Fig. 1 shows the data flow starting from the participants' data collection passing through PCT then onto the CRS. At every epoch, a period of time, participants start the process by sensing the required data using their devices with embedded sensors. Participants send the sensed data to PCT to filter the data and obtain the most accurately sensed data. Then, PCT sends the accurate sensed data to the CRS. The cycle of PCT goes through three major stages: (1) dividing the entire affected area into smaller sectors, (2) filtering participant contributions and (3) updating participant reputation values.

In stage one, PCT splits the area into multiple sectors by creating multiple zones and four cardinal directions (north, east, south and west) as explained in Section III.D. Each sector belongs to a specific zone and direction, as shown in Fig. 2. By creating these multiple sectors, the next stage can treat each direction separately.

In stage two, PCT runs a filtration steps in one cardinal direction at a time as in Algorithm 1, Section III.B. Filtering participant contributions passes through two steps: (1) from the outermost sector to the innermost sector, then (2) from the innermost sector to the outermost sector. The order of these two major steps depends on the crisis environment and rescue crew requirements. Through these two steps, PCT computes the Average Sensed Data (*ASD*) of the High Participant Reputation Values (*HPRV*) in every sector it passes through. Computing the reputation value depends on the participant's contributions history, as in Algorithm 2, Section III.C. PCT compares the computed *ASD* with other contributions of either the same sector (*intra-sector*) or a different sector (*inter-sector*). The comparison phase allows the scheme to decouple the Inaccurate Sensed data (*IS*) from the Accurate Sensed data (*AS*).

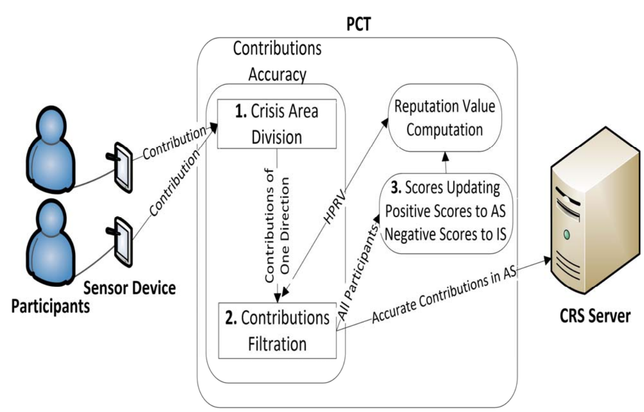


Fig. 1: The PCT Architecture

Stage three updates participant reputation values at the end of the filtration task of each direction. When PCT decouples the *IS* from the *AS*, it assigns a negative score (*ns*) to every participant in *IS* and a positive score (*ps*) to every participant in *AS*. These new assignments will change the participant reputation value either up or down in the next contribution in a different epoch.

B. The PCT Algorithm

PCT collects contributions from participants in an affected area in every epoch. In Algorithm 1, PCT filters the sensed data in one cardinal direction (*d*) at a time. The filtration step of one cardinal direction in Algorithm 1 starts from the outermost sector, $Sector_{n,d}$, to the innermost sector, $Sector_{1,d}$ as in Fig. 2, to compare participant contributions and keep the accurately sensed data. Then, it reverses the steps from the innermost sector, $Sector_{1,d}$, to the outermost sector, $Sector_{n,d}$ as in Fig. 2, to apply extra filtration steps of the remaining participant contributions and gain the most accurate contributions as a final result. PCT, then, updates the participants' scores for their next contributions.

In the first section of Algorithm 1, the scheme computes the ASD_i of the $HPRV_i$ of $Sector_{i,d}$ and compares it with all participants in $Sector_{i-1,d}$, where $i = \{n, ..., 1\}$. This *inter-sector* comparison filters out some of the inaccurate contributions in $Sector_{i-1,d}$ by checking if the sensed data of *j-th* participant (S_j) is greater than or equal to the ASD_i. Any contribution which passes the condition is added to the Filtered Sensed data group of $Sector_{i-1,d}$ (FS_{i-1}), line 8. On the contrary, any contribution which does not pass the condition is added to the Inaccurate Sensed data group of $Sector_{i-1,d}$ (IS_{i-1}), line 9. In the next sector ($Sector_{i-1,d}$), the scheme computes the ASD_{i-1} of the $HPRV_{i-1}$ of only those who were added to FS_{i-1} in the previous comparison. PCT keeps applying the same steps to all the sectors until it reaches the innermost sector.

At the innermost sector, $Sector_{1,d}$, the scheme compares the ASD_1 of the $HPRV_1$ with all participants in FS_1, line 26. The condition, line 27, of this *intra-sector$_a$* comparison accepts the sensed data within an upper and lower percentage *u* of the ASD_1. Those who pass the condition are added to AS_1, line 28. On the contrary, those who do not pass the condition are added to IS_1, line 29.

In the second section of Algorithm 1, line 12, the scheme applies same steps as in the first section with minor differences. Unlike the first section, the scheme computes the ASD_i of the contributions in AS_i that reflects the accurate contributions of $Sector_{i,d}$. The main purpose of this section is to apply an extra filtration step by applying the opposite condition of the first section, line 16. As a result of applying the condition in line 16, the scheme gets AS_i and IS_i of all sectors until it reaches the outermost sector.

At the outermost sector, $Sector_{n,d}$, the scheme applies the *intra-sector$_a$* comparison function to filter out the inaccurate contributions within the $Sector_{n,d}$ and get the AS_n and IS_n.

The scheme sends all the sensed data in AS_i of each epoch to the CRS, lines 19 and 30, as the most trusted contributions by PCT.

Finally, the PCT algorithm updates participant reputation values based on the accuracy of their contributions, lines 21 to 25. Every participant's sensed data is elected as an accurate contribution and belongs to AS_i receives an extra *ps*, lines 22 and 23. On the contrary, the rest of the participants that belong to IS_i receive an extra *ns*, lines 24 and 25. Those new *ps* and *ns* scores affect the participant reputation value in the next contribution either positively or negatively based on the extra score it receives.

Algorithm 1 Participant Contribution Trust (PCT)

Input: Participant Contributions
Output: Trusted Contributions

1. **Get** *P* Reputation Value // *Section III.C*
2. **Get** *P* Sector // *Section III.D*

From Outermost Sector to Innermost Sector

3. **for** $i \leftarrow n$ **to** 1 **do**
4. **compute** ASD_i of $HPRV_i$

Compare ASD_i with each S of $Sector_{i-1,d}$ // *inter-sector*

5. **if** $i > 1$,
6. **then for** $j \leftarrow 1$ **to** $|Sector_{i-1,d}|$ **do**
7. **if** $S_j \geq ASD_i$
8. **then** add S_j to FS_{i-1}
9. **else** add S_j to IS_{i-1}
10. $Sector_{i-1,d} \leftarrow FS_{i-1}$
11. **else** $a \leftarrow 1$ and **Call** *Intra-sector$_a$* Comparison Function

From Innermost Sector to Outermost Sector

12. **for** $i \leftarrow 1$ **to** n **do**
13. **compute** ASD_i of AS_i

Compare ASD_i with each S of FS_{i+1} // *inter-sector*

14. **if** $i < n$
15. **then for** $j \leftarrow 1$ **to** $|FS_{i+1}|$ **do**
16. **if** $S_j \leq ASD_i$
17. **then** add S_j to AS_{i+1}
18. **else** add S_j to IS_{i+1}
19. Send S_j of AS_{i+1} to the CRS
20. **else** $a \leftarrow n$ and **Call** *Intra-sector$_a$* Comparison Function

Update Participants Reputation Scores

21. **for** $i \leftarrow 1$ **to** n **do**
22. **for** $j \leftarrow 1$ **to** $|AS_i|$ **do**
23. $ps_j \leftarrow ps_j + 1$
24. **for** $j \leftarrow 1$ **to** $|IS_i|$ **do**
25. $ns_j \leftarrow ns_j + 1$

***Intra-sector$_a$* Comparison Function**

Compare ASD_a with each S in FS_a // *intra-sector*

26. **for** $j \leftarrow 1$ **to** $|FS_a|$ **do**
27. **if** $(ASD_a + (ASD_a * u)) \geq S_j \geq (ASD_a - (ASD_a * u))$
28. **then** add S_j to AS_a
29. **else** add S_j to IS_a
30. Send S_j of AS_a to the CRS

C. Reputation Value Computation Algorithm

Participants reputation values reflect their trustworthiness. Algorithm 2 shows the steps of computing a participant reputation value (*rv*). The algorithm considers two modes of operations, *newcomers* and *aging*, that allows more accuracy in computing participant reputation value. A newcomer participant receives an initial $rv = nc$ for the first k contributions to avoid the fluctuation of the newcomer reputation value, lines 2 and 3. On the contrary, if the total number of contributions, X, is more than k, then the scheme considers the last Z contributions to satisfy aging requirement that only considers the most recent contributions in the participant reputation value computation, lines 4 to 9. Finally, the reputation value of *j-th* participant (rv_j) is the Total Positive Scores TPS_j in the considered contributions over the considered contributions number Y, line 10, as follows:

$$rv_j = \frac{TPS_j}{Y} \tag{1}$$

Algorithm 2 Participant Reputation Values Computation

Input: Participants ID
Output: Participant Reputation Values

1. **for** $j \leftarrow 1$ **to** m **do**
2.   **if** $X_j < k$ *// newcomers*
3.   **then** $rv_j \leftarrow nc$
4.   **else if** $X_j < Z$ *// aging*
5.   **then** $Y \leftarrow X_j$
6. $TPS_j \leftarrow ps_j$
7.   **else** $Y \leftarrow Z$
8.   **for** $b \leftarrow X_j - (Z-1)$ **to** X_j **do**
9. $TPS_j \leftarrow \sum ps_b$
10. $rv_j \leftarrow \frac{TPS_j}{Y}$

D. Crisis Area Sectors Division

Dividing the crisis area into multiple sectors allows PCT to have a more accurate measurement. The scheme determines a participant location by checking its position to the zones. The scheme centers the crisis location, R_0, and creates n zones by considering radius R_i, $i = \{1, \ldots, n\}$, that takes on a shape of nested circles, as shown in Fig. 2. The innermost zone, $Zone_1$, is the closest to the crisis and the outermost zone, $Zone_n$, is the closest to the nature condition. Next, the scheme splits the map into the four cardinal directions by creating two ordinal direction lines from the northwest to the southeast and from the northeast to the southwest. The main purpose of splitting the area into the four cardinal directions is to allow the CRS to better estimate the movement direction of the crisis. As a result, the scheme creates n sectors in each direction and determines the participants of each sector, where $Sector_{i,d}$ refers to the sector in $Zone_i$ and $direction_d$.

IV. Experimental Evaluation

In this section, we discuss PCT experimental evaluation results. We review the implementation setup and evaluation environment in Section IV.A. Section IV.B explains the dataset we use in the implementation. Section IV.C discusses the evaluation metrics to assess the accuracy of PCT results.

A. Evaluation Environment

The PCT scheme is intended to use on a dataset collected by a group of participants who are within the vicinity of the crisis (dataset detail is in Section IV.B). Each record in the dataset represents a contribution of a participant. The participant collects sensor data, includes its metadata such as participant location, date and time, and sends them to PCT. This action continues by participants from all sectors to the end of the collection epoch. PCT receives all the contributions by the end of the epoch and then applies the steps of locating participants and filtering their contributions as described in Section III. The result of the scheme is filtering the data to only have the most accurate contributions to send to the CRS. As the last step of the evaluation environment of PCT, it applies a reward/penalty mechanism to all participants based on their contributions accuracy.

B. Dataset

Due to the lack of real-world data collected from handheld sensor devices of an actual crisis, we generated our dataset. In our dataset, we assume a crisis at a randomly selected location and generate random dynamic participants located within a certain distance from the crisis. Participants use their smartphones' sensors to collect sensor data in addition to spatiotemporal data such as location, date and time.

A fire crisis is our use case. We center the crisis and generate a heating map by creating four heating levels around the crisis. In such situations, data follows a certain trend. Therefore, the closer the level to the crisis, the higher the temperature range. We consider an area of a radius of 1.5 km from the crisis. The dataset consists of 500 participants contributing for eight days. The data collector operates 24 hours a day and collects data every 30 minutes (epoch). In every epoch, we have a different number of participants that are randomly selected. Since participants are mobile, participant positions may change in different epochs. The sensing temperature values range between 10 and 90 degrees Celsius[1] that depends on the participant's heat level.

Participants are randomly distributed in the considered area. We generate a temperature value for every participant in a certain epoch by applying Gaussian distribution[2]. In every run, we assign a mean (μ) and standard deviation (δ) as required

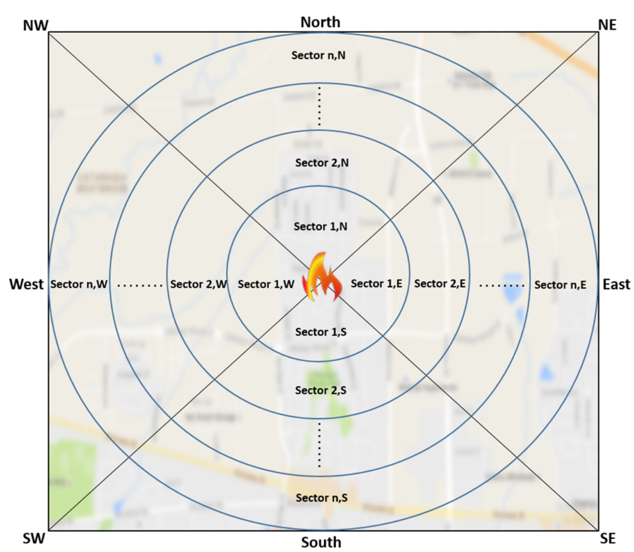


Fig. 2: A crisis map after splitting the area into sectors in each direction

1 Typical smartphones cannot function in temperatures above 90 degrees Celsius

2 We followed the data generator function in [5]

parameters for Gaussian Function. The mean value (μ) corresponds to the ground truth temperature for every level in every epoch. For every participant, we assign a fixed error range (δ) that remains the same in all of its contributions. For the sake of measuring the success of the scheme, we randomly classify participants into three groups: (1) honest, (2) dishonest and (3) misleading. Honest participants usually sense accurate temperatures with a 10% error range from (μ). Honest group consists of 50% of all participants. Dishonest participants usually sense inaccurate temperatures with error range between 10% and 30% from (μ). This group consists of 25% of all participants. Misleading participants, the last 25% of all participants, sense accurate or inaccurate temperatures based on the data generator function decision. In the results of the scheme, this group plays a major role because of the inconsistency of its contributions accuracy [5].

C. Experiment Results

Since we have generated the dataset and predetermined honest and dishonest participants, we can take advantage of this and measure the accuracy of PCT. In addition to filtering participant contributions, PCT evaluates participants by rewarding the accurate contributions with positive scores and the inaccurate contributions with negative scores, which will impact the reputation value of the participants. Hence, we measure the results of PCT using two metrics: *False Positive (FP)* and *False Negative (FN)* rates.

FP is a rate of the participants whose reputation values are above the *threshold* while they are originally classified as dishonest. On the contrary, FN is a rate of the participants whose reputation values are below the threshold while they are originally classified as honest. The threshold is a percentage that is applied to the participant reputation values to distinguish honest from dishonest participants.

We set the threshold into three values: 70%, 80% and 90% to assess PCT results accuracy. We produce three sets with different sizes of participants to evaluate PCT using the FP and FN rates. Set_1 and set_2 consist of 100 and 250 randomly selected participants, respectively, while set_3 consists of all 500 participants. To evaluate PCT results, we implement the FP and FN rates metrics by applying each threshold on the three sets as in Eq. 2 and Eq. 3:

$$FP\ rate_x = \frac{D_x}{|subset_x|} \tag{2}$$

$$FN\ rate_x = \frac{H_x}{set_x - |subset_x|} \tag{3}$$

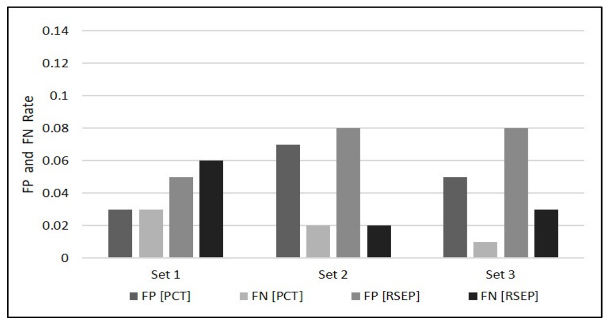
D_x is the total number of dishonest participants whose reputation values are above the threshold in set_x, $x = \{1, 2, 3\}$. H_x is the total number of honest participants whose reputation values are below the threshold in set_x. The *Subset* is the total number of participants whose reputation values are above the threshold in set_x.

From the analysis of PCT results, we find that the total number of participants whose reputation values are above the threshold ($subset_x$) in set_1, set_2 and set_3 are 62, 167 and 318, respectively, with a threshold of 70%. As a result of implementing the metrics, the FP rates are 3%, 7% and 5%, and the FN rates are 3%, 2% and 1% for the three sets, respectively. The FP rate of set_1 is 3% because of two participants who have been classified as dishonest and their reputation values are above the threshold. On the contrary, the FN rate of set_2 is 2% because of two participants who have been classified as honest and their reputation values are below the threshold.

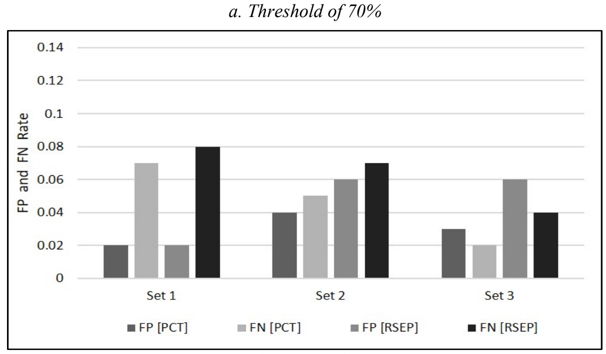
With a threshold of 80%, the FP rate are 2%, 4% and 3%, and the FN rates are 7%, 5% and 2%, for set_1, set_2 and set_3, respectively. With a threshold of 90%, the FP rate are 0%, 2% and 1%, and the FN rates are 9%, 8% and 6%, for set_1, set_2 and set_3, respectively, as shown in Fig. 3.

We compare PCT with our previous work, RSEP [5], to distinguish the accuracy levels of their results. We implement RSEP on this paper's dataset to get reasonable results. Then, we analyze the results by applying the FP and FN rate metrics to evaluate the accuracy of the scheme results. The selection of RSEP for the comparison is due to the similarities in its features with PCT. However, the methodology that RSEP uses to reach the target results is different, in addition to the environments that it can be applied for.

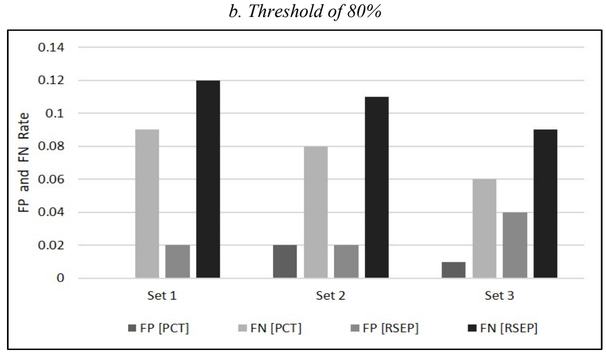
RSEP aims to provide accurate contributions to end users. It is designed to deal with participant contributions participating



a. Threshold of 70%



b. Threshold of 80%



c. Threshold of 90%

Fig. 3: FP and FN rates of PCT and RSEP with three thresholds

for an application service. RSEP evaluates those contributions using their participant reputation values. Then, it sends the accurate contributions to the application service. At the last step, it rewards/penalizes participants based on their contribution accuracy.

The two major differences in RSEP are: (1) the process it goes through to evaluate the contributions and (2) the limitation of receiving the contributions from one sector at a time. Relating to the former, when RSEP receives the contributions from participants, it clusters the participants into multiple groups based on the similarities of their contribution values. Then, it evaluates each group by computing the total reputation value - derived from the group's individuals' reputation value. The highest group value is the winner to send its contributions to the application service. The second difference is, that RSEP can only treat the contributions that originate from a single sector at a time. This limitation could lower the contributions evaluation that may impact the results.

We applied the same settings to RSEP by creating the same three set sizes and three threshold values. In the comparison, the lower the metric rate, the better the accuracy in assessing participants. In Fig. 3.a, for example, which the threshold is 70%, the FP rates in PCT are 3%, 7% and 5%, and the FN rates are 3%, 2% and 1%, for set_1, set_2 *and* set_3, respectively. On the contrary, the FP rates in RSEP are 5%, 8% and 8%, and the FN rates are 6%, 2% and 3%, for set_1, set_2 *and* set_3, respectively.

Considering participant contributions from one sector at a time limits RSEP to assess these contributions by using participant reputation values only. This limitation decreases the evaluation accuracy; thus, it causes higher FP and FN rates in the comparison with PCT. In contrast, assessing participant contributions by comparing them with other *intra-* and *inter-sector* contributions, and the fact that data follows a certain trend in crisis situations, give PCT an advantage of better evaluation accuracy. The contributions comparison is applied in two directions, from the outermost to the innermost sectors and vice versa. Consequently, the results of the comparison, Fig. 3, show that PCT has a better performance than RSEP in both the FP and FN rates.

V. Conclusion

Allowing individuals to contribute to crisis response systems is essential for better understanding the crisis and making rescue plans. Since those contributions are received from distinct participants, we proposed the PCT scheme. The goal of PCT is to provide trusted sensed data by eliminating the inaccurate ones, and keeping only the accurate contributions. PCT goes through three stages to achieve this: dividing the crisis area into multiple sectors, filtering participant contributions, and updating participant reputation values. Dividing the area into sectors addresses the fact that different sectors have different sensing levels. This allows the scheme to have a better assessment in treating those distinct contributions. Filtering participant contributions takes place by comparing contributions with other *intra-* and *inter-sectors* contributions to confirm the accuracy of the sensed data. Through this step, the scheme eliminates the inaccurate contributions during the comparison. Participant reputation values are updated by assigning positive and negative scores to participants based on their contributions accuracy. These new scores change the reputation values of the participants in the next contribution.

We compared PCT to RSEP by applying the false positive and false negative rate metrics. The experimental results showed that PCT provides a higher detection rate for eliminating inaccurate contributions resulting in the delivery of the most accurate data to the crisis response system.

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References

[1] S. B. Liu, "Crisis crowdsourcing framework: Designing strategic configurations of crowdsourcing for the emergency management domain," *Computer Supported Cooperative Work (CSCW)*, vol. 23, no. 4, pp. 389–443, 2014.

[2] J. E. Hale, R. E. Dulek, and D. P. Hale, "Crisis response communication challenges: Building theory from qualitative data," *Journal of Business Communication*, vol. 42, pp. 112–134, 2005.

[3] J. Burke, D. Estrin, M. Hansen, A. Parker, N. Ramanathan, S. Reddy, and M. B. Srivastava, "Participatory Sensing," in *Proceedings of the ACM International Workshop on World-Sensor-Web*, pp. 117–134, 2006.

[4] M. A. Alswailim, M. Zulkernine, and H. S. Hassanein, "Classification of participatory sensing privacy schemes," in *IEEE 39th Conference on Local Computer Networks Workshops (LCN)*, pp. 761–767, Sept 2014.

[5] M. A. Alswailim, H. S. Hassanein, and M. Zulkernine, "A reputation system to evaluate participants for participatory sensing," in *IEEE Global Communications Conference (GLOBECOM)*, pp. 1–6, Dec 2016.

[6] V. Tundjungsari and H. Yugaswara, "Supporting collaborative emergency response system with reputation-based trust peer-to-peer file sharing," in *International Conference on Technology, Informatics, Management, Engineering Environment (TIME-E)*, pp. 6–11, Sept 2015.

[7] S. Tan, X. Li, and Q. Dong, "A trust management system for securing data plane of ad-hoc networks," *IEEE Transactions on Vehicular Technology*, vol. 65, pp. 7579–7592, Sept 2016.

[8] S. P. Conrado, K. Neville, S. Woodworth, and S. ORiordan, "Managing social media uncertainty to support the decision making process during emergencies," *Journal of Decision Systems*, vol. 25, no. sup1, pp. 171–181, 2016.

[9] F. Restuccia and S. Das, "Fides: A trust-based framework for secure user incentivization in participatory sensing," in *IEEE 15th International Symposium on a World of Wireless, Mobile and Multimedia Networks (WoWMoM)*, pp. 1–10, June 2014.

[10] A. Manzoor, M. Asplund, M. Bouroche, S. Clarke, and V. Cahill, "Trust evaluation for participatory sensing," in *Mobile and Ubiquitous Systems: Computing, Networking, and Services*, pp. 176–187, Springer, 2013.