Final Team Report: A Novel GWAP Disaster Monitoring System

Team *Hotpot*

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CONTENTS

ABSTRACT Disaster Monitoring is a challanging problem due to the lack of infrastructures in the disaster areas. This report contributes to Disaster Monitoring with the description of a Game With A Purpose (GWAP), which analyzes tagging results from players from satellite pictures and exports aggregated results to Disaster Monitoring stakeholders. We illustrate our system mockup with proposed implementation technology stack first, then we gives the mathematical model of system scheme. As justification and evaluation, we prove the correctness of the model, discusse issues caused by this system and possible solutions extensions for future works as well.

1 INTRODUCTION

In this chapter, we gives an introduction about the general backgrounds and challanges of disaster monitoring. Then we briefly introduce the related technics that used in the report, and put forward our general purspose of this report.

1.1 RELATED WORKS

1.1.1 UNICEF CHALLANGES AND SATELLITE RESOURCES

The United Nations Children's Fund (**UNICEF**) [1] is a United Nations programme headquartered in New York City that provides humanitarian and developmental assistance to children and mothers in developing countries. It works in 190 countries and territories to protect the rights of every child. UNICEF has spent 70 years working to improve the lives of children and their families. Defending children's rights throughout their lives requires a global presence, aiming to produce results and understand their effects. For example, in Syrian, the UNICEF works on providing and transporting critical medicine, aid and supplies to the refugees living in the war areas [2].

The challenges UNICEF meet is that there are many hard-to-reach and besieged areas (lake of infrastructure), the supplies are extremly difficult to be delivered to these zones if the UNICEF is not aware of the real time war situation and the disaster level. It leads huge costs for the UNICEF which is just a nonprofit organization if they entirely hire employees to collect the data of war situation.

With limitations of infrastructure, disaster can only be monitored from the sky level. Satellite sensors may be used to observe the disaster areas, which mainly gives image information of monitoring areas. Zhang et al. [3] discussed the application of a national integreated system using remote sensing, geographic information for monitoring and evaluating flood disaster. Their system has been applied for three years, which gives a proof of the success of satellite sensor informations.

1.1.2 Human Computation System and Game With A Purpose

Human Computation system is a paradigm for utilizing the human processing power to solve problems that computers cannot yet solve [4]. It is the system of computers and large numbers of humans that work together in order to solve problems that could not be solved by either computers or humans alone [5]. **Game With A Purpose (GWAP)** was first proposed in 2006 [6], it is a human computation technique of outsourcing steps within a computational process to humans in an entertaining way (gamification). Neverthless, the data collection mechanisms for a game is variety that should be considered in a proper way [7].

1.2 Purpose of the System

The general purpose of this report is to design a system by using satellite images that monitor the disaster level of a region based on GWAP, which helps organizations like UNICEF. For the collection mechanism of this game, we require game players to select a region upon the presented satellite images and tag the most relevant tags from the provided tags. However, with this gameplay, we need to design carefully to solve issues like malicious player detection, game incentivization, disaster level calculation, etc. In the subsequent chapters, we will discuss the system functionalities first by presenting the system mockups, then gives the comprehensive design of the system backend models for malicious player detection and disaster level calculation as well.

2 Functionalities

In this chapter, we introduce two interactive mockups of our disaster monitoring model. The first mockup is built for game players, which is used for collecting human inputs. The second mockup is built for some collaborative organisations, such as UNICEF and some non-governmental organizations (NGOs), who wants to dispatch their rescue teams in disaster area more properly.

2.1 Functionalities as Seen by a Player

2.1.1 Disaster Monitoring Game Introduction

The idea behind our human computation system is GWAP. We have sketched a mockup of image tagging game, which is similar to the ESP game on Artigo [8]. In our game, A player can finish infinity round tasks, a Round task contains n image tagging tasks and a tagging task is to: interpret one picture. Within one round task, the player will see n images. Each time he/she will be asked to tag one of these images. At first, the player needs to draw a rectangle area which indicates that he/she has seen some objects in this area. Thoses objects are often considered as a sign of danger or damage. They are mostly like:

- “Rocket Launcher”
- “Armoured vehicles”
- “Tanks”
- “Burning building”
- “Heavy vehicle tracks”
- “sign of explosion”

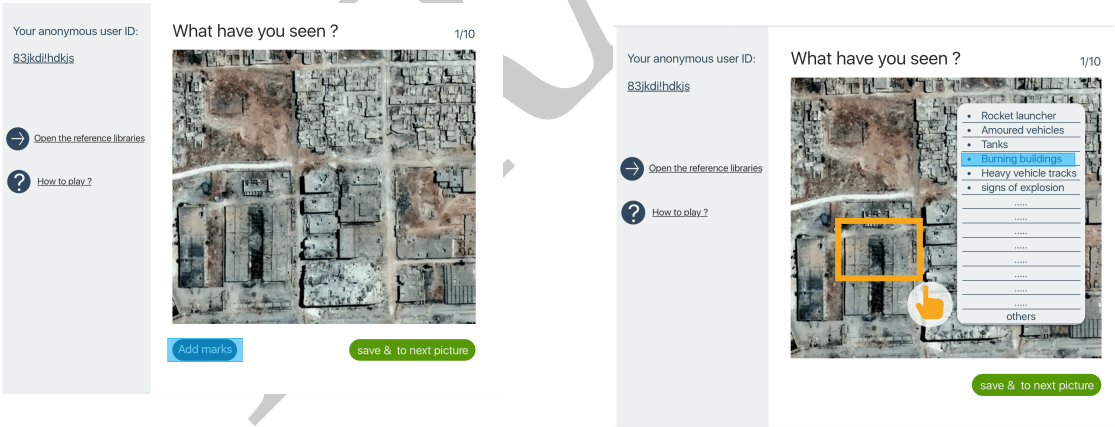
The system organisation shall predefine a tag list into this system, which is done by a initial trusted group (discuss in section 3.3).

A submenu list (“Pre-provided item list”) which contains all of these items will pop up after the area has been selected. In this step, the player can decide which one of these items matches and then choose it. The player can also obtain helps from the reference panel which provides the player with examples. Besides, if the player does not find the expected item in the “Pre-Provided item list”, he/she can also create a new tag.

In a tagging task, the player also has a choice to add multiple tags to one picture, or he/she dosen't need to add any tags when he/she thinks that this region is safe. After finishing one tagging task, the player will be directed to the next task till the end of the game.

2.1.2 Examples

In this section, An example of a user journey is provided in order to illustrate the game process.



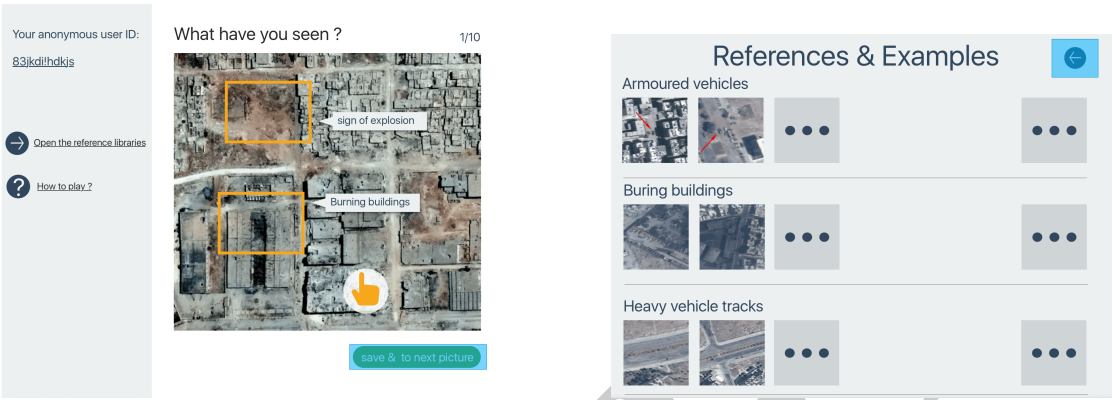
(a) Overview (b) Tag List

Figure 2.1: Game panel Mockups, satellite image from [9]

Imaging that user A is now at the very first begining of the game. What he will see, are a

side bar on the left side, which contains some information like: user ID, game guide and a reference library, and a main panel on the right side (Figure **??**). If user A finds a sign of damage or danger in the picture on the right side. He can click the button “add marks” and then hs is able to draw a rectangle area which indicates the location of the sign. A selection box will then pop out automatically and user A can select the suited item or add a new tag (Figure 2.1b).

As already mentioned above, user A can also add multiple tags to one picture (Figure 2.2a).



(a) Multiple Tags (b) Reference library

Figure 2.2: Game panel Mockups, satellite image from [9]

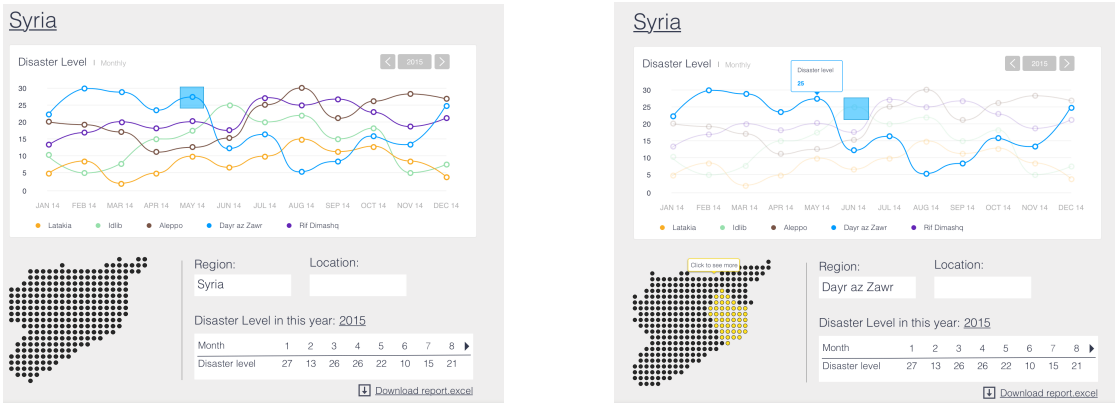
After user A finishes this tagging task, i.e. tagging the first picture, he can click the button “save and to the next picture” so that he can save the tags and go to the next task. Figure 2.2b illustrates how a reference library can be, whose aim is to help user A to identify different signs of danger or damage.

TODO: where is the final incentivization picture?

2.2 Functionalities as Seen by a Stakeholder

In our disaster monitoring system, we take image taggings from players as our input. In the next step, we will filter and analyse the data. The final output of our work is a disaster level report in some certain region, which can be used by some organasitions, like: Unicef, some NGOs and even governments.

Under this consideration, we also sketches a mockup for this user group, which gives them an overview of the disaster level and to download the report at the same time (see figure 2.3a).



(a) Overview (b) Selecting one area

Figure 2.3: Disaster level report platform Mockups

The platform is composed of a curve chart, a map and some statistics. In the curve chart, each curve shows the the yearly disaster level of a smaller region. Like here in figure 2.3a, the whole region is Syria and each curve stands for a province in Syria. The user can click the “dot” on curves, which stands for the disaster level of that month. Meanwhile, the corresponding area will be highlighted on the map (figure 2.3b).

In the statistic part, the user gets an overview of the yearly disaster level of a region. He/she also have the opportunity to download it. If the user wants to dig deeper, he/she can click on the highlighted area on this map, which will direct him/her to that region (figure 2.4).

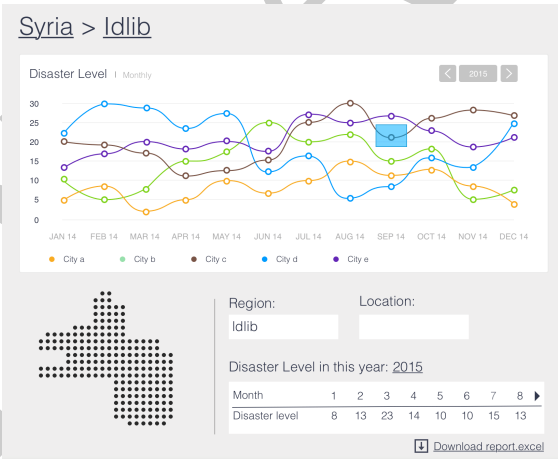


Figure 2.4: Disaster level report platform Mockup: Sub-area selection

In figure 2.4, the user is directed to the province Idlib and now each curve stands for a smaller region in this province, in other words, different cities in Idlib.

2.3 Possible Technology Stack for Implementation

Our system should be capable of easily acessing by both Android and iOS users. We suggest to build our system sketched above as a web-based application since Web App is wide-used nowadays and cross any platform, which gives huge benefits for reducing development costs. In addition, we suggest to choose **Polymer**, a Google front-end framework, as our front-end tool and as back-end tool, we suggest to use **Nodejs** as well as **Python**. For our database, we suggest then to choose **MongoDB**, since it is more suitable for a web-application.

3 Design and Models

In this chapter, we describe the overall design of our disaster monitoring backend system in details. Firstly, we propose our system architecture of this disaster monitoring; Then we specify and justify our most critical system components such as databases design, **Player Task Generator (PTG)**, **Player Rating Model (PRM)** as well as **Disaster Evaluation Model (DEM)**.

With these components, model and databases, the disaster monitoring system can handle common problems in human computation system, such as cold start, malicious player detection, etc. It is also expandable, portable and can be easily applied to any other same image selection and tagging based human computation system in different areas.

3.1 System Architectures

Figure 3.1 illustrate the overall disaster system design. The system databases are composed of two different type of databases. The first database **PlayerDB** combines **TrustedDB** and **UntrustedDB** where persistent the player property and raw tagging inputs whether the overall result is reliable or not. The second database is called **ResultDB** where persistent the reliable player inputs.

For this architecture design, one can simplify the overall data flow into tree main steps that describes as follows:

Step 1. Player task generating: We propose the **PTG** that combines trusted results from TrustedDB, and separate new images from satellite, then assign this binding to the future players.

Step 2. Malicious player detection: A reliable player shall pass the malicious detection algorithm (describe in algorithm 1) inside the **PRM**. Once the player is not a malicious player, then system will mark all the results from this player as a reliable result and then send it into next step.

Step 3. Evaluating disaster level: the system reuse the reliable player inputs into **DEM** and calculate the disaster level of the monitoring region as well as persistent it in the second database ResultDB.

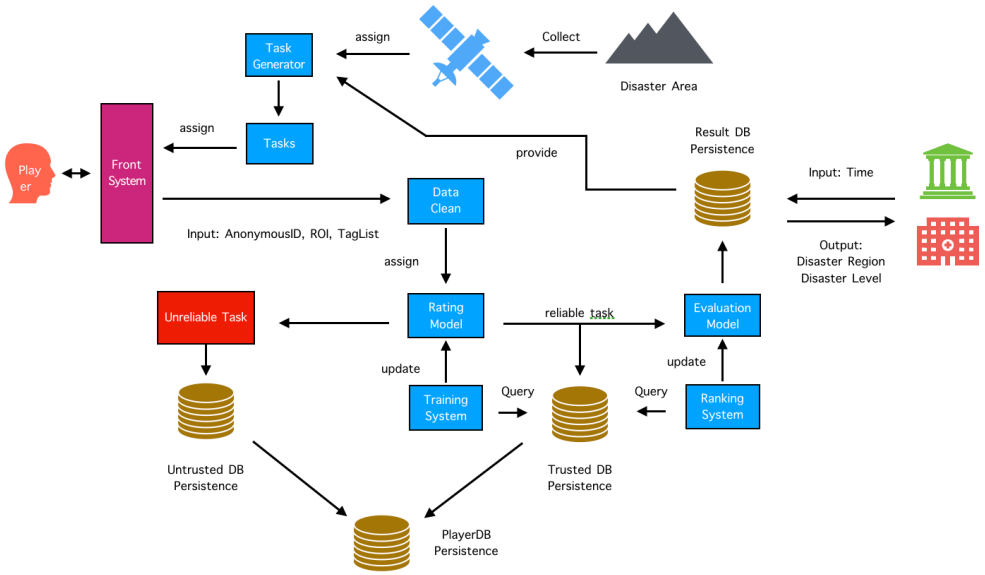


Figure 3.1: System Design Overview

After these three main steps, stakeholders are able to retrieve monitoring results from the database ResultDB.

3.2 System Components

3.2.1 Database Fields

We describe the system database PlayerDB fields as well as the fields of database ResultDB first in listing 1 and 2.

In this disaster monitoring system, our participants **do not need to register accounts**, and the system backend shall **generate and assign an** *player_id* **to each player** according to the user scenario (such as IP address, network status, system information et cetera). This function significantly accelerate player to participate in this game. Thus, the **PlayerDB** stores the *player_id* to detect the same players if they participate next time. The player will accomplish different game tasks; each task result shall store in the tasks filed.

```
[
 {
  "player_id": "E3A6F124-4A6C
   -4C6E-B7F1-F8BC9A7381CC",
  "tasks": [
   {
    "image_id": "3A21E99E-
    F074-454B-A590-8
    D8C5ABD8E77",
    "image_at": "2017-07-31
    11:28:40",
    "reliable": true,
    "ROIs": [
     {
      "x": 103, "y": 121,
      "height": 56,
      "width": 78,
      "tags": ["burning
    building", "explosion"]
     }
    ]
   }
  ]
 }
]
```

Listing 1: Example of PlayerDB Data

```
[
 {
  "region_id": "FBEB6204-0B94
   -4811-94F0-9DDC5FBBE6D8",
  "history": [
   {
    "image_id": "3A21E99E-
    F074-454B-A590-8
    D8C5ABD8E77",
    "image_at": "2017-07-31
    11:28:40",
    "ROIs": [
     {
      "x": 103, "y": 121,
      "height": 56,
      "width": 78,
      "tags": ["burning
    building", "explosion"]
     }
    ]
   }
  ]
 }
]
```

Listing 2: Example of ResultsDB Data

In the **ResultDB**, a *region_id* is unique and assigned by our system. A region has its monitoring history and composed by its separate images, the only difference between PlayerDB and ResultDB is ResultDB only stores reliable data (no *reliable* field) and images organized by its related region.

To explain other fields and establish our models, we describe few basic definitions for the system models first.

Definition 3.1. *The **Region of Interests (ROI)** is an indicator that represents the one of the selected two dimensional regions from player. The i-th ROI from player p in image k at image creation time t is denoted by $ROI_{p,i,k,t}$.*

Considering image k **implies** its creation time t (an image alwasy has its creation time), for convenience, we usually **simplify** $ROI_{p,i,k,t}$ **to** $ROI_{p,i,k}$. For instance, figure 3.2 shows few examples of ROI on different images.

With this definition, our system players are able to select ROIs for each image as well as capable of select tags for each ROI. Thus, the *tasks* field in PlayerDB is an array object, stores each player image result with an assigned *image_id*. Each object in the *tasks* array has a field *reliable*, which indicates the reliability for this object task; Each object also contains a *ROIs*

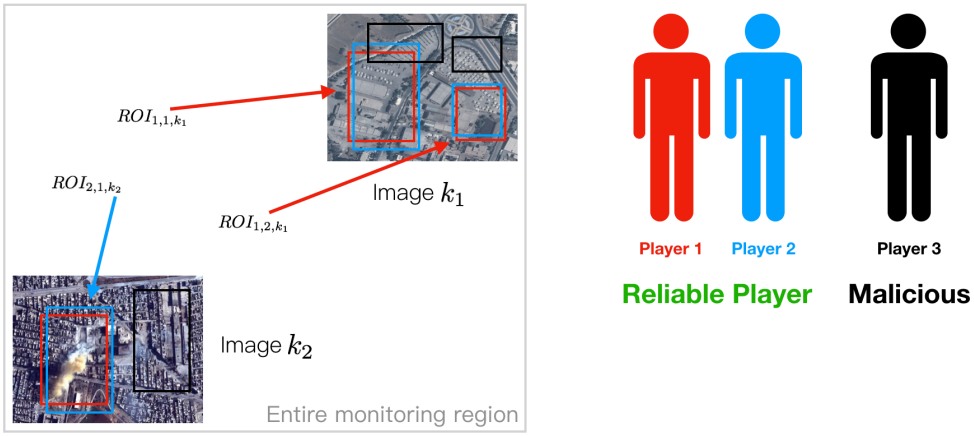


Figure 3.2: Examples of Region of Interests (ROI)

field, which is an array object that contains the player inputs for this object image; Each ROI object in the ROIs field has four properties that describes the ROI geometric location: *x, y, height, width*, and also a *tags* array field that describes the input tags for this image from this player.

For *tags* field, game players can select the related tags for each ROI, and stores in this array. However, systems like ESP [10], ARTigo [8] have proved that human inputs are valuable and useful. Therefore we allows player input their own tags. That is, **each tag can only selects once, and players allow to input their own new tags for the selected ROIs.** Then, We define the ROI tag vector for the model design:

Definition 3.2. *Assuming the database stores n different tags $tag_1, tag_2, ..., tag_n$ for a certain image k, the **Tag Vector** $T_{p,i,k}$ of $ROI_{p,i,k}$ (the i-th ROI in image k of player p) is a vector that is donated by the following formula:*

$$T_{p,i,k} = (|\text{tag}_1|, |\text{tag}_2|, ..., |\text{tag}_n|) \tag{3.1}$$

where

- *tag_i is the i-th tag;*
- *n is the number of tags;*
- *$|tag_i|$ is the count of tag_i in a player task object.*

Note that due to each tag can only selects once, the components of tag vector is **either 1 or 0** in reality. For instance, for a certain image k, there are 5 different tags $\text{tag}_1, \text{tag}_2, \text{tag}_3, \text{tag}_4, \text{tag}_5$ were inputed by our game player. Assuming player p selects the first ROI and inputs tags for $ROI_{p,1,k}$: $\{\text{tag}_1, \text{tag}_2, \text{tag}_3, \text{tag}_4\}$, player q selects the first ROI and inputs tags for $ROI_{q,1,k}$: $\{\text{tag}_1, \text{tag}_3, \text{tag}_4, \text{tag}_5\}$. Then tag vector $T_{p,1,k}$ of $ROI_{p,1,k}$ is $(1,1,1,1,0)$ and tag vector $T_{q,1,k}$ of $ROI_{q,1,k}$ is $(1,0,1,1,1)$.

3.2.2 Player Task Generator

The **PTG** combines task images from satellite and ResultDB. A player task contains $2n$ different images in random order, that n images are the untagged new satellite images and n images are tagged images of ResultDB, which means PTG contains two generating steps:

Step 1. PTG shall split a monitoring region into small pieces of images, and also assign a unique **image_id** for each piece (The reason is discussed in section 4.1.2 for the leakage of data).

Step 2. PTG shall retrieve tagged images from ResultDB. Then combine all images as a user task assign to a new upcoming player.

3.2.3 Player Rating Model

This subsection describes the **PRM** as well as its detection algorithm inside our Disaster Monitoring system. The PRM is responsible for detect malicious players regarding their game task inputs.

PageRank was first proposed by Lary Page [11] and applied to social analysis in [12]. It is commonly used for expressing the stability of physical systems and the relative importance, so-called **centralities**, of the nodes of a network. We transfer the basic idea of centralities of a network and use eigenvalue as the trust value for each player to distinguish malicious players and reliable players.

We establish the model in image dependent perspective. For a certain image k, considering a directed **Player Rating Graph (PRG)** between players who tagged the image k. Each player is a node of PRG, as illustrated in figure 3.3.

Definition 3.3. *Assuming the database stores n different tags $tag_1, tag_2, ..., tag_n$ in the system, The **System Weight Vector** $v = (p(tag_1), p(tag_2), ..., p(tag_n))$ **of all tags** can be calculated by the following Equation 3.2:*

$$p(tag_i) = \frac{|tag_i|}{\sum_{j=1}^{n} |tag_j|} \tag{3.2}$$

where $|tag_i|$ is the count of tag_i in the system.

Definition 3.4. *Assuming there are r_s different tags $tag_{r_1}, tag_{r_2}, ..., tag_{r_s}$ were tagged in a certain image k, the **Image Weight Vector** is a vector for image k that is composed by part of the System Weight Vector, which is donated by $v_k = (p(tag_{r_1}), p(tag_{r_2}), ..., p(tag_{r_s}))$ with $r_i (i = 1, 2, ..., s) \in \{1, 2, ..., n\}$, $r_i \neq r_j (i \neq j, j = 1, 2, ..., s)$ and $s \leq n$.*

For instance, the system have 2 different images. The first image is tagged by two players. One is tag_1, tag_2, tag_5 and another is tag_1, tag_2; The second image is tagged by three players, their results are: tag_1, tag_2, tag_5; tag_2, tag_4, tag_5; tag_3, tag_4, tag_5. Thus, the system currently have 5 different tags $tag_1, tag_2, tag_3, tag_4, tag_5$. Each tags (tag_1 to tag_5) have corresponding counts:

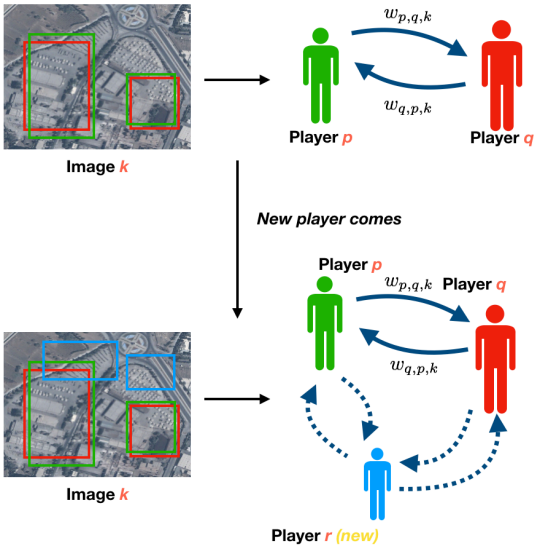


Figure 3.3: Player Rating Graph for Certain Images

3,4,1,2,4; Therefore the System Weight Vector is $(\frac{3}{14}, \frac{2}{7}, \frac{1}{14}, \frac{1}{7}, \frac{2}{7})$; the Image Weight Vector of the first image is $(\frac{3}{14}, \frac{2}{7}, \frac{2}{7})$ since the first image only is tagged by $\text{tag}_1, \text{tag}_2, \text{tag}_5$, and the Image Weight Vector of the second image is as same as the System Weight Vector due to the second image is tagged by all exist tags.

Obviously, we have $0 \leq p(\text{tag}_i) \leq 1$, $\sum_{i=1}^{n} p(\text{tag}_i) = 1$ and $\sum_{i=1}^{s} p(\text{tag}_{r_i}) \leq 1$.

To go so far as to this system, our player have two different type of inputs: **the ROI, and its Tag Vector**. To define the PRG edge weight, we introduce two input measurements in the subsequent Definition 3.5 and 3.6.

Definition 3.5. *The **Players ROI Matching Ratio (PRMR)** is an importance measurement that measures the proportion of two different ROI intersection surface from player p, q and the ROI surface from player p in a certain image k, which is donated by the following formula:*

$$PRMR(p,q,i,j,k) = \frac{|ROI_{p,i,k} \cap ROI_{q,j,k}|}{|ROI_{p,i,k}|} \tag{3.3}$$

where

- $ROI_{p,i,k}$ *is the i-th selected ROI from player p;*
- $|ROI_{p,i,k}|$ *is the surface of $ROI_{p,i,k}$;*

Lemma 3.1.

$$0 \leq PRMR(p,q,i,j,k) \leq 1 \tag{3.4}$$

Proof. According to the Definition of ROI, $|ROI_{p,i,k} \cap ROI_{q,j,k}|$ can archive its maximum value only and only if $ROI_{p,i,k} = ROI_{q,j,k}$ as well as its minimum value only and only if $ROI_{p,i,k}$ has

no intersection with $ROI_{q,j,k}$. Thus:

$$0 = \frac{0}{|ROI_{p,i,k}|} \leq \text{PRMR}(p,q,i,j,k) \leq \frac{|ROI_{p,i,k} \cap ROI_{p,i,k}|}{|ROI_{p,i,k}|} = \frac{|ROI_{p,i,k}|}{|ROI_{p,i,k}|} = 1.$$

□

Definition 3.6. *The **Players Input Tag Correlation (PITC)** is an importance measurement that measures the proportion of the covariance of two different Tag Vector $T_{p,i,k}, T_{q,j,k}$ from player p,q and the covariance of $T_{p,i,k}$ from player p with itself under the Image Weight Vector v_k, which is donated by the following formula:*

$$PITC(p,q,i,j,k) = \frac{Cov(T_{p,i,k}, T_{q,j,k}; v_k)}{Cov(T_{p,i,k}, T_{p,i,k}; v_k)} \tag{3.5}$$

where $Cov(X,Y;w)$ is the weighted covariance between X and Y, which donated by:

$$Cov(X,Y;w) = \frac{\sum_{i=1}^{n} w_i (x_i - \frac{1}{n}\sum_{i=1}^{n} w_i x_i)(y_i - \frac{1}{n}\sum_{i=1}^{n} w_i y_i)}{\sum_{i=1}^{n} w_i} \tag{3.6}$$

with $X = (x_1, x_2, ..., x_n)$, $Y = (y_1, y_2, ..., y_n)$, $w = (w_1, w_2, ..., w_n)$.

Note that

1. **The definition of PRMR and PITC share the same intent for measureing asymmetric importance between player p and player q (how p think of q)**;
2. The definition of **PRMR is inspired by** a wide-used computer vision criteria, the so called **Intersection over Union (IoU)**, also as known as **Jaccard Index** [13, 14], which is a statistic used for comparing the similarity and diversity of sample sets. However, in our case, we only divided by to guarantee the asymmetric property for directed graph weight;
3. The definition of **PITC is inspired by the Weighted Pearson Correlation Coefficient** [15], which is a measure of the linear correlation between two variables. In our case, with the same intent of PRMR, we **drop** the part of covariance of player q in denominator to guarantee the asymmetric property for directed graph weight;
4. The PRMR and PITC both **are not metrics** due to $\text{PRMR}(p,q,i,j,k) \neq \text{PRMR}(q,p,i,j,k)$ as well as $\text{PITC}(p,q,i,j,k) \neq \text{PITC}(q,p,i,j,k)$.

Lemma 3.2.

$$-1 \leq PITC(p,q,i,j,k) \leq 1. \tag{3.7}$$

Proof. We know that the weighted Pearson Correlation Coefficient [15] lies on $[-1,1]$, i.e.

$$-1 \leq \frac{Cov(T_{p,i,k}, T_{q,j,k}; v_k)}{\sqrt{Cov(T_{p,i,k}, T_{p,i,k}; v_k) Cov(T_{q,j,k}, T_{q,j,k}; v_k)}} \leq 1$$

To prove Equation 3.7, we have to show:

$$\frac{Cov(T_{p,i,k}, T_{q,j,k}; v_k)}{Cov(T_{p,i,k}, T_{p,i,k}; v_k)} \leq |Cov(T_{q,j,k}, T_{q,j,k}; v_k)\sqrt{Cov(T_{p,i,k}, T_{p,i,k}; v_k)Cov(T_{q,j,k}, T_{q,j,k}; v_k)}| \leq 1 \tag{3.8}$$

and

$$\frac{Cov(T_{p,i,k}, T_{q,j,k}; v_k)}{Cov(T_{p,i,k}, T_{p,i,k}; v_k)} \geq -|Cov(T_{q,j,k}, T_{q,j,k}; v_k)\sqrt{Cov(T_{p,i,k}, T_{p,i,k}; v_k)Cov(T_{q,j,k}, T_{q,j,k}; v_k)}| \geq -1 \tag{3.9}$$

Then we need to show:

$$0 \leq Cov(T_{p,i,k}, T_{p,i,k}; v_k)Cov(T_{q,j,k}, T_{q,j,k}; v_k)^3 \leq 1 \tag{3.10}$$

Considering $T_{p,i,k}, T_{q,i,k}$ are described in general, with Equation 3.6, we only need to show (s **is an vector components index** instead of exponential):

$$0 \leq Cov(T_{p,i,k}, T_{p,i,k}; v_k) = \frac{\sum_{s=1}^{n} v_k^s \left(T_{p,i,k}^s - \frac{1}{n}\sum_{s=1}^{n} v_k^s T_{p,i,k}^s\right)^2}{\sum_{s=1}^{n} v_k^s} \leq 1 \tag{3.11}$$

According to the definition of Tag Vector and Image Weight Vector, the components of $T_{p,i,k}$ are either 1 or 0, the components of v_k lies on $[0,1]$, then we have:

$$0 \leq \left(T_{p,i,k}^s - \frac{1}{n}\sum_{s=1}^{n} v_k^s T_{p,i,k}^s\right)^2 \leq 1 \tag{3.12}$$

Therefore,

$$0 = \frac{\sum_{s=1}^{n} v_k^s \cdot 0}{\sum_{s=1}^{n} v_k^s} \leq Cov(T_{p,i,k}, T_{p,i,k}; v_k) \leq \frac{\sum_{s=1}^{n} v_k^s \cdot 1}{\sum_{s=1}^{n} v_k^s} = 1 \tag{3.13}$$

which proves Equation 3.11. □

Thus far, we have enough techniques to define the edge weight of PRG. The definition is shown in Definition 3.7.

Definition 3.7. *For a certain image k, the edge weight of the PRG from player p to player q is donated by the formula 3.14:*

$$w_{p,q,k} = \sum_{j=1}^{n}\sum_{i=1}^{m}\left(PRMR(p,q,i,j,k)\left(PITC(p,q,i,j,k)+2\right)\right) \tag{3.14}$$

with player p selected m ROIs, player q selected n ROIs.

Our goal is to calculate the centrality of the nodes (players) of the network graph. The **Perron Frobenius theorem**, proved by Oskar Perron (1907) [16] and Georg Frobenius (1912) [17], guarantees our goal can be drifted to the calculation of the adjacency matrix of PRG. In consequence, one can use the normalized adjacency matrix through the following formula 3.15:

$$A_k = (a_{p,q,k}) = (\frac{w_{p,q,k}}{\sum_q w_{p,q,k}}) \tag{3.15}$$

where k is the image indicator.

Theorem 3.3. *The normalized adjacency matrix A_k of PRG of a certain image k is irreducible, real, non-negative, column-stochastic, and diagonal element being positive.*

Proof. **Irreducibility**: As shown in figure 3.3, for a certain image k, the PRG is strong connected because the player who selected ROIs in image k has a direct connection to any other player who also selected ROIs in image k (the edge weight is well defined according to Equation 3.14). Thus, since A_k is an normalized strong connected PRG adjacency matrix, which proves A_k is irreducible.

Real elements: With Lemma 3.1 and 3.2, each part of the Equation 3.14 are real number. Thus, of course, the matrix A_k elements are calculated by Equation 3.15 that are real elements.

Non-negative elements: With Lemma 3.1 and 3.2, we have:

$$w_{p,q,k} = \sum_{j=1}^{n}\sum_{i=1}^{m}\big(\mathrm{PRMR}(p,q,i,j,k)\big(\mathrm{PITC}(p,q,i,j,k)+2\big)\big) \geq \sum_{j=1}^{n}\sum_{i=1}^{m}(0\cdot(-1+2)) = 0$$

that $w_{p,q,k}$ has its minimum value when $\mathrm{PRMR}(p,q,i,j,k) = 0 (for all i = 1,...,m; j = 1,...,n)$ and $\mathrm{PITC}(p,q,i,j,k) = -1 (\text{for all} i = 1,...,m; j = 1,...,n)$. Meanwhile,

$$w_{p,q,k} = \sum_{j=1}^{n}\sum_{i=1}^{m}\big(\mathrm{PRMR}(p,q,i,j,k)\big(\mathrm{PITC}(p,q,i,j,k)+2\big)\big) \leq \sum_{j=1}^{n}\sum_{i=1}^{m}(1\cdot(1+2)) = 3mn$$

that $w_{p,q,k}$ has its maximum value when $\mathrm{PRMR}(p,q,i,j,k) = 1 (\text{for all} i = 1,...,m; j = 1,...,n)$ and $\mathrm{PITC}(p,q,i,j,k) = 1 (\text{for all} i = 1,...,m; j = 1,...,n)$.

Positive diagonal elements: According to Lemma 3.2, the diagonal elements can be formalized by follows:

$$
\begin{aligned}
w_{p,p,k} &= \sum_{j=1}^{m}\sum_{i=1}^{m}\left(\mathrm{PRMR}(p,p,i,j,k)\left(\mathrm{PITC}(p,p,i,j,k)+2\right)\right) \\
&\geq \sum_{j=1}^{m}\sum_{i=1}^{m}\left(\frac{|ROI_{p,i,k}\cap ROI_{p,j,k}|}{|ROI_{p,i,k}|}(-1+2)\right) \\
&= \sum_{j=1}^{m}\sum_{i=1}^{m}\frac{|ROI_{p,i,k}\cap ROI_{p,j,k}|}{|ROI_{p,i,k}|} \\
&= \sum_{i=j}\frac{|ROI_{p,i,k}\cap ROI_{p,j,k}|}{|ROI_{p,i,k}|}+\sum_{i\neq j}\frac{|ROI_{p,i,k}\cap ROI_{p,j,k}|}{|ROI_{p,i,k}|} \\
&\geq \sum_{i=j}\frac{|ROI_{p,i,k}\cap ROI_{p,j,k}|}{|ROI_{p,i,k}|} \\
&= \sum_{i=1}^{m}\frac{|ROI_{p,i,k}\cap ROI_{p,i,k}|}{|ROI_{p,i,k}|} \\
&= \sum_{i=1}^{m}\frac{|ROI_{p,i,k}|}{|ROI_{p,i,k}|} \\
&= m>0
\end{aligned}
\tag{3.16}
$$

Column stochastic: according to the definition of matrix A, the sum of the column elements are:

$$
\sum_{q} a_{p,q,k} = \sum_{q}\frac{w_{p,q,k}}{\sum_q w_{p,q,k}} = \frac{\sum_q w_{p,q,k}}{\sum_q w_{p,q,k}} = 1 \tag{3.17}
$$

□

From the proof of property of positive diagonal elements, we see that the number "2" is a translation that guarantees $\mathrm{PITC}(p,q,i,j,k)$ lies on $[1,3]$ which helps us prove this property successfully.

According to **Perron Frobenius theorem** [16, 17] and Theorem 3.3, one can infer that there exists an uniqueness eigenvector $V_k = (TV_{1,k},...,TV_{n,k})$ of A_k, the so-called Perron vector, with an uniqueness eigenvalue $\rho(A_k)$ is the spectral radius of A_k, the so-called Perron root, such that:

$$
A_k \cdot V_k = \rho(A_k)\cdot V_k, TV_{i,k} > 0, \sum_{i=1}^{n} TV_{i,k} = 1.
$$

Therefore, we define the trust value of a player:

Definition 3.8. *A **Trust Value** $TV_{i,k}$ of player i on image k is a score that equals to the i-th component of the Perron vector of the normalized PRG adjacency matrix A_k.*

This definition represents the rating score from player p to player q for a certain image k, as same as the centrality of the player q. With the trust value of players, we propose our classification algorithm:

Algorithm 1: Malicious Player Detection Algorithm

input : New Player p,
Trusted Player $p1, p2, ..., p_m$,
Task Images $k_1, k_2, ..., k_{2n}$,
Acceptance Threshold δ
output: Reliability of Player p
begin
  counter $\longleftarrow$ 0
  for $k \in [k_1, k_2, ..., k_{2n}]$ **do**
    if k *is tagged image* **then**
      calculate $TV_{p,k}, TV_{p_1,k}, ..., TV_{p_m,k}$
      if $TV_{p,k} \geq \frac{1}{m}\sum_{i=1}^{m} TV_{p_i,k}$ **then**
        counter $\longleftarrow$ counter +1
      end
    end
  end
  if *counter* $\geq \delta$ **then**
    reliability $\longleftarrow$ true
  else
    reliability $\longleftarrow$ false
  end
end

The purpose of this algorithm is simple, the criterion of classifying new players performs the action that the trust value of a new player should not be less than the mean value of overall trust value of players on image k, which means the tagging performance of new player should not worth than result performance of former players. The acceptance threshold is a customizable parameter that can be set by system manager. For instance, if $\delta = 1$, then the new player only need pass one singular image of all tagged images; if $\delta = n$ (half images of the task), then the new player have to pass all tagged images;

Note that sometimes new player carries new tags to the system, this will influence the Tag Vector calculation, which causes the weight are not computable due to the dimension of the Tag Vector of new player and old player inequal. We also address a solution for this issue via the following steps:

- If a new player does not provide new tag: directly perform the calculation with Algorithm 1;
- If a new player carries new tags: Directly drop, it is an unreliable result;
- If a player carries selected tags and also new tags:

1. Perform the calculation with Algorithm 1 without new tags;
2. Merge and update all weight vector v via formula 3.14 if the player is reliable,
3. Otherwise drop and mark the result is unreliable.

3.2.4 Disaster Evaluation Model

For a monitor region at time t, we address the **DEM** via disaster level definition as follows:

Definition 3.9. *Let a monitor region is composed by images $k_1, ..., k_n$, and players $p_1, p_2, ..., p_m$ are tagged these images. The player p_j tagged $r_{j,i}$ ROIs in image k_i with $j = 1, ..., m; i = 1, ..., n$. The **Disaster Level (DL)** of a monitor region is calculated by the following:*

$$DL = v \cdot \left(\frac{1}{m} \sum_{j=1}^{m} \sum_{i=1}^{n} T_{p_j, r_{j,i}, k_i} \right) \tag{3.18}$$

with v is the System Weight Vector and $T_{p_j, r_{j,i}, k_i}$ is the Tag Vector of the $r_{j,i}$-th ROI of player p_j in image k_i.

With this Definition 3.9, we can calculate the disaster level for a monitoring region. In fact, due to the System Weight Vector is a kind of frequency vector of all exist tags, the definition is a kind of expectancy of the exist tags of the monitoring region, which gives the disaster level of this region.

3.3 Model Initialization

A cold start of such a system is a common problem in human computation system that is avoided by hiring people to play or learn as long as the number of users or the quantity of data is insufficient. In this system, we have only have to consider one system initialization issue of cold start.

The issue appears in the PTG. To initialize the whole system, we need to address an **initial trusted group** for PTG; they shall tagging enough initial trusted result as well as a fixed pre-defined tag list (contains all of the most important tags that organisation need to monitoring) for PTG and then assign the tagged images to new upcoming players. In this system, we do not need to hire people to player and keep the system runs well. This is because: when a new player is reliable, then the result of this player will become reliable. Meanwhile, the trusted group and available dataset grow larger with this step repeatedly, as shown in figure 3.4.

Thus, the final question of our system relate to the minimum number of the initial trusted group. Our Player Rating Model is based on graph centrality calculation, which means we need a (at least) two dimentional matrix to perform the overall model calculation. Hence, with the new player, **the minimum number of the inital trusted group is 1**. Then the initial trusted group (one person) with the new player composed to a two dimentional adjacency matrix that makes the model computable.

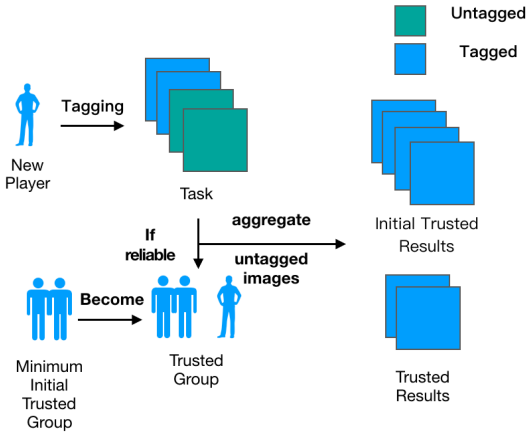


Figure 3.4: Initialization of PRM

4 Evaluation

This chapter discusse the evaluation criteria as well as the issues and solutions on social and ethical aspects. Surely, our system still has limitations, we then discusse the most important three limitations within our system: outdated evaluation, information loss and playability.

4.1 Success Criterias

4.1.1 Model Evaluation by Simulation

Malicious player detection is a classification problem. One can generate random data and test the performance of PRM through accuracy and recall, even ROC curve [18]. TODO: explain here.

The click behavior has been researched for years and address by FFitts Law [19]. It modeled and proved the distribution of click behavior for a certain click goal point is a normal distribution. Thus, with probablistic view, the top left corner of ROI exists, then the user click selection for this point should follows normal distribution, as shown in figure 4.1. TODO: explain precisely. also justify the start point is not important.

Therefore, to generate ROIs, let (x, y) is the player ROI start point, (H_{ROI}, W_{ROI}) is the height and width pair of this ROI, then we generate the random dataset for these variables by a given parameter δ: $(x, y) \sim (x + N(0, \delta), y + N(0, \delta)), (H_{ROI}, W_{ROI}) \sim (H_{ROI} + N(0, \delta), W_{ROI} + N(0, \delta))$. To generate tags, we propose randomly pick random number of tags.

Then one can perform this random dataset on our system to evaluate the classification accuracy and recall rate to evaluate the overall performance of this system, which gives the theoretical evaluation results.

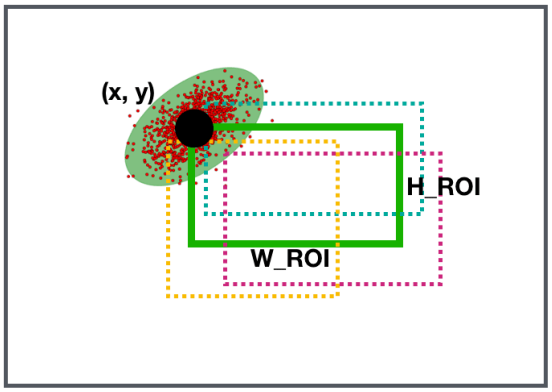


Figure 4.1: Data Simulation

4.1.2 Issues on Social and Ethical Aspects

Intellectual Property Rights: Our disaster monitoring HC system is an non-commercial project which invites volunteers to contribute to it. It is used to help the UNICEF and other non-profit organizations deliver supplies in disaster areas safer. So the IPR on the annotations should not belong to the volunteer users. In an appropriate manner, user will be informed that his or her contribution to the system is volunteering and the produced data will be used only for monitoring disasters in Syria.

Leakage of data: We cut big satellite image into small segmentations in our HC system to prevent data leakage to ordinary users, but the **data security** (TODO: explain here) is still very important and needs to be considered with high priority. For example, the backend database should not be entirely accessible to every employee of UNICEF. Each of them can only visit the part of data that they need at present. This principle is made to guarantee that data will not be wrongly used and will be included in our future work.

Information Loss We cut big region images into small fragements areas to prevent leakage of data. But this method will cause some information loss problem if some important ROIs are located at the intersection of two dividing lines. A possible solution for this limitation is to consider new regions that contains the loss informations, as shown in figure 4.2. Note that this solution that only increases the number of region pictures, it does not influence any model and system design.

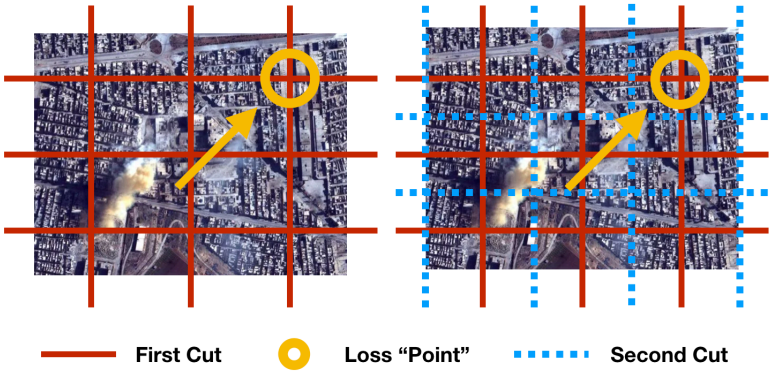


Figure 4.2: **Information Loss**: TODO: fix here. Information loss may occurs on the intersection lines, as shown on the left; a possible solution is to provide additional regions (blue rectangles) for these special area as shown on the right.

4.2 Limitations of the System

4.2.1 Evaluation Outdated

TODO: rewrite this section, gives few time series prediction method.

A limitation occurs in our social network based model is each disaster level evaluation get invalid if the region image is outdated. We assume the satellite monitors an area and take pictures between intervals. However, our evaluation the model only calculate the disaster level at a unique moment, which means the disaster level need transvaluation when a new image comes out. If our player is not enough so that the region images always have to wait for new evaluation, then the disaster level will never be calculated.

A possible solution is to consider the region disaster level history as a time series. Then we can apply some prediction method for it. For instance, we have time series: $(t_1, t_2, t_3, ..., t_n)$ and its corresponding disaster level: $(DL_1, DL_2, DL_3, ..., DL_n)$. Then we can use these time series to predict the disaster level at time t_{n+1}.

At the same time, we also have the historical data of trust value of a player. We can also use time series prediction to predict the player's trust value. But in all of these, the time series of disaster level is not stationary but the time series of trust value is stationary.

TODO: Fix here by given few prediction method suggestions.

4.2.2 Gameplay and Playability

TODO: add image here, rewrite this paragraph.

The GWAP collects satellite photos of disaster areas. But even if in the disaster areas, not ev-

ery part of the areas has a disaster. Most parts of the earth are lake, forest, desert and so on, which means the users may meet the situation that there is no available ROI in several continuous rounds. Obviously, it will decrease the playability and enjoyment of the game. Our system is just a very simple tagging game at present, users can not get enough enjoyment they want in it. And it is too reliant on the unpaid volunteers to donate their time to contribute information. We should make the system more interesting and appealing in the future work.

5 Conclusions and Future Works

5.1 Conclusions

In this report, we proposed a comprehensive design of a human computation system for disaster monitoring, and we discussed its mathematical foundations as well as the possible issues caused by this system, then gives few options to solve these issues.

In the chapter of Functionalities, we illustrated a mockup of GWAPs-based disaster monitoring human computation system for game players as well as stakeholders, and then described its necessary functions and interaction logic. On thoughts of system implementation, we discussed the possible technology stack of this system on the Web.

Afterward, in the chapter of Design and Models, we modeled the entire system theoretically in details that make sure it can run consistently. First of all, we defined a **Player Rating Model** based on eingenvalue centralities for calculating trust value of a player, and then we put forward an algorithm that can be used in malicious user detection. As justification, we proved the correctness of this model. Meanwhile, as the data aggregation, we transferred the problem of calculating disaster level of regions into processing the expectancy of user tagging task inputs and proposed the **Disaster Evaluation Model**. Surely, we addressed the solution of cold start of the human computation system. It is worth mentioning that the minimum initial trusted group under this scheme design only requires one person theoretically.

Furthermore, in the chapter of Evaluation, we discussed theoretical evaluation criteria for this system, and then declared the challenges and corresponding solutions for facing issues like data security, information leakage and loss, malicious detection as well as the lack of players. Undoubtedly, the current system design still contains defects. Thus, we presented three analysis and possible improvements for evaluation outdated and gameplay playability.

5.2 Future Works

Our system was described in general. We collect human inputs by ROI tagging tasks, which means any other human computation system that related to ROI tagging tasks can easily use this system backend design. In addition, due to the fact that we do not have enough user inputs at present, we use a certainty algorithm instead of uncertainty probablistic-based algorithm to detect malicious groups. Considering malicious detection is classification problem,

which seperate users into trusted groups and untrusted groups. One can apply any classification machine learning algorithms that are more suitable for the detection of malicious groups if our user input dataset is large enough.

Besides, as we mentioned before, the game player may encounter a situation that there is no ROI in some pictures which contain only landscapes like mountains, rivers and forests. In this case, the game playability is significantly reduced. However, for future work, we can filter out those images from our image database previously with collaborative computing of image recoginition technique, so that one can collect more data from the game and make our image tagging game more efficiently.

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The resources of this project are open source on GitHub, such as paper LaTeX code, mockup drafts as well as lab session beamer slides:
https://github.com/changkun/hc-ss17-disaster-monitoring.

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