On Virtual Emotion Barrier in Internet of Things

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***Abstract*—A barrier-coverage has attracted much interests of researchers because it can guarantee to detect any movement of mobile objects. Also, thanks to recent advancement of technology, it is possible to recognize human emotion by facial expression and human motion or activity. Then, the emotion recognition can be applied to various services and applications appropriately. Recently, it has been developed to sense emotion by wireless signal. One of issues for emotion recognition is to increase the recognition accuracy. In this paper, we introduce a new type of barrier, virtual emotion barrier, which is able to detect emotion by devices with wireless signal in Internet of Things (IoT) environment. Then, we formally define a problem whose objective is to construct virtual emotion barrier in the given area including IoT devices such that the detection accuracy of emotion by virtual emotion barrier is maximized. To solve the problem, we propose a greedy-emotion-accuracy approach. Moreover, we discuss future issues and possible research directions for virtual emotion barrier.**

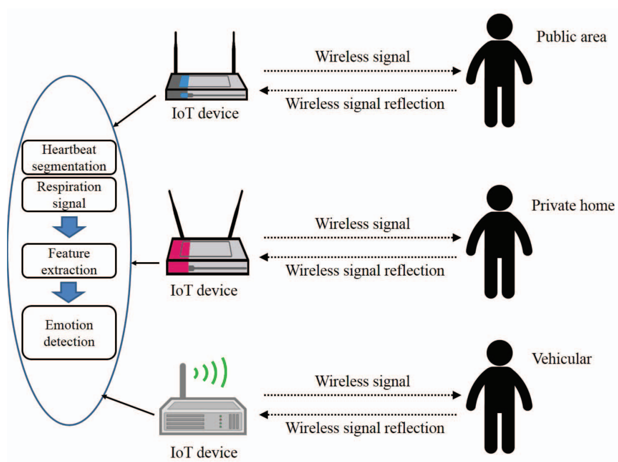

Fig. 1. An example of emotion detection by wireless signal.

I. Introduction

Recently, barrier-coverage has been studied by many researchers because it has much potential to be utilized to numerous applications with surveillance, intrusion detection, border patrol, etc [1], [2], [3]. After completing a barrier by a set of nodes in the given field, any penetration or movement from one region to another is guaranteed to be detected by at least one node in the formed barrier. Due to the its valuableness, the concept of barrier-coverage can be applied to various environments and areas such as wireless sensor networks (WSN), UAV networks, Internet of Things (IoT) [6], [8], [9]. In particular, it is highly anticipated that IoT plays a key role for future smart city with heterogeneous IoT devices [10], [11], [12], [13]. Hence, we consider the barrier-coverage by IoT-based devices towards advanced future smart city.

For human emotion, many researchers focused on human emotion and its recognition because the its correct recognition with computational models can provide appropriate services to people according to different objectives and environments [14], [15].

To recognize human emotion by computing and cyber-physical devices, there are a lot of research results by three approaches. First, the emotion can be recognized by audio visual information such as human voice, facial expression, activity [19], [20], [21], [22]. Second, the emotion is recognized by physiological signals such as body temperature, heart rate, which are measured by on-body sensors or wearable devices [23], [24], [25]. The ECG evaluates these signals and correlate their changes with emotions. Recently, the third approach has been developed by researchers, which recognizes emotion using wireless signals [26], [27], [28]. Fig. 1 shows an example of emotion detection by wireless signal. Basically, IoT device can transmit wireless signal to person and get its reflection. Then, through heart segmentation and respiration signal, the emotion is derived based on their feature extraction. However, because the emotion accuracy by wireless signal depends on the distance between device and person, the issue should considered carefully to support emotion detection with high accuracy. Also, it is highly reasonable to apply the barrier of emotion detection to IoT environment because the solution by wireless signals has clear advantages such as better coverage, better privacy compared with the solution by visual camera. If we can verify groups or areas with any emergent or serious emotion such as extreme anger using IoT devices equipped with wireless signals, we can rapidly provide the people in the specific area with emotion-based services such as a reinforced patrol for the region. Such a proper emotion-based service for citizen should be one of goals toward the advanced smart city.

Based on the above observation, we introduce a framework of virtual emotion barrier which creates a barrier to detect human emotion by IoT device equipped with wireless signal. By [26], [29], our system deliberates on four types of human emotion including joy, pleasure, sadness, anger. Also, the proposed system considers that the recognized four different emotions by IoT device can be stored into the device such as a kind of information. Also, the information can be sent to other entities. Then, we define the detected information by IoT device with wireless signal as *virtual emotion*. To the best of our knowledge, this is the first approach to apply the concept of barrier-coverage to the detection of emotion in IoT environment. Moreover, we formally define the problem whose objective is to build *virtual emotion barrier* in the given area with IoT devices such that the detection accuracy of emotion by the formed virtual emotion barrier is maximized. To solve the problem, we develop a *Greedy-Emotion-Accuracy* approach which returns the virtual emotion barrier with possible high accuracy recognition.

The rest of the paper is organized as follows. The next section reviews previous related work for human emotion with its recognition and several concepts of barrier-coverage using wireless sensors and UAVs. Then, in Section III, we introduce our proposed system for virtual emotion barrier in IoT environment and explain the system setting and assumption as well as the description of virtual emotion barrier. And, in Section III, we formally define a problem to form a virtual emotion barrier that has the maximum cumulative accuracy, followed in Section IV by a system initialization and a novel approach we propose to solve the problem. Moreover, in Section V, we discuss several future issues of virtual emotion barrier system. Finally, we conclude the paper in Section VI.

II. Related Work

A spiritual world of human have attracted much interests of people for a long time. In particular, such an interest is moving to human emotion because the emotion can be one of critical reference within spiritual world of human. In [14], [15], authors evaluated a computational model of human and compared the behavior of the computational model based on a clinical instrument. And, in [16], authors investigated various computational models of emotion which reflect principal aspects of psychological theories. Also, in [17], Chmiel et al. discussed the impact of emotional expressions and quantitative aspects of the trajectories by Internet users. In [18], Sun et al. proposed multivariate Gaussian model and joint probability density for sensing users' anomalous emotion using social media as well as developed an approach to model user and group emotions.

On the other hand, many researchers have focused on recognition of human emotion detectable by computing devices. In [20], Suk et al. developed a system of a real time mobile facial expression with emotion recognition using smart phone with camera so that the featured facial expression for emotion recognition is derived. In [22], Kahou et al. proposed multimodal deep learning approaches for emotion recognition through visual features. Also, Kim et al. [23] introduced an interactive emotion communication model to provide emotion recognition using a portable wireless biofeedback device. In [24], Agrafioti et al. studied ECG sinal and evaluated its psychological aspects for emotion modeling and recognition. Recently, several studies have been done towards emotion detection or activity recognition using wireless signal. In [26], Zhao et al. introduced a new technology which sense a human emotion by relying on wireless signals reflected off person's body and proposed EQ-Radio's key enabler to analyze individual heartbeats and their differences from reflected wireless signals. Then, Raja et al. [27] developed a system to recognize human emotion from body movements based on device-free activity recognition in realistic situations. The proposed system can sense person's behavior and emotion within a vehicle. In [28], Wang et al. introduced a channel state information (CSI) based human activity recognition and monitoring system consisting of two sub-models: One is to estimate the relation between CSI dynamics and movement speed. Another is to measure the relation between movement speed and human activities.

For the barrier-coverage, various researches have been studied. Initially, Gage [1] introduced the paradigm of barrier-coverage. In [2], [3], Kumar et al. devised the concept of k-barrier-coverage in WSN, which guarantees that the penetration into the given region is detected by at least k number of sensors. They also proposed optimal sleep-wakeup scheduling algorithms. In [4], Li et al. introduced the concept of a weak-k-barrier coverage with a consideration of lower bound derivation for the probability of the coverage. In [5], Kong et al. defined a problem which automatically forms a barrier surrounding the region by mobile sensors. Then, Kim et al. [6] introduced event-driven partial barrier and its resilience to support continuous k-event-driven partial barriers. In [7], Wang et al. studied the barrier-coverage using mobile sensors, which covers how to handle the case of sensor location errors. Furthermore, Kim et al. [8], [9] expanded the applicability of barrier-coverage into Unmanned Aerial Vehicles (UAV) networks as well as multi domain IoT environment. They

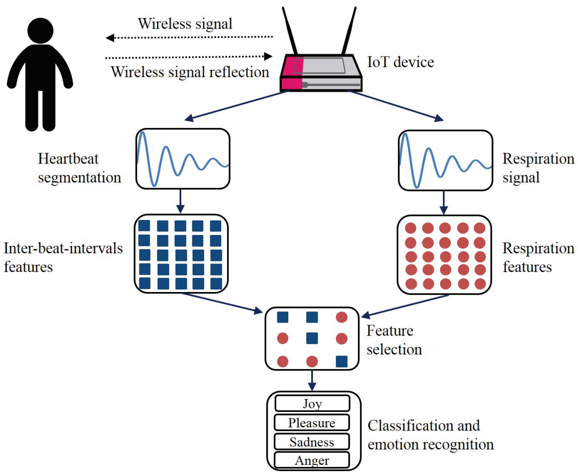

Fig. 2. Emotion derivation process through IoT device.

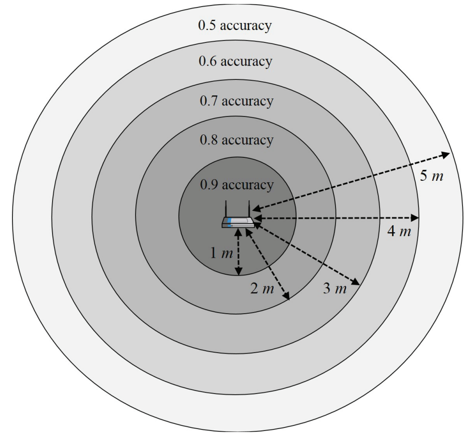

Fig. 3. An example of accuracy rate according to the distance between human and IoT device.

focused on how to construct collision-free reinforced barriers which are able to detect any movement variation of mobile objects.

III. A Framework for Virtual Emotion Barrier

In this section, we introduce our proposed framework of *virtual emotion barrier*. Also, we explain the system setting and assumption. Then, we formally define a problem which we seek to solve in the proposed framework.

A. Assumption and System Setting

To perform our system, the below assumptions and settings are considered.

- The proposed system detects four types of emotion: joy, pleasure, sadness, anger.
- IoT device is equipped with wireless signal and it has procedures to discriminate different emotions by wireless signal reflection [26].
- Heterogeneous IoT devices with different signal ranges can be positioned within a square-shaped area A.
- Each IoT device is capable of sensing emotion of people within own signal range whose shape is a circle.
- The detected emotion can be processed as a kind of data and be sent to other entities through communication [29].
- A table Y of accuracy rate depending on the distance is given.

B. Virtual Emotion Barrier

As an emerging research branch, the emotion recognition has attracted much interests from academic communities and industry companies. Compared with visual, physiological signals on body, the emotion recognition by wireless signal has clear advantages because it provides better coverage and privacy than other schemes. On the other hand, the technology based on IoT will play a significantly critical role toward future advanced smart city. One of goals by IoT is to provide services to specific people appropriately.

With the motivation, we introduce a new type of barrier, *virtual emotion barrier*, which detects human emotion by IoT devices with wireless signal. It follows that the system endeavors to give specific area or people proper services with a highly expected matching probability based on the detected emotion by IoT devices in the virtual emotion barrier. It is assumed that IoT devices in the proposed framework are equipped with wireless signals. And, those devices are capable of deriving emotion through wireless signal's reflection, feature extraction using heartbeat segmentation and respiration signal. Fig. 2 describes how to recognize emotion through IoT device by [26].

Also, note that as the distance between person and device increases, the accuracy of emotion recognition decreases [26]. Fig. 3 shows the case of accuracy rate according to the increased distance between person and device. For example, in Fig. 3, the accuracy with the distance 1 m between device and person is higher than the accuracy with the distance 5 m.

Hence, when we construct virtual emotion barrier, we pursue to form the virtual emotion barrier with possible high accurate probability so as to support the possible high matched service to people or area based on the detected emotion by the barrier. Fig. 4 depicts the constructed virtual emotion barrier with possible high accuracy. As it can be seen in Fig. 4, two barriers vb_1 and vb_2 with cumulative accuracy are formed by a set of IoT devices, respectively. The cumulative accuracy of the built barrier can be calculated by multiplying accuracy of each edge in the barrier. Because vb_2 has higher accuracy than vb_1, vb_2 can be chosen in the area to provide possible high matched service to people. Also, Fig. 5 shows the transformed graph express from Fig. 4. In Fig. 5, we can choose vb_2 so that vb_2 constructs *VEmoBar* with high cumulative accuracy between virtual source S and destination T.

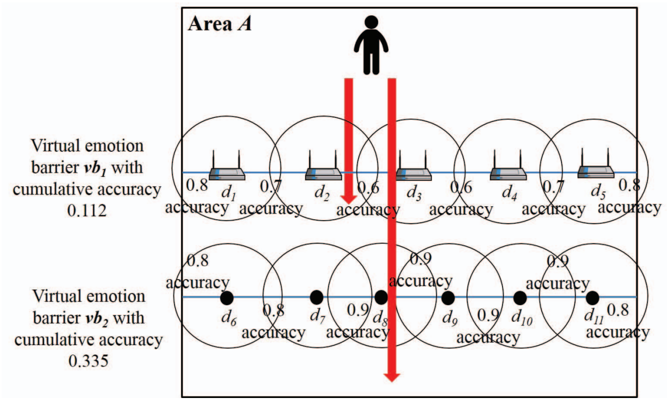

Fig. 4. An example of virtual emotion barrier with a consideration of cumulative accuracy.

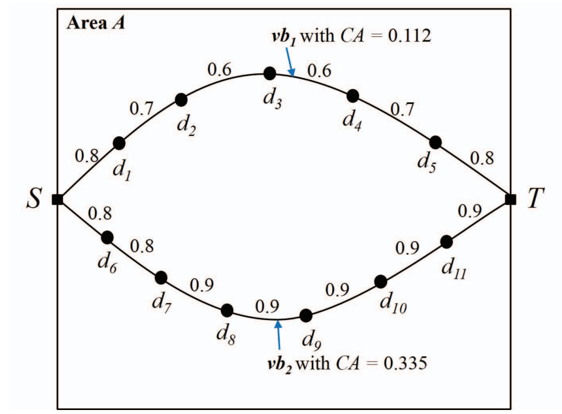

Fig. 5. An example of A graph expression for virtual emotion barrier.

C. Problem Definition

Based on [29], we define *virtual emotion* in the proposed IoT system as follows.

Definition 3.1 (Virtual emotion): IoT device is equipped with wireless signal. The Wireless signals reflect off the human body. Also, IoT device can derive the emotion of the person through pre-installed processing units for heartbeat segmentation, respiration signal and feature extraction. The derived emotion of human by IoT device is defined as *virtual emotion* which can be stored as a kind of information and can be transmitted to other entities.

Also, the proposed concept of barrier is defined as follows.

Definition 3.2 (Virtual emotion barrier (VEmoBar)): The square-shaped area A is given and within A, we have a set of IoT devices D which enable detect emotion through wireless signal and its reflection. A *virtual emotion barrier (VEmoBar)* is a barrier that senses the emotion of any person moving from one side to another side by at least one IoT device within A.

Now, we formally define the *MaxDAEmo* problem which is to be solved in the proposed system.

Definition 3.3 (MaxDAEmo): It is given that a set of IoT devices D with a list of different signal ranges R are within a whole area A. Also, suppose that the detection accuracy information depending on a distance between device and person is given. Then, the maximum detection accuracy of emotion (*MaxDAEmo*) problem is to find a virtual emotion barrier which has the maximum cumulative accuracy where the accuracy of emotion detection is estimated according to the distance between two devices and the cumulative accuracy (*CA*) is calculated by the multiplication of those estimated accuracy between IoT devices.

D. ILP Formulation

Now, we formulate *MaxDAEmo* problem using ILP. Then, we represent the notations of ILP formulation as follows.

n: the number of IoT devices in A.
D: a set of heterogeneous IoT devices, $D = \{d_1, d_2, ..., d_n\}$.
R: a list of signal range of IoT devices, $R = \{r_1, r_2, ..., r_n\}$.
i: index of IoT device and sensing range $(1 \leq i \leq n)$.
j: index of IoT device and sensing range $(1 \leq j \leq n)$.
$\lambda_{i,j}$: accuracy between d_i and d_j.

Also, we define integer variables as follows.

$$X_{i,j} = \begin{cases} 1, & \text{if } d_i \text{ and } d_j \text{ are within their signal ranges} \\ 0, & \text{otherwise.} \end{cases}$$

$$Y_{i,j} = \begin{cases} 1, & \text{if } d_i \text{ and } d_j \text{ with accuracy are selected} \\ & \text{as a part of } \textit{VEmoBar} \\ 0, & \text{otherwise.} \end{cases}$$

$$Z = \begin{cases} 1, & \text{if the complete } \textit{VEmoBar} \text{ is constrcuted} \\ 0, & \text{otherwise.} \end{cases}$$

An objective function is to maximize the cumulative accuracy in the constructing virtual emotion barrier. Then, the objective function is formulated as follows.

$$\textbf{Maximize } [\prod(\lambda_{i,j} \cdot X_{i,j} \cdot Y_{i,j})] \cdot Z \tag{1}$$

Subject to:

$$\sum_{j=1}^{n} X_{i,j} \leq 1, (\forall i) \tag{2}$$

$$\sum_{j=1}^{n} Y_{i,j} \geq 1, (\forall i) \tag{3}$$

$$Y_{i,j} \leq X_{i,j}, (\forall i, \forall j) \tag{4}$$

For above constraints from (1)-(3), it is imposed that two devices of d_i, d_j is at most one edge by constraint (2). And, it is satisfied that the edge with accuracy between d_i and d_j can be participated into *VEmoBar* at most once by constraint (3). Also, constraint (4) forces that there should exist an edge with accuracy between d_i and d_j so as to select the edge as a part of *VEmoBar*.

IV. Proposed Approach

A. Initialization

In order to form *VEmoBar* in IoT environment, we fist implement *Initialization* which returns IoT graph $\mathcal{G}_{\mathcal{I}}$ = $(V(\mathcal{G}_{\mathcal{I}}), E(\mathcal{G}_{\mathcal{I}}))$. Then, the *Initialization* is performed as follows.

- Identify a square-shaped IoT domain A and a detection direction for virtual emotion.
- Verify a set of IoT devices D with the number of devices n within A and their different signal ranges R.
- Create virtual source S and destination T which are positioned at two opposite sides of region A.
- Each IoT device should recognize the neighbor relationship. It follows that two devices d_i and d_j can be neighbors if *euclidean distance* $Euc(d_i, d_j)$ between two devices is at most a sum of their wireless signal ranges $r_{d_i} + r_{d_j}$ where $d_i, d_j \in D$, $r_{d_i}, r_{d_j} \in R$, $i \neq j$.
- Then, we can generate the initialization graph $\mathcal{G}_{\mathcal{I}}$ = $(V(\mathcal{G}_{\mathcal{I}}), E(\mathcal{G}_{\mathcal{I}}))$ where $V(\mathcal{G}_{\mathcal{I}})$ is the set of vertices, $E(\mathcal{G}_{\mathcal{I}}))$ is the set of edges. Note that the set of IoT devices is matched to the set of vertices and the neighbor relationships are converted into $E(\mathcal{G}_{\mathcal{I}})$.
- Using given accuracy table Y and $\mathcal{G}_{\mathcal{I}}$, we also generate the accuracy graph $\mathcal{G}_{\mathcal{C}}$ = $(V(\mathcal{G}_{\mathcal{C}}), E(\mathcal{G}_{\mathcal{C}}))$.
- Add virtual source S and destination T to $V(\mathcal{G}_{\mathcal{I}})$ and $V(\mathcal{G}_{\mathcal{C}})$.

Also, the pseudocode of *Initialization* is represented in Algorithm 1 in more detail.

Algorithm 1 ***Initialization***

Inputs: A, D, R, n, Y, S, T, Output: $\mathcal{G}_{\mathcal{C}}$ = $(V(\mathcal{G}_{\mathcal{C}}), E(\mathcal{G}_{\mathcal{C}}))$

set $\mathcal{G}_{\mathcal{I}}$ = $(V(\mathcal{G}_{\mathcal{I}}), E(\mathcal{G}_{\mathcal{I}})) = \emptyset$;
set $\mathcal{G}_{\mathcal{C}}$ = $(V(\mathcal{G}_{\mathcal{C}}), E(\mathcal{G}_{\mathcal{C}})) = \emptyset$;
identify target area A and its detection direction;
verify the set of IoT devices D;
for $i = 1$ to n **do**
    set $V(\mathcal{G}_{\mathcal{I}}) \leftarrow V(\mathcal{G}_{\mathcal{I}}) \cup d_i$;
    set $V(\mathcal{G}_{\mathcal{C}}) \leftarrow V(\mathcal{G}_{\mathcal{C}}) \cup d_i$;
end for
for $i = 0$ to $n - 1$ **do**
    for $j = i + 1$ to n **do**
        if $Euc(i, j) \leq r_{d_i} + r_{d_j}$ **then**
            set $E(\mathcal{G}_{\mathcal{I}}) \leftarrow E(\mathcal{G}_{\mathcal{I}}) \cup e(d_1, d_2)$;
            set $E(\mathcal{G}_{\mathcal{C}}) \leftarrow E(\mathcal{G}_{\mathcal{C}}) \cup e(d_1, d_2)$ with accuracy rate from Y;
        end if
    end for
end for
set $V(\mathcal{G}_{\mathcal{I}}) \leftarrow V(\mathcal{G}_{\mathcal{I}}) \cup S$;
set $V(\mathcal{G}_{\mathcal{C}}) \leftarrow V(\mathcal{G}_{\mathcal{C}}) \cup T$;
return $\mathcal{G}_{\mathcal{C}}$ = $(V(\mathcal{G}_{\mathcal{C}}), E(\mathcal{G}_{\mathcal{C}}))$

B. Greedy-Emotion-Accuracy-Approach

Based on the above initialization, we propose *Greedy-Emotion-Accuracy* approach which returns vb_{max} which is *VEmoBar* with possible high accuracy recognition. Then, *Greedy-Emotion-Accuracy* approach is executed by the following steps.

- Create current status graph $\mathcal{G}_{\mathcal{C}}'$ = $(V(\mathcal{G}_{\mathcal{C}}'), E(\mathcal{G}_{\mathcal{C}}'))$ and it is transferred from $\mathcal{G}_{\mathcal{C}}$.
- Then, we do perform the following iterations.
  - From $\mathcal{G}_{\mathcal{C}}'$ = $(V(\mathcal{G}_{\mathcal{C}}'), E(\mathcal{G}_{\mathcal{C}}'))$, select the edge $e(d_i, d_j)$ with high accuracy.
  - Add the chosen $e(d_i, d_j)$ to the current *VEmoBar*, vb_{max}.
  - Update the cumulative accuracy $CA_{max} = CA_{max}$ $\times$ the accuracy of $e(d_i, d_j)$.
  - Remove d_i, d_j from $V(\mathcal{G}_{\mathcal{C}}')$ and $e(d_i, d_j)$ from $E(\mathcal{G}_{\mathcal{C}}')$, respectively.
  - If vb_{max} includes both source S and destination T, then return vb_{max}.
  - Or if $\mathcal{G}_{\mathcal{C}}'$ is empty and vb_{max} does not cover both S and T, then return $false$.

The pseudocode of *Greedy-Emotion-Accuracy* approach is presented in Algorithm 2 in more detail.

Algorithm 2 ***Greedy-Emotion-Accuracy***

Inputs: $A, D, R, n, \mathcal{G}_{\mathcal{C}}$, Output: vb_{max} or $false$

set $vb_{max} = \emptyset$;
set $CA_{max} = 1$;
set $\mathcal{G}_{\mathcal{C}}' = \emptyset$;
set $\mathcal{G}_{\mathcal{C}}' \leftarrow \mathcal{G}_{\mathcal{C}}$;
while $\mathcal{G}_{\mathcal{C}}' \neq \emptyset$ **do**
    choose the edge $e(d_i, d_j)$ with high accuracy from $\mathcal{G}_{\mathcal{C}}'$ = $(V(\mathcal{G}_{\mathcal{C}}'), E(\mathcal{G}_{\mathcal{C}}'))$ where $i \neq j$;
    $vb_{max} \leftarrow vb_{max} \cup e(d_i, d_j)$;
    $CA_{max} = CA_{max}$ $\times$ accuracy of $e(d_i, d_j)$;
    $V(\mathcal{G}_{\mathcal{C}}') \leftarrow V(\mathcal{G}_{\mathcal{C}}') - d_i$;
    $V(\mathcal{G}_{\mathcal{C}}') \leftarrow V(\mathcal{G}_{\mathcal{C}}') - d_j$;
    $E(\mathcal{G}_{\mathcal{C}}') \leftarrow E(\mathcal{G}_{\mathcal{C}}') - e(d_i, d_j)$;
    if $\mathcal{G}_{\mathcal{C}}' = \emptyset$ and $S, T \notin vb_{max}$ **then**
        return $false$;
    end if
end while
return vb_{max}

V. Discussion of Future Issues

First of all, this paper handled the problem whose objective is to maximize cumulative accuracy of the *VEmoBar* which is created from one side to another opposite side of given square-shaped area. As a variation of the problem, we plan to consider the problem whose goal is to maximize cumulative accuracy using only q number of IoT devices within *VEmoBar*.

Secondly, the proposed system in the paper assume that each IoT device is capable of four different emotion such as joy, pleasure, sadness, anger. Different from the system, we plan to consider that each IoT device with a lightness is detectable to only one emotion. Given the deployment of all IoT devices in the area, it is possible to consider k-*VEmoBar* which forms k number of *VEmoBar* to detect a specific emotion type. So, we will solve the problem whose objective is to look for the maximum number of *VEmoBar* such that k-*VEmoBar* with high cumulative accuracy can be maintained continuously by applying to sleep-wakeup strategy alternately among the found maximum number of *VEmoBar*.

Thirdly, as a future work, we plan to simulate the defined problem and its approach in the paper as well as the above variation problems and novel approaches through extensive experiment with practical scenario and setting.

VI. Concluding Remarks

In this paper, we introduced a new barrier system for a virtual emotion barrier, called as *VEmoBar*, which is able to detect human emotion using wireless signal and its reflection in IoT environment. The proposed framework covers four different emotion types of human for joy, pleasure, sadness, anger and considers that the detected emotion by IoT devices in the *VEmoBar* can be stored in the device as a kind of data. After the definition of *VEmoBar*, we also formally defined the *MaxDAEmo* problem whose goal is to build *VEmoBar* on condition that the detection accuracy of emotion in *VEmoBar* is maximized. To solve the problem, we proposed *Greedy-Emotion-Accuracy* approach with *Initialization*, which returns the *VEmoBar* with possible high accumulative accuracy. Furthermore, we discussed future issues and possible research directions for virtual emotion barrier.

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