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Human Sensing Meets People Crowd Detection – A Case of Developing Countries

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ABSTRACT

Purpose: The main purpose of this study was to examine the application of sensors and sensor networks for detection of people crowds in developing cities. This paper discusses unique challenges associated with people crowd detection especially in the urban towns of developing countries and gives a comparative review and analysis of popular human sensing approaches in the detection of people crowds.

Methodology: This study provides a survey and categorization of popular human sensing approaches using literature especially published within the past two decades. The paper then analyzes current human sensing technologies vis-à-vis people crowd detection in developing cities. The respective strengths and shortfalls of various approaches are highlighted. Finally, by means of examples, a comparative analysis of different human sensing categories is carried out.

Findings: The spontaneous, dynamic and chaotic nature of people crowds, together with the poor infrastructural development characteristic of developing economies pose unique challenges to the effectiveness of people crowd detection systems. Although there are advances in crowd detection, most of these are in the area of non-people crowds, while most of the research done on people crowd detection have been on indoor crowd settings. In addition, challenges unique to people crowd detection in developing countries include: scalability and cost of crowd detection systems, security of the detection system infrastructure, confidentiality of subjects being monitored, requirements for incentives and the ability to support passive and real time people crowd detection.

Unique contribution to theory, practice and policy: This study emphasizes the need for both indoor and outdoor people crowd detection systems appropriate for the needs of developing cities. The study contributes to the body of knowledge since people crowds unlike other types of crowds present a unique set of challenges that call for special attention.

Keywords: *People Crowd Detection, Human Sensing, Sensor Networks.*

1. INTRODUCTION

The growth of the events industry together with general population increase, especially in developing countries, has attracted a big proportion of people to urban cities. This has led to an increased demand on the already strained public infrastructural resources. Social gatherings have become breeding grounds for wrong elements, while public demonstrations continue to become a source of insecurity and have led to vandalism of public infrastructure by disgruntled persons. In addition to these hindrances, detecting people crowds in urban cities presents unique challenges accruing to the dynamics of people crowds. A part from these concerns however, knowledge of crowd density can advise relevant authorities and event organizers to better plan service delivery. All these underscore the need for people crowd detection. Various proactive and reactive methodologies have been explored for detection of people crowds. These approaches have been both vision and non-vision based. Vision based approaches extract facial structure, hand movement and gait to detect the existence of humans. Vision based approaches are however faced by occlusion, high implementation costs and privacy concerns compared to other non-video and camera based alternative (Gong, Loy, & Xiang, 2011).

Lately, driven by advances in micro-electromechanical systems technology, the application domain of sensors and wireless sensor networks (WSNs) has continued to evolve and expand. These advances have led to an emergence of a varied number of embedded computing platforms that offer the ability to sense physical phenomenon in real time. They are light weight, more energy efficient and relatively cheaper. Sensors are devices or modules that produce output signals for purposes of sensing physical phenomena, while WSNs are infrastructure-less wireless networks that deploy a number of sensor nodes in an adhoc manner to monitor physical phenomena and systems (Farhan, et al., 2017). WSNs comprise sensor nodes, cluster heads and one or more sink nodes. The sensor nodes collect phenomena data and route them to sink nodes for analysis. Over time, sensors and WSNs have also been used in crowd detection. For example, work has been carried out in battle field surveillance (Arjun, Indukala, & Menon, 2017; Bhadwal et al., 2019), target tracking (Ez-Zaidi & Rakrak, 2016; Darabkh, Albtoush, & Jafar, 2017), and event human localization (Yang, Sheng, & Zeng, 2015). All these point to the potential of sensors and WSNs in detection of people crowds.

People crowd detection in developing countries is challenging because of the less developed communication infrastructure within urban towns and the chaotic nature of people crowds that are known to be both unpredictable and spontaneous. People crowds form anywhere and at any time, and therefore require special attention. Besides, sensors and WSNs have known inherent challenges of battery life, coverage and connectivity.

In this paper there are numerous human sensing approaches (Passive radio sensing, Wi-Fi based sensing, Vibration sensing, Mobile crowd sensing, RFID/Bluetooth based sensing and Sensor fusion) that have been explored for people crowd detection. The vast majority however, are not specifically applicable for detection of people crowds in developing countries. Subsequently, this paper investigates the possibility of applying human sensing in people crowd detection. The strengths and shortfalls of the sensing approaches are highlighted. The rest of the paper is structured as follows: The general sensing model is introduced in the next section before an overall review of human sensing approaches and applications in Section 3. Challenges to people crowd detection in developing countries and a comparative analysis of the sensing approaches with respect to people crowds are presented in Section 4. The paper concludes with a discussion of results and suggestions for further research in Section 5.

2. HUMAN SENSING APPROACHES AND CROWD DETECTION

Human sensing encompasses a range of technologies for detecting human presence in an area without intentional participation of the subjects being detected. A people crowd can be looked at as an emergent group of individuals. An insight on human-centric sensing modalities and approaches can enhance appreciation of wave propagation generated by humans and people crowds, which are important for sensors and WSNs.

Recently, crowd sensing and urban sensing surveys have been carried out (Teixeira, Dublon, & Savvides, 2010; Rashid, & Rehmani, 2016). However, many of these did not take into account challenges in developing countries such as the state of communication infrastructure and chaotic nature of people crowds. For example, authors in (Bouchabou, et al., 2021) looked at activity recognition in smart homes based on Internet of Things (IoT) sensor algorithm, and (Liu, et al., 2019) discussed challenges and opportunities of wireless human sensing for smart IoT world. In literature, approaches to human sensing have been classified as human-centric and crowd-centric, depending on the type of input detected. Crowd-centric sensing models properties of a group of people, while human-centric approaches detect individual human activities. Human centric sensing (HCS) models have been used in personal security (Carreño, 2013), health (Kiehl et., 2020; Wu et al., 2015) and sports (Zhao & You, 2021). Crowd sensing approaches have also been categorized as device free and device present. Device free sensing is when no special equipment or cooperation is required from the subjects, while device present crowd sensing requires that the individuals possess a special device. In this case, the term environment sensors is used to refer to sensor nodes/devices that capture information about their environment.

Crowds in urban cities take the form of; i) individuals moving randomly, ii) individuals moving at pace in the same direction such as in a Christian procession, and iii) individuals stationed in one place. They possess several properties that can be used as a basis for their detection. These properties include: footsteps vibration generated by people crowds, effect of human bodies on Received Signal Strength (RSS) and Channel State Information (CSI), and noise disturbances generated by riotous crowds. Different approaches employ different properties for human-sensing. The next section provides an overview of the different human sensing categories while highlighting their strengths and shortfalls when used for people crowd detection especially in the urban towns of developing countries. This review focusses on the technologies, methodologies and implementation of notable crowd sensing applications, their tradeoffs and advantages when used in specific scenarios. The section starts with a discussion of notable human-sensing approaches, followed by key factors worth taking into account when developing people crowd detection systems in developing countries. The focus is exclusively on alternatives to video and camera based approaches..

2.1 Radio Sensing

Passive radio sensing is based on real time processing of CSI used by wireless communication systems. Moving bodies and objects create a disturbance on electromagnetic waves. This can be measured directly from CSI. Unlike its counterparts such as camera-based and wearable devices, radio-based sensing does not require cooperation of monitored subjects or specialized infrastructure or images. This approach detects existence or presence of people from the RSS. Human presence is determined by the effect of humans on the RSS. Water represents 70% of the human body which absorbs part of the 2.4GHz radio signals and thus resulting into a significant decay in the RSS.

Sensing techniques that employ RSS include: 1) Multi-Input Multi-Output (MIMO) sensors, 2) radio tomography, and 3) Doppler sensors. The array sensor approach exploits the multiple antennas on a receiver to detect different aspects of human dynamics such as seating and falls (Hong, & Ohtsuki, 2015). MIMO sensors base on the multiple propagation channels to detect people presence. In recent years, MIMO has transmitted large capacity in high speed using multiple antennas. Authors in (Nishimori et al., 2011) proposed an intrusion detection method using MIMO channels. They analyzed the antenna arrangement suitable for MIMO sensing in an indoor environment. Radio tomography on the other hand employs the multiple transceivers of radio waves focused towards a Region of Interest (ROI) or target. Presence of a person results into absorption and reflection of propagated radio waves. Human detection is thus based on attenuation resulting through the links. The Doppler sensors compare the frequency of transmitted radio waves to the frequency of the received in detecting the speed and movement of a person. These have been used in speed guns. Doppler Effect has been proposed for fall detection (Erol, Amin & Boashash, 2017). Figure 1 below is a depiction of a crowd density estimation system that has a base station and sensor nodes deployed to receive radio waves from cellular phones carried by people crowds. Collected data is forwarded to a remote server via a gateway or LTE technology to determine the existence of a people crowd.

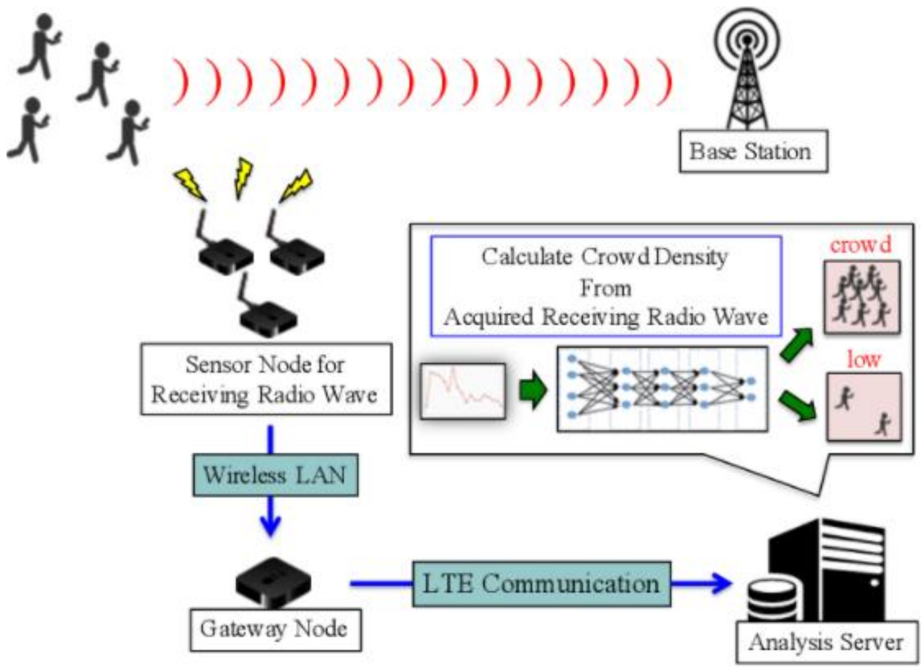

Figure 1: A depiction of crowd density estimation system using cellular technology (Shibata & Yamamoto, 2019)

There are several limitations to radio sensing. The approach assumes device present sensing which requires persons to be in possession of radio devices. In addition, radio waves are affected by fading and noise, and they face interference in indoor environments. In a study by Kostoff et al., evidences to the effect of 5G mobile technology on the human eye and skin, together with their adverse systemic effects were presented (Kostoff et al., 2020).

2.2 Wi-Fi based

Wi-Fi based crowd detection approaches exploit data available on Wi-Fi infrastructure to provide local crowd monitoring solutions. They leverage on the geospatial information collected by access points to enable real time monitoring of people crowds. Popular crowd counting approaches that have been used in crowd monitoring include approaches based on Channel State Information (CSI) (Liu et al., 2019; Wang, Y., Liu et al., 2014) and Received Signal Strength (RSS) (Depatla, Muralidharan, & Mostofi, 2015). In addition, probe requests used by smart phones to find nearby access points have been used to estimate people counts. Authors in (Kurkcu & Ozbay, 2017) exploited device and AP addresses to estimate pedestrian count. The strong point with Wi-Fi based sensing is that they are non-intrusive, free of occlusion and are relatively cheaper because they utilize already existing infrastructure. Successful application of Wi-Fi sensing have been shown in smart home activity sensing (Wan, O'grady, & O'Hare, 2015), pedestrian counting in urban traffic (Guillén-Pérez & Baños, 2018), and estimation and forecasting crowd counts (Determe et al., 2020). Wi-Fi based sensing have also been used for crowd monitoring (Mu, 2020). The depiction in Figure 2 below has a Wi-Fi listening device that senses individuals with Wi-Fi devices in their possession. The devices access the Wi-Fi network via the different Access Points (APs).

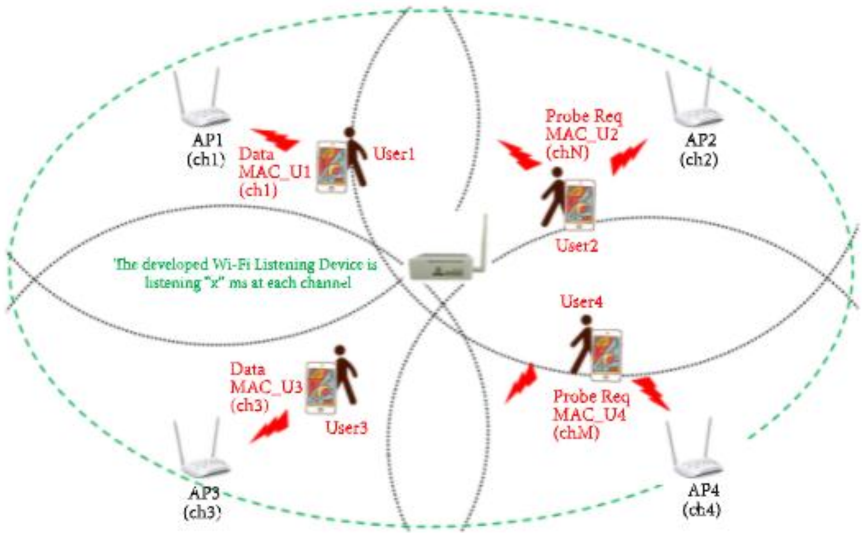

Figure 2: Deployment of a MAC address listening device (Andión et al., 2018)

Wi-Fi sensing will however require a dense Wi-Fi Access Point (AP) implementation. In addition, other Wi-Fi sensing challenges include: privacy and security issues attributed to the many Wi-Fi applications that can infer Wi-Fi logs and be used for malicious purposes. Wi-Fi signals are also sensitive to a number of environmental factors, and coexistence of Wi-Fi sensing and networking that can affect the performance of each other (Ma, Zhou & Wang, 2019).

2.3 Mobile Crowd Sensing

In the past few decades, the world has undergone a revolution from crowdsourcing models that involved the use of people crowd to collect data that could otherwise have been collected expensively using traditional methods. MCS paradigms emerged for the collection of smart city and Internet of Things (IoT) data. It leverages on the extensive penetration of smart phones with several embedded sensors: GPS, cameras, accelerometers, light sensors and proximity sensors to form a large sensing system that can support a number of sensing applications. Examples of MCS applications include: gaming (Dasari, et al., 2020), hotspot identification (Guo et al., 2014), pilgrim tracking and identification (Koutsopoulos, 2013), and public information sharing (Yu et al., 2015). It has also been applied in Smart Social Distance (SSD) monitoring. The MCS model has taken the form of large reference analyzers, street level monitoring and participatory sensing. Unlike other traditional approaches, the MCS sensing framework is divided into levels that include crowd sensing, data collection, data transmission and application levels as shown in Figure 3 below.

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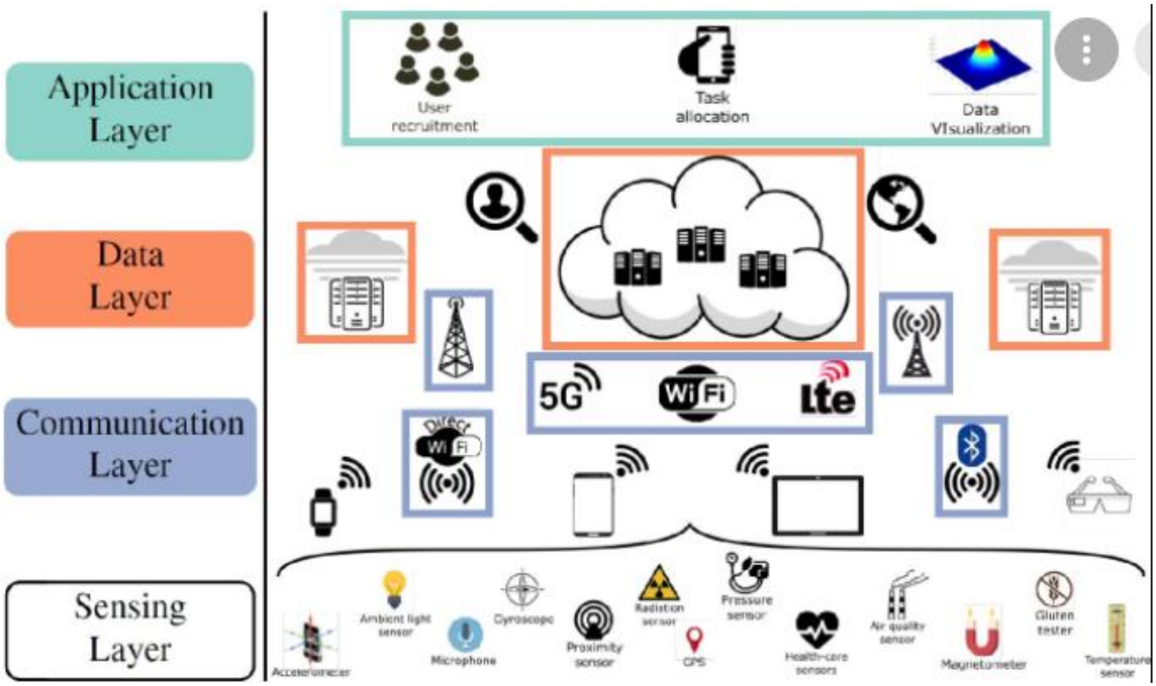

Figure 3: A depiction of the mobile crowd sensing layers (Capponi et al., 2019)

The advantage with mobile crowd sensing is that they may not require specialized fixed sensor infrastructure and as a result are relatively cheaper. Unlike embedded systems, smart phones carried by humans are rechargeable and hence have a loosened power constraint.

The varying radio ranges of different mobile devices however have strong impact on the design and implementation of MCS systems. A number of existing systems use a two-step process characterized by a first probing and then a processing stages that demand for a portable and easy to deploy design to enable tracking of large crowds (Musa & Eriksson, 2012). In addition, mobile sensing for large networks may not be achievable due to the high costs associated with the large number of sensing and relay nodes. And although there has been a high penetration of smart phones, many people still make use of low end mobile devices. As a result it is hard to come up with an attractive incentive model for MCS.

2.4 Wearable Tags (RFID/BLE/Bluetooth tags)

Radio Frequency Identification (RFID) is a technology that uses electromagnetic fields to automatically identify and track tags attached to objects. The object is identified by a unique tag. The RFID system is composed of RFID tags, RFID readers, antennas and a computer used for connecting the readers. There are three different ways of using a wearable multi-sensing device: human-centric, environment-centric and crowd-centric. Human-centric or people-centric sensing, is intended for collecting data on personal traits such as movement and stress. The goal of environment-centric sensing, is to capture information such as data on weather and pollution around a person. Finally, the third category emphasizes collecting spatial temporal data on the behavior of groups of people for example crowd density, and size. Examples of RFID based crowd sensing systems include; the pilgrim tracking and identification system that used mobile phones in an area covered by 3.5G network and saves data on mobile devices whenever there are internet outages (Mohandes, 2011; Bolic, Rostamian, & Djuric, 2015).

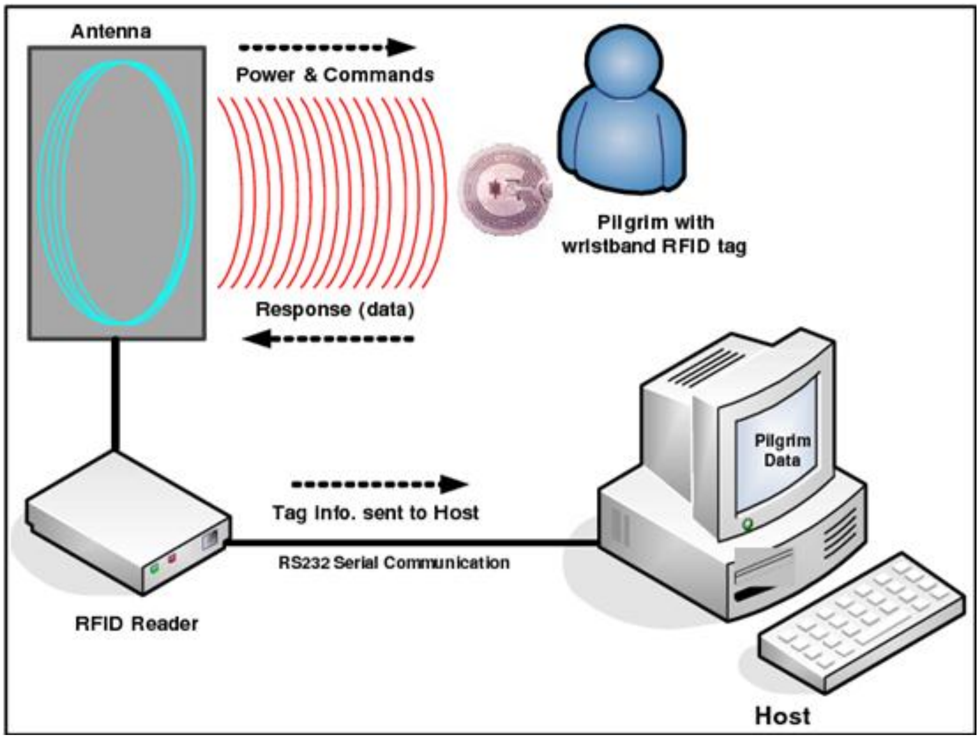

Figure 4: An RFID Pilgrim identification system (Mohandes, 2008)

A shortfall with RFIDs and other devise based crowd monitoring approaches is that they may require consent from the subjects. While, out of bound crowds are very difficult to manage because of the RFID range limitations. The approach may therefore call for additional crowd control mechanisms or a fusion of data from more than one sensor type to ensure effective crowd detection. Also, although their prices have fallen down over the years, the initial configuration is relatively costly, sometimes difficult and time consuming. And materials such as metal and liquid can have a negative impact on the signal.

2.5 Wireless Sensor Networks

A Wireless Sensor Network (WSN) is a group of spatially distributed sensor nodes interconnected using wireless infrastructure and intended to collect data about a physical environment. The sensor nodes that make up a WSN comprise of a positioning, mobility and power unit. Each sensor node spread over a Region of Interest (ROI) measures fluctuations in conditions adjacent to it. And data about the parameter of interest is then forwarded to a specialized node called the sink. To detect subjects of interest, k sensors with range r, are randomly deployed in a ROI. Assuming sensor, s_i *is* placed at a point K (x_i, y_i). The Euclidean distance, d (s_i, P) between K and any point P $(x. y)$, and the binary sensing model (Ghosh, & Das, 2008) that expresses coverage, $c_{xy}(s_i)$ of a point P are given by Equations 1 and 2 below respectively.

$$d(s_i, P) = \sqrt{\{(x_i - x)^2 + (y_i - y)^2\}} \qquad 1$$

$$c_{xy}(s_i) = \begin{cases} 1, & if d(si, P) < r \\ 0, & Otherwise \end{cases} \qquad 2$$

The advantages with binary sensing is that they are relatively cheap, have low power requirements and follow a simplistic implementation procedure. But since the binary model has been considered imprecise because it takes on unrealistic assumptions of no uncertainty associated with a node's sensing process, a probabilistic model that expresses coverage in probabilistic terms as shown in Equation 3 below has been used to explain sensing (Zou & Chakrabarty, 2003). Variations of the probabilistic sensing models include: the shadow-fading (Tsai, 2008)) and Elfes' sensing models (Elfes, (2013).

$$c_{xy}(s_i) = \begin{cases} 0, if r + r_c \leq d(s_i, P) \\ e^{-\lambda\alpha^{\beta}}, if r - r_c < d(s_i, P) < r + r_c \\ 1, if r - r_c \geq d(s_i, P) \end{cases} \qquad 3$$

With regard to human sensing, sensor nodes have been deployed for crowd density estimation (Yuan et al., 2011), and intrusion detection (Yang et al., 2014). Authors in (Tang, Huang, & Mandal, 2017) used low power sensor networks for sparse aware smart buildings to detect human steps and track person positions with a detection accuracy of 98.3% and localization error of less than 25cm recorded. The collaborative mode of WSNs enables simultaneous acquisition of sensor data over a wider area. In addition, advances in macro-electromechanical technology have enhanced sensing, processing and communication capabilities of small sized nodes that are now able to support an ever growing range of applications that may leverage on WSN to provide additional or complementary services. Figure 5 below is an application of WSNs for people crowd monitoring.

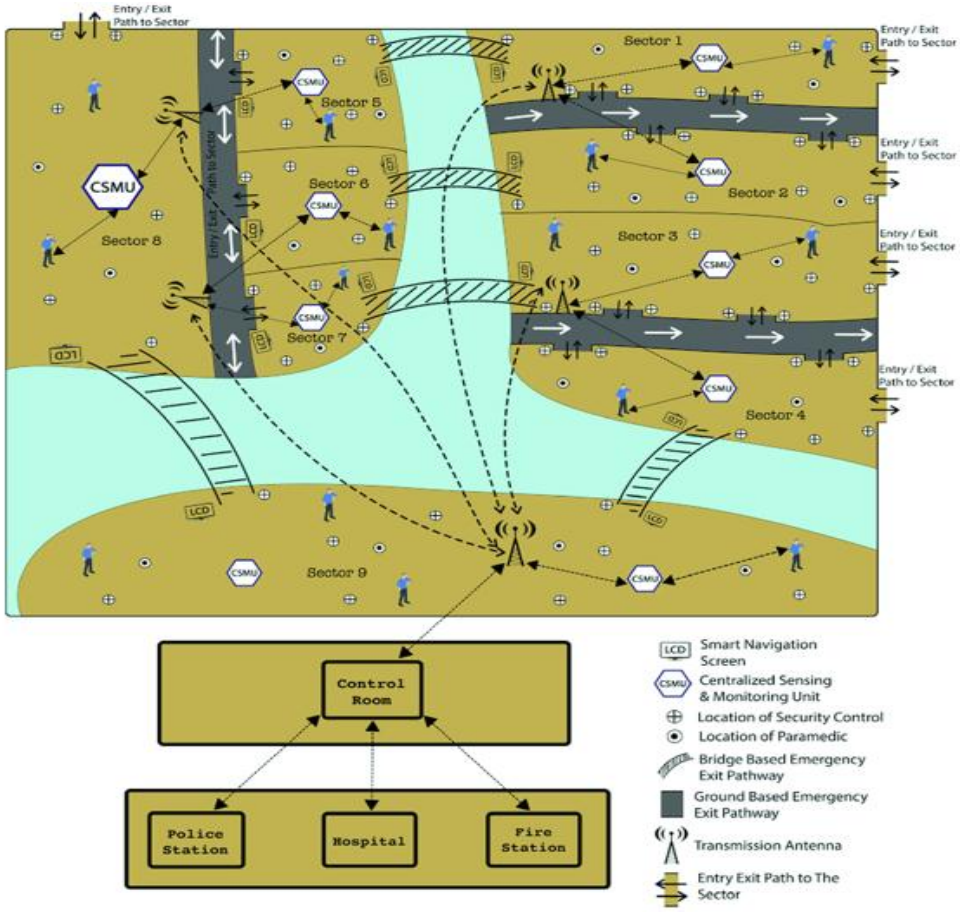

Figure 5: A wireless sensor network for people crowd monitoring (Kasudiya, Bhavsar & Arolkar, 2020)

Despite technological advancements registered in WSNs, their application for detection of people crowds in developing countries still presents a number of challenges: The poor communication infrastructure and chaotic nature of people crowds in less developing lands are a hindrance to the use of WSNs for people crowd detection. For example the lack of respect towards the different service infrastructures means that if implemented, they require additional physical security. While the limited and poor infrastructure cannot be relied upon to accelerate innovation. In addition, WSNs have inherent challenges of battery life, transmission range, data collection and data security. For example vibration sensing systems are sensitive to gait variations caused by different walking speeds and floor variations as a result of structural heterogeneities. Despite their short falls however, work continues to be done to improve the use of vibration sensors (Hu et al., 2019) and the functionality of WSN at large.

2.6 Crowdsourcing

Crowdsourcing is a participatory and normally online activity in which individuals are invited to participate in a task through a flexible voluntary open call. Examples of crowdsourcing models include: iReport (Toffoli, 2008), wikipedia. Mechanical Turks (MTurk) (Turk, 2010).), and the Amazons Mechanical Turk (MTurk) [Schmidt & Jettinghoff, 2016). Their shortfalls however are that reliability of collected data is not guaranteed and that it requires sensitization of participants. Despite the proliferation of several incentive mechanisms (Yu et al., 2015; Yang et al., 2012; Lin et al., 2017; Jaimes, et al., 2015) they do not provide a comprehensive guide to the most appropriate incentive mechanism (Guo et al., 2015). Only a small number of smart phone users in developing cities have full time internet connectivity to enable application of location information.

2.7 Sensor fusion

Sensor fusion is an approach that employs multiple sensing modalities in order to combine the advantages while canceling their respective limitations. Input from multiple sensors such as radars and sensor nodes form a single model capable of detecting different aspects of a target(s) of interest that could not have otherwise be collected by a single sensor. As a result, the approach provides a better estimation of accuracy over a wide range of conditions. An example of the fusion approach was the integration of PIR sensors, CO_2 detectors and cameras to derive building occupancy (Sun, Zhao, & Zou, 2020). While Schulz et al. presented a system for estimation of people location that involved detection, counting, localization, tracking, and identification (Schulz, 2003). Unlike traditional frameworks that rely on a network of dedicated and fixed sensing nodes that were culpable to inefficient sensing coverage, high maintenance costs and limited scalability, a new sensing infrastructure is the Mobile Crowd Sensing and Computing (MCSC). MCSC extends the concepts of participatory sensing to leverage online and offline mobile sensing devices (Guo et al., 2015). This framework addresses a fusion of both human and machine in the sensing and computational processes.

Deployment of multiple modalities is however relatively expensive in terms of resource requirements, yet the reason for detection of people crowds may have required only a single or few aspect of the crowd. Despite the shortfalls, with a good needs analysis sensor fusion can be a potentially successful crowd detection or sensing approach.

3. KEY FACTORS AFFECTING PEOPLE CROWDS SENSING IN DEVELOPING COUNTRIES

People crowds sensing in developing countries entails dealing with large numbers of chaotic people crowds that build up in environments that are characterized by under developed infrastructure and communication networks. People crowds are also spontaneous and cannot be predicted when it comes to time and location of appearance. Some of the approaches described above have been employed in detecting and tracking individual persons, whereas crowds involves detection of multiple persons at a given time. Furthermore a number of the people detection approaches have been for indoor environments. In addition, a number of these applications were intended for demonstrating the feasibility of particular technologies and only for a limited period of time. In developing countries the following properties need to be put into consideration when designing people crowd detection systems.

3.1 Ease of Deployment.

Node deployment is an important factor in the implementation of sensor networks. There are two deployment methods: 1) Deterministic and, 2) random deployments (Deif & Gadallah, 2013). In deterministic deployment nodes are positioned selectively to achieve a desired objective. While a random sensor deployment, randomly distributes nodes in an area of interest normally by a plane. Selective deployment is appropriate when sensors are expensive and the application of the sensor network is highly dependent on location of the nodes. Developing countries in the 21st century are spending a reasonable portion of their budget on infrastructural development. This has called for modification and sometimes overhaul of already existing infrastructure. It means that any implementations in addition to ensuring optimal deployment, coverage and connectivity, need to meet existing budgets and adopt to ongoing minor and major renovations. It is especially true for infrastructure-based solutions. While mobile based solutions must be supported and available on platforms that have already penetrated the populace such as Google play and play store.

3.2. Scalability

The scalability property of a system is its ability to be modified to support changing loads. Critical to scalability of a sensor network is the scalability of the routing protocols (Snigdh & Gosain, 2016; Sajwan, Sharma & Verma, 2020) and, the topology of the network (Yu, Sun, & Mei, 2007). The evident economic development being realized in most developing countries necessitates that implementable solutions adopt to the increasing number of users, and extended period of use with minimal or without any significant cost implications. The sheer number of nodes that may be required to monitor wide expanses of urban cities pauses great challenges, given that WSNs are adhoc and impose big physical constraints at both the node and system level. Therefore, in addition to optimizing throughput, focus should also be directed towards extending the lifetime and robustness of outdoor nodes that are also constantly subjected to fluctuations in temperature and frequent climatic changes. Furthermore, scaling costs to be taken into account include: infrastructure implementation, server-side system support, marketing and building of customer base for the case of application based solutions. Figure 6 below is Kigondo town which is a transit area in Kigali-Rwanda. And next is the proposed 30 year plan for Kigali, which is also the capital city of Rwanda. Rwanda is an example of a fast growing country located in central Africa and therefore with demand for fast adopting and flexible technologies.

Figure 6: Kigali transit area and Kigali's proposed 30 year master plan respectively (Google, n.d; *Singh, 2019*).

3.3. Security

Just as WSNs have attracted interest both from industry and academia, so have the threats (Bhushan, & Sahoo, 2020). Threats to sensing systems take the form of threats on data stored in both mobile devices and remote servers or on the physical infrastructure themselves. The chaotic and lawless nature characteristic to people crowds in developing countries call for special attention. So, in addition to privacy, confidentiality and integrity of sensor data, the system physical infrastructure must also be protected from intentional vandalism by chaotic crowds and disgruntled individuals.

3.4. Incentives.

The proliferation of smartphones and wireless devices have been an incentive to many mobile sensing applications. To guarantee performance however, it is essential to motivate participants. In their survey, Zhang et al. described three major categories of incentives: entertainment, money and services (Zhang et al., 2015). The principle behind the entertainment motivation is to reward players as a motivation to participate. And examples include; the Tycoon game (Broll & Benford, 2005) and the Treasure game (Barkhuus et al., 2005). In service motivation, a service quota is allocated to a participant in exchange to their contribution. Many incentives frameworks rely on the assumption of truthful participants (Hoh et al., 2012). This is however a rare quality among imperfect human beings. And thirdly, with money as an incentive, workers undertake advertised tasks in exchange for payment (Antin & Shaw, 2012). There is also a high likelihood of participants being influenced by monetary payments.

3.5. Accuracy

The accuracy of a sensor is the measure of the maximum difference that exists between the actual value and the indicated value at the output of the sensor. The high precision requirements in both industry and academia, makes accuracy of sensor applications an important area of research. For example, to overcome inaccuracies resulting from synchronization, central clocks have been employed (Álvarez et al., 2019). The accuracy of the GPS sensing technologies using smartphones, is affected by the type of GPS receivers and device chipset (Menard et al., 2011), platform (Hess et al., 2012) and localization technology (Zandbergen, 2009). In addition, work has also been done on the accuracy of sensing systems. For example Merry, & Bettinger in their work on accuracy confirmed the average horizontal position accuracy of iPhone 6 (Merry & Bettinger, 2019). However, on the other hand applying strict anonymization in crowd sensing can lead to poor accuracy of provided data.

3.6. Transparency.

The word "transparency" is coined here to imply a sensing paradigm that will allow data collection without necessarily requiring involvement of participants. Participatory sensing such as in MCS, relies completely on users' willingness to submit accurate information for analysis. It is a paradigm that has taken advantage of smartphones to collect and analyze data that was previously impossible. Wireless sensor networks and the Radio waves approaches on the other hand require less intervention from participants. While RFID and mobile sensing will at call for consent from participants.

3.7. Resource Consumption.

Resources considered limited in sensors and sensor networks include: battery, CPU, and memory. Detection algorithms can be designed to both minimize resource consumption and intelligently utilize available resources. This is especially critical in areas where nodes can easily be destroyed. Node deployment must be planned for areas not expecting routine maintenance. Algorithms that improve resource utilization in IoT wireless mesh networks, reduce network energy consumption and increases network capacity have been proposed (Nurlan et al., 2021). In addition, work by Wietfeld & Dusza showed that by changing the resource allocation scheme and without spending spectrum resources, power consumption can be reduced by over 70% (Wietfeld, Ide & Dusza, 2014). The authors proposed an Energy Efficient Scheduling (EES) mechanism. This is a predictive Channel-Aware Transmission (pCAT) that leverages on the favorable channel conditions and requires much less spectrum resources. While a Wi-Fi based indoor positioning system eliminates the need for the laborious task of the offline calibration phase but uses radio maps generated by deployed sensors (Ali, Hur, & Park, 2019).

Overall, a people crowd detection system is dependent on the application for which it is designed. However in developing countries, the factors discussed above are critical to a successful implementation of crowd detection systems.

4. ANALYSIS OF HUMAN SENSING FOR URBAN CROWD DETECTION

Table 1 below presents a comparative review of the strengths and shortfalls of popular human sensing approaches with regard to their ability to detect people crowds in developing countries. There are a number of human sensing approaches and systems, the following examples to a reasonable extent represent the major sensing categories.

Table 1: Approaches to Crowd Sensing/Detection

Solution/Article	Year	Basis	Strength	Shortfalls
Radio				
(Shibata, & Yamamoto, 2019)	2019	• Signal strength of radio waves	• Mitigates privacy issues	• RF based approaches may require subjects to be in possession of RF-based devices • Require labor intensive training phase
(de Brito Guerra et al., 2019).	2019	• Narrow band radio frequency	• Accuracy in classification performance and low noise bandwidth	• Lower data rates • Subjects must be in possession of cellular phones or devices • Require labor intensive training phase
(Ding et al., 2018).	2018	• Background radio frequency	• Subjects do not require to be in possession of RFID tags	• Requires consent from subjects • Tags are still required within the area of interest • Require labor intensive training phase
Wi-Fi				
Frog Eye (Xi et al., 2014)	2014	• Channel State Information (CSI)	• CSI is highly sensitive to environmental variation • Does not require subjects to be in possession of specialized device(s) • Relatively accurate, scalable and reliable	• Like any Wi-Fi system, it requires an initial configuration and implementation cost
Wicount (Yang et al., 2018)	2018	• CSI	• Device free • Does not require training phase.	• Tested only for crowds of up to 5 • It is an indoor system

			• Can count multiple people at the same time • High counting and direction detection accuracy	• Predetermined position of counting system. This calls for well-planned infrastructure deployment
Freecount (Zou et al., 2017)	2017	• CSI	• Device free • Only requires commodity Wi-Fi routers plus a software upgrade	• Experimented only in indoor environments
Deepcount (Zhao et al., 2019)	2019	•CSI	• Implemented on commercial Wi-Fi devices • Achieved high accuracy results	• Great complexity and Works in a closed environment • Tested for environments of up to 5 people
Mobile Crowd Sensing				
TRESIGHT (Sun et al., 2016)	2016	• Basing on FI-WARE technology, Integrates Crowd sensing with data repositories	• Infrastructure deployment is cheaper than traditional approaches that are considered costly to a majority of the cities • Can be used to provide additional functionalities such as in tourism, health and marketing drives • Provides open data for industries and other public bodies.	• If wearable bracelets are used, participants need to be convinced to participate • When implemented with mobile applications, they require additional resources and configurations • Support for multiple applications increases the number of vulnerabilities.
SensorPlanet (SensorPlanet.org)	2006	Integrates data from many different mobile phone sensors	• Provides a central test repository for sharing information • Enables collection of data from a wider scale	• Data from different datasets may need to be queried first • Data Heterogeneity from different sources

Twitter (http://twitter.com/)	2006	Twitter posts	• Has many subscribers. • Twitter APIs can retrieve latest twitter posts	• Participants may requires incentives to participate. While people will normally participate in issues making headlines and only of interest to them • Security vulnerabilities as a result of using open source languages related to java and XML
Wearable-based systems (RFID/BLE/Bluetooth tags)				
(Weppner & Lukowicz, 2013)	2016	Bluetooth scan data	• Can leverage on relative features that do not exclusively depend on the number of devices	• Assumes all people have their Bluetooth devices on discoverable mode which is not always the case • Scan is limited only to about 10m radius • Signal attenuation due to the high absorption coefficient of the human body • Variations in life style. Bluetooth enabled devices are mainly used by the urban population • User privacy may be at risk.
(Alhmiedat & Aborokbah, 2021).	2021	Smart Social Distance (SSD)	• Easy to deploy and maintain • Dependable and cheap.	• May require incentives to guarantee participation
(Galinina et al., 2018)	2018	Power transfer in exchange for sensed data	• Provides user access to aggregated data contributed by the wearables.	• User has to move towards a designated charging terminal, for their devices to charge.

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			• Provides redundancy of non-personal data coming from collocated sensors • Identifies data sources for purposes of quality assessment and reward sharing	• Requires relatively more infrastructure compared with many devise free mechanisms.
Wireless Sensor Networks				
ExScal project (Arora et al., 2005)	2005	Dense deployment of sensor nodes	• Wider area coverage of approximately 3km • Its design requirements include longer perimeter coverage, accuracy and robust operation, lower human operation and reliability.	• Requires a tired dense deployment of sensor nodes
Crowd Sourcing				
CrowdMonitor (Ludwig et al., 2015,)	2015	Assesses physical and digital activities of citizens	• Facilitates collection of both real and virtual data • The platforms map feature enables a good situational overview that enables direct communication with data collectors • Incorporates approaches to coordinate and avoid needless duplication and conflicts in data collection	• Data collectors may not be that good at situational assessment.
Amazon Mechanical Turk (MTurk) (Schmidt, & Jettinghoff, 2016)	2016	Data is contributed by invited participants	• Can perform tasks that could have otherwise not been performed by few individuals	• High skepticism about the validity of data • Incentives necessary for participation

Sensor Fusion				
Metro Sense Project (Eisenman et al., 2006)	2006	Integrates concepts from WSN and Mobile networking and the internet.	• Has a simplified service model that supports heterogeneous networks • Enables large scale people –centric sensing • Enables low cost, scalable and improved performance • The sensor architecture can benefit from already existing infrastructure and services	• May lead to a sub-optimal process flow in service provision • Implementation calls for availability of initial infrastructural requirements
mCrowd (Yan et al., 2009)	2009	Interfaces MCS with crowd sourcing	• Encapsulates multiple crowdsourcing services • Maximizes on the popularity of multiple crowdsourcing services.	• Leveraging resource asymmetry may result into a sub-optimal process flow to provide a particular service

By means of examples, table 1 above provides a comparative review of human sensing categories as reviewed in Section 2 above. Their strengths and shortfalls are highlighted.

5. CONCLUSION

The spontaneous, dynamic and chaotic nature of people crowds, together with the underdeveloped infrastructure characterizing developing economies present unique challenges to people crowd detection using sensors and sensor networks. In addition, the different categories of sensors and sensor networks for human sensing do have their own inherent challenges that require special attention to appropriately be adopted for human sensing in developing countries. And although a number of research papers have been published on crowd detection, not much has been in the area of people crowd sensing. While the few publications on people crowd sensing have mainly been for application in indoor environments.

Advancement in the micro-electromechanical technology have led to production of small sized, light weight and affordable sensor nodes that have in turn extended the application domain of sensors and sensor networks. Given that people crowd detection continues to be an essential feature that can be especially important in planning of service delivery, security and infrastructure, this paper reviewed popular human sensing approaches and highlighted their respective strengths and shortfalls when applied for people crowd detection with special focus on resource constrained economies. By means of examples, a theoretical analysis of the various human sensing categories has been presented.

While efforts have been invested in many crowd detection applications, there remains need for people crowd detection approaches that will factor in the dynamic and chaotic nature of people crowds that is characteristic of many developing economies today. The detection system should also take into consideration the state of communication infrastructure.

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