Living with Rules: An AR Approach

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Abstract

The Social distancing rule has proven to be an effective measure against the spread of the infectious COronaVIrus Disease 2019 (COVID-19). Even with a lot of research focusing on static camera based solutions for monitoring the rule, the real issue with visualising and monitoring rules for public spaces still remain an open question. In this work we propose a Social Distancing Helmet (SDH) with basic prototyping for an outdoor augmentation system using body worn sensors for visualising and monitoring rules for shared spaces using AR. First results with some software components of the prototype are presented.

Index Terms: Rules for shared spaces —Visualization—Protective systems—Safety; Enabling rules with AR—Control—Visualization design and evaluation methods

1 Introduction

CoViD 19 has forced the world to reconsider social interactions with social distancing proving to be the best counter measure to contain the virus. Social distancing methods can be classified into public and individual measures. Public measures include closing or reducing access to education institutions and workplaces, canceling mass gatherings, travel restrictions, border control, and quarantining buildings.

Individual measures consist of isolation, quarantine, and encouragement to keep physical distances between people [8]. Restrictions over the minimum inter-personal distance between people can be metaphorically referenced as a rule for public space. Like all other human corona viruses that have known to impact elderly people disproportionately [9], the COVID-19 virus too has proven not to be an exception. Protective systems for these vulnerable groups would help them cope with the virus without self isolation. However neither these vulnerable groups nor the general public are used to keeping an imaginary safety bubble around themselves. Effective implementation of these rules would heavily depend on regulations and the monitoring that are in place. Considering the ethical issues with camera based surveillance systems, our approach is a user centric smart rule recommendation and monitoring system using body worn sensors and AR. We denote all pedestrians around the user as Field of View (FOV) pedestrians. The FOV pedestrians are all participants within the camera FOV. The proposed Social Distancing Helmet (SDH) is a body worn apparatus consisting of a Lidar sensor, a smartphone camera and a HoloLens. The ranging capabilities of the Lidar sensor, and the real time object detection capabilities of deep learning models on smartphones as well as the visualisation capabilities of the HoloLens have been used to monitor and control the behaviour of pedestrians to follow rules.

2 Related Work

Social Distancing and AR. Google has launched it own WebXR platform to visualise social distancing rules with AR [10]. With its experimental augmented reality tool, Google helps to superimpose a 6 foot virtual boundary hence guiding on how far people should stand while obeying the rules. AR based training have also found its way in helping young people grasp the abstract concept of social distancing [1]. The major design elements of MAR (Mobile Augmented Reality) were summarised in [12] which could be directly applied for impaired and non-impaired visitors to practice social distancing in museums and art galleries.

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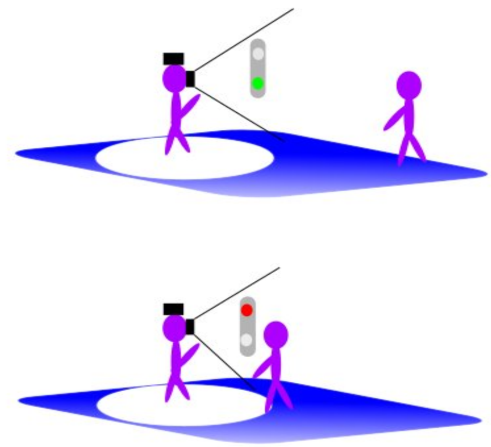

Figure 1: Pedestrian equipped with SDH interacting with FOV pedestrians

Much of the approaches on controlling behaviour for social distancing has been proposed using static camera based surveillance. Amazon introduced its AR approach with the Distance Assistant, which augments and updates any violations of rules in real time. The system helps individuals maintain 6 feet distance [4] . Audio augmentation has been used [24] to control pedestrian behaviour to follow rules based on active surveillance system. The system also prevents overcrowding beyond a threshold by emitting a non-alarming audio-visual clue.

Other works have focused along social distancing monitoring to evaluate and understand the effectiveness of these rules in public spaces. A specific social distancing approach [18] utilises machine learning to detect and track pedestrians followed by the calculation of a violation index for non-social-distancing behaviors. On the challenges of using visual data for social distancing, as outlined by the author in [7], robustness to severe self and other objects/people occlusions, different image scales, and indoor/outdoor scenarios are some of the shortcomings that have to be addressed for effective systems. However the visual approach does aid with contextual information helpful to understand whether social distancing rules are actually being broken or not. Camera based compliance monitoring are prone to false alarms as the system relies on intention prediction based on contextual information. Not much work has been done considering user worn rule recommendation and compliance monitoring systems even when AR has

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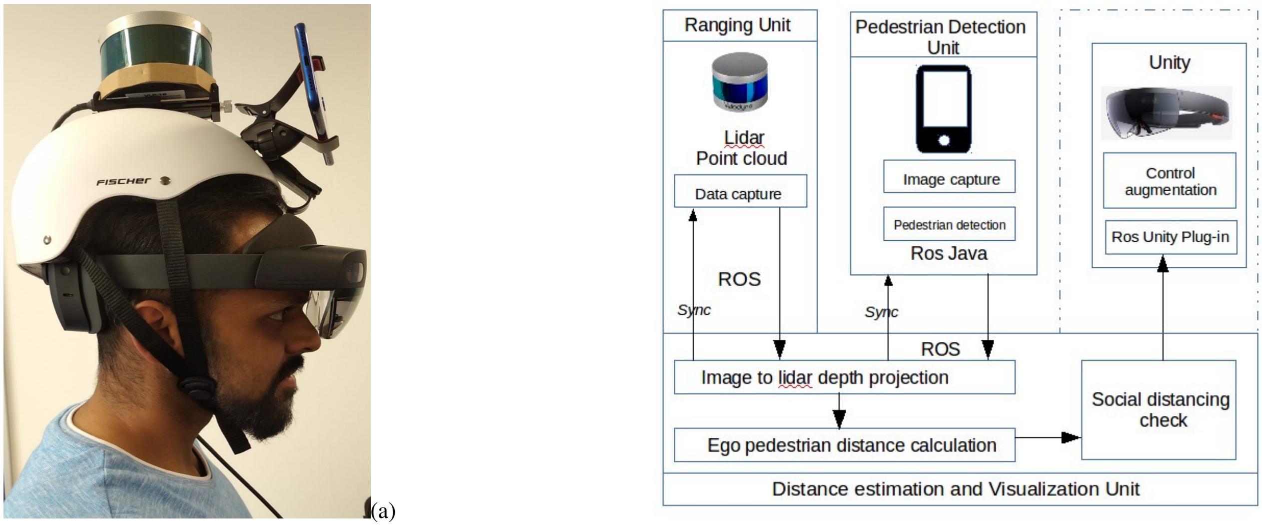

(a) (b)

Figure 2: (a): Pedestrian with the social distancing helmet, (b): Different components of the SDH interacting with the system

proved to be an effective visualisation tool for social distancing rules.

Body Worn Sensors

A social distancing belt is designed in [15] using body worn sensors to measure social distances. The ultrasonic distance sensor was used to measure and create a dataset to validate the pressure of pedestrians with social distancing during the pandemic. The work studied the behavioural changes of pedestrians to fellow pedestrians in a crosswalks. With the widespread use of smartphones, bluetooth technology along with other sensors have been reviewed [17] for localisation to detect crowds in indoor environments to practice social distancing considering the latest advances with Bluetooth localization techniques [22], [21]. However the drawbacks of the technology with social distancing considering its accuracy when the users devices are located inside the pockets or bags and the restrictions to activate Bluetooth on these devices are some of the limitations.

Body worn Lidar localisation approaches are useful in GPS denied and outdoor environments. Thanks to the active research with autonomous vehicles, the cost of Lidar sensors are expected to drop with new market players entering the market. A Helmet based SLAM was proposed in [6] with localisation capability and also building a contextual information in the form of the map of the environment. The Zena dataset was proposed for outdoor localisation in [19] to further research on Search & Rescue scenarios. Camera and Lidar vision were fused in [2] using a Multi-SLAM approach to support localisation of pedestrians using a shoulder mounted Velodyne VLP-16. To understand the behavioural changes, a portable Lidar apparatus with localisation capability was worn by a pedestrian and used to observe the long-term and wide-area behaviour of pedestrians in [11]. The measurement from the system were used to observe *"Personal distances"* and *"Social distances"* between a caregiver and an elderly person in the indoor environment.

Pedestrian detection on Smartphones

Considering the computation capabilities and considerations of offloading server based Deep Learning approaches, many deep learning frameworks have released mobile compatible versions. These frameworks include TensorFlow Lite (TFLite) from Google, Caffe2 from Facebook, Core ML from Apple, ncnn from Tencent, and MDL from Baidu. These frameworks all share the same goal of executing the Deep Learning inference task solely on smartphones.

Pedestrian detection can be regarded as either a part of a general object detection problem or as a specific task of detecting pedestrians only. With the release of many Deep Learning Network frameworks for smartphone platform, the on-device Deep Learning inferences have proven to better protect user privacy without uploading sensitive data [23]. Hence considering the privacy issues faced with existing approaches, we leverage the recent advances to identify FOV pedestrians using on board computing with our apparatus.

Adaptive Augmentation Systems and Behaviour Control

The control of behaviour for shared spaces has been studied in [20] were a system design for the control of pedestrian behaviour has been proposed. The system highlights how the augmentation mediates negotiations using predefined rules allowing priority participants have the right of way in conflicts. As augmentation has a lot of relevance with virtual traffic system, research has investigated the feasibility of the use of smartphones for virtual traffic controls [16], demonstrating its capability in controlling diving behaviour in connected traffic environments.

3 Social distancing Helmet

With the development of various sensors and cross-domain data processing methods, AR applications are gradually being applied in outdoor environments [13]. LIDAR based outdoor visualisation using AR have helped to model and understand Solar Radiation Data [5]. Recently Apple announced the integration of a LIDAR Scanner measures the distance to surrounding objects up to 5 meters away, works both indoors and outdoors [3], hence enabling a whole new class of AR experiences on iPad Pro. Our proposed apparatus, inspired from the recent advances on LIDAR for AR is based on networked sensors which would move towards an integrated on device unit with the the increasing complexity and power of smartphone in future.

The Social Distancing Helmet (SDH) as shown in Figure 2 (a) is a portable VLP-16 LIDAR unit with a smartphone camera and a portable power supply. The smartphone camera which is extrinsically registered to the LIDAR sensors capture the visual information of the field of view visible to the user pedestrian. The smartphone was chosen as the image capture medium considering its relevance with Mobile Augmented Reality (MAR) while the system proposed herein using a Hololens as the visualisation medium. The system as

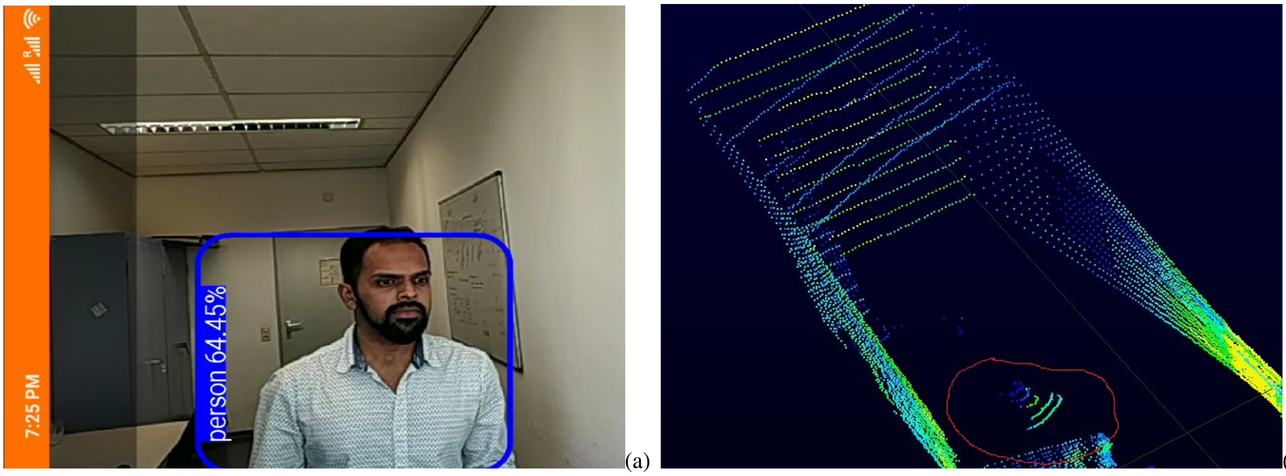

Figure 3: (a): Smartphone based FOV pedestrian detection, (b): Point cloud of the environment with the upper body of FOV pedestrian as captured by the Lidar senor and highlighted in red

illustrated in Figure 2(b) is supported with the pedestrian detection unit (PDU) running a camera application with Deep Learning object detector TensorFlowLite, the Ranging unit (RU) which captures the surrounding environment in 3d point cloud and the Distance estimation and visualisation Unit (DEVU) which computes the distance information of the detected neighbouring pedestrians using the PDU responses and corresponding 3d to 2d projection. The DEVU computes FOV pedestrian distances which are compared to the social distance (6 feet) to control a virtual traffic signal in Hololens to control pedestrian motion information to follow rules.

The DEVU periodically broadcasts the *sync* (Figure 2 (b)) trigger to the PDU and RU. This trigger acts as a time synchronisation pulse between the image and LIDAR sensor for data capture. The PDU unit communicates wirelessly the image coordinates of the detected FOV pedestrians for every detected frame which are mapped to the corresponding frame data from the RU. Using the extrinsic calibration information of the two sensors, 3D to 2D correspondences are exploited to calculate the depth information for the detected FOV pedestrian image boundaries. The system can be described as multiple ROS nodes communicating with each other across multiple device.

Once the FOV pedestrian positions are estimated in the local coordinate system, the system compares the estimated distance with the social distance, the social distancing check would communicate control augmentation to the visualisation medium. The visualisation medium would rely a traffic signal synonymous indication to stop within safe distances from the fellow FOV pedestrians, hence following the safety rules as recommended by the system.

4 First Results

The apparatus has been evaluated for its suitability for real time operation for Augmented Reality based behavioural control considering FOV pedestrian distance estimation. The smartphone based pedestrian detection was found to perform inferior in low lighting conditions and with low detection rates. The lidar point cloud as illustrated in the Figure 3 (B), however captured enough points to calculate pedestrian positions from the apparatus. The smartphone based pedestrian detection models have to be fine turned for better performance for higher system reliability. However to prove the concept, an additional hardware based processing unit can also be considered to support real time detectors like YOLO. The social distancing check and augmentation interface can be integrated once the FOV pedestrian distance estimation is accurate; this is part of the future work of the proposed system.

5 Conclusion

Rule based behaviour control has always been part of the traffic management research centering around the control of traffic participants for smooth and collision free mobility. This has fostered research on vehicles with sensing capabilities. However pedestrians are hugely ignored due to the computation complexity of user worn systems. However in the new post Covid era, research focused on directions to preparing to live with the virus can solve economic isolation's, considering also future pandemics and their preparedness. In another context, such rule based systems can also find their relevance with traffic conflict resolution for pedestrians vehicle conflicts based on ad hoc rules; this has been of paramount interest to the intelligent transportation community considering the introduction of autonomous vehicles and their subsequent interactions [14].

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