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Prediction of Human Movement in Open Public Spaces: Case Study of Sarajevo

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ABSTRACT

Imposed changes in social conduct and the dynamics of living in cities, during COVID-19 pandemic, triggered an increase in the demand, availability, and accessibility of open public spaces. This has put forward questions of the relationship between open public spaces and disease transmission, as well as how planning and design strategies might be used to improve resilience in the face of future pandemics. Within this academic framework, this study focuses on object detection and human movement prediction in open public spaces, using the city of Sarajevo as a case study. Video recordings of parks and squares in morning, afternoon and evening are utilized to detect humans and predict their movements. Frame differentiation method proved to be the best for object detection and their motion. Linear regression is used on a dataset collected using the space syntax observation technique gate method. The best R^2 values, 0.97 and 0.61, are achieved for weekdays, for both parks and squares. Authors associated it with the dynamics of space use and frequency of space occupancy, which can be related to physical conditions and activity content of selected locations. The results of study provide an insight into analysis and prediction of direction, as well as density of pedestrian movement, which could be used in decision making directed towards more efficient and health oriented urban planning.

1. INTRODUCTION

Human movement prediction models can be used in different real-world applications such as autonomous driving cars or pedestrian location prediction, to prevent accidents and to improve movement of robots through the crowds [1]. Similarly, these models could be used for more adequate urban planning and use of open public spaces.

Current health crisis of COVID-19 pandemic has impacted everyday living of the entire human population. More than two years into the pandemic, it is evident that this is not a temporary situation, but a long-term condition that demands permanent change in consolidated behavior and social interaction. As all other mega-events, the COVID-19 pandemic is associated with changes in the morphology of the society that could be traced through spatial alterations.

Marked as centers of pandemic, due to the higher population density and intense social interaction, cities all over the world are undergoing comprehensive, rapid city-wide profiling, aimed at providing a more appropriate response plan. Public spaces are defined as an important asset in a time of present crisis, as promoting health through space by directing and changing behavior is likely to impact large proportions of population and create long lasting effects. To preserve public health, it is necessary to analyze spatial properties of open public spaces and associate them with patterns of social conduct. Due to their variableness in terms of disposal, dynamics of use, culture of living, as well as social interaction and human movement, individual studies related to the assessment of spatial vulnerability and risk are essential. Results of such investigation may direct us towards defining spatial interventions that could ensure safer use of open public areas.

Aiming to understand how human movement is generated in relation to urban layouts, this study uses machine learning methods to train a model for the decision making of human movement and retention in open public spaces [2]. The application of machine learning methods is widely used for many different applications in the world. Moreover, data processing is a key step, including many different stages such as data validation, summarization, sorting, analysis, aggregation and reporting, for the data translation into useful information [1].

According to the epidemiological data from Bosnia and Herzegovina, it is noticeable that the largest cities became the national epicenters of the pandemic [3]. The spread of the infection is intensified due to increased population density, active transport city and intercity network, but also the lack of discipline regarding compliance with measures of social interaction. Therefore, this study evaluates open public spaces in Sarajevo, proposing a model for tracking and prediction of human movements in open public spaces. It analyses squares and parks located in municipality Novi grad - most populated district of Sarajevo (residential square and park), and municipality Centar - administrative hub of the city. Data was collected at the time when movement in space was not restricted due to the COVID-19 pandemic, from April to July 2021, during weekdays and weekends, at morning, afternoon, and evening rush hours. The aim of the work is to interpret and predict direction - circulation routes, and densities of pedestrian movement, and points of pressure, using video analysis and linear regression.

The rest of the work is organized as follows: in section 2 a review of works related to human movement analysis and prediction are presented. Section 3 describes the data gathering process, and methodology. Section 4 provides details about results. Finally, the work is concluded with section 5.

2. LITERATURE REVIEW

Human movement analysis and predictions in open spaces was a topic in various previous studies.

Al-Molegi et al. [4] built a model for movement prediction which combines spatial and temporal data. Authors stated that temporal information brings value to spatial information and that is why they used attention techniques. Move, Attend and Predict (MAP) method was used on Recurrent neural networks (RNN) with attention techniques to predict location. Two datasets were used: Geolife which contains timestamp details with latitude and longitude, and Gowala which provides location details and corresponding timestamps. First dataset is collected from 182 persons and contains 18,670 records, while the second dataset contains 6,442,890 inputs. Precision, Recall and F1 score are used to evaluate the performance of the model. Conducted experiments showed that MAP outperforms RNN due to a combination of time and space data using attention techniques. Authors used an alignment function with MAP and achieved accuracy 73.8%.

Vasquez [5] analyzed Markov Decision Process Motion Prediction (MDPMP) method and found several weaknesses such as computational complexity, limited ability to make predictions for specific time and goal assumption which means that destination cannot be changed during movement. Author in this work proposed a method to overcome these limitations: computational complexity is decreased using the Fast Marching Method, velocity-dependent probabilistic motion model is used to make prediction for specific time and gradient-based approach is used for destination prediction. Subset of ground video surveillance dataset is used for this study. Results showed that the proposed method decreases computational complexity and increases accuracy of the prediction model.

Manh and Alaghband [6] developed a human movement prediction model that incorporates human movement trajectories and scene information. Two LSTMs networks (scene and trajectory networks) are used to train a model to predict movements. Scene features are extracted using convolutional neural networks. The proposed method scene has been divided into smaller grid cells which are trained together with pedestrian LSTMs to show importance of scene features in the movement prediction. Instead of using absolute location like it is used in previous researches, authors used location offset to define movement behavior. Model has been evaluated using two datasets: dataset provided by ETH Zurich and dataset provided by University of Cyprus. These datasets contain video sequences of a total 1536 pedestrians with different movement patterns. Video sequences contain 4 different scene backgrounds. Model is implemented using PyTorch deep learning framework and it is evaluated using average displacement distance, average non-linear displacement error and average final displacement error. Proposed method achieved better results than compared methods such as Social-LSTM and Attention-LSTM. Prediction error is decreased by 68% compared to Social-LSTM and 83% compared to Attention-LSTM.

Du et al. [7] present application of biomechanically recurrent neural networks (Bio-LSTM) to predict location and pose of pedestrians in 3D coordinate frames. Network takes estimated pose parameters from the past frames. Experiments are done using a PedX dataset which is collected in USA cities with high pedestrian traffic. Skinned Multi-Person Linear model is used to present 3D pose of pedestrians and LSTM network is used with two layers because it is noticed that root mean square error did not decrease after adding three or more layers. Implementation is done using Python and Keras framework. Results showed that method achieves around 85mm error in the outdoor intersection data. Also, prediction is done under different conditions such as cycling, walking, playing with something and the proposed method outperformed other compared methods in all cases except for cycling.

Suzuki [8] compares space syntax metrics and maximum entropy inverse reinforcement learning (MEIRL). This result shows that MEIRL predicts movement better than the space syntax matrix. Dataset contained virtually generated pedestrians and trajectories. API was created to generate shortest paths between random initial and goal points. Performance is measured using correlation and MEIRL achieved higher correlation 0.49 than space syntax matrix 0.45.

Muramatsu et al. [9] did a research to see if pedestrians are following similar trajectories and if two pedestrians follow the similar trajectories does the third pedestrian follow similar trajectories too. To observe trajectories, they used 2D and 3D laser scanners. The result showed that about 70% of pedestrians follow similar trajectories. That means that the trajectory of other pedestrians could be predicted using trajectories of other pedestrians. The second part of work was to see whether pedestrians of the same crowd moved to the similar destination. According to the results, around 84.5% of pedestrians get through a similar destination, which means that it is possible to predict movement direction by observing movement directions of previous pedestrians.

Latah [10] used 3D convolutional neural networks to extract temporal and spatial features from adjacent video frames. KTH dataset was used with a split 70% training and 30% test dataset. A support vector machine algorithm has been used for classification of instance actions based on extracted features. Experiments are implemented using Ubuntu OS and an OpenCV python library. Total 15 frames were extracted for each instance. Each frame was resized to the 80x60 resolution and L2 normalization is applied to extracted features. Performance was evaluated using accuracy which was equal to 90.34%.

Franch-Pardo et al. [11] collected 63 studies related to spatial analysis and GIS related to COVID-19. The study provides an overview of different spatial analysis to understand the geographical consequences and effectiveness of the containment of the disease. There are six factors that prevent establishment of basic hygienic and social distancing conditions: crowded living conditions, sharing of water, dependence on public health services, limited access to communication tools and dependence on public transport. Geo-environmental factors and their influence on the virus transmission are studied. Analysed factors are distance from the sea, latitude, population density, air pollution levels, average temperature, relative humidity, predominant wind speed, rainy and foggy days. Moreover, GIS played an important role to aggregate, visualize and track the data to predict transmission and risk zones.

Poiesi and Cavallaro [12] proposed a method for prediction of meeting areas using sparse motion information. Position, relative distances among groups, velocities and orientations could be used to detect interactions such as a merging, splitting and evacuation. Proposed method predicts movement direction by calculating prediction lines. Prediction lines are further used to accumulate intersection points which present meeting areas and are modeled using Gaussian Mixture Models. Experiments are performed using more than 8000 frames and the main constraint of the model is computational complexity of finding those areas. Study presents a list of different datasets which could be used for experiments such as Student003, Friends Meet and BIWI Walking Pedestrian for social interactions, PETS2009 to detect panic situations, UT interaction to detect interaction between two or four people.

Pant and Elmasri [13] presented a study which predicts user's future movements using Varied-K Means and Hidden Markov Model techniques. Future movements are predicted based on previous, and authors introduced day of the week and time interval in the prediction model. Dataset GeoLife which contains inputs from 178 users collected during four years has been used. The goal of the study is to find the locations in which users spend most of their time and to detect on which day and time. Firstly, they found locations where users are most likely to be on a specific day. In order to calculate this, a Bayes theorem was used. When a cluster with higher probability is found, authors run an experiment to find clusters for all weekdays separately and match clusters with actual map locations. Calculated cluster size was 0.2 miles. Furthermore, the Hidden Markov Model is used to find the most likely location for a specific time. Prediction model achieved average accuracy 22% for 150 users. Authors emphasized that this presents improvement around 70% compared to the similar studies. For the future work, authors are planning to introduce neural networks to improve prediction model accuracy.

Table 1 shows a summary of experiments mentioned above. It presents authors of studies, used methods and achieved results.

Table 1. Overview of works related to prediction of human movements in open space

#	Author	Methods	Results
1	A. Al-Molegi, M. Jabreel, and A. Martínez-Ballesté	Move, Attend and Predict (MAP), Recurrent neural networks (RNN)	MAP achieved accuracy 73.8%
2	D. Vasquez	Fast Marching Method, velocity-dependent probabilistic motion model, gradient-based approach	Decreased computational complexity, prediction for specific time
3	H. Manh and G. Alaghband	Scene LSTMs	prediction error is decreased by 68% compared to Social-LSTM and 83% compared to Attention-LSTM.
4	Xiaoxiao Du; Ram Vasudevan and Matthew Johnson-Roberson	Bio-LSTM, Skinned Multi-Person Linear model, LSTM	around 85mm error in the outdoor intersection data
5	S. Suzuki	MEIRL	correlation = 0.49
6	S. Muramatsu, H. Matsuda, S. Nakamoto, D. Chugo, T. Suehiro, and H. Hashimoto	2D and 3D laser scanners	about 70% of pedestrians follow similar trajectories, around 84.5% of pedestrians get through a similar destination
7	M. Latah	3D convolutional neural networks, Support vector machine	accuracy = 90.34%
8	I. Franch-Pardo, B. M. Napoletano, F. Rosete-Verges, and L. Billa	Review of spatial analysis and GIS in COVID-19 study	Geo-environmental factors
9	F. Poiesi and A. Cavallaro	Gaussian Mixture Models	
10	N. Pant and R. Elmasri	Varied-K Means and Hidden Markov Model	average accuracy 22%

Even though human movement prediction in open spaces was the topic in previous studies, where authors achieved good results in terms of prediction, none of them performed a study of human movement considering the measures taken for COVID-19 pandemic control. Therefore, this study aims at detecting a human movement pattern in open public spaces, such as parks and squares, to suggest the space adaptation, aligning the human needs for open space utilization and measures taken to control the pandemic (such as distancing).

3. METHODOLOGY

There are two main parts of the study which are object detection and object movement prediction. Presented Figure 1 describes steps performed in the phase of object detection, while Figure 2 describes the steps performed during object movement prediction. Object recognition phase includes video recording, object detection, object tracking and creation of movement routes. Object movement prediction phase starts with data collection followed by data preparation and results in object movement prediction. All included steps are explained in detail in the following subsections.

Figure 1. Object detection phase workflow

Figure 2. Object movement prediction workflow

3.1 Data collection

In the first phase of the project, video recordings of two types of locations, squares and parks, were recorded and analyzed. For this purpose, drone Mavic DJI Mini 2 was used. Recordings are created in two parks and two squares named:

Park Prijateljstva (Friendship Park) [14] and Park Svjetlosti (Park Light) [15], Teheranski Trg (Teheran Square) [16] and Trg Oslobođenja (Liberation Square) [17]. Recordings are performed during a weekday and weekend in three different time periods: in the morning (11:00-12:00), noon (15:00-16:00) and the afternoon (18:00-19:00). Duration of each video is 5 minutes long.

These video recordings are used in the further processing and analysis of human movement. Additionally, same video recordings are used to obtain datasets that are used for determining the density of the human movement and routes that are used frequently.

The second part of the dataset is obtained using the space syntax gate method. These datasets are gathered for the same locations and periods as in video recordings. Datasets contain gate number, time period and number of moving persons. Moreover, it is marked whether the person moving is men, women, or children. Below is an example of one table created for the weekend at Liberation Square. This Table 2 and tables created for other locations are used to create a dataset which is used to build a linear regression model. All other tables have the same format.

Table 2. Frequency of entrance into location collection with gate method

<table>
<tr><th>Location:
Date:</th><th colspan="4">TRG OSLOBODJENJA
07.06.2021</th></tr>
<tr><th>Gste no</th><th>Time</th><th>Moving Men</th><th>Moving Women</th><th>Moving Children</th></tr>
<tr><td></td><td>10:00</td><td></td><td></td><td></td></tr>
<tr><td>1</td><td>14:00</td><td>||||</td><td>||</td><td></td></tr>
<tr><td></td><td>18:00</td><td>|||</td><td></td><td></td></tr>
<tr><td></td><td>10:10</td><td>||||</td><td>|||</td><td></td></tr>
<tr><td>2</td><td>14:15</td><td>|||||</td><td>||||</td><td></td></tr>
<tr><td></td><td>18:10</td><td></td><td></td><td></td></tr>
<tr><td></td><td>10:16</td><td>|||</td><td>|</td><td></td></tr>
<tr><td>3</td><td>14:23</td><td>||</td><td>|</td><td></td></tr>
<tr><td></td><td>18:15</td><td></td><td></td><td></td></tr>
<tr><td></td><td>10:22</td><td>|</td><td></td><td></td></tr>
<tr><td>4</td><td>14:30</td><td>|||</td><td></td><td></td></tr>
<tr><td></td><td>18:25</td><td></td><td></td><td></td></tr>
<tr><td></td><td>10:30</td><td>||</td><td>||</td><td></td></tr>
<tr><td>5</td><td>14:35</td><td>|||</td><td>||||</td><td></td></tr>
<tr><td></td><td>18:30</td><td>||</td><td></td><td></td></tr>
</table>

3.2 Video analysis and object detection

Analyzing the recordings, different activities of the humans such as walking through locations, standing, playing with the ball, etc., were noticed. Moreover, there are people who are moving forward-backward in the place. Beside humans, there are other objects such as cars and birds.

The analysis of video recordings and extraction of useful information from them was done with OpenCV [18] python library. Firstly, video recordings are transferred to the images. There were 9003 frames obtained from the video of Teheran Square. Obtained images are used to detect changes in frames, which signifies that movement is happening in space.

Figures 3, 4 and 5 present examples of human movement in space, more precisely, it could be noticed that a person has a different position in each of the figures (frames).

Secondly, background subtraction from the recordings was applied [19] by creating the binary image which contains pixels of the objects which are moving. The challenge presented with this method are the shadows, as the shadows of moving objects need to be detected and removed. Next, focus was on the detection of the moving objects in the recordings. Authors started using the Image Gradients method [20] with which various functions were applied such as: cv2.Sobel(), cv2.Scharr(), cv2.Laplacian() to separate objects from the background. Moreover, Morphological Transformations (methods of morphological transformation) [21] such as mask, dilation, erosion, opening, closing were used. These methods are applied to images with the aim of sharpening and emphasizing the shapes found on them. The main methods are erosion and spreading methods. However, these methods did not give the desired results, i.e., movement detection could not be performed as expected, so methods of frame differentiation and contour-based shape differentiation were applied to detect the human movement, as the most effective method. This method is also most often used in the literature for the purpose of motion detection and distinguishing elements in video recordings.

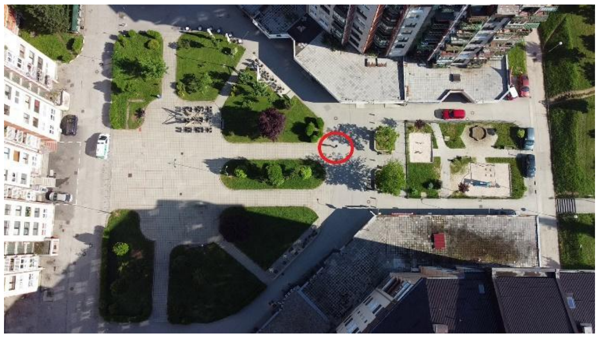

Figure 3. Object movement detection (1)

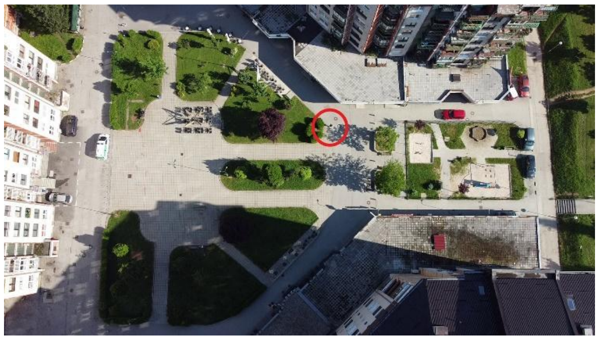

Figure 4. Object movement detection (2)

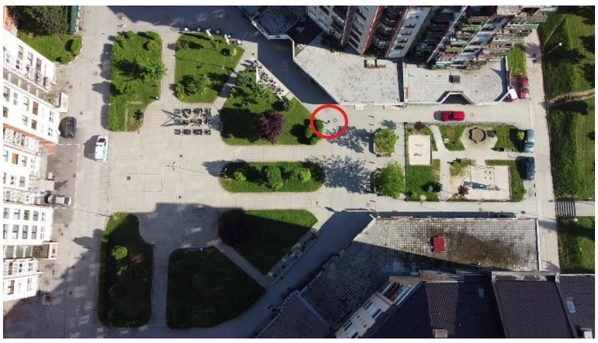

Figure 5. Object movement detection (3)

Frame differencing [22] works by finding an object in motion, by analyzing and comparing the difference in pixels for adjacent frames. If there is a difference in pixels that is less than a given value (threshold) then it is considered a change of background, and in the case when the difference is greater than the set thresholds then it is the movement of the object. Using a frame differencing method, it was possible to recognize the movement of people and cars, and to distinguish them based on the size of the observed object. Examples of observed objects are shown in the Figures 6, 7 and 8 (it successfully recognized a car and a human in motion).

In addition to object detection, it was possible to detect the size and position of objects. Size can be used to distinguish object types, while position can be used to track an object and create a movement route. The position of detected objects is shown in Figure 9 and Figure 10.

Figure 6. Car movement detection (1)

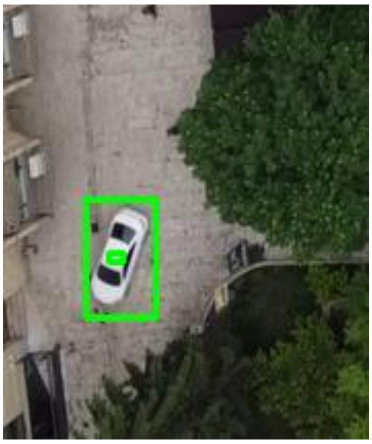

Figure 7. Car movement detection (2)

Figure 8. Human movement detection

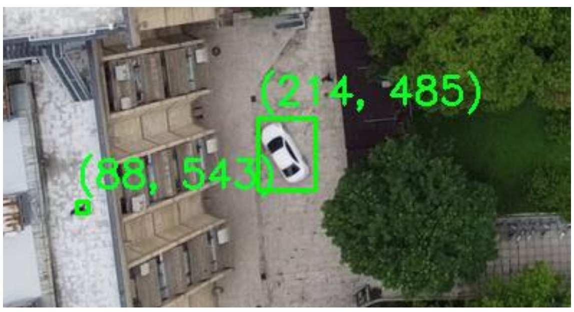

Figure 9. Object position detection (1)

Figure 10. Object position detection (2)

3.3 Object tracking

In order to detect the movement pattern, the tracker was engaged. For this purpose, authors applied an openCV tracker algorithm called Boosting [23]. Boosting tracker is one of the eight trackers available within OpenCV library. It is based on AdaBoost algorithm. It is one of the oldest trackers, a little bit slower and it is good for comparison of other algorithms. An experimental data set which is obtained by tracking objects marked at the beginning of the video was used. Content of the box created around the object is taken as a moving object and everything outside it is considered as a background. Algorithm compares the pixel values of the background in each frame and determines the new location. During data capturing, every 30th frame is taken since there are more than 9000 frames per video and most successive frames do not provide a huge difference. Obtained data set is used to perform different analysis such as to find average location per each captured frame and to draw polygons and lines that present object movements.

3.4 Object movement prediction

Next, the prediction model which aims at predicting the number of people in a specific location is built. Tabular dataset obtained using the Gate method [24] is used for the prediction of the number of people in the location. Prediction model was built using Linear Regression. Linear regression [25] is a supervised machine learning algorithm used to predict the continuous values. Linear regression takes independent variables and predicts dependent variables. The algorithm can work with single or multiple independent variables (depending on what problem is solved). The goal is to find the line that fits as many data points as possible from the dataset.

In this part, two tables (Tables 3 and 4) that present data of the total number of people detected within observed locations (parks and squares) and periods (morning, afternoon, evening) during weekdays and weekends were created. These numbers were used as an input to the linear regression.

Table 3. Number of people detected in parks

time	# of people weekday	# of people weekend
1	26	18
2	55	28
3	70	12

Table 4. Number of people detected in squares

time	# of people weekday	# of people weekend
1	47	39
2	**55**	**68**
3	5	56

Dataset collected using the space syntax method is used to predict the number of people for specific location and time of the day. Authors used a smaller set of features to perform analysis and build a model. This set of features could be expanded for the purposes of future project development.

4. RESULTS

The results of the study will be presented in two segments: a) object tracking results and b) object movement prediction.

4.1 Object tracking

This section presents results obtained from the object tracker explained in the previous section. Figure 11 shows a polygon obtained by taking the average point for each calculated frame and could be used to find the most crowded area in this square.

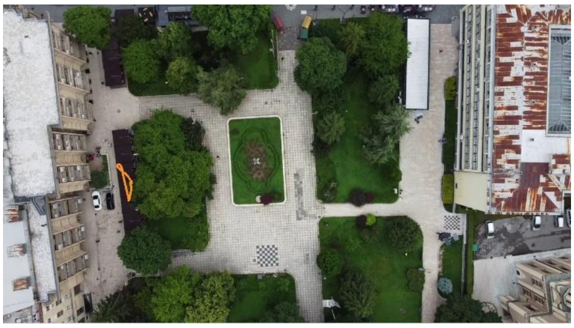

Figure 11. Most crowded area in the square

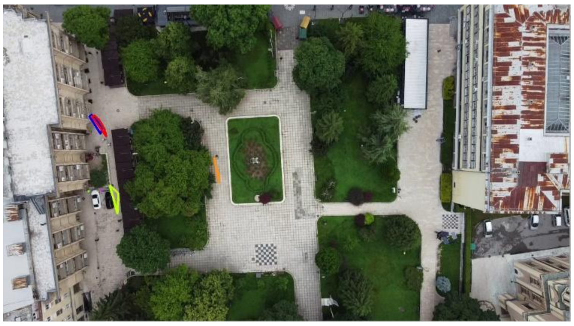

Figure 12. Visited locations for each object

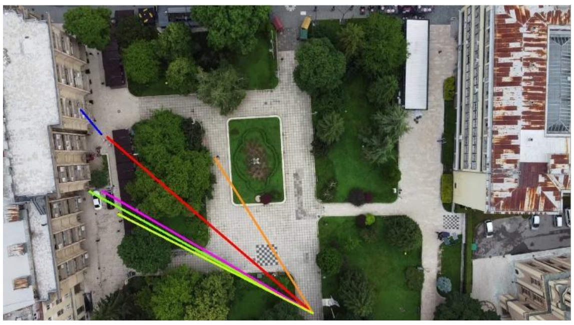

Figure 13. Line between start and end point of each object

Figure 12 shows the polygons of visited locations for each object being tracked, while Figure 13 shows the line that connects start and end point for each of those objects.

Object tracking analysis, from the perspective of spatial planning, demonstrates that no significant points of occupancy pressure have been identified in this location. This is indicative of the type of activities that occur on site, which in this case are activities that are compulsory (circulation, waiting for a bus or a person, etc.) and are defined as necessary type activities. To improve the quality of outdoor areas, possibilities for optional and social activity types must be created, by redesigning public space primarily through circulation patterns and activity content.

4.2 Object movement prediction

Here, results obtained for object movement prediction using space syntax observation technique Gate method are presented. Tables 3 and 4 show the frequency of entrance into selected locations, or the number of people entering parks and squares at the given time and day.

The study indicates that parks are used more frequently during weekdays than during weekends, and that dynamics of use are different - greater occupancy is during evening hours during the week, while weekend is more occupied during afternoon. Opposite to that, squares are used more frequently on weekends than weekdays, with the peak of the occupancy coinciding with the afternoon rush-hour.

Frequency of people entering and staying at location were input to linear regression, to obtain the prediction of human movement in parks and squares. To evaluate the results, the R^2 value [26] was calculated. This value denotes the level of how well data is fitted to the regression line. Value can be between 0 and 1. Higher values indicate the better fit. Table 5 below summarizes the results of R^2 for different tests. Better results are obtained for weekdays, for both parks and squares.

Table 5. Number of people detected in parks

	Park		Square	
	weekday	weekend	weekday	weekend
R^2	0.97	0.13	0.61	0.34

The reason could potentially be associated with the dynamics of space use and frequency of space occupancy, which can be related to physical conditions and activity content of selected locations, but it can also be an indicator of the local social habits and usage patterns of open public spaces. Identified consistency in the number of people entering public spaces during weekends, insinuates that the type of the activities that occur are necessary activity type, as social patterns suggest that Sarajevans look for alternatives to urban public spaces during weekdays for social and optional activities, that are outside of the city.

5. DISCUSSION AND CONCLUSION

In this work, authors performed human movement analysis and prediction using data analysis tools and linear regression method. Initial dataset is obtained in the form of video recordings using a drone. Different location types such as parks and squares are recorded. Moreover, recordings are taken during weekdays and weekends in different periods. Later, data is processed using the openCV library which provides a wide range of the methods and algorithms suitable for the purpose of processing and analysis of movement data. Authors presented different methods and approaches for object detection and recognition.

Firstly, background subtraction, image gradients and morphological transformation methods are used to detect objects. But these methods did not result as expected for the human movement detection, and frame differentiation method was applied. There were problems detecting persons at the beginning of the frame differencing. The written algorithm in some situations noticed the background as a moving object. This could have been caused by inappropriate threshold values, light changes, and smaller objects that were observed.

Another challenge was the size at which the person is shown in the video. To solve this problem, video recordings are zoomed, so a video that makes it easier to spot people's movements is obtained. At the end, moving objects were detected and beside detection it was possible to differentiate between cars and people based on their sizes.

Later, object tracking using a Boosting algorithm was performed. This algorithm allows us to gather the location of each object in a particular frame and to find their routes, which later allows us to find mostly used areas within the analyzed locations.

Finally, machine learning algorithm linear regression was used to perform human movement prediction within public spaces. This algorithm predicts the number of people visiting the particular location on weekdays and weekends. The results show that the built model works better with workday data.

The pandemic of the virus COVID-19 calls for reexamination of the links between urban planning, public space, and public health. In this context presented study explores syntactic properties of urban areas, aiming to interpret and predict direction and density of pedestrian movement. It has the potential to be used as a tool in establishing methodological framework for decision making directed towards more efficient urban planning, particularly significant for the time of pandemic. Same methodology could be used in future analysis on distribution, availability, and function of the existing open public space inventory. From the aspect of urban planning, it could influence the initiation of the necessary change in the culture of living through spatial and functional changes in open public spaces in the city of Sarajevo.

The limitation of the study is the limited number of the data used for the movement prediction. Future work will be extended by adding more features for the movement prediction such as: exterior factors, timeframe of observations, which lead to greater number of input data, entrance and exit gates and other spatial factors. Additionally, future work will associate detection and tracking algorithms and create one approach in data collection, analysis, and model building process.

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