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An Improved Scalable Approach to Detect Black Spots on Roads using DBSCAN Algorithm

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Key words: GPS, DBSCAN, FHC, FJP, FCM, SLINK, CLINK

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Abstract: Localization of road accident hotspots where the number of accidents is above expected supported the quality values. The user will receive a notification while it localizes a disease within the encircling with the assistance of worldwide Positioning System (GPS). We use DBSCAN method which may be a two-dimensional coordinate which helps to record the accident location (Black Spots). On an average, nearly 2,48,000 road accidents were reported between January and June each year between 2014 and 2019. Around 53 crashes and loss of 17 lives are occurring in India every hour. However, though you're careful on the roads does not imply that the opposite drivers also will do an equivalent. There are several incidences when the drivers aren't wrong while driving. There are various methods like strict rules, heavy fines, use of speed detection devices, etc., are taken for reducing accidents but still accidents are happening. Folks that are driving aren't conscious of spots where an accident usually happens. Though there are accident zone signs people while driving with maps won't see those signs. To scale back these numbers of accidents, we proposed a idea of detecting the black spots, especially surrounding path we travel. However, this idea proposed for identification of the black spots requires accident data during an outsized note and since, the knowledge is time-consuming and casualty-intensive to accumulate. It are often very beneficial to present this method which may identify the black spots within a fast time, so on reduce the fatalities and achieve safe roads for travelling.

INTRODUCTION

Nowadays, road safety has become a heavy concern throughout the Earth. Road accidents could also be a pressing drawback leading to live loss, property loss and severely impacting the society. Supporting the recent statistics, quite a million individuals died because of road accidents and just about twenty to 50 million individuals were physically disabled as a result of road accidents for the past few years. As transportation will increase, on the alternative hand accident rate additionally rises steady. The main cause of road accidents deals with numerous parameters like road sort, vehicle fault, intoxicated drive, etc. Beside of those reasons the shortage of correct road aspect sign boards plays a vital role in accident count. The road aspect sign boards indicating the accident spots were placed solely at the precise spot, so, the drivers weren't responsive to the disease areas in their manner. Road accidents cannot be completely avoided however by exploitation appropriate traffic engineering safety set up and management measures, the accident rate square measure typically reduced.

LITERATURE SURVEY

Analysis of road accident locations using DBSCAN algorithm: Li *et al*.[1] applied statistics analysis and data processing algorithms on the fatal accident dataset. It's an effort to offer road safety suggestions. They found Association rules by Apriori algorithm, classification model was built by Naive Bayes classifier and clusters were formed by k-means clustering algorithm. The connection between fatal rate and other attributes including light condition, collision manner, surface condition, weather and drunk driver were investigated. They used the Fatal Accidents Dataset that contains all fatal accidents on public roads in 2007.

Data mining approach to characterize road accident locations: Sachin Kumar and Durga Toshniwal used data mining techniques to identify high-frequency accident locations and analyze them to spot various factors that affect road accidents at those locations. They first split the accident places into k groups supporting the accident frequency counts using k-means clustering algorithm. The association rule mining algorithm is applied on these to reveal the correlation between different attributes within the accident data and understand the characteristics of those locations.

Association rules mining algorithms for traffic accidents: El Tayeb *et al*.[2] used association rule mining algorithms to deliver rules from larger dataset. First data preprocessing is applied on collected records. They collected 1887 traffic records from Dubai police authority then they applied association rules to seek out frequent pattern sets. They used data processing software, Weka tools to urge these association rules.

Borah and Bhattacharyya[3] used an improved sampling-based DBSCAN which can cluster large-scale spatial databases effectively. DBSCAN can be found to be expensive as it requires large volume of memory support due to its operations over the entire database. Experimental results included to establish that the proposed sampling-based DBSCAN outperforms DBSCAN as well as its other counterparts, in terms of execution time, without losing the quality of clustering.

EXISTING SYSTEM

There are several methods to find accident black spots. At present methods, we typically[4] use a one-dimensional model (Sliding Window Method) which examines only one road at a time and uses milestone location identification system. This existing system does not use Global Positioning System (GPS) for identification.

Types of methods:

- Peak searching method
- Window sliding method
- Planar sliding method

Peak searching method: Peak searching method is one of the easier techniques for identifying the black spot. It divides the road into equal length intervals (the first parameter of the tactic is that the length of this interval) with none[5] overlap and calculates the amount of accidents within these intervals. If the amount of accidents is above a given threshold (it is that the second parameter of the algorithm), we consider it as a possible plant disease. These need some further (usually manual) investigation to make a decision on any longer actions.

Window sliding method: The window technique basically executes a one-dimensional search. The main input of the algorithm is that the accidents of a given road, where the road number is usually the same and only the road sections (kilometre section of the accident) identify the precise positions of the accidents. This approach[6] was satisfactory for several years but within the last decade, there are several additional location identification methods. The spreading of GPS (Global Positioning System) technology[7] has led to the extensive use of planar coordinates. For instance, within the case of road accidents, the scene investigators use GPS coordinates to record the precise location of the accident.

Planar-sliding window method: This is a two-dimensional search, therefore, the accidents are identified by GPS coordinates and not by road name+ milestone[8] pairs. the essential idea is analogous but during this case, not enough to define a window length, we must define the window size by two parameters: the width and therefore the height.

The appropriate values support the goal of the search. The definition of the minimal density is additionally different. In contrast[9] to the previous method (where the dimension of the accident density was accident/metre), this algorithm uses the world[10] of the planar window because the divisor; therefore, the dimension of the minimal density is accident/metre2.

The steps of the tactic are similar; consisting of two main parts. First, it collects the windows during which the accident density is larger than the given limit. For this, it's necessary to slide the window in both horizontal and vertical directions. If the amount of accidents within the window is above the given limit, it's considered as a plant disease candidate. It is worth noting that these windows aren't mutually exclusive.

As an extra step, it's necessary to get rid of all previously selected plant disease candidates where there's another window with a bigger density containing a minimum of one among equivalent accidents.

Limitations of existing work:

- There are several methods to find accident black spots
- At present methods, we typically use a one-dimensional model (Sliding Window Method) which examines only[11] one road at a time and a uses milestone location identification system
- This existing system does not use Global Positioning System (GPS) for identification
- But GPS technology which makes it possible for accident scene investigators to use two-dimensional coordinates to record the accident location

PROPOSED WORK

There are two steps in the proposed system. They are the registration phase and detection phase. In registration, we have the following steps (Fig. 1 and 2). The following is advantages of proposed system:

- The most significant advantage of the DBSCAN algorithm over the other method is the ability to work with irregular shapes
- This is a very resource-intensive algorithm but a GPU-based implementation can eliminate this disadvantage

MODULES DESCRIPTION

Peak searching method: Peak searching algorithms perform a peak search within the time or frequency domain to detect either one or multiple peaks during a magnitude or power spectrum with a specified magnitude threshold and set range to fine tune the peak search[12]. We usually detect the peaks during a loud signal and mark them with cursors. A "peak" is defined as a neighborhood maximum within the magnitude and thus the sole practical constraints to be made within the peak search is to possess a variety and a magnitude threshold.

Peak search methods vary by algorithm implementation like correlation, filtering, demodulation, sliding average, etc techniques. Correlation correlates the two signals by generating reference far-end and normalised near end signal and performs peak search to

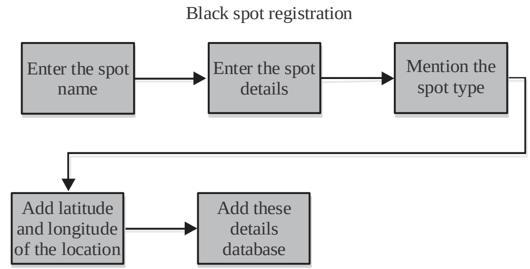

Fig. 1: Architecture diagram-registration process

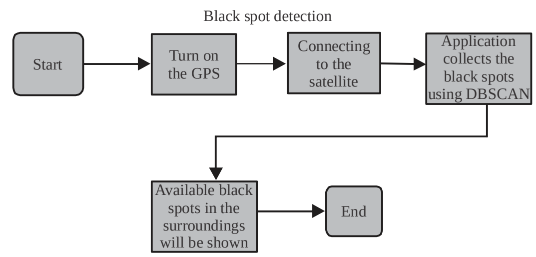

Fig. 2: Architecture diagram-black spot detection

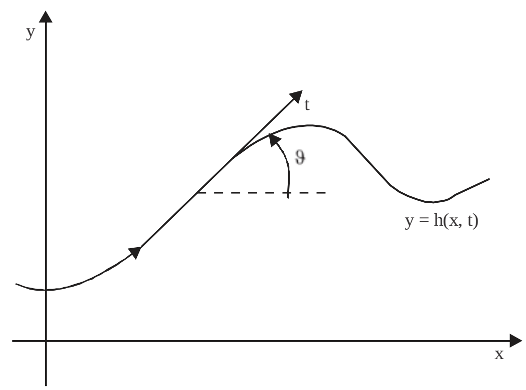

Fig. 3: Peak searching algorithm

hunt out peaks within the echo tail but we should check for unusual behaviour of the cross-correlated signal[13]. Peak formation is an integral process while peak searching could also be a differential one while display could also be a proportional process (Fig. 3). The peak search methods:

- Estimate peak location accurately
- With faster performance
- With integration time deciding algorithm
- Reduce processor loading
- Find indices of local extrema (minina, maxima) and zero-crossings
- Reduce the susceptibility of a peak search to signal noise
- Correct the baseline of sample values

1D sliding window method: Object detection employing a window has existed before the recent rise of machine learning in computer vision. While interacting[14] with non-technical client's data science consultants at Datalya often do get asked what window algorithm is. During this study, we'll attempt to explain the window algorithm for everybody.

Like any machine learning algorithm, the primary requirement of a window[15] algorithm is to organize[16] a labeled training set. Imagine we would like to create a car detection algorithm employing a window. Our training images (X) are going to be images[17] with and without a car object. We'll closely crop cars out of car images and label cropped images with y = 1. In our training set, we also need negative examples where a picture doesn't have any car but background. For negative examples, we'll set y = 0.

Now, we will feed labeled training examples to the convolutional network (convnet) in order that it can find out how to detect a car in a picture. Once we've trained on closely cropped training images, the subsequent question would be, how can we set about detecting vehicles in test images as test images wouldn't be closely cropped. This is often where window algorithms involve rescue.

To detect a car during a test input image, we start by picking a window of size (x) then feeding the input region (x) to trained convnet by window over every part of the input image. For every[3] input region, convnet outputs whether it's a car or not. We run a window multiple times over the image with[18] different window sizes, from smaller to larger, hoping a window size would fit the car and permit convnet to detect it.

Computational cost may be a considerable disadvantage of the window algorithm. We've to crop numerous regions and run convnet for each of them individually. Increasing window and stride size makes it faster but at the value of decreased accuracy.

Until the recent rise of Duan *et al*.[6] machine learning, object detection using windows has been working fine for linear and easy classifiers, typically supported hand-engineered features. Classifiers with traditional settings usually don't require substantial computational resources. However, modern convnets are computationally very demanding which makes the window algorithm very slow. Additionally, the window doesn't localize objects accurately unless the window and strides are tiny[4].

DB SCAN method: Cluster analysis plays a crucial role in application areas like data processing, pattern recognition, geographic information systems, etc. The most objective of clustering is to facilitate the analysis process by constructing similar objects during a cluster. Clustering methods are often divided into two groups like hierarchical and prototype based[14]. In hierarchical clustering, the remoteness of elements is the cornerstone. First of all, closer elements are put into an equivalent cluster and within the next step, elements a[19] touch bit distant from the previous ones are put in the cluster, etc. In prototype based methods, however, prototypes which have common features of some certain classes are formed then the elements are taken into these classes with reference to the proximity degrees to the prototypes. Namely, in such a situation, not the remoteness of above-mentioned elements from each other but their remoteness from the prototypes is taken into account[20]. Some samples of these methods are k-means, k-medoids and Fuzzy c-Means (FCM). Besides, single-linkage (SLINK), complete linkage (CLINK), DBSCAN (Density Based Spatial Clustering of Applications with Noises), Ordering Points to Identify Clustering Structure (OPTICS), Fuzzy Graph Connectedness (FHC), Fuzzy Joint Points (FJP) and Noise Resistant Fuzzy Joint Points (NRFJP) are some samples of hierarchical methods. In methods like DBSCAN, so as to work out the core points of clusters or noise points, classical neighborhood density[21] analysis is employed. Thus, some extent is conceived as a core point if the amount of points during a certain radius is larger than a specified threshold. However, FJP-based methods use fuzzy neighbor-hood cardinality, so as to work out core points[3, 22]. Papers[17, 23] are samples of studies in density based methods containing fuzzy objects and relations. In study[24], distances between[25] fuzzy objects are defined and a F DBSCAN algorithm integrated onto the clustering algorithm is proposed. It's also shown that the computing speed of this algorithm is more advantageous than those of EXP DBSCAN, UNION, INTERSECTION[15]. By Kumar *et al*.[23], fuzzy neighborhood[26] relation supported the intersection of the properties is proposed.

This relation employs some classification algorithms like NN (Nearest Neighbor), KNN (k-Nearest Neighbor), Fuzzy[22] kNN and a few agglomerative hierarchical clustering algorithms. In study, Dong *et al*.[11], the dataset is partitioned into sub-clusters and a fuzzy graph connectedness measure is used among them. Then, hierarchical clustering is applied[7] to support the extent sets of the graph. FCM-based clustering algorithms are successful in specifying datasets with spherical or ellipsoidal shape and number of clusters and[27] initial cluster centers must be pre-determined. Unless these information are true, clustering results might be far away from perfect. On the other hand, in DBSCAN-based algorithms, it's not necessary to specify either number of clusters or initial cluster centers. These sorts of algorithms are[28] ready to detect clusters in any shape. However, in such algorithms, adjusting the parameters that specify neighborhood radius and neighborhood density consistent[23] with the density of clusters causes some problems. In datasets with various dense clusters, if the parameters are found out for low dense clusters, high dense[29] clusters could be merged. Conversely, if the parameters are found out for high dense clusters, then the low-dense clusters might be perceived as noise. During this sense, algorithms which are ready to run correctly in a wide selection of change intervals are often more advantageous. Thus, algorithm's robustness through parameters provides the datasets[30] with different densities to be classified accurately. Local density based DBSCAN algorithm is proposed to handle this problem[6]. Another approach is FJP-based NRFJP algorithm[19]. This algorithm is strong through parameters since it uses fuzzy relations in neighborhood analysis. Also it's easier to fine tune on the parameters. However, DBSCAN algorithm's computation speed is quicker than that of NRFJP algorithm. In this study, a new Fuzzy Neighborhood DBSCAN (FN-DBSCAN) algorithm that mixes DBSCAN[26, 31] algorithm's speed and NRP algorithm's robustness is proposed. It's proved by experiments that the FN-DBSCAN algorithm gives more ro-bust results than the DBSCAN algorithm for various shaped and dense datasets.

Why db scan method: The reasons for using DBSCAN is given below:

- Here, we use the DBSCAN method because it gives high accuracy in normal conditions since we use GPS systems
- Existing 1D method do not include some large cities, it is common to use only street[30] names and house numbers for positioning in inhabited areas
- These differ in their geometric characteristics and traffic technological design too

Our DBSCAN method:

- DBSCAN (Density-Based Clustering of Application with Noise) is a very promising density-based data-mining algorithm
- It aims to find clusters of any shape in the search space and as it is visible from its name, it is extremely[21] useful in noisy environments

The input parameters of the method are:

- A radius-type value
- Min Pts.: a lower limit for accident numbers. Min Density: a lower limit for accident density (Fig. 4)
- The simplest method is to use the Euclidean distance between the two elements (accidents) identified by the two dimensional coordinates[1] (GPS latitude and GPS longitude)
- The DBSCAN algorithm calculates the "transitive closed domain" of directly dense[2] accessibilities (the maximum domain of densely accessible elements from a starting point) (Fig. 5)

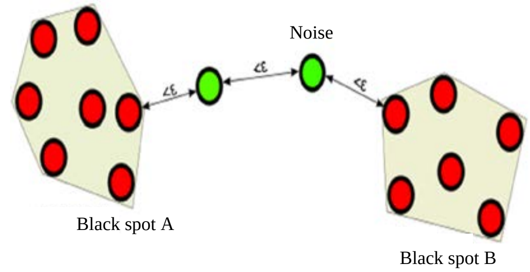

Fig. 4: Density-based data-mining algorithm

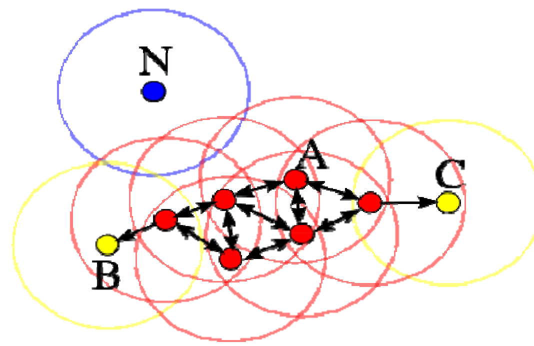

Fig. 5: Transitive closed domain

DBSCAN algorithm:

1. Initialize the setting
2. Add a new attribute Cluster ID for storing the clustering result in the original database D
3. Form a new data set D1
4. TempList = distance between two points is less than the radius
5. Set the parameters Minpts and EPS
6. Traverse the set D1
7. i = 1, j = 1 and Cluster = 1
    1. If ClusterID = 0, search for its EPS neighborhood
    2. if Neps(pi)≥Minpts, then point pi is the core point
    3. Let it's ClusterID = Cluster and it's EPS neighborhood
8. Traverse the TempList and examine each point as a seed point

DBSCAN advantages:

- The most significant advantage of the DBSCAN algorithm over the other method is the ability to work with irregular shapes
- It makes it possible to use the accurate GPS positions directly
- DBSCAN[32] method is clearer in the case of junctions
- Inside inter-urban areas, these are the only effectively suitable methods
- This is a very resource-intensive algorithm but a GPU-based implementation

IMPLEMENTATION

Our proposed system has the following steps in the detection phase.

Fig. 6: Login page

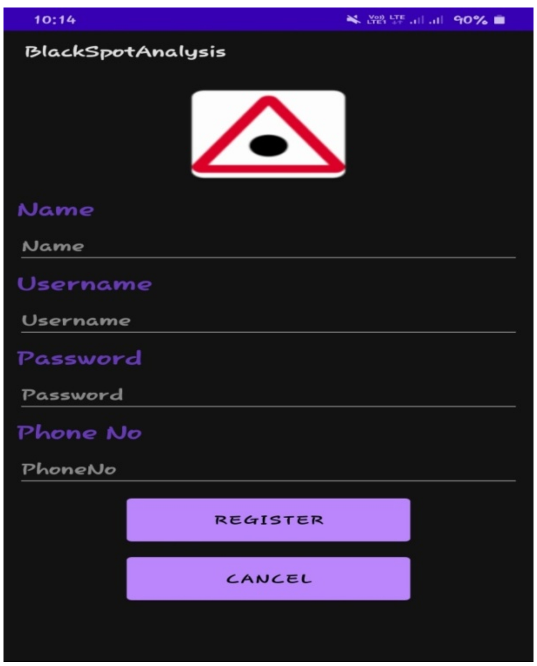

Fig. 7: New register

Step 1: Open the application with enabling the internet.

Step 2: Enable the Global Positioning System (GPS).

Step 3: Application will detect the précised location

Step 4: Black Spots core points around the location will be detected.

Step 5: The black spot points will be notified as a danger zones to the user who drive (Fig. 6 and 7).

After enabling the GPS the administrator need to enter the spot details like name, spot type. The Location can be automatically detected based on latitude and longitude (Fig. 8).

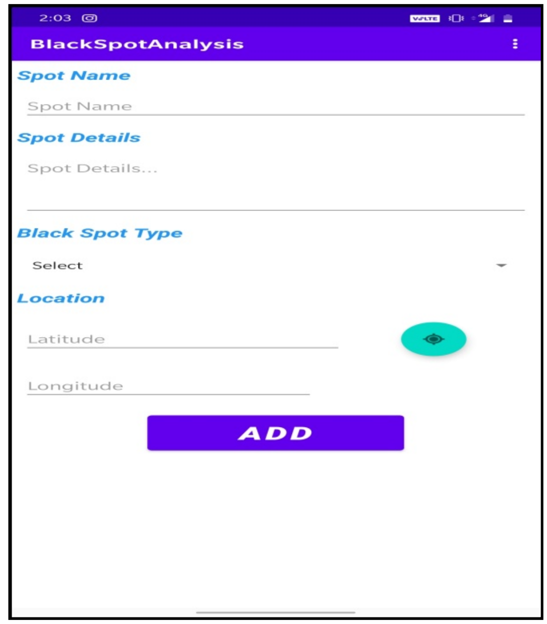

Fig. 8: Black spot details entry

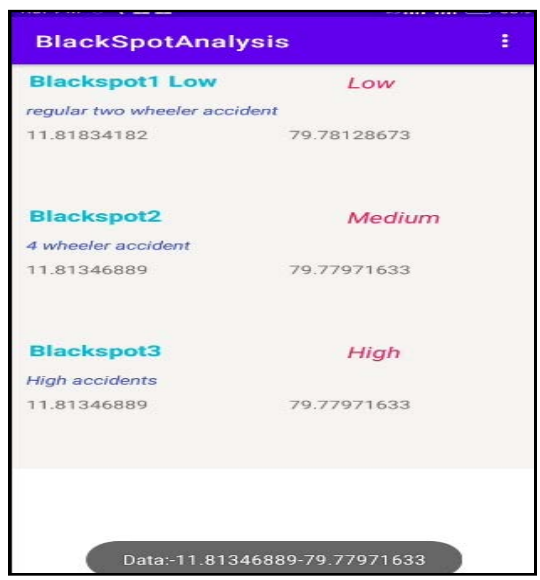

Fig. 9: Identifying black spot severity

Based upon the past data our application will categorize the black spot severity as low, medium, high (Fig. 9). The black spot points will be notified as a danger zones to the user who drive as shown in Fig. 10[10].

Various processing techniques like clustering, association rule mining are widely[33] utilized within the system to identify reasons that affect the severity of road accidents. Association rule mining could also be a really fashionable technique which can be used to identify the connection among different sets of attributes that often

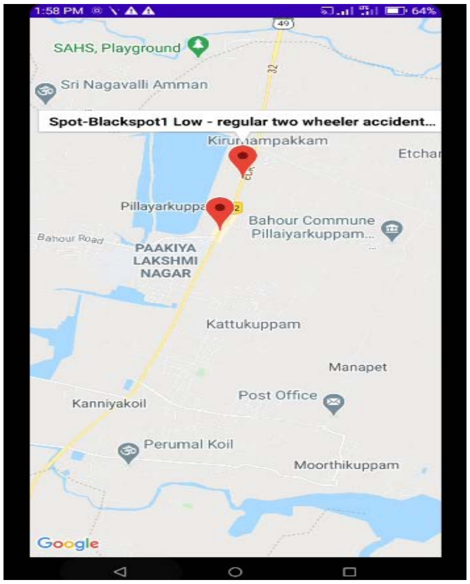

Fig. 10: Black spot alert notification to users

occur together when an accident takes place. In our system, we applied[34, 24] association rule mining algorithms on different groups of accident locations. The rules generated for every group exposed the numerous factors associated with road accidents in these locations. The results[35] obtained from DBSCAN clustering gives the cluster of accident areas. When he\she enters to the accident area there will be the accident decreased .Where this project is used to reduce less number of accidents in the environment .We hope that our idea will reduce the accident and save number of lives.

CONCLUSION

Various processing technique like clustering, association rule mining are widely utilized within the system identify the reasons that affect the severity of the road accident. Association rule mining could also be the really fashionable technique which can be used to identify the connection among different set of attributes that often occurs together when an accident take place. DBSCAN is very useful for the user. Where this project is used to reduce less number of accidents in the environment .We hope that our idea will reduce the accident and save number of lives.

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