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Application of Spatiotemporal Fuzzy C-Means Clustering for Crime Spot Detection

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ABSTRACT

The various sources generate large volume of spatiotemporal data of different types including crime events. In order to detect crime spot and predict future events, their analysis is important. Crime events are spatiotemporal in nature; therefore a distance function is defined for spatiotemporal events and is used in Fuzzy C-Means algorithm for crime analysis. This distance function takes care of both spatial and temporal components of spatiotemporal data. We adopt sum of squared error (SSE) approach and Dunn index to measure the quality of clusters. We also perform the experimentation on real world crime data to identify spatiotemporal crime clusters.

Keywords: Fuzzy clustering; Spatiotemporal data; Crime data

1. INTRODUCTION

In the current era, huge amount of spatiotemporal data are available pertaining to various domains such as Oceanography, Seismology, Criminology, and Epidemiology etc. To extract useful knowledge, their analysis is important. Spatiotemporal data incorporates spatial, temporal and attribute information. Spatial information denotes location, temporal comprises timestamp associated with data and attribute specifies non-spatial features of the data[1] The spatiotemporal data are of various types. Kisilevich[2], *et al*. talks about spatiotemporal data and further classified it into five types that includes events, geo-referenced variables, geo-referenced time series, moving objects and trajectories. A set of events occurred at a spatial location with a timestamp forms spatiotemporal events data[3]. The example of spatiotemporal event includes crimes which occurred at a point of time[4], seismic activities and geo-referenced records of epidemic[2]. Spatiotemporal event object is a triplet <*longitude, latitude, timestamp*>.

To know the natural structure of spatiotemporal data, clustering techniques are most appropriate. In clustering, the data with similar properties are grouped in a cluster, while dissimilar data kept in different clusters[1]. Fuzzy clustering permits an object to belong to two or more clusters, where degree of membership varies between zero and one[5]. Hard clustering is a mathematical problem of set partitioning, where in, we try to partition a crisp set into K number of partitions or non-overlapping clusters. In hard clustering a point belongs to one cluster only and thus hard clusters provide crisp interpretations. Sometimes, we don't have enough information to create hard clusters in those situations soft clustering techniques like Fuzzy C-Means algorithm (FCM)[6] can be used effectively. FCM is a soft clustering algorithm which creates fuzzy (overlapping) clusters; thus a point belongs to multiple clusters at the same time. These overlapping clusters are used to capture one aspect of uncertainty which is known as 'vagueness'[7-9]. The advantage of using soft clustering is that we can create fuzzy clusters with insufficient information but these can be defuzzified eventually to hard clusters with the availability of sufficient information in future.

The clustering technique is helpful to investigate the criminal events that are related with the common offenders and also aids to discover unknown serial offenders[10]. To cluster individual crime events generally K-Means algorithm is used, which is effective in marking area of higher or lower criminal activities. The result of this hard clustering is used for the hot-spot crime analysis. The ambiguous data demand a more comprehensive approach of crime analysis. One of the approaches is fuzzy clustering. Grubesic[11] employs Fuzzy C-Means algorithm for hot-spot detection. The author also analysed the result of FCM, K-Mediods and K-Means algorithms. The outcome indicates that FCM is more capable in handling intermediate cases and outliers. To deal with large number of point events Fuzzy clustering are more adequate[12].

Various researchers have modified the objective functions of the FCM algorithm to address the problem. Wu[5], *et al*. define a generalised distance function that preserves the simplicity of FCM by using centroids of arithmetic means. They showed that we can derive any distance measure from a differentiable convex function to use in FCM. Cao[13], *et al.* developed Fuzzy C-Means algorithm by reformulating FCM objective function by using gain field. The authors applied the proposed algorithm to the segmentation and classification of M-FISH images to

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detect chromosomal abnormalities for cancer and genetic disease diagnosis. Mei[14], *et al*. proposed a fuzzy clustering approach for multi-type relational data to cluster different types of objects by reformulating objective function. The objective function of the proposed approach is optimised by updating membership matrix and ranking matrix. The membership matrix denotes membership degree of objects to clusters, whereas ranking matrix contains ranking of an objects with respect to other objects in different clusters. Izakian[3], *et al*. provided the algorithmic framework of fuzzy clustering for spatiotemporal data by revisiting and augmenting the distance function. The authors demonstrated that the different nature of spatial and temporal components of geo-referenced time series, different treatment are realised through augmented distance function.

To the best of our knowledge, literature do not contain any instance of reformulation of distance function for spatiotemporal events, therefore to handle spatiotemporal events, which is a kind of spatiotemporal data, we define a distance function to take care of both spatial and temporal components of data. We adopted sum of squared error (SSE) approach and Dunn index to measure the quality of clusters. We also perform the experimentation on real world crime data to identify spatiotemporal crime clusters.

2. RELATED WORK

Kisilevich[2], *et al.* talks about spatiotemporal data and further classified it into five types that includes events, geo-referenced variables, geo-referenced time series, moving objects and trajectories. Spatiotemporal events data[3] is a set of events occurred at a spatial location with a timestamp. Clustering of spatiotemporal events intends to find set of events that are similar with respect to both space and time. Kulldorff[15] employs scan statistics to cluster spatiotemporal events. They propose a disease surveillance system to detect spatiotemporal clusters of disease. Martino[12], *et al.* have used extended Fuzzy C-Means algorithm to find circular clusters of fire point events in spatiotemporal geographical information system. The authors also studied spatiotemporal evolution of fire hotspots by comparing fire point events for each pair of consecutive years. Malleson[16], *et al.* analysed the hotspots of criminal activities in space and time using crowed-sourced data. The authors also estimated the population which can be considered at risk for mobile crimes such as street robbery.

Izakian[3], *et al.* proposed an augmented Fuzzy C-Means algorithm for spatiotemporal data. In order to optimise the performance of clustering, the authors employ reconstruction error and prediction error. The algorithm performs clustering of time series data that are associated with fixed spatial locations (i.e. geo-referenced time series) such as meteorological stations. Liu[17], *et al.* proposed a fuzzy clustering algorithm which is based on Fuzzy C-Means algorithm for analysing weather time series data. They use cluster validity index to get optimal number of clusters. Ji[18], *et al*. proposed a dynamic fuzzy clustering algorithm for time series data whose class labels are unclear and further partitioned them into different clusters over time. Their approach can reveal the evolution property of time series data.

Mayorga[19], *et al*. proposed a Fuzzy C-Means based method for analysing crime events that occur in space and time. The authors also developed a cluster reorganisation algorithm that performs clustering to obtain time series of evolution of cluster center which helps to analyse criminal directionality.

The clustering technique is used to group crimes based on spatial and temporal attributes. Other characteristics are also used on an individual basis. Borg[20], *et al.* employs a combined characteristics distance metric to cluster residential burglaries and examine its effectiveness on different clustering algorithms. The outcome indicates that the performance of combined characteristics is better than spatial characteristics. Multiple evaluation metrics is also employed to measure quality of clusters. Reich[10], *et al.* proposed a Bayesian model-based technique to cluster criminal events that integrates spatial and temporal information with crime features, crime scenes and offenders. The approach is partially-supervised which has ability to incorporate identifying information about known offenders of crime when that information is available. This hierarchical model has ability to tackle crime data complexities such as missing data and mix of discrete and continuous variables. Further the model produces the posterior probabilities that each pair of crimes is linked, which helps analysts to work on only appropriate evidence.

3. FUZZY C-MEANS ALGORITHM FOR SPATIOTEMPORAL DATA

The characteristics of data derive the clustering task[2]. A spatiotemporal data is made up of spatial and temporal parts. In order to make use of spatiotemporal characteristics of data especially event type, we intend to define a distance function having capability to balance the effect of both spatial and temporal parts for computation of overall Euclidean distance.

The proposed work uses Fuzzy C-Means (FCM) algorithm[19] as a main procedure to carry out fuzzy clustering. Suppose $X = \{x_1, x_2, ..., x_n\}$, $x_j = (x_{1j}, x_{2j}, ..., x_{nj})$, is dataset, where x_{ij} is the j^{th} component of vector x_i, $j = 1, 2, ..., n$. The algorithm tries to minimise the following objective function iteratively.

$$J = \sum_{i=1}^{C} \sum_{j=1}^{N} u_{ij}^m d_{ij}^2$$

where C is initial number of clusters, u_{ij} is the membership degree of x_j in i^{th} cluster ($i=1,\dots,C$). m $(m>1)$ is fuzzification coefficient. $V = \{v_1, ..., v_C\}$ is the set of cluster centers and d_{ij} is the distance between the center v_i of the i^{th} cluster and j^{th} vector x_j The fuzzy partition matrix U is formed by $u_{ij} \in [0,1]$ i.e. $U = [u_{ij}]$

The distance function d_{ij} used in the objective function is usually Euclidian distance measure and is suitable for spherical shaped clusters[6]. In case of spatiotemporal data, especially event type, we can define a distance function considering spatial and temporal parts as follows:

$$d_{ij}^2 = \lambda \left\| x_j(s) - v_i(s) \right\|^2 + (1-\lambda) \left\| x_j(t) - v_i(t) \right\|^2, \lambda \in [0,1]$$

is weight coefficient

The above distance function enables us to control the effect of spatial and temporal components for determining Euclidean distance. For $\lambda = 1$, only spatial part is considered and temporal part is completely ignored. For $\lambda = 0$, only temporal part dominates without considering the spatial part. For $\lambda \in (0,1)$, both spatial and temporal parts are normalised and then considered for computation of Euclidean distance.

The center of each cluster prototype can be defined as

$$v_i = \frac{\sum_{j=1}^{N} u_{ij}^m x_j}{\sum_{j=1}^{N} u_{ij}^m}$$

for ($i=1,\dots,C$) the membership degree u_{ij} is given by

$$u_{ij} = \frac{1}{\left(\sum_{k=1}^{C} \frac{d_{ij}^2}{d_{kj}^2}\right)^{\frac{2}{(m-1)}}}$$

Subject to constraints:

$$\sum_{i=1}^{C} u_{ij} = 1 \forall j \in \{1,\dots,N\}$$

$$0 < \sum_{j=1}^{N} u_{ij} < N \forall i \in \{1,\dots,C\}$$

Initially u_{ij} and v_i are assigned random values and are updated iteratively. If $U^{(l)} = \left(u_{ij}^{(l)}\right)$ is the matrix U calculated at the l^{th} step, algorithm terminates when $\left\| U^{(l)} - U^{(l-1)} \right\| = \max_{ij} \left| u_{ij}^{(l)} - u_{ij}^{(l-1)} \right| < \varepsilon$. The parameter $\varepsilon > 0$ is the measure for accuracy.

To measure the quality of clusters we employ the Sum of Squared Error (SSE) approach[21] and Dunn index[22]. The SSE is defined as follows.

$$SSE = \sum_{i=1}^{C} \sum_{x \in C_i} \text{STdistance}(x, v_i)^2$$

The Dunn index[22] is a relative criteria for evaluating cluster validity and is mainly used to evaluate the compactness and separation of clusters. The large value of this index indicates that the clusters are compact and well separated. The goal is to maximise the inter-cluster distance while keeping the intra-cluster distance as minimum as possible. For a specified number of clusters the Dunn index is defined as follows.

$$\text{DUNN}(C) = \min_{i=1,\dots,C} \left\{ \min_{j=i+1,\dots,C} \left(\frac{\text{STdistance}(C_i, C_j)}{\max_{k=1,\dots,C} \left(\text{diam}(C_k)\right)} \right) \right\}$$

where $\text{STdistance}(C_i, C_j)$ is a function to calculate the spatiotemporal distance between the clusters C_i and C_j which is defined as

$$\text{STdistance}(C_i, C_j) = \min_{u \in C_i, v \in C_j} d(u, v)$$

here, $\text{diam}(C_k)$ is the diameter of the cluster C_k which is the maximum spatiotemporal distance between any two elements of the cluster and is defined as follows:

$$\text{diam}(C_k) = \max_{u,v \in C_k} d(u, v)$$

4. EXPERIMENTS

In this section we apply our proposed method to crime data set[23]. The crime dataset is prepared by Montgomery County Police Department, USA, under Criminal Justice Information Services (CJIS) Division Uniform Crime Reporting (UCR) Program. Montgomery County Police Department uses a law enforcement records-management system namely EJustice to compile the dataset. The raw data set contains 80,389 event of crime of various type during the period from July 2016 to December 2017 for the County of Montgomery in the US state of Maryland. There are 26 Dimension in the dataset namely: Incident ID, Offence Code, CR Number, Dispatch Date/Time, NIBRS Code, Victims, Crime Name1, Crime Name2, Crime Name3, Police District Name, Block_Address, City, State, Zip Code, Agency, Place, Sector, Beat, PRA, Address Number, Start Date/Time, End Date/Time, Latitude, Longitude, Police District Number and Location.

For spatiotemporal clustering and analysis of criminal activities we have used spatial, temporal and attributes which are required for analysis of criminal activities namely: Description, City, StartDateTime, EndDateTime, Latitude and Longitude to create crime event using dimension reduction technique.

Data cleaning includes identification of outliers and smoothing out noisy data by removing records having inconsistent longitude and latitude attributes and handling of missing values pertaining to start date-time and end date-time attributes. The raw data set contains 80,389 event after pre-processing step we obtain 73,895 spatiotemporal event data, on which we apply our proposed algorithm. We have discarded 6494 data point with missing values.

The different outcomes are obtained, when K-Means algorithm is applied on randomly selected initial clusters[24], therefore to get good result, we ran the algorithm 10 time for each λ and C values and selected the value out of 10 different values which has minimum SSE or maximum Dunn index value.

To improve the result, user can give more importance to a specific dimension[25]. Therefore to obtain optimal values of weight coefficient (λ) and number of clusters (C), the value of λ is varied from 0.1 to 0.9 and C from 5 to 21 and recorded corresponding Sum of Squared Error (SSE) values and Dunn index. The SSE is depicted in the Fig. 1. The minimum value of SSE represents the compactness of clusters. The minimum value of SSE is obtained at $\lambda = 0.7$ and C = 20 as shown in Fig. 1. Smaller SSE produces high quality clusters, therefore we choose $\lambda = 0.7$ and C = 20.

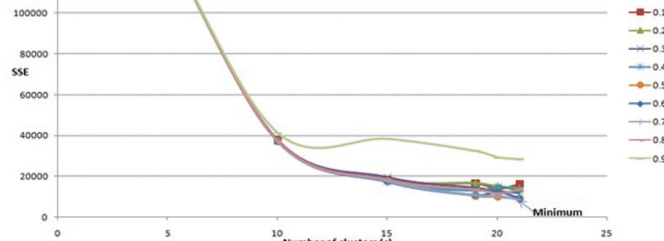


Figure 1. Sum of squared error for crime data set.

We applied proposed algorithm on the above mentioned data set and obtained spatiotemporal clusters which is depicted in Fig. 2, where latitude and longitude are represented in horizontal axis and time on the vertical axis.

Cluster 11 which is depicted in Fig. 3(a) contains 5308 crime event, which is maximum in number, whereas cluster 13 depicted in Fig. 3(c) contains 1991 crime event, which is minimum in number. The second largest cluster is cluster 9, which is depicted as Fig. 3(b) and contains 5058 crime event. Clusters 0, 1,2,3,4,5,6,7,8,10,12,14,15,16,17,18, and 19 have 2481, 4555, 3845, 4886, 2870, 4325, 3067, 2645, 2761, 2649, 3789, 4304, 4304, 2523, 4698, 2940 and 4896 number of crime events.

We plotted obtained spatiotemporal clusters in spatial dimension; they overlap to great extent as shown in Fig. 4(a). We also choose $\lambda = 1.0$, where only spatial part is involved in the clustering process. The result of spatial clustering is depicted in the Fig. 4 (b).

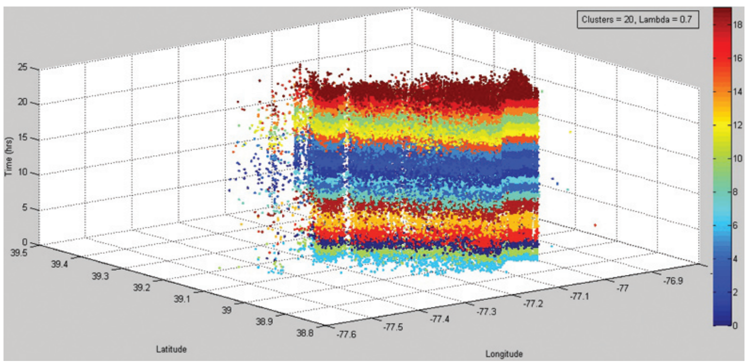


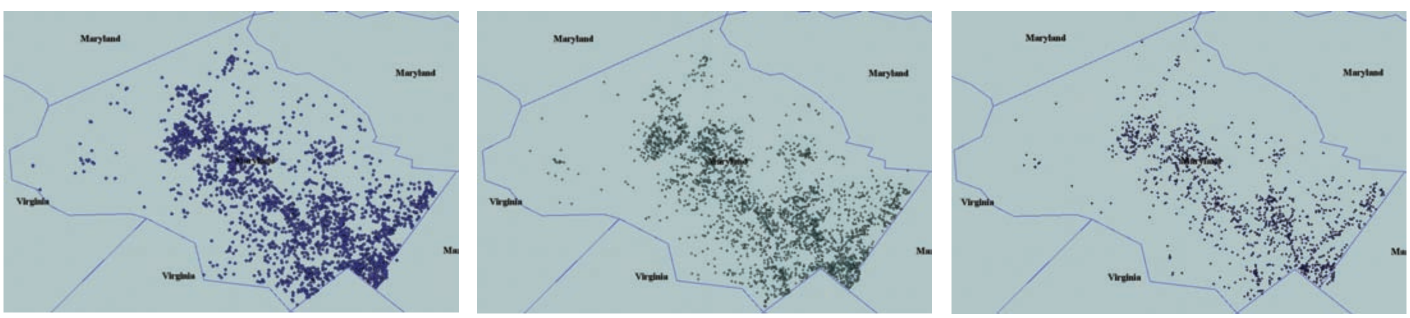
Figure 2. Illustration of spatiotemporal clusters using time dimension for crime dataset using SSE.

The Dunn index is depicted in the Fig. 5. The large value of this index indicates that the clusters are compact and well separated. The maximum value of Dunn Index is obtained at $\lambda = 0.6$ and $C = 10$ and its value is 0.0025465429913296 therefore we choose $\lambda = 0.6$ and $C = 10$ to get quality clusters. We apply our proposed algorithm on the above mentioned data set and obtained spatiotemporal clusters which is depicted in Fig. 6, where latitude and longitude are represented in horizontal axis and time on the vertical axis. Cluster 5 which is depicted in Fig. 7(a) contains 8900 crime event, which is maximum in number, whereas cluster 1 depicted in Fig. 7(c) contains 5515 crime event, which is minimum in number. The second largest cluster is cluster 7, which is depicted as Fig. 7(b) and contains 8816 crime event. Clusters 3, 8, 4, 9, 2, 0 and 6 have 8511, 8417, 8406, 6938, 6478, 6040 and 5874 number of crime event.

We also plotted the obtained spatiotemporal clusters in spatial dimension; they overlapped to great extent as shown in Fig. 8(a). We also choose $\lambda = 1.0$ and $c=10$, where only spatial part is involved in the clustering process. The result of spatial clustering is depicted in the Fig. 8 (b).

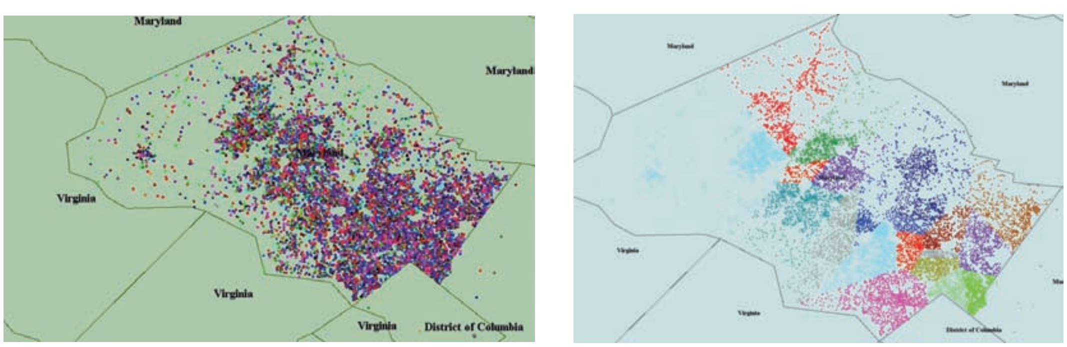
5. DISCUSSIONS

The comparison is made when spatial and temporal components have same weight and when they have different weight. When we give same weight to both spatial and temporal components, by choosing $\lambda = 0.5$, and $C = 20$ the computed SSE value is 10600 and when we give different weight to spatial and temporal components, we



(a) (b) (c)

Figure 3. Based on SSE approach (a) Cluster containing largest crime events, (b) Cluster containing second largest crime events (c) Cluster containing smallest crime events.



(a) (b)

Figure 4. Based on SSE approach (a) Spatiotemporal clusters for crime dataset, (b) Clusters for crime dataset where only spatial part is involved in clustering.

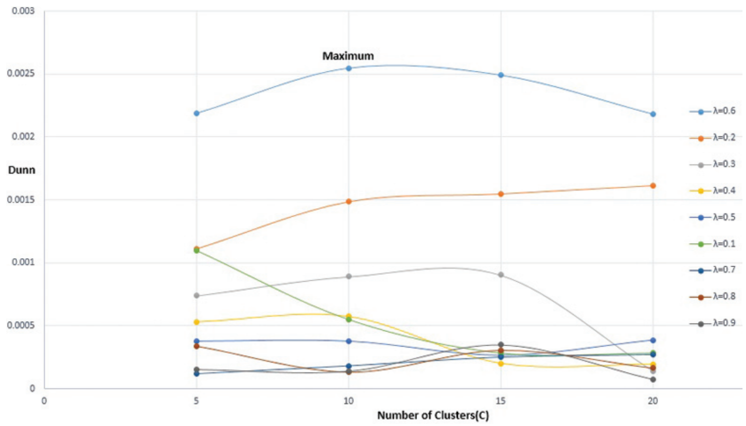


Figure 5. Dunn index for crime data set.

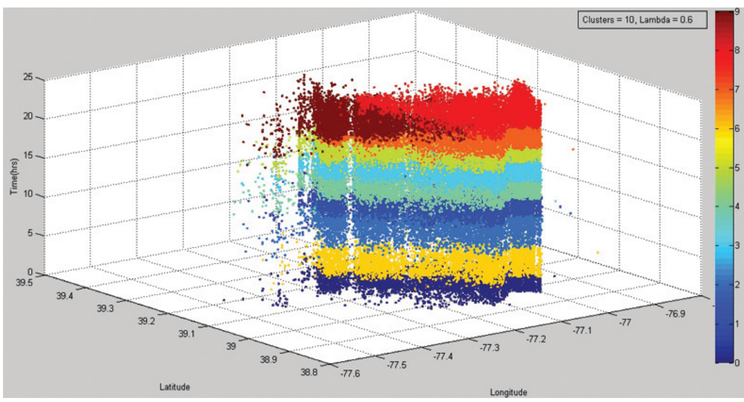
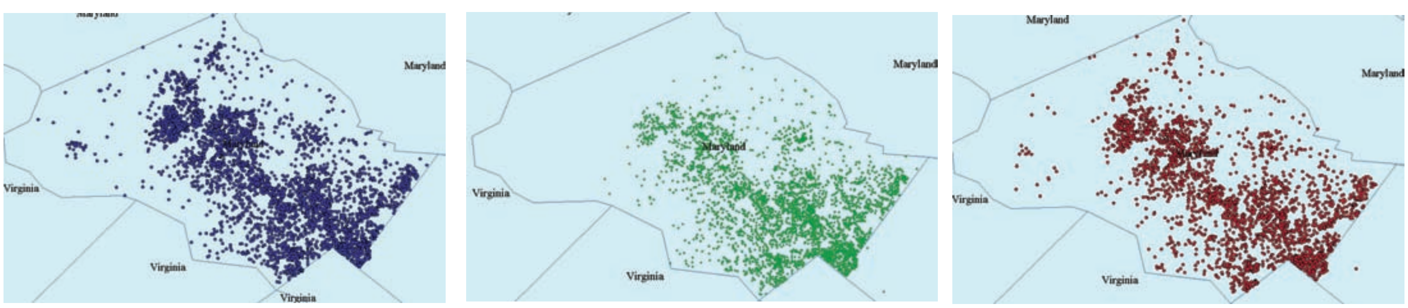


Figure 6. Illustration of spatiotemporal clusters using time dimension for crime dataset based on Dunn index.

obtain minimum SSE value (10300) for λ = 0.7, C = 20. Smaller SSE value is indicative of high quality clusters. The comparison is also made using Dunn index. When we give same weight to both spatial and temporal components, by choosing λ = 0.5 and C = 20 the computed Dunn index value is 0.000387025 and when we give different weight to spatial and temporal components, we obtained maximum Dunn index value (0.0025465429913296) for λ = 0.6, C = 10. The larger Dunn index value is indicative of high quality clusters.

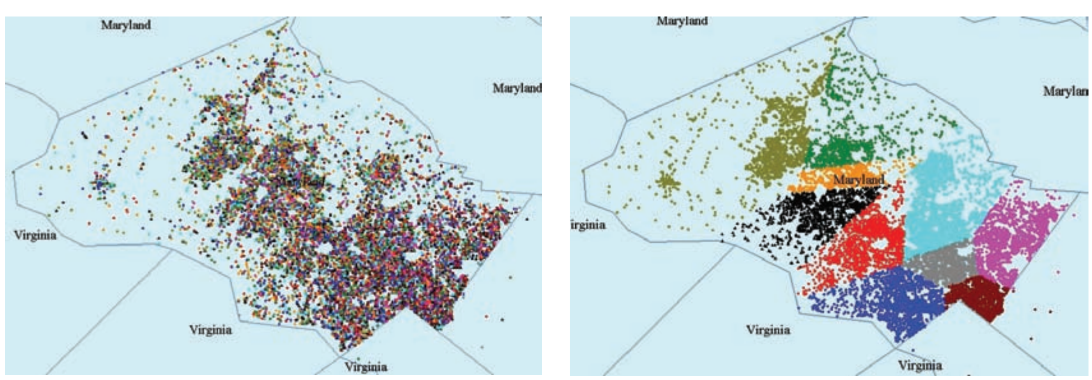
After analysing the experimental results that was computed by adopting SSE approach, we found that cluster 11 contains 5308 crime event, which is maximum in numbers and occurred during time period of 18.47 h to 19.49 h. Cluster 9 contains 5058 crime event, which is second largest in number and occurred during the period 19.47 h to 20.54 h. Cluster 14 containing 4304 event occurred from 20.53 h to 21.6 h. Cluster 17 containing 4698 event occurred from 21.6 h to 22.73 h. Cluster 19 containing 4896 event occurred from 22.73 h to 23.98 h. Cluster 13 contains 1991 crime event, which are minimum in number and occurred during the period of 4.0 h to 6.47 h. The spatiotemporal behaviour of crime events indicates that 33 per cent of the crime occurs from 18.47 h to 24.00 h in larger part of County of Montgomery.

After analysing the experimental results based on Dunn index, we found that cluster 5 contains 8900 crime event, which is maximum in numbers and occurred during time period of 16.23 h to 18.83 h. Cluster 7 contains 8816 crime event, which is second largest in number and occurred



(a) (b) (c)

Figure 7. Based on Dunn index: (a) Cluster containing largest crime events, (b) Cluster containing second largest crime events, and (c) Cluster containing smallest crime events.



(a) (b)

Figure 8. (a) Spatiotemporal clusters for crime dataset based on Dunn index and (b) Clusters for crime dataset where only spatial part is involved in clustering based on Dunn index.

during the period 18.0 h to 20.85 h. Cluster 3 containing 8511 event occurred from 13.98 h to 16.46 h. Cluster 8 containing 8417 event occurred from 20.81 h to 23.98 h. Cluster 4 containing 8406 event occurred from 11.75 h to 14.15 h. Cluster 9 containing 6938 event occurred from 18.71 h to 23.98 h. Cluster 2 containing 6478 event occurred from 5.32 h to 9.5 h. Cluster 0 containing 6040 event occurred from 0.0 h to 1.7 h. Cluster 6 containing 5874 event occurred from 1.63 h to 5.4 h. Cluster 1 contains 5515 crime event, which are minimum in number and occurred during the period of 9.51 h to 11.8 h.

The spatiotemporal behaviour of crime events indicates that 45 per cent of the crime occurs from 16.23 h to 24.00 h in larger part of County of Montgomery. However, only 16 per cent crime occurs from 0.0 h to 5.4 h.

The analysis based on both approaches reveals that the time period 18.00 h to 24.00 h is crucial one. These spatial area and time period may be informed to the police and other security agencies to take appropriate actions such as patrolling to curb criminal events.

6. CONCLUSIONS

Currently huge amount of spatiotemporal data of different types are available pertaining to various fields including criminal activities. A spatiotemporal data is made up of spatial and temporal parts and crime events are spatiotemporal in nature. We have reformulated a flexible distance function and employed it in Fuzzy C-Means algorithm for analysis of criminal activities. It has got the capability to handle spatial and temporal components of spatiotemporal data. The Sum of Squared Error (SSE) approach and Dunn index are adopted to measure the quality of clusters. Our proposed approach is applied on real world crime dataset of County of Montgomery in the US state of Maryland and it is concluded that it effectively discovers spatiotemporal crime clusters of good quality. In future, we intend to employ other clustering algorithms for crime analysis and compare with proposed work. We will make use of more cluster validity measures in the proposed work and also to compare other clustering algorithms. Finally, we aim to carry out more experiments with other datasets.

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