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ST-AGRID: A Spatio Temporal Grid Density Based Clustering and Its Application for determining the Potential Fishing Zones

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Abstract

This paper is aimed to propose a grid density clustering algorithm for spatio-temporal data that is based on the adaptation of the grid density based clustering algorithm. The algorithm is based on AGRID+ algorithm with 7 steps: partitioning, computing distance threshold, calculating densities, compensating densities, calculating density threshold (DT), clustering and removing noises. The adaptation is for the partitioning and calculating the distance threshold (r). The data utilized in this study is spatio-temporal fishery data located around the India Ocean from year 2000 until 2004. We utilized the fishery data in three types of aggregate , daily data, weekly data and monthy data. The result of this study shows that the time complexity for ST-AGRID is outperform the AGRID+. ST-AGRID improves the time complexity and at the same time maintains the accuracy. By utilizing the thresholding technique, clustering result of the ST-AGRID algorithm is identified as the potential fishing zone.

Keywords: *spatio-temporal clustering, grid-density based clustering, potential fishing zone, temporal aggregate*

1. Introduction

Since the last decade, the development of the data storage and data presentation has undergone a tremendous improvement, this includes the spatial and temporal data. It is due to the accumulation of transaction of multi dimensional data such as remote sensing technology, geographic information system and the development of the wireless technology [1]. The development of the information technology is resulting a spatio-temporal data repository that commonly utilized in many studies to reveal knowledge, the spatio-temporal reations and other patterns implied from the data repository, this process referred to as spatio-temporal data mining [2, 3]. The spatio-temporal data mining application is widely utilized in many fields of study such as medicine, security, environment, Biology and including the study on determining the prediction of the potential fishing ground [4].

The spatio-temporal data has both spatial and temporal dimension at once. The data shows the information of space and the time [5]. Spatio-temporal data embodies spatial, temporal, and spatio-temporal data concepts, and also captures spatial and temporal aspect of data that deal with geometry changing overtime and location of object moving over [6].

Clustering for spatio-temporal data is grouping the data object without knowing the class label [7], DBSCAN is a clustering method that is utilized for big volume and densed

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spatial data and also good in identifying noise [8]. The issue for the spatio-temporal clustering is concerning the time complexity. Regarding the big volume of the spatio-temporal data, there are many adaptations and modifications to yield optimal time complexity such as grid based density clustering. This method proposed a clustering method for data object as in a grid not for point to point [9]. This enhanced the optimum computing time however it did not improve the accuracy [10]. It requires an algorithm that covers enhancement both in time complexity and accuracy. The AGRID+ treats data objects both in grid and the smallest element in the clustering result, so it will enhance the time complexity and at the same time preserve the accuracy [11]. This method is also utilizing the i-th order neihghbor concept that reduces the computational complexity, while for increasing the accuracy, AGRID+ applies the density compensation function. In this spatio-temporal study, the AGRID+ algorithm can not be directly implemented, there should be some adaptations and adjustments regarding the nature of the spatio-temporal data which consists of 3 data dimension (longitude, latitude and temporal). It is because in determining the temporal interval, AGRID+ produces real numbers instead of integer number. Whereas for spatio-temporal data, the temporal dimension, the interval should be in integer, as in the daily temporal aggregate, weekly temporal aggregate and monthly aggregate. Thus, the adaptation for the algorithm is only for these phases that have relation to the calculation of each interval from each dimension, they are partitioning phase and calculation distance threshold phase.

Based on the explanation above, our contributions in this paper are:

- To propose spatio-temporal grid density based clustering algorithm ST-AGRID adapted from clustering algorithm AGRID+,
- To perform an analysis of the potential fishing zone based on the spatio-temporal clustering result.

2. Related Works

Spatio-temporal data mining is frequently utilized in analysing the data from remote sensing and application of geographic information system [1][2][12]. The big volume of data and the dependency on spatial and temporal that contains multidimensional interactions, seasons and weather patterns, is applied to see the association rules [13]. One approach in spatio-temporal data mining is spatio-temporal clustering that does not require the class label to analyze the data object. The clustering method is appropriate to be implemented in extracting information from a big repository without knowing the data label [7]. This approach is widely utilized in many fields of study such as medicine, security, environment, Biology, health and fisheries [3, 14]. The spatio-temporal clustering method is implemented either for 3 dimensions at once or in two phased clustering. Each two-phased clustering yields stressing in each dimension, spatial or temporal [15, 16, 17].

Study in density based spatio-temporal clustering is done by [18] known as ST-DBSCAN. The algorithm is an improved algorithm of the DBSCAN algorithm [8] for spatio-temporal data. ST-DBSCAN is expected to find not only spatial clusters but also temporal clusters and the non spatial clusters. [19] proposed two spatio-temporal based algorithms, ST-GRID and ST-DBSCAN to analyse the sequence of the earthquakes. Aside from the study in density based spatio temporal clustering there is also grid density spatio temporal clustering to tackle the time computation problem that occurred due to the point to point processing [9]. Another study that is relevant to the grid density clustering algorithm is CLUGD that first construct a grid of relevant portion, next the algorithm finds references by grid and classifies these references to core references and bound references after that it attaches the data of the bound references to the nearest core references and aggregation the core references in neighboring portions. At last, in-direct graph is used to classify these core references and maps cluster to original data, clusters formed [10].

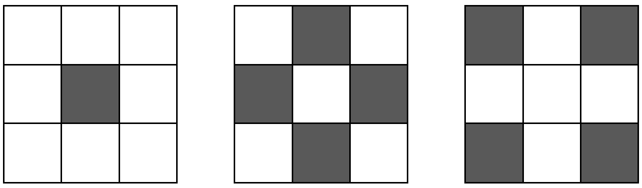
3. AGRID+

Another approach in grid and density based clustering study is AGRID+ [11]. The algorithm is appropriate for high dimensional data clustering. The method is enhancing the clustering with 4 features. First feature is determining the object or data point which is treated as an atomic unit in which the size of the cell clusters are not specified while at the same time preserving accuracy. Second feature is introducing the i-th order neighboring concept so that the process of the neighboring cell is in groups and it can reduce the computational complexity. Third feature is the idea of calculating the density compensation to increase the clustering accuracy. The last feature is to propose a subspace distance to assist the clustering proses in domain.

In the AGRID+ algorithm, first step, dimension is divided into many intervals and data objects are partitioned into hyper-rectangular cells, a 3d-rectangular cells used for spatio-temporal data. The interval value is calculated based on the number of 3d-rectangular cells to be formed. Interval values for each dimension will be different according to the number of rectangular in its dimension. The length of cell's interval in each dimension obtained from the dimension's range divided by the number of cells in that dimension. The computation of interval length can be formulated in Equation (1).

$$L_d = \frac{\max(data_d) - \min(data_d)}{m_d} \tag{1}$$

where, L_d is the interval length for each cell at *d*th-dimension, $data_d$ is the feature of the data at *d*th-dimension, and m_d is the number of cells at *d*th-dimension. We have to do a feature normalization before the clustering process due to the difference in scale between spatial features and temporal features.



(a) C_a (i = 0) (b) i = 1 (c) i = 2

Figure 1. The ith-order Neighbor of c_a

After the length of intervals for each dimension, the partition step is done by assigning each object to the corresponding cell based on the value of its features. Next step, calculate the distance between object *a* in a cell and the objects in its neighboring cells, and its density is the count of objects that are close to object *a*. Determination of the neighbor is based on the *i*th-order neighbor. Zhao *et al.*, [11] defined the *i*th-order neighbor as a cell in *D*-dimensional space which shares $(D - q)$ dimensional facet with cell C_a, where cell C_a is a cell in the *D*-dimensional space that contain an object *a*, and *q* is an integer between 0 and *D*. The 0th-order neighbors of C_a is C_a itself. Examples of *i*th-order neighbors in a 2D space are shown in Figure 1. *Neighborhood* is a point / data objects and the surrounding neighbors is an area or space while the *neighbor* is the neighboring cells and the surrounding cells that are adjacent to the cell.

To determine the neighborhood of the object required an *r* parameter, the radius of neighborhood. Choosing the value of *r* is not so easy, because if *r* is large enough, this algorithm will become like a grid-based clustering. On the other hand, if *r* is too small, this algorithm will become like a density-based clustering. So that, to determine this parameter Zhao *et al.*, said that the value of *r* must be less than *L*/2, where *L* is the minimum interval length in all dimensions [11]. The value of r can be calculated using Equation (2).

$$r = \lambda * \frac{\min(L)}{2} + (1 - \lambda) * \frac{\max(L)}{2} - \varepsilon \tag{2}$$

where, λ is a weight coefficient ($0 < \lambda < 1$), L is the interval length for all dimensions, and ε is a very small number, so that we achieved the value of $r < L/2$. The next step is to compute the densities of each object. The pseudo code of computing densities is shown in Figure 2.

```
/* Pseudo code for computing densities*/
Set all densities(i) to zero;
For all cell C_i;
  For all C_j, non-empty k-th order neighbors of C_i;
    For all objects O_m in C_i
      For all objects O_n in C_j
        If dist(O(m,spatial),O(n,spatial))<=r_spatial And
dist(O(m,time),O(n,time))<=r_temporal
          densities(m) = densities(m)+1;
          densities(n) = densities(n)+1;
        end if
      end for
    end for
  end for
end for
```

Figure 2. Pseudo Code for Computing Densities

After we have the densities value, we continue the process with compensating density with Equation (3) as in [11].

$$C\_densities(O_i) = densities(O_i) \times \frac{(2r)^{d'}}{\sum_{j=0}^{d} k_j (r+a)^{d'-j} (r-a)^{k}} \tag{3}$$

where, r is $r_{spatial}$, a is the object's spatial coordinate relative to its cell ($a = \frac{1}{2}(C_i(1) + C_i(2))$, d' is number of dimensions where $a < r_{spatial}$, and k_i is the number of ith-order neighbors. The clustering result is also determined by the value of density threshold *DT* that can be computed with Equation (4).

$$DT = \frac{mean(Density_i)}{\theta} \tag{4}$$

where, θ is the coefficient that can be tuned to get the cluster results at different levels. A small value of θ will lead to a big *DT* and vice versa. The appropriate cluster level can be decided by the needs of user itself. In this experiment, we use DT = 5 or equivalent with set θ = 1, based on the criteria to determining the potential fishing zone.

Continue to the clustering process, each object that have a density greater than *DT* is labeled as a cluster. Then, every pair of objects which is in the neighborhood of each other is checked. If that pair of objects is close enough (distance $\leq r$) and has a density that meets the criteria as a cluster (density $\geq DT$), then these two clusters that contain the pair of objects are merged into one cluster. The clustering process is shown in Figure 3.


```
/* Pseudo code for clustering*/
Set all objects whose density is equal or greater than DT as a
cluster
For all cell C_i;
  For all C_j, non-empty k-th order neighbors of C_i;
    For all objects O_m in C_i
      For all objects O_n in C_j
        If dist(O_m,O_n)<=r And densities(O_m)>= DT And
densities(O_n)>=DT
          Merge that two clusters as one cluster;
        end if
      end for
    end for
  end for
end for
```

Figure 3. Pseudo Code for Clustering

And the last step is removing noises. From those clusters obtained, clusters with the average density less than *DT* is considered as a noise and will be removed.

4. Problem of Clustering Spatio-Temporal Data with AGRID+

In general, spatio-temporal data has 3 dimensions, 2 spatial dimensions and 1 temporal dimension. The spatio-temporal data has specific type, for spatial dimensions, the longitude and latitude are represented by negative and positive real numbers, while for temporal dimension is adjusted to the data time units for instance daily (1 day), weekly (7 days) or monthly (± 30 days).

To determine the similarity between one object data to another in the neighbor cell, a distance threshold parameter is used. In AGRID+ algorithm, there is only one distance threshold parameter *r* for n-dimensional data to determine the similarity of one object to other objects in all n-dimensions. It does not support the spatio-temporal data where the interval of the temporal dimension is quite different from the two other dimensions (longitude and latitude). Therefore, in order to support both the spatial and temporal dimensions, our study proposes a different distance threshold parameter for each dimension. For calculating the distance threshold for spatial dimension, the parameter is based on the equation (5), while for temporal dimension is adjusted to the time units applied (daily, weekly, or monthly)

5. ST-AGRID Algorithm

In this study, we adopted the AGRID+ clustering algorithm for processing the spatio-temporal fishery data. From the AGRID+ algorithm, the adaptations for spatio-temporal clustering are in the partitioning phase and the computing the distance threshold (r). The following are the steps in the clustering method in Figure 4:

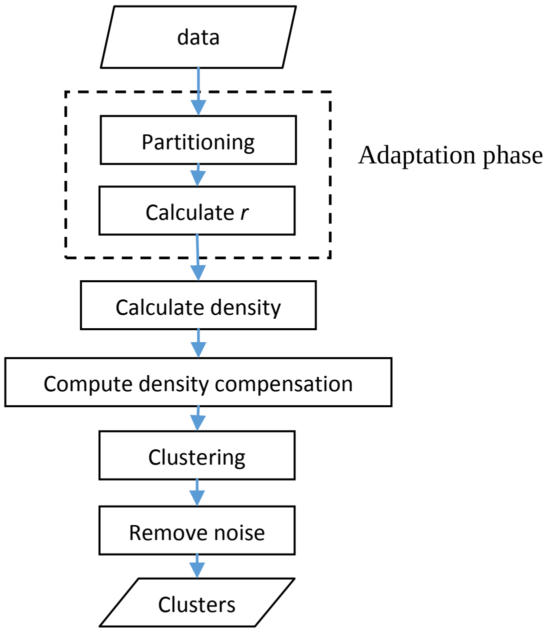


Figure 4. Adapted Method for ST-AGRID

Adaptation in partitioning phase is to divide the data space/ object into cubes. It requires a calculation for cubes interval in defining the number of cubes. The value of cubes interval (L) is gained by dividing each range of dimensions (upper bound – lower bound) with the number of m cell. The number of interval (L) is for spatial dimension only (longitude and latitude), while for temporal dimension, due to its data structure, the cell interval for the dimension is using aggregate temporal. The aggregate from temporal dimension is determined based on the temporal units, daily, weekly and monthly. As each cube (spatial and temporal) is formed, each data object is stored in each cube that is relevant to its spatio-temporal coordinates. The following is the partitioning algorithm in ST-AGRID shown in Figure 5:

```
/* Pseudo code for ST-AGRID partitioning*/
for i=1 to number of Objects
   cell_ID = spatial coordinate of object Oi / length of interval;
   cell_time_ID = aggregate of temporal/s /* days, weeks, or, months */
   if the cell_ID and cell_time_ID not yet in the cells
       add cell_ID and cell_time_ID to cells;
   else
       add object to the cell with corresponding cell_ID and cell_time_ID
   end if
end for
```

Figure 5. Algorithm for ST-AGRID Partitioning

The next is adapting the phase in computing the distance threshold (r). Computing the distance threshold is much depends on the partitioning phase in finding the value of L. Since the value of L is used in spatial dimension only, so the ratio/distance threshold in spatial dimension in ST-AGRID as in Equation (5) in AGRID+ algorithm:

$$r_{spatial} = \lambda * \frac{\min(L)}{2} + (1-\lambda) * \frac{\max(L)}{2} - \varepsilon \quad (5)$$

where λ is interval weight parameter used, L is interval, and ε is a small integer number, so that the value of $r < L/2$. For the temporal dimension, the calculation of $r\_temporal$ is the aggregate of temporal dimension used, for instance daily is 1, weekly = 7 and monthly $\pm$ 30.

The following in Figure 6 is the pseudocode for the calculation of distance threshold (r):

```
/* Pseudo code for computing r*/
r1 = (minimal L)/2;
r2 = (maximal L)/2;
r_spatial = λ*r1+(1-λ)*r2-ε; /* 0≤λ≤1; ε= small number
r_temporal = 1; /* range temporal is 1 aggregate time */
```

Figure 6. Algorithm for Calculating the Distance Threshold

after the adaptation step has been done, the rest of the steps will be implemented similarly to those in the AGRID+.

6. Application of ST-AGRID to determine the Potential Fishing Zones

In order to achieve the objective of the study, we attempted to utilize the ST-AGRID algorithm for clustering spatio-temporal data. the objective is to determine the Potential Fishing Zones based on fishery data. There are four phases in the application: conducting data preparation, clustering with ST-AGRID, validating the cluster result, and determining the potential fishing zones as illustrated in Figure 7.

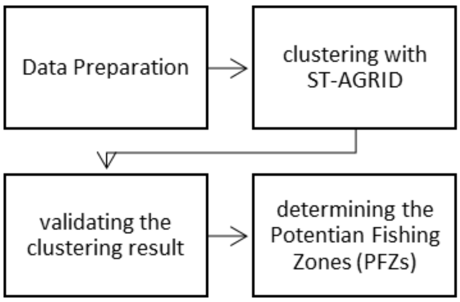


Figure 7. Block Diagram of the ST-AGRID Application

6.1. Data Preparation

The fishery data utilized in this study is spatio-temporal data consisting daily fish catch data. The data structure of the fishery data is longitude, latitude, data, month, year, number of fish catch. The fishery data is from the Indian Ocean, 2-16,59° S and 100,49-140° E. The fishery data is taken from year 2000 until 2004. The temporal data is aggegate in daily, weekly and monthly. There will be 60 months, 300 weeks and 1600 days for range of study. Figure 8 shows the location of the fishing zone. The image is generated utilizing the Ocean Data View software [20].

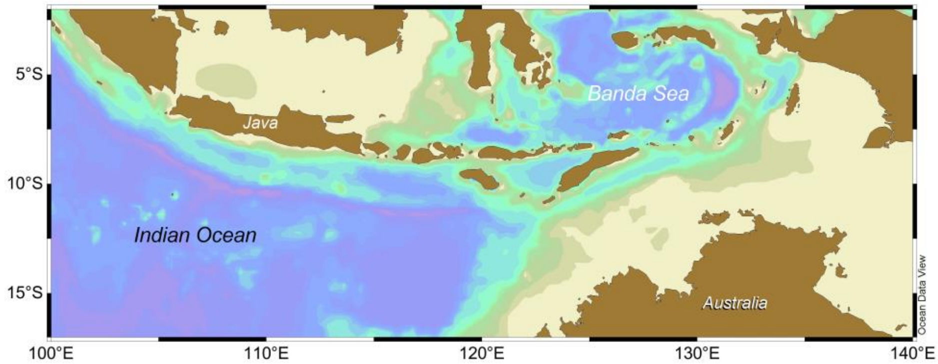


Figure 8. The Location of the Fishing Zone

6.2. Clustering with ST-AGRID

In this step of our study, our clustering algorithm, ST-AGRID is applied to the fishery data.

Later on, the result of the clustering will be processed with thresholding to discover the spatial temporal distributions of the potential fishing zones.

(1) Partitioning. The whole data space of the fishery data consisting of the location and time of fishing is partitioned into cells according to *m* and *p*. Each object is then assigned to a cube according to its coordinates and non-empty cubes are inserted into a hash table. The cube is data stucture with 3 dimension (spatial and temporal) where spatial dimension is longitude and latitude and the third dimension is time.

(2) Computing distance threshold. Determine the neighborhood radius (r) for each data point to other data point in a neighbor. After that we have $r_{spatial}$ and $r_{temporal}$ based on the appropriate time unit.

(3) Calculating densities. For each object of data, count the number of objects both in its neighboring cells and in its neighborhood as its density using the pseudocode in Figure 2.

(4) Compensating Densities. For each object of data compute the ratio of the volume of all neighbors and that of neighbors considered, and use the product of the ratio and the density of the cell as the new density as in Equation (3).

(5) Calculating density threshold DT. The average of all compensated densities is calculated and then the density threshold DT is computed by finding the average of the density compensation divided by theta parameters which are coefficients that can be tuning in to get a different cluster levels as in Equation (4).

(6) Clustering automatically. At first, each object whose density is greater than DT is taken as a cluster. Then, for each object check each object in the neighboring cells to see whether its density is greater than the density threshold and whether its distance from object is less than the distance threshold. If yes, then merge the two clusters which the two objects belong to respectively. Continue the above merging procedure until all eligible object pairs have been checked.

(7) Removing noises. In these clusters obtained, many are too small to be considered as meaningful clusters, so they are removed as noises.

6.3. Validating the Clustering Result

Silhouette index is utilized to validate the clusters formed from the algorithm execution. The silhouette index is gained by calculating the similarity of one object to other objects in the same cluster compared to other objects in different clusters [21]. The silhouette index is more familiar in the usage than Davies – Bouldin Index in clustering label [22]. The silhouette index range between -1 until 1, the higher the silhouette index (close to 1) the better the cluster result. The following is the silhouette Equation (6) and (7):

$$s(i) = \frac{b(i) - a(i)}{\max\{a(i), b(i)\}} \tag{6}$$

Or it can be written as:

$$s(i) = \begin{cases} 1 - \frac{a(i)}{b(i)}, & if\ a(i) < b(i) \\ 0, & if\ a(i) = b(i) \\ \frac{b(i)}{a(i)} - 1, & if\ a(i) > b(i) \end{cases} \tag{7}$$

where $s(i)$ is the value of the i-th silhouette object, $a(i)$ is average distance of the i-th object to other object in a cluster, and $b(i)$ is average distance of the i-th object to other object in different cluster.

After the clustering has been implemented with the ST-AGRID algorithm, there are results regarding the best temporal. The testing is done in different temporal which are daily, weekly (7 day) and monthly (30 day) and so is for the m value, ranging from m = 2 until m = 54 with multiples of 2. The clustering from daily temporal shows the best result within the number of cell interval in spatial dimension is 12, or equal to 144 cells in spatial dimension. Whilst, in the weekly and monthly temporal, the best clustering result from the number of interval in spatial dimension m = 6 or equal to 36 cells in spatial dimension. Figure 9 shows the Silhouette index of each temporal aggregate utilizing the ST-AGRID algorithm.

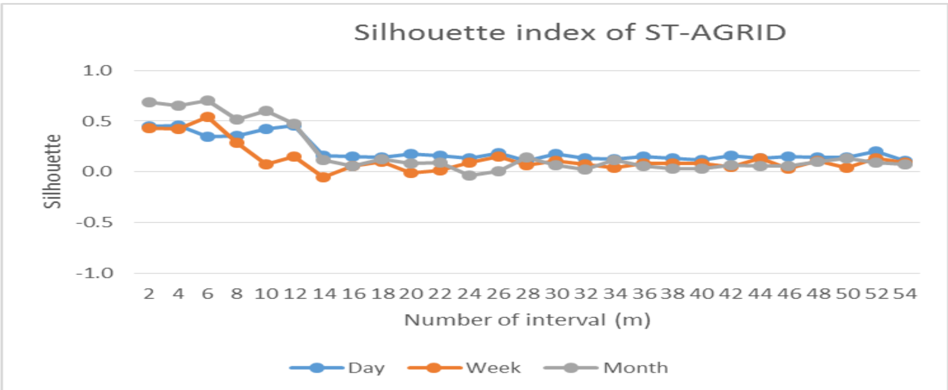


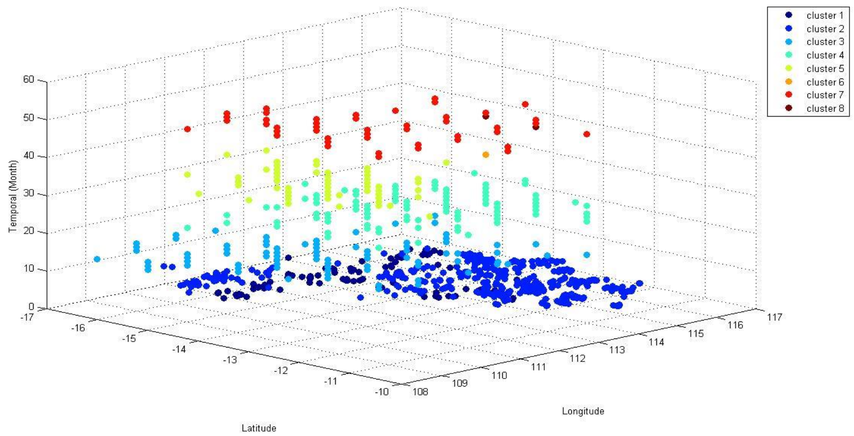
Figure 9. The Silhoutte Index of ST-AGRID at Different Temporal Aggregate

Table 1 shows further details for the clustering result from each algorithm, the value of silhouette index of each algorithm and the best number of cell utilized in each temporal aggregate.

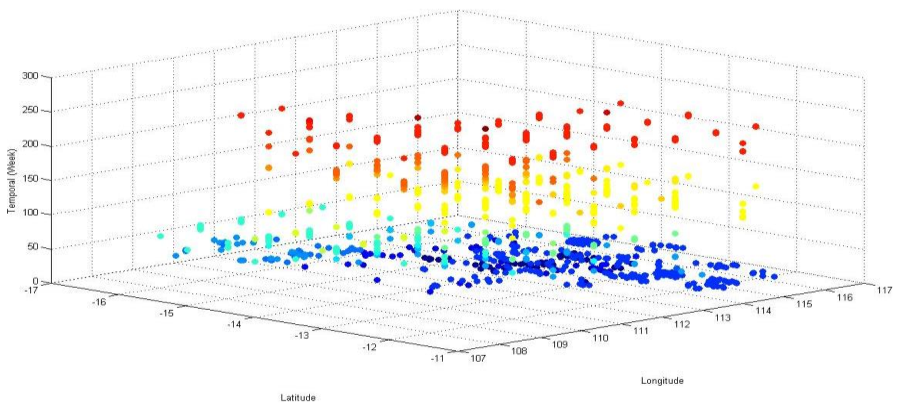
Table 1. The Comparison of Number of m and Number of Cluster Between ST-AGRID and AGRID+

	ST-AGRID			AGRID+		
	m	# of clusters	Silhoutte index	m	# of cluster	Silhoutte index
Daily	12	175	0.4572	14	50	0.9813
Weekly	6	37	0.5425	54	676	0.8771
Monthly	6	8	0.7017	54	639	0.8317

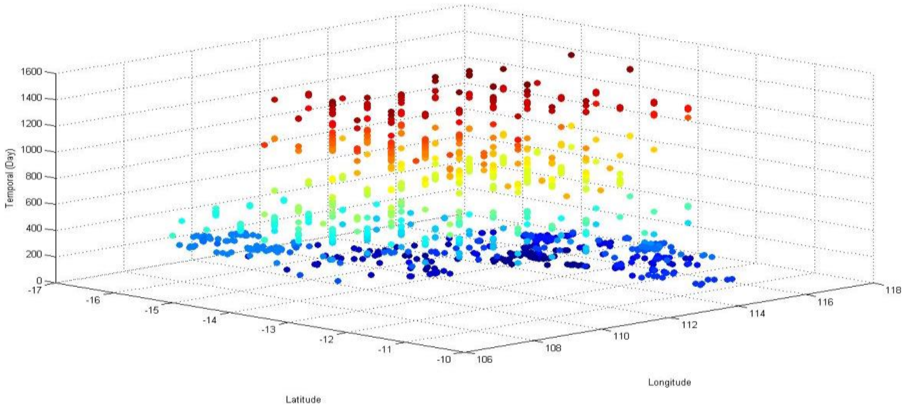
From each temporal aggregate, the best result from the spatio-temporal clustering result is the monthly temporal aggregate. This is also shown by the number of clusters formed in monthly temporal which is more compact and more meaningful with a significant number of clusters. Figure 10 shows visualization of cluster result plot of fish catch data for each temporal aggregate. Figure 10 (a) shows there are 8 clusters in monthly temporal aggregate with m = 6. The result of cluster from weekly aggregate temporal is 37 clusters formed with m = 36 in Figure 10 (b), and in Figure 10 (c) shows there are 175 clusters formed with m = 12 for daily aggregate temporal.



(a)



(b)



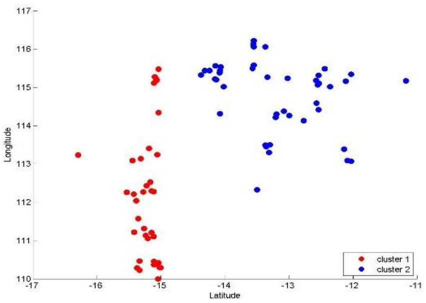
(c)

Figure 10. Spatio-temporal Clustering Results (a) Monthly, (b) Weekly, (c) Daily

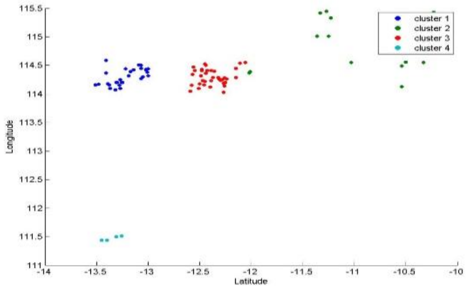
The bigger the temporal aggregate implemented, the bigger the size of cluster formed. It happened because the size of the temporal aggregate affected the ratio of the temporal dimensions.

From the spatio-temporal cluster formed, we can retrieve a slice from the cluster representing 1 particular temporal dimesion. Each slice from each temporal aggregate, monthly, weekly and daily is shown in Figure 11 (a), (b), (c) respectively.

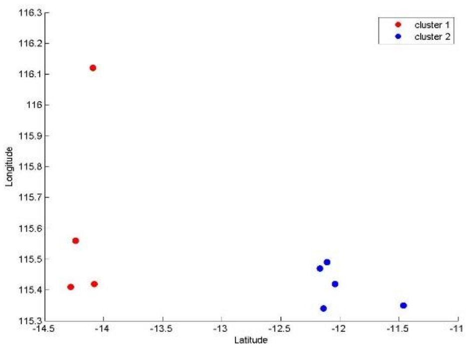
In Figure 11 (a), the slice shows that there are 2 clusters with m = 6 in the 4^{th} month. Figure 11 (b) shows that there are 4 clusters with m = 24 in the 24^{th} week and from day slice, there are 2 clusters with m = 12 in the 143^{rd} day as it is shown in Figure 11 (c).



(a)



(b)



(c)

Figure 11. Clustering Results at Certain Temporal Dimension (a) Monthly, (b) Weekly, (c) Daily

From the study with all temporal aggregate and m variations, the time execution of the ST-AGRID algorithm is better than the AGRID+ algorithm. Whilst, for the silhouette index shows that AGRID+ algorithm is better. Table 2 shows the average comparison of time execution and silhouette index of each algorithm in three different temporal aggregates.

Table 2. Execution Time and Silhouette Index in Different Temporal

	ST-AGRID		AGRID+	
	Exec.time (sec)	Silhoutte index	Exec.time (sec)	Silhoutte index
Daily	8.4117	0.2060	37.4082	0.6346
Weekly	13.9306	0.1246	53.6410	0.7260
Monthly	38.8747	0.1899	135.2700	0.5787

The Table 2 shows that ST-AGRID has the best time execution compared with AGRID+, it is due to the fact that ST-AGRID works very well with the specific temporal aggregate, while for AGRID+ outperformed in the silhouette index because the thoroughness of the parameter checking in each dimension, causes a more accurate results.

6.4. Determining the Potential Fishing Zone

In order to determine the PFZ of the clustering result, we need to select the cluster with certain threshold. This is very much dependant on the determination of the used threshold. In determining the threshold to identify the potential fishing zone for particular area, the threshold is determined by the opinion of some experts in some fishing companies. One of them is PT. Perikanan Nusantara Indonesia. A fishing ground is stated as a potential fishing zone if the number of fish catch is equal or greater than 5. Thus the thresholding formula for determining the potential fishing zone is in Equation (7):

$$PFZ = \begin{cases} 1, & \dfrac{\Sigma Catch_{ij}}{N_i} \geq th \\ 0, & otherwise \end{cases} \tag{7}$$

where $\Sigma Catch_{ij}$ is the total number of fish catches at ith-cluster, N_i is the number of catch points at ith-cluster, and th is a threshold. Later on, the number 1 is identifying as the potential area and 0 is non-potential area.

Refer to the threshold, Figure 12 shows the visualization of the potential fishing zone with the minimum catch.

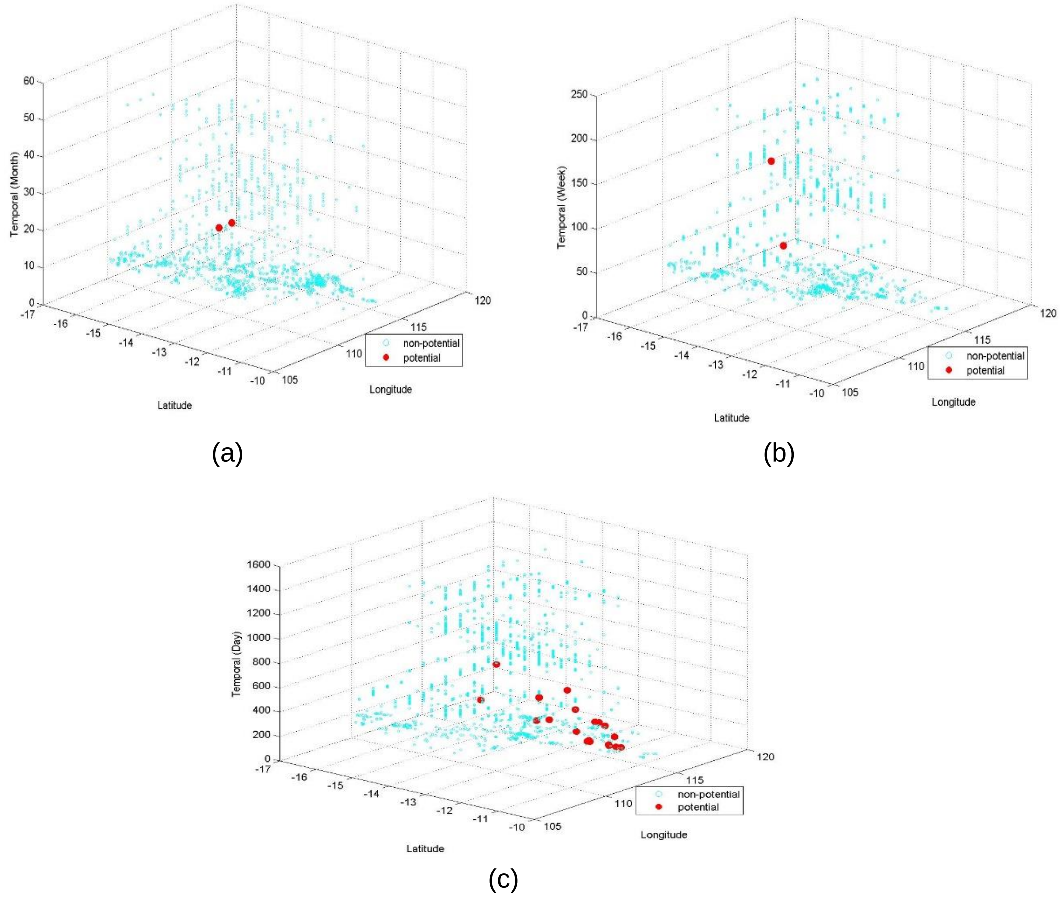


Figure 12. Potential Fishing Zone in (a) Monthly, (b) Weekly, and (c) Daily

From the potential fishing zone, the red dots represent the spatio-temporal potential fishing zone while the blue dots are the non-potential area. Each of these potential areas is based on aggregate temporal with the best m value. At monthly temporal aggregate, there are 3 points that are identified as potential fishing zones. At weekly temporal aggregate,there are 2 points identified as potential fishing zones and 20 points identified as potential fishing zone for daily temporal aggregate.

In monthly temporal agregate, 3 points identified as potential fishing zones are all in November 2001. For weekly temporal aggregate are identified in January 2001 and October 2003 and for daily temporal aggregate are in May and June 2010, June 2001, March 2002 and June 2003.

7. Conclusion

From this study, it is shown that the proposed algorithm ST-AGRID is successfully applied. The adaptation on the partitioning and calculating the distance threshold steps are proven to be appropriate with the spatio-temporal data. The result also shows an improvement in the algorithm execution time. The time execution for ST-AGRID is better than AGRID+, 8.41 second for daily temporal aggregate, 13.93 seconds for weekly temporal aggregate and 38.87 seconds for monthly temporal aggregate. Aside from the improvement in execution time, ST-AGRID is also at the same time maintain the accuracy of the clustering result. It can be seen from the sillhouette index value that is approaching the positif value of 1.

The study also shows that the application of ST-AGRID algorithm with the thresholding technique on fishery data can successfully identify the potential fishing zone.

The determination of the potential area is based on the minimal number of fish catch. The result of the potential fishing zone is different according to its temporal aggergate. In future study, we will be more focused in increasing the cluster validation result for ST-AGRID.

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