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Extracting Spatial Semantics in Association Rules for Ocean Image Retrieval

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***Abstract*—Several research institutions and governmental departments provide ocean images for research purposes. For example, Argo, a worldwide ocean research organization, produces ocean salinity and temperature images and researchers can download those images from the Internet. One may build an image system to store ocean images and retrieve them later for further research, for example, to predict future salinity or temperature variation. Image retrieval technology is therefore important. This paper describes an ocean image retrieval system based on content-based image retrieval. Currently, content-based image retrieval technology does not exploit high-level semantics, and it is hard to obtain predictive information from retrieved images. Our improvement involves a spatial reference method that is used to help get the spatial relationships between objects for a certain image. This allows the spatial semantics between the query image and images in database to be considered. Spatial association rules are also mined and are subsequently used as a basis for retrieving additional images. As the spatial semantics in both the query image and spatial association rules, the retrieved images are more accurate. The experimental results verify that the system effectively predicts the occurrence of salinity or temperature variations.**

***Keywords*—content-based image retrieval, spatial association rules mining, ocean salinity and temperature images**

I. Introduction

The ocean is an important part of the Earth's natural system, and it influences the transformation of energy and materials and it is important to the climate system. Many countries are now concerning about global climate change and its regional impacts [1] and are investing more resources to do research into environmental changes in the oceans. Argo is a global research organization that deploys over 3,000 free-drifting profiling floats that measure the temperature and salinity of the upper 2000 meters of the ocean. This facilitates continuous monitoring of the temperature and salinity of the upper ocean. The data collected, including ocean images, are made available to the public. One can build a database system to store ocean temperature and salinity images and retrieve them later for research purposes. In order to get effective retrieval results, the image retrieval technology is critical to image database systems. Currently, content-based image retrieval technology is still desirable, especially when the image volume is large. Several content-based image retrieval strategies have been proposed [11]. These strategies usually use low-level features such as color, texture and shape to calculate the similarity between images. However, the spatial relationships between the objects within the image are ignored since these low level features do not reveal spatial information such as the location of an object. Another disadvantage for content-based image retrieval is that it is hard to get predictive information from the retrieved images. Users may not only want to retrieve images with similar low level features, but rather images that have spatial relationships between the image objects that match those of the query image. Moreover, the system will be more valuable if the system shows images that predict future variation trend based on the query image.

This paper describes an ocean salinity and temperature image retrieval system where content-based image retrieval and inter-transaction association rules mining methods are employed to achieve the above goals. First, ocean images are downloaded and stored in image database. A spatial reference method is used to help build a spatial transaction database. Next, the inter-transaction association rules algorithm is applied to get salinity or temperature variation patterns. An example of such an ocean salinity variation pattern is as follows: if salinity rose from 0.05 psu to 0.15 psu in the area that is in the west-south sector near Taiwan, then salinity will rise from 0.05 psu to 0.15 psu in the east sector far away from Taiwan the next 3 months. This pattern reveals not only the salinity variation relationship, but also location and time information.

In the query stage, the system retrieves images based on low level features and its semantics extracted from query image. Then, the mined patterns are used to retrieve additional images to predict future variation trends. The experiments show that the retrieved images from the proposed system are more accurate since the spatial semantics are considered during retrieval.

The remaining parts of this paper are organized as follows. Section 2 summarizes the problems at hand and introduces related work. Section 3 describes the proposed algorithm and section 4 provides experimental evidence. Section 5 concludes the paper.

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II. Related Works

This section describes works related to content-based image retrieval and mining of inter-transaction association rules.

A. Content-based Image Retrieval

Modern multimedia technologies have led to huge and growing archives of images in diverse applications such as medicine, remote-sensing, entertainment, education and on-line information services. Traditional DBMS does not work well for image data due to the lack of semantic information in the data. To exploit the full benefit of the explosive growth of image data, there is an urgent demand to develop efficient techniques for storage, browsing, indexing and retrieval. In recent years, automatic indexing and retrieval based on image content has become more desirable for developing large volume image retrieval applications [9]. Color, shape and texture are the main features both humans and computers used to recognize images. Several systems have been proposed in the research community for content-based information retrieval such as QBIC (Query by Image Content) by IBM, and VisualSEEK by Columbia University.

Most content-based image retrieval techniques employ the following two steps to retrieve the images. First, each image's feature vector is computed and then stored in the image database. Secondly, given a query image, the feature vector of the query image is computed and then is taken to be compared with the feature vector of each image stored in the image database. A certain image's feature vector that is close to the feature vector of query image is returned to the user. Weighting Euclidean distance is used to measure the distance between images:

$$|Q,T| = \sum_i \omega_i |q_i - t_i|, \tag{1}$$

where Q is query image and q_i is low level feature of Q. T is a certain image in database and t_i is low level feature of T. w_i is the weight factor.

B. Argo Ocean Image

Argo is a global array of 3,000 free-drifting profiling floats that measures the salinity and temperature of the upper 2,000 m of the ocean [1]. The monthly ocean salinity and temperature images are made freely available to members of the International Argo Project and the national contributing programs (http://www.argo.ucsd.edu, http://argo.jcommops.org).

This paper describes an ocean image system where users can download the Argo ocean images and retrieve them later for further research reference. Content-based image retrieval is desirable for this system. The system's users may not be interested in retrieving images that are only similar to the query image according to low level features; they may want the locations of objects to be similar. In addition, this system is helpful to users as it provides future variations trend from the retrieved images.

Traditional content-based image retrieval strategies that are based on comparing low level features do not consider the spatial semantics. In order to tackle the problems, a data mining method is applied to the proposed system. Data mining helps extract the spatial semantics in images and define a spatial transaction database which allows spatial association rules to be discovered and hence enhance the retrieval effectiveness.

C. Spatial Transactions and Spatial Semantics

Fig. 1 shows a monthly salinity image, and Fig. 2 shows a monthly temperature image downloaded from Argo [2]. In order to simplify our research, only the variations in the waters surrounding Taiwan are considered. Inter-transaction association rules mining is employed for discovering salinity or temperature variation patterns. However, association rule mining algorithms assume that a finite set of disjoint transactions are given as input to the algorithms [3, 8], and there is no explicit finite set of transactions in an ocean image. This study adopts the strategy proposed in [8], where the spatial transaction is defined around the instances of a special reference feature. Taipei is chosen as the reference site and concentric circles are used to define neighboring regions to the reference site. Fig. 3 shows this reference centric model. The salinity or temperature variations are extracted first from each image. The variations within the concentric circles are treated as a single transaction.

The concentric circles are also used to annotate the location of the salinity or temperature variations. The sub-zones defined by the concentric circles represent different distances and directions to the reference site. For example, sub-zone A2 is in the east-northeast sector far from Taiwan, and sub-zone A1 is in the east-northeast sector close to Taiwan. Thus, spatial semantic information is maintained.

D. Inter-transaction Association Rules Mining

This section introduces fundamental concepts and definitions related to inter-transaction itemset and inter-transaction.

Let $I = \{i_1, i_2, ..., i_u\}$ be a set of items. Let D be a dimensional attribute and $Dom(D)$ be the domain of D. A transaction database is a database containing records in the form (d, I_j), where $d \in Dom(D)$ and $I_j \subseteq I$. We call this type of database a one-dimensional database. The dimensional attribute usually describes the occurring time or location of an item.

An inter-transaction association rule that spans p intervals is found if an association exists between items that are p intervals apart. Since an inter-transaction association rule may encompass many intervals, finding all such rules is time-consuming. In order to minimize the effort involved in mining uninteresting rules, a sliding window denoted by w is introduced. When mining inter-transaction association rules, only the rules spanning shorter than or equal to w intervals are considered. The sliding window is thus used to avoid mining rules that span many consecutive intervals [4].

Each sliding window forms an inter-transaction. An inter-transaction M that is contained within W can be described as follows:

$M = \{i_k(j) \mid i_k \in W[j]; 1 \le k \le u, 0 \le j \le w-1\}$, where W is a sliding window with w intervals and u is the number of items in $I = \{i_1, i_2, ..., i_u\}$.

To distinguish the items in an inter-transaction from the items in a traditional transaction, the items in an inter-transaction are called inter-transaction items. The set of all possible inter-transaction items are denoted I'. Given I' and w, then:

$$I' = \{i_1(0), ..., i_1(w-1), i_2(0), ..., i_2(w-1), ..., i_u(0), ..., i_u(w-1)\}.$$

An inter-transaction itemset is a set of inter-transaction items $B \subseteq I'$ such that $\exists i_k \in B, 1 \le k \le u$.

An inter-transaction association rule has the form $X \Rightarrow Y$, where

1. $X \subseteq I', Y \subseteq I'.$
2. $\exists i_k(0) \in X, 1 \le k \le u.$
3. $\exists i_k(j) \in Y, 1 \le k \le u, j \ne 0.$
4. $X \cap Y = \{\}.$

The support and confidence of an inter-transaction association rule $X \Rightarrow Y$ can be defined as:

$$\sup port = \frac{|T_{xy}|}{S}, confidence = \frac{|T_{xy}|}{|T_x|}. \quad (2)$$

where T_{xy} is the set of inter-transactions that contains a set of extended items $X \cup Y$ and T_x be the set of inter-transactions that contains X. S is the number of transactions in the transaction database.

As with intra-association rules mining algorithms, a minimum support, minsup, and a minimum confidence, minconf, are given and the task is to discover the inter-transaction association rules from the transaction database with support and confidence greater than or equal to the minimum requirements.

III. Ocean Image Retrieval and Mining Strategy

This study builds a database to store ocean salinity and temperature images that are downloaded from Argo. The objects (salinity and temperature variations) are cut from those images according to their colors. In order to annotate the location of each object, a set of concentric circles are applied to each image before objects are cut. Thus, each object's spatial information is maintained, and the spatial semantics of a single image is obtained.

Another advantage of the concentric circles is that it helps define spatial transactions. Once the spatial transactions are determined, the next step is to get variation patterns by employing the inter-transaction association rule mining algorithm. However, previous studies on inter-transaction association rules, for example, the framework proposed by Tung et al. [10], explains how to discover Boolean inter-transaction association rules.

The spatial transaction attributes are quantitative and need to be mapped to several intervals [7]. Quantitative inter-transaction association rules are mined from a one-dimensional database in three steps: quantitative attribute transformation, the discovery of frequent inter-transaction itemsets and salinity and temperature patterns generation.

A. Quantitative Attribute Transformation

The first step is to map each quantitative attribute into its intervals. Fig. 4 shows an example of transformation a quantitative attribute to binary attributes. We can see that "age" attribute is mapped to "young" and "old" two intervals. The age less than 50 will be mapped to "young". Fig. 4(a) is the original database and Fig. 4(b) is the result of quantitative attribute transformation.

B. Frequent Inter-transaction Itemsets Discovery

The next step is to get inter-transaction items and the Apriori algorithm can be used to find frequent inter-transaction itemsets. Since the quantitative attribute transformations and inter-transactions result in large quantities of data, it takes longer to process. To solve the problem, one can employ a reduced prefix-projected itemsets method based on PrefixSpan [6] algorithm to expedite the efficient search for the frequent itemsets. The main idea behind PrefixSpan is that, instead of projecting sequence databases by considering all the possible occurrences of frequent subsequences, the projection is based only on frequent prefixes. This holds, because any frequent subsequence can always be found by growing a frequent prefix. The reduced prefix-projected itemsets method was employed in this study to get frequent itemsets. Further details of the method can be found in [5, 12].

C. Variation Patterns Generation

The generation of inter-transaction association rules (salinity and temperature variation patterns) is similar to the generation of classic association rules. The calculation of rule support and confidence is shown in (2).

D. Ocean Image Retrieval

Previous sections describe how to build the image database and its corresponding spatial transaction database. In this section, the process of how to retrieve the ocean image is introduced.

Content-based image retrieval is employed in the proposed system. Before retrieving images in the database, the objects are cut from query image according to their color in ocean image and a set of concentric circles is also applied to the query image to help annotate location information to objects cut from query image. The following method is used to identify the location of an object.

The object location is denoted by its coordinate $(x, y) = (r_i \cos\theta, r_i \sin\theta)$. r_i is either the inner circle radius r_1 or the outer circle radius r_2. θ is the angle to x-axis. Now, an object can be represented by its feature vector (c, x, y), where c is the color of the object. x and y are the coordinate of the object.

Assume an object qo in the query image is represented by its feature vector $qo = (c_q, x_q, y_q)$, and $to = (c_t, x_t, y_t)$ is an object in an image. Euclidean distance is used to measure the distance between these two objects:

$$|qo,to|_{color} = |c_q - t_q|, \tag{3}$$

$$|qo,to|_{location} = |x_q - x_t| + |y_q - y_t|, \tag{4}$$

where $|qo,to|_{color}$ is color distance and $|qo,to|_{location}$ is the location distance between two objects. Two objects are similar if both the color distance and location are close enough. That is, two objects are similar if the color distance is less than a pre-defined threshold T_{color} and location distance is less than threshold $T_{location}$.

The target image in a database is similar to the query image if the total number of similar objects is greater than the threshold T_{image}. For example, there are three objects in the query image and the threshold is set to 60%, and the target image is similar to query image if at least two objects in the target image are close to the objects in the query image.

The above descriptions illustrate how the system retrieves images according to the query image's color feature and its spatial semantics. The following example explains how to get additional images to predict future variation trends.

Example 1. Assume there are total n objects $\{O_1, O_2, ..., O_n\}$ cut from the query image.

Step 1. Select one object each time and the variation pattern that its antecedent part is the selected object will be selected. For example, assume O_1 is the selected object, then all the variation pattern has the form $O_1 \Rightarrow X$ will be selected. The consequent part X may be any possible objects.

Step 2. Repeat step 1 until each object in $\{O_1, O_2, ..., O_n\}$ is checked.

Step 3. Get 2 objects each time, and the variation pattern that its antecedent part is the selected objects will be selected. For example, assume O_1, O_2 are the selected objects and all variation patterns such as $O_1, O_2 \Rightarrow X$ will be selected. The consequent part X may be any possible objects.

Step 4. Repeat step 3 until all combinations of object pairs are checked.

Step 5. Get 3, 4, ..., and n objects and select all variation patterns that their antecedent parts that match the selected objects.

Step 6. Based on the selected variation patterns, list the images according to the consequent part of the pattern. For example, if $O_1 \Rightarrow X_1$ is the selected pattern, the images match the consequent part X_1 will be retrieved.

IV. Experimental Results and Discussion

This study utilized ocean salinity and temperature image at depth of 100 meters from January 2001 to December 2006. A database was built comprising these images. A set of concentric circles was used as a reference model as it allows location information for objects in image to be easily defined. Taipei, Taiwan is the reference site and the radii for inner and outer circles were 900 km and 1800 km, respectively. Only the salinity or temperature variation within the concentric circles was used together with contextual information, i.e., direction and distance relative to Taipei.

For each image in the database, the objects (salinity variations and temperature variations) were cut according to their color. The location information was annotated to its corresponding object. Fig. 5 shows the salinity variations cut from an image. The same monthly variations are defined as a single transaction. Table I shows the market-basket type transaction set of salinity and temperature variations. Each transaction is recorded with spatial and temporal information. Table II shows the intervals that the salinity and temperature variations are mapped to. NOR events are used to classify situations where no variations occur in a specific sub-area. Table III shows the results of the quantitative attributes in Table I mapped to several intervals.

The maxspan window size is set to 6 months. In order to reduce the computational complexity, the PrefixSpan based algorithm is employed to find large inter-itemsets (the minimum support is set to 25%). Inter-transaction association rules are derived from these large inter-itemsets as the minimum confidence is set to 70%. Table IV shows part of the discovered inter-transaction association rules. For example, the rule, H1SRL(0) -> A2SRL(3), means that if salinity rose from 0.05 psu to 0.15 psu in the area that is in the west-south sector near Taiwan, then salinity will rise from 0.05 psu to 0.15 psu in the east sector far away from Taiwan the next 3 months.

Next, the experiment used salinity image of January 2007 as the query image. Fig. 6 shows that there were a total of 8 variations cut from the query image. Table V shows the radius and angle to x-axis for each sub-zone in the concentric circles. The threshold T_{color} of measuring the color distance between objects is set to 5, and $T_{location}$ is set to 200. The low color distance threshold ensures the color is very close between two objects, and the location distance threshold limited the two objects either at identical location or at neighbor zones. T_{image} was set to 60% that means at least two objects are needed in the target image to be close to the objects in the query image. Fig. 7 shows partial results of image retrieval. Only images that have spatial semantics similar to the query image were retrieved.

Fig. 8 shows that the additional images were retrieved according to the variation patterns mined by the inter-transaction association rules mining algorithm. One can see that the object "salinity rose little (SRL)" can be found in H1 sub-zone in the query image (Fig. 6). According to the salinity variation pattern "H1SRL(0)->A2SRL(3)", the system can retrieve images to predict future salinity variations. In Fig. 8, the images from January 2001 and February 2001 are from Fig. 7, and the images from April 2001 and May 2001 are the retrieval results according to the above pattern. The image from April 2007 is also shown to verify the effectiveness of the system.

If the spatial semantics are not considered during retrieval, the system will get a lot of images that are similar to the query image according to colors. This means that users have to manually browse the retrieved images, which is time-consuming and inefficient. Besides, if the system cannot provide information of future variation trend, it is much harder to monitor the ocean environment.

V. CONCLUSIONS

This study proposes a strategy where concentric circles are used as a reference model to annotate location information to the objects in image. This allows the spatial semantics to be maintained for either the images in database or the query image. In order to obtain additional information from images that are used to predict future variation trend, an improved inter-transaction association rules algorithm is employed to discover salinity and temperature variation patterns. In query stage, images similar to the query image in both color and spatial semantics are retrieved. The retrieval results are more accurate. The proposed intelligent image retrieval system can get more images to help user predict future salinity or temperature variation trends.

ACKNOWLEDGMENT

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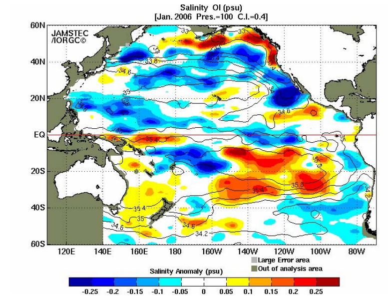

Figure 1. Monthly salinity image downloaded from Argo.

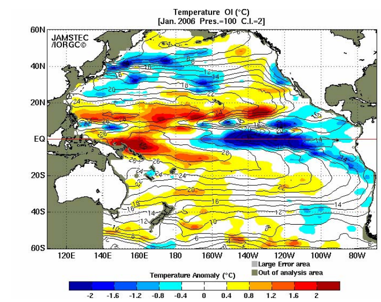

Figure 2. Monthly temperature image downloaded from Argo.

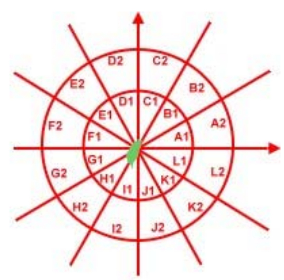

Figure 3. The reference model with concentric circles surrounding Taipei, Taiwan.

Name	Gender	Age
Peter	Male	35
Mary	Female	52
...	...	...

(a). The original table.

Name	Gender	Young	Old
Peter	0	1	0
Mary	1	0	1
...	...	...	...

(b). The "Age" attribute is mapped to two intervals, "Young" and "Old".

Figure 4. An example of quantitative attribute transformation.

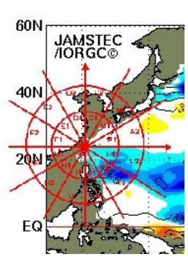

Figure 5. Salinity variations occurred in sub-zone K1, K2, L1 and L2.

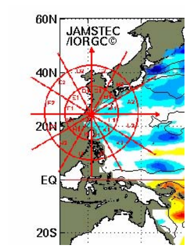

Figure 6. The salinity image of 2007/01 is used as the query image.

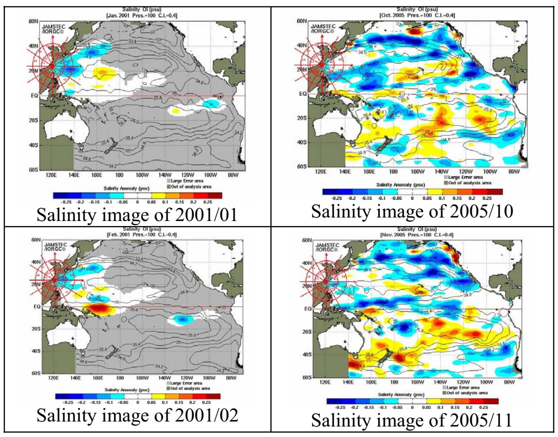

Figure 7. Partial results of image retrieval. The retrieved images are similar to the image in Fig. 6.

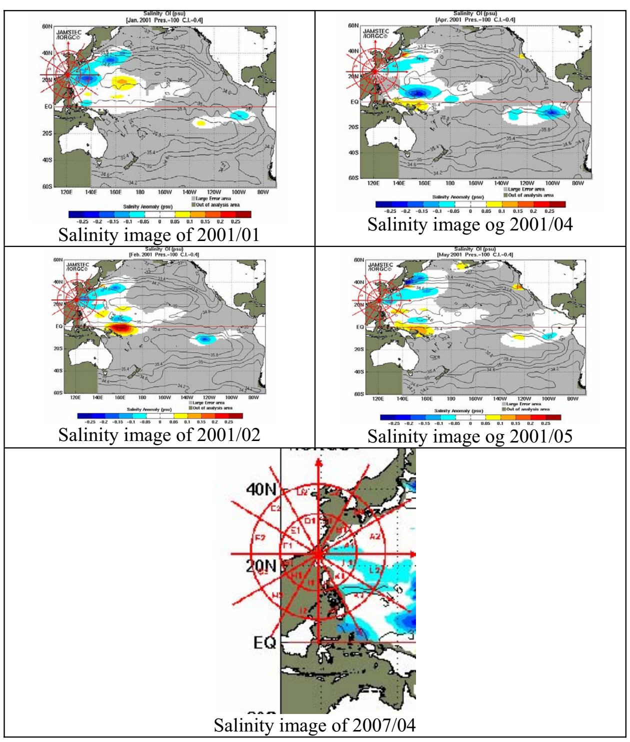

Figure 8. According to the salinity variation pattern "H1SRL(0)->A2SRL(3)", the system can retrieve images to predict future salinity variations.

TABLE I. A DATABASE WITH QUANTITATIVE ATTRIBUTES "SALINITY VARIATION" AND "TEMPERATURE VARIATION".

Date	Salinity variation in A1 (psu)	Salinity variation in A2 (psu)	…
2001/01	-0.05	-0.05	…
2001/02	-0.10	-0.10	…
2001/03	0.00	0.00	…
…	…	…	…

TABLE II. THE MAPPING INTERVALS FOR SALINITY AND TEMPERATURE QUANTITATIVE VALUES.

Mapping intervals (event)	Meaning
TRL	Temperature rose little [0.4, 1.2], unit:℃
TDL	Temperature dropped little [-1.2, -0.4], unit:℃
TRM	Temperature rose much (1.2, 2], unit:℃
TDM	Temperature dropped much [-2, -1.2), unit:℃
SRL	Salinity rose little [0.05, 0.15], unit: psu
SDL	Salinity dropped little [-0.15, -0.05], unit: psu
SRM	Salinity rose much (0.15, 0.25], unit: psu
SDM	Salinity dropped much [-0.25, -0.15), unit: psu
TNOR	Temperature variation in (-0.4, 0.4), unit:℃
SNOR	Salinity variation in (-0.05, 0.05), unit: psu

TABLE III. THE "SALINITY VARIATION" AND "TEMPERATURE VARIATION" MAPPING RESULTS FROM TABLE I.

Date	Salinity variation in A1	Salinity variation in A2	…
2001/01	SDL	SDL	…
2001/02	SDL	SDL	…
2001/03	SNOR	SNOR	…
…	…	…	…

TABLE IV. PARTIAL DISCOVERED INTER-TRANSACTION ASSOCIATION RULES.

2-item rules	H1SRL(0) -> A2SRL(3) A1SRL(0) -> A2SRL(1) A1SRL(0) -> A2SRL(2) A1SRL(0) -> A2SRL(3) …
3-item rules	I1TRL(0) J1TRL(0) -> L2TNOR(1) I1TRL(0) J1TRL(0) -> B1TNOR(1) …
…	…

TABLE V. THE RADIUS AND ANGLE TO X-AXIS FOR EACH SUB-ZONE IN THE CONCENTRIC CIRCLES.

Sub-Zone	**A1**	**B1**	**C1**	**D1**	**E1**	**F1**
Angle	30	60	90	120	150	180
Radius	900	900	900	900	900	900
Sub-Zone	**G1**	**H1**	**I1**	**J1**	**K1**	**L1**
Angle	210	240	270	300	330	360
Radius	900	900	900	900	900	900
Sub-Zone	**A2**	**B2**	**C2**	**D2**	**E2**	**F2**
Angle	30	60	90	120	150	180
Radius	1800	1800	1800	1800	1800	1800
Sub-Zone	**G2**	**H2**	**I2**	**J2**	**K2**	**L2**
Angle	210	240	270	300	330	360
Radius	1800	1800	1800	1800	1800	1800