MODELLING AND VISUALISATION OF FISH AGGREGATIONS USING 3D DELAUNAY TRIANGULATION AND ALPHA SHAPES

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ABSTRACT: This paper presents a new method for modelling and visualising fish aggregations in a 3D space. The concepts related to the construction of the 3D model, particularly the Delaunay triangulation generalised for a 3D space and the 3D clustering algorithm called α-shapes, are discussed. Then, the proposed approach is applied to an acoustic fisheries dataset obtained from split-beam echosounder to extract and visualise fish aggregations. Finally, some results are presented, and the benefits and limitations of the proposed 3D model are discussed.

KEYWORDS: FISH AGGREGATIONS, 3D MODELLING, 3D DELAUNAY TRIANGULATION, CLUSTERING, 3D ALPHA SHAPES ALGORITHM

INTRODUCTION

Many of the world's fish stocks have declined during the past decades. For example, Atlantic Cod stocks collapsed dramatically between 1960 and the early 1990s in the Northwest Atlantic area off Newfoundland and Labrador, with no significant reconstruction since then (Rose, 2004). Stock decline in this region can be mostly explained by overfishing, but may also be related to other factors such as changes in the oceans' conditions and in the trophic chain. Researchers have been studying this problem for many years, trying to develop new strategies to help stock recovery. An understanding of the spatial and temporal dynamics of fish stocks is essential to achieve such a goal.

The dynamics of fish stocks include, among other features, aggregation and disaggregation of fishes at different spatial and temporal scales. An aggregation can be defined as a number of fish that have come together and form a group having a much higher density than in other areas in a given region. The phenomenon of aggregation and disaggregation for many species is a fundamental bioecological property typically related to reproduction, feeding and predator defence. Changes in aggregation-disaggregation properties may be informative about stock condition (see for instance Rose, 1993).

Currently, fish aggregations and disaggregations are not well understood. This problem is partly due to the fact that although fish aggregations are three-dimensional (3D) phenomena, they are traditionally represented and studied in 2D using Geographical Infomation Systems (GIS) and other mapping tools which causes loss of valuable information and precision. With recent technological advances, researchers are now able to capture and observe fisheries data in three dimensions. Indeed, acoustic technologies are becoming increasingly accurate in measuring fish aggregations in a water column (Gerlotto et al., 1999) as well as tracking individual fishes in some cases. In order to better represent, visualise, analyse and understand fish aggregations in 3D space, users and decision makers need a spatial data model that can handle three-dimensional fisheries data. There are currently some tools providing the capacity to visualise 3D fisheries data, but such tools are often limited as they do not offer full 3D spatial analysis capabilities. Hence, the development of an efficient representation, visualisation and spatial analysis tool for fisheries data may assist users and decision makers to better estimate fish distribution, density and abundance. Moreover, this tool may help marine biologists to study the behaviour of individual fishes and their displacement within fish aggregations over time, the internal structure of the fish aggregations and the factors that influence the aggregation-disaggregation of fish schools over time.

This paper proposes a 3D data structure based on the 3D Delaunay triangulation for modelling and visualising fish aggregations and their evolution in time. First, the existing methods for the representation of fish aggregations, mostly in 2D, are revised and their limitations are discussed. Then, a new method for the representation of fish aggregations in 3D, based on the Delaunay triangulation and on 3D clustering method using α-shapes algorithm, is proposed. Next, the important aspects of this data structure and the related algorithms for its construction are described. Finally, an overview of the possible applications of the proposed approach for fish aggregations modelling and analysis is given and the limits of this approach are briefly discussed.

STATE OF THE ART

Fish Aggregations Representation
Many approaches were proposed for the representation of fish aggregations, but despite this fact, this phenomenon remains poorly documented, mainly at local scales. As previously mentioned, this situation is partially related to the fact that although fish aggregations are 3D phenomena, they are often modelled in 2D using GIS. Currently, the most widespread method to represent fish aggregations at a regional scale consists in mapping the abundance of fishes on thematic maps using proportional symbols, such as in figure 1(a). Fish aggregations are also represented on maps where fish densities are interpolated. Moreover, some other techniques such as spatial statistics or geostatistics, frequently applied in GIS field, can be used to mathematically characterise fish aggregations (see figure 1(b)). Valavanis (2002) observed that geostatistics are commonly used in fisheries GIS applications to describe spatial relationships among sample data, predict spatiotemporal phenomena, and interpolate values at unsampled locations.

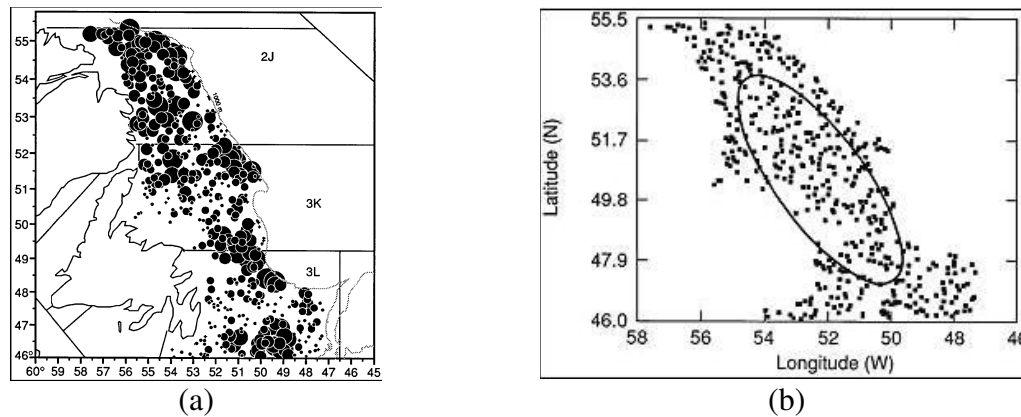|	
(a)	(b)

Figure 1. (a) Thematic map where the abundance of fishes is shown using proportional symbols, (b) Representation of fish aggregations for the same region but for a different year using an ellipse (Atkinson *et al.,* 1997)

Although most researchers in fisheries management recognize that the use of commercial 2D GIS can bring important benefits to their fields, they agree that these tools are limited for realistic representation of marine environment and its resources. Indeed, 2D representations causes the loss of important information related to the 3rd dimension. Thus, researchers generally admit that a tool with 3D dynamic capabilities would be better adapted to their analyses since it would represent the real nature of their data. For example, Wright & Bartlett (2000) pointed out that "much geography, particularly in the coastal and marine realms, requires all three spatial dimensions to be considered equally, whether simply for visualisation, or else for more demanding spatial analyses."

3D Modelling

Space can be seen as a continuous field or entirely filled by discrete objects. The two most popular methods for representing space are based on vector and raster methods. Vector representation defines objects with a set of points, lines, polygons and polyhedra with their topological relations, while raster representation describes objects by a set of regularly distributed pixels or voxels. To represent 3D objects, we need an extension of these representations to a 3D space. There are several techniques and data structures to achieve this goal. Many of them only characterize the surface of the objects, while others can be used for modelling their interior (Li, 2000).

For the representation of a continuous phenomenon, raster representation is the most commonly used in GIS applications. In 3D, the raster data structure divides space into regular regions such as voxels. The main advantage of this technique is its simplicity. However, this structure can handle, but with great difficulties, data that are irregularly distributed, especially if a fine resolution is used. Indeed, in this case, the size of the data structure can become enormous. Another way to model 3D phenomena is to use hierarchical tessellations such as octree data structures (Samet, 1984), where a tree is created. One of the problems of this structure is that, when the data distribution is

irregular, the tree can be unbalanced (de Berg *et al*., 2000). Irregular tessellations as the Delaunay triangulation can also be used to model a 3D phenomenon that is observed with a set of irregularly distributed points. The main advantage of these tessellations is that they usually follow the outline of the data points and that they can be adapted to the point distribution. The partition of space made with irregular tessellations is potentially better than that resulting from regular tessellations or octree techniques because there are no constraints involved when subdividing the space (Ledoux & Gold, 2007).

Even if there are several techniques for the modelling of three-dimensional objects, 3D tools are mostly used for graphic presentation of data and visualisation. Moreover, they are often very limited for spatial analysis. Wright & Bartlett (2000) observed that "some attempts have been made to extend capability into the third dimension, most notably with Intergraph's Voxel Analyst, but so far such developments, while welcome, are still limited in the functions they provide."

PROPOSED APPROACH FOR FISH AGGREGATIONS REPRESENTATION

The approach that we propose for the 3D modelling and representation of fish aggregations is based on the 3D Delaunay triangulation coupled with 3D clustering techniques. Delaunay triangulation has been frequently used for two-dimensional GIS-related problems such as digital terrain modelling (Li *et al*., 2005) and for three-dimensional applications in several domains such as in geology. The Delaunay triangulation has been shown to have many advantages over raster and other spatial data structures, particularly because it can deal with irregularly spaced data points.

In order to carry out the spatial modelling of fish aggregations in a 3D space, two main steps are performed. First, 3D data points representing fish observations are used for the construction of the 3D Delaunay triangulation. For this purpose, the generalisation to 3D of the concepts of the 2D Delaunay triangulation is employed. The 3D Delaunay triangulation of the dataset is constructed using an incremental algorithm. Following the creation of the 3D tetrahedral model, the 3D α-shapes algorithm (Edelsbrunner & Mücke, 1994), which is based on the 3D Delaunay triangulation, is applied to detect and extract fish aggregations. This algorithm has initially been developed for shape reconstruction from dense unorganized datasets, but for this research, it is implemented for the clustering of fish aggregations in 3D. Using the 3D α-shapes algorithm, data points that belong to the same "object", a fish school for instance, are identified and the fish aggregations are then reconstructed and visualised (Buelens *et al*., 2004). The data structure used in this work also has the useful properties of being dynamic, and even kinetic. This means that objects (i.e. points) can be added, deleted, and even moved, with efficient algorithms (Mostafavi *et al*., 2003, Ledoux & Gold, 2006). Hence, the data structure could be locally adapted to get an interactive model.

Step 1: 3D Delaunay Triangulation

As previously mentioned, the starting point of the approach is the construction of the 3D Delaunay triangulation. For a set of points in 3D space, the Delaunay triangulation divides the space into tetrahedra which have empty circumspheres, i.e. which do not contain any other point of the triangulation. This property is known as Delaunay criterion for 3D triangulation. Each vertex of the 3D Delaunay triangulation is a point of the data set. Each tetrahedron of the 3D Delaunay triangulation has exactly four vertices and four adjacent tetrahedra, except the points that are at the boundary of the triangulation. Tetrahedra completely fill the space without overlapping.

To build the Delaunay triangulation in 3D, various methods such as the divide and conquer method, or the incremental method, can be employed. However, they do not all allow local modifications in the model. The incremental method, which is discussed in detail in Ledoux & Gold (2006), is a dynamic method where local modifications such as insertion, deletion or movement of points are possible. Thus, the development of the model by the incremental method is done by incorporating the points one by one in the model and by updating the triangulation after each insertion in order to make sure that every tetrahedron respects the Delaunay criterion.

The construction of the 3D Delaunay triangulation includes several steps such as the initialisation of the model, insertion of a new point into the model, search for a point in the model and optimisation of the model for the criterion of 3D Delaunay tetrahedra. The first step consists in initiating the model by creating a tetrahedron that contains all the points in the studied area (universal tetrahedron). Then, each point in the dataset is inserted in the triangulation one by one. For this purpose, a search operation is carried out in order to locate the tetrahedron containing the new point. Then, the point is inserted in the tetrahedron, which is subdivided into four new tetrahedra. All of the new tetrahedra created must be tested in order to make sure that they respect the Delaunay criterion. If it is not the case, the tetrahedra must be optimized by topological operations (flips) (Edelsbrunner & Shah, 1996). The sequence of the flips is controlled by a stack structure which contains all the tetrahedra which were not tested yet. The stack starts with the four new tetrahedrons created by the insertion of the point and each time a flip is done, the new tetrahedra are added to the stack. When the stack is empty, it means that all the tetrahedra forming the triangulation are Delaunay. This procedure is repeated until all the points in the dataset are inserted in the triangulation. At the end of the process, we get the 3D data structure that constitutes the basis for the 3D fish aggregations model.

Step 2: 3D Clustering with the Alpha Shapes Algorithm
After the construction of the Delaunay triangulation, the obtained 3D model must be refined to get the fish aggregations. This step is performed using clustering algorithm to classify objects into different groups sharing common characteristics. These groups are called clusters. The clusters are often defined by measures of distance thus gathering the data having proximity in space. Many techniques can be used to perform clustering from a set of objects (Jain *et al*., 1999). The α-shapes algorithm, which is one of these techniques (Buelens *et al*., 2004), is often used to identify shapes that are implied by a set

of points irregularly distributed in the space. The proximity between the points in space is defined using the 3D Delaunay triangulation where the topological relations between objects are explicitly stored and can be retrieved using the underlying data structure. In order to model the fish aggregations, the α-shapes algorithm can rely on 3D triangulation of the fisheries data obtained from acoustic surveys to detect and represent fish aggregations.

To figure out the concept of α-shapes of a distribution of points, Edelsbrunner & Mücke (1994) suggest that one can think of a 3D space filled with Styrofoam containing the points of a dataset made of more solid material. Using a spherical eraser with radius α, we carve out all the Styrofoam we can reach without taking any point. The resulting object will be bounded by arcs, caps and points and is not guaranteed to be connected. Then, the α-shape of the point distribution is obtained when we substitute the arcs by straight edges and the caps by flat triangles. In this manner, one can understand that if the radius of the eraser gets smaller, more Styrofoam will be removed.

The α-shapes can also be defined as a generalisation of the convex hull of a set of points. The α-shapes are the family of shapes derived from Delaunay triangulation parameterised by α. The α-shape is neither necessarily convex, nor essentially connected. For a given value of α, where $0 < \alpha < \infty$, the α-shape is composed by all the elements of the 3D Delaunay triangulation with a circumsphere that do not contain any point of the dataset. Notice on figure 2(a) that for $\alpha = \infty$, the α-shape is identical to the convex hull of the distribution of points. However, as the α value decreases, the α-shape shrinks and gradually forms cavities, tunnels and even holes such as in figure 2(b). When $\alpha = 0$, we can observe on figure 2(c) that the corresponding α-shape is composed of the points of the dataset.
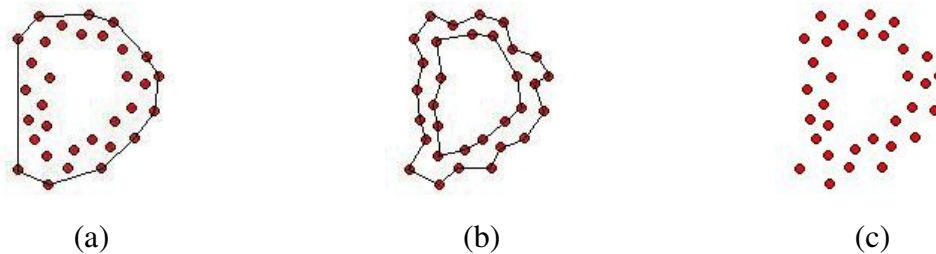

| (a) | (b) | (c) |

Figure 2. Intuitive 2D α-shape

The computation of the α-shape of a set of points involves several steps and geometric tests. In order to implement the α-shapes in our 3D model, we have used the 3D α-shapes algorithm as described by Edelsbrunner & Mücke (1994). Based on 3D Delaunay triangulation, the algorithm inspects each tetrahedron and lower-dimensional elements (i.e. triangle, edge and point) and calculates the radius of its smallest circumsphere to find the boundaries of its α-interval or α-thresholds. Indeed, for any element of the 3D Delaunay triangulation, there is an interval such as the element become member of the α-shape if and only if the α value belongs to its interval. Two geometric tests must be

defined for the calculation of the intervals. First, the lower boundary of the interval for an element of the 3D Delaunay triangulation corresponds to the radius of its smallest empty circumsphere. Hence a test to check whether or not the circumsphere of an element is empty is needed. Second, a test to verify if an element lies on the convex hull is required. For this test, let's assume that the 3D Delaunay triangulation algorithm returns, for every element, whether or not it lies on the boundary of the convex hull. If the element is on the convex hull, then the higher boundary of its interval is ∞. On the other hand, if the element is not on the convex hull, the higher boundary of its interval is calculated taking in account all the tetrahedra containing the element. The higher boundary of the interval then corresponds to the radius of the biggest circumsphere of the tetrahedra. Finally, when the optimal α value is found, only the elements that belong to objects such as fish aggregations or ocean bottom are drawn in the 3D model.

APPLICATION TO FISHERIES DATA

To apply the approach to fisheries data, we used an acoustic dataset from split-beam echosounder describing the dynamics of aggregation-disaggregation of a group of coastal Northwest Atlantic cod at high resolution. When these data are displayed in echograms (see figure 3), the distribution pattern of fish aggregations can be detected visually. For this work, only the spatial coordinates of the soundings are taken in account. The result is a set of irregularly distributed points with three independent coordinates (latitude, longitude and depth). The points are dense in areas where there are objects as fish aggregations or ocean bottom and sparse everywhere else.
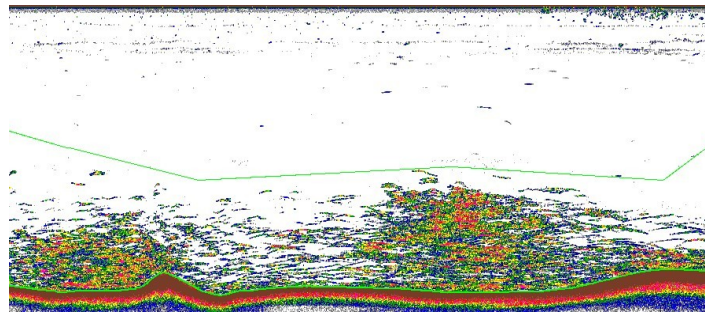

Figure 3. Echogram of acoustic data showing the ocean seabed at the bottom, individual and aggregations of fishes (Atlantic cod) above the seabed, and the water column above it

Application of the proposed method for 3D fish aggregations modelling

Modelling of the fisheries data using 3D α-shapes can help detecting the presence of fish aggregations in large acoustic data files where individual fishes' positions are known at a given time. It should be mentioned that, in order to find fish aggregations from acoustic datasets using the 3D α-shapes algorithm, the resolution of these acoustic data should be very high. Figure 4 shows the results obtained from the application of the proposed method for 3D modelling and visualisation of the fish aggregations.
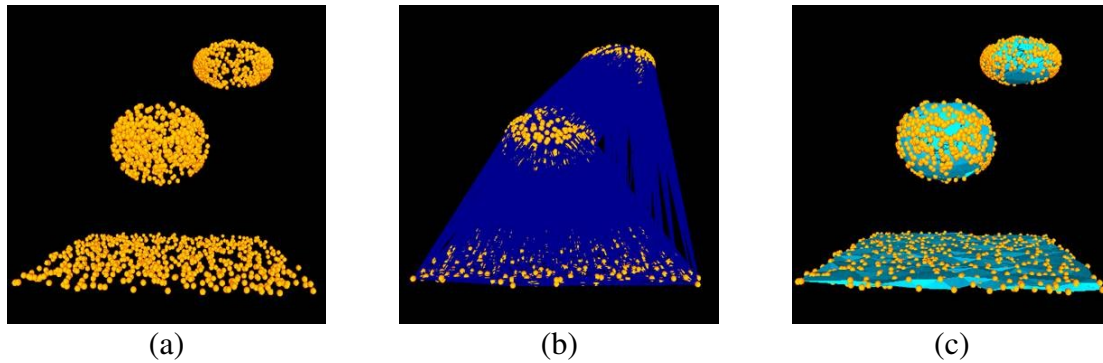
Figure 4. (a) Test dataset containing two fish aggregations and the ocean bottom, (b) Result obtained with 3D Delaunay triangulation, (c) Result obtained with 3D α-shapes algorithm

The 3D model obtained from the proposed approach offers new possibilities to display and analyse acoustic data in 3D and to observe fish aggregations more effectively. For instance, this kind of realistic visualisation could be an effective way to assist the fisheries and marine environment managers to better understand and manage marine resources. Furthermore, the 3D representations produced by the proposed approach can be visualized to extract some other useful information. For example, the morphological properties of fish aggregations such their position and spatial extension, their shape, their volume or other measurements can easily be established using these models. In the field of fisheries, the volume of fish aggregations is an important parameter for the calculation of the biomass. However, at present, there exists few software, already available but expensive, providing some of this kind of information with a high degree of accuracy.

In addition to the characterization of fish aggregations, the benefits of the resulting 3D model are that it facilitates the analysis of the observed dynamics of fishes. Indeed, an aggregation is a process in which fishes enter and leave constantly. Hence, the 3D model allows describing fish aggregations spatial and temporal patterns by visualising the actual structure of the fish aggregation and the location of individuals in it as it changes over time. For example, the changes in the aggregation morphology are quantified on a monthly scale and seasonal differences in distribution patterns are displayed and studied using dynamic visualisation techniques. The changes in the fish aggregations are shown by a series of snapshot where each snapshot is a representation of the fish aggregations studied at a given time. Moreover, further developments could lead to understand how those changes are related to the environmental changes in which the fish live by adding information on the ocean's parameters into the model. Another application of the 3D model obtained is to better measure the 3D physical aspect or swimming position of individual fishes that affects the quantitative acoustic measures of density and abundance.

Limits of the approach
Although the 3D modelling of the fisheries data using 3D α-shapes algorithm has many advantages, it also has some limitations as well. First, it can be difficult to determine the optimal α parameter for the modelling of fish aggregations. Indeed, the α parameter must be determined by trial-and-error because there is no explicit rule. But with the

visualisation interface, we can see how the α-shape changes when we modify the parameter. Moreover, as the α-shapes algorithm is based on distances between data points to determine which ones are connected together, it could be difficult to find a satisfying α value if the concentrations of points which we identify as fish aggregations show very different densities. Another problem of the suggested approach is that it does not take in account, at present, the dynamic nature of the fisheries data. However, it could be done if we recomputed after each move the intervals for every element involved in the move. Finally, the uncertainty associated to the data is not shown in the model.

CONCLUSION

The main objective of this work was to develop an approach to create a 3D model of fish aggregations suitable for analysis, since with classical 2D representations this cannot be easily performed. We have studied the concepts related to 3D Delaunay triangulation and 3D α-shapes algorithm and discussed some of their potential uses with acoustic fisheries data. The approach suggested in this work combines these two algorithms and brings some benefit for the representation of fish aggregations, particularly to observe dynamics of fishes through time. However, few limitations, mostly due to the α-shapes algorithm, have been noted and should be addressed. Both algorithms have already been implemented in Delphi language but some improvements are still possible. Further works should study the evolution of the fish aggregations with respect to ocean's physical parameters such as temperature and salinity.

ACKNOWLEDGEMENTS

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