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3D Stockpile Modelling to Improve the Quality Control in Iron Ore Handling

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Abstract -This paper describes a 3D stockpile modelling algorithm to improve quality control and increase operational efficiency in iron ore handling. The 3D model, generated from real measuring data, approximates a stockpile using a group of 3D volumetric element, which able to store information inside it, such as quality compositions of the ore. By associating this model with the cutting geometry of a real reclaimer, the quality of reclaimed material can be calculated and it is then possible to adjust the reclaiming according to the end objective with an optimised and continuous machine movement. This will help convert the current reactive and discontinuous reclaiming procedure into a proactive and unbroken mode. The proposed modelling algorithm was tested on a scaled down stockpile model and results demonstrate good, precise and fast performances.

Keywords**:** Stockpile modelling, Laser scanning, Voxelziation, Quality control.

1. Introduction

Iron ore quality is evaluated by two measures during exports: the quality composition of the ore and the short-term grading consistency. The first one represents the composition of several minerals in the ore body (e.g. iron, alumina, silica and phosphorus). The second one evaluates short-term variations of the quality composition, for instant, differences in quality between each ship transport. To reduce fluctuations among deliveries, iron ore is normally stockpiled into different geometric shapes layer-by-layer before uploading onto ships. When a batch of iron ore is transported to a stockpile, the ore is stacked selectively according to the quality composition so that it would optimize the homogeneity in quality of that stockpile. A complete stockpile may contain more than hundred thin layers. The mix of these layers occurs when the stockpile is recovered by a reclaimer slice-by-slice. For example, when a bucket wheel reclaimer (BWR) is used, materials in different layers are excavated almost simultaneously by the rotating bucket and mixed inside the wheel. Thereby, the fluctuation of delivered material is decreased. The entire process is called the blending operation in iron ore handling.

Bed blending theory was firstly discussed by Gerstel in 1977 (Gerstel, 1977). Not far from that, Gy presented a new bed blending theory to suppress the continuous input variations for a steady output quality grade (Gy, 1981). Several crucial assumptions were made to convert the quality of the material flow on the conveyor belt into a discrete random variable. The average content of iron oxide, its standard deviation and the covariance in the material flow can be represented by probability density functions. Using these functions, the quality of a stockpile can be calculated. They also defined the blending efficiency of a pile as the ratio of the standard deviations of the input and of the output flow of the pile. However, some assumptions are not always justifiable due to a large number of variables involved in the blending. For example, the quality of the ore body and the flowing speeds of the material at the observing point.

Several approaches have been proposed to optimize stacking operations. Such as the goal programming (Lyu et al., 1995), the genetic algorithm (Dahal et al., 2003) and the pain function (Everett, 1996). These studies aim to use mathematical equations to assist operators with decisionmaking tasks. The optimal strategy was to minimize increments in percentage of impurities inside a stockpile. Simulation results indicated that these approaches had cumulative effects in improving the quality control. However, quality compositions of the material are assumed to be known exactly before the stacking. This assumption is not always true in real practices because stockpiles are also used as buffers between the reception and the shipment. Iron ore is expected to be stacked immediately after the crushing and screening operations.

Lu and Myo described an ideal triangular prism model of the middle section of a chevron stockpile to optimize the reclaiming operation. The prism model was divided horizontally according to the bench height and then vertically along the stacking directions. Different sized voxels are obtained after the partition. The grades of these voxels were assumed to be known in advance. The optimization aimed to minimize the BWR movement between two stockpiles by reclaiming optimal voxels to achieve predefined quality and quantity combinations (Lu and Myo, 2011). To predict the quality in the conical ends, Robinson and Ross used three differential equations to describe the shape of the conical end (Robinson and Ross, 1991). By solving these differential equations, a mathematical model of the stockpile was obtained. This model provides a method to calculate the volume and the grade of a stockpile using simple equations. However one weakness of such ideal geometric models is they cannot faithfully represent a real stockpile. Quality calculated based on such ideal models may be not accurate.

Currently, stockpiles are modelled mathematically or geometrically in most stockpile management systems. With mathematic models, it is assumed that the quality composition is known before stacking operations and such quality information has the highest degree of accuracy. However, these assumptions are hard to be satisfied using current sampling and element analysis techniques. The chemical composition of the ore body cannot be analysed until the ore is crushed and a complete analysis costs one to two hours. To save storage space, iron ore may be stacked before the assay results are obtained. Under such circumstance, the quality data used for stacking are adapted from previous sampling results. If any mixing or crushing operations are applied, such data may be not up to date. This problem may happen more frequently if a port receives mined ore directly from several mining sites. With geometric models, most of them are based on the ideal geometric shape of a stockpile or without ability to update the model in real-time. In a stockyard, frequently performed stacking and reclaiming operations change the geometric shape of the pile and as well as the quality distribution within the pile. As a consequence, the quality grade of the stockpile becomes more difficult to estimate over time using current geometric models. To summarize, the building of stockpile models has far-reaching implications for the quality control purpose.

In this paper, the authors present a method to acquire profiles of a chevron stockpile and to build a voxel model of the stockpile for quality calculation in real-time. This model is not represented in terms of surface and edges but a group of voxels (volumetric pixels). Each voxel is in a cubic shape to store measureable properties (e.g., quality, quantity and density) and with an index number assigned to it. By recording real geometric shape of a stockpile and building the 3D model, it is possible to utilize quality assay results, which has the highest degree of accuracy, to re-calculate the quality of an entire stockpile. Also, by integrating positional data together with quality information contained within the voxel models, it is then possible to predict the tonnage and quality grade during reclaiming operations with a greater degree of accuracy. The authors believe this model is able to assist operators to make logical and efficient decision for day-to-day operations.

The rest of this paper is organized as follows. Section II presents the automatic algorithms used to generate this 3D model. Section III gives the experiment setups and results with discussions. Finally, conclusions and suggestions are presented in Section IV.

2. Stockpile Modelling

Nowadays, laser has becoming a common method for range measurements and object modelling. Its performance has been proven to be extremely good even in some extreme conditions, such as an underground mining tunnel (Scheding et al., 1997). Therefore, a 2D laser scanner (Sick LMS200) was adapted in this paper for the research purpose. It is expected to be mounted to the end of the boom of a BWR to scan profiles of a stockpile. The position of the laser scanner is proposed to be localized using the unscented Kalman Filter (UKF). According to simulation results, the average position errors are better than 15cm using the UKF based sensor data fusion (Zhao et al., 2012a). Before mounting the laser scanning device to a BWR, a prototype 3 DOF laser scanning system (Lu et al., 2011) was firstly adapted to test the modelling algorithms. In this system, the LMS200 2D scanner measures profiles of a stockpile along the *X* and *Y* axis and a distance sensor (O1d100) measures the travelling distance of the LMS200 along the *Z* axis as shown in Fig. 1. A complete scan of a stockpile (or a layer of a stockpile) in *X*, *Y* and Z axis is stored by three 2D $m \times n$ matrices separately. The *m* and *n* represents the number of measurements obtained from LMS 200 in the *XZ* plane and from the O1d100 along *Z* axis.

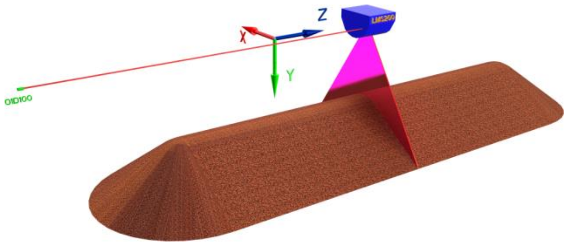

Fig. 1. A sketch drowning of the laser scanning system and the coordinator definition.

2. 1. Point Data Segmentation

A complete laser scan normally contains both the stockpile and other object, such as the ground. The segmentation aims to extract points that belong to the stockpile surface only. Considering the trade-off between the computational time and the processing precision, image processing techniques are employed. The *Y* matrix is firstly converted into a 2D grey image using Eq. (1).

$$Y_{gray} = \frac{255}{\max(Y_{(i,j)}) - \min(Y_{(i,j)})} \times \left(\left| Y_{(i,j)} \right| - \min(Y_{(i,j)}) \right) \tag{1}$$

where image $Y_{(i,j)}$ represents measurements in *Y* axis and $i = 1,\ldots,m$ and $j = 1,..n$.

Pixels in the grey image have an intensity range of possible values from 0 to 255, the ground and other small objects are closed to 0 while the stockpile and protruding objects are closed to 255. The grey image is then thresholded to isolate foreground objects (pixel value close to 255). The optimal threshold is determined by the Otsu's method (Otsu, 1975). The binary image is given by Eq. (2).

$$Y_{bw} = \begin{cases} 1 & if\ Y_{gray} \geq T_o \\ 0 & if\ Y_{gray} \leq T_o \end{cases} \tag{2}$$

where T_O is the Otsu threshold.

Because the stockpile is the largest object in the binary image, all other foreground objects can be eliminated. Mathematical morphology (MM) dilation and erosion are then applied to improve the boundary detection accuracy. The dilation combines all points in the foreground object and a structuring set through translation foreground object with respect to each element of the structuring set. A structuring element is a set used to probe or interact with a given image. The shape and size of a structuring element control the specific operation manner and result. After dilation operation, objects in the binary image are expanded and most small holes are filled. Therefore, broken segments are joined and contours are smoothed. On the contrary, the erosion operation combines two sets using vector subtraction of all elements in the structuring set. It shrinks objects and removes small objects. With the dilation, an octagonal structuring element *O* is used:

$$Y_o = Y_{bw} \oplus O = \cup_{e \in O} Y_{bw_e} \tag{3}$$

where *O* is a 15 octagonal structuring element.

With the erosion operation, a disk structuring element *D* is used:

$$Y_d = Y_o \ominus D = \cap_{e \in D} Y_{o_{-e}} \tag{4}$$

where D is a 4 disk structuring element.

After the dilation and erosion, the foreground object left in the binary image is considered to be the stockpile. Its boundary can be detected directly. By indexing the detected boundary matrix into the *X*, *Y* and *Z* matrix, the real boundary of the scanned stockpile can be obtained. Although the proposed segmentation method seems simplistic, it is fast and efficient for real-time application. The detection results will be discussed in the experiment and results section in this paper.

2. 2. Stockpile Modelling

The modelling procedure aims to partition the laser scanning data and represents the stockpile a set of discretized regular volumetric elements. It is achievable using geometric modelling techniques, such as the octree, which subdivides a space into eight octants recursively (Meagher, 1982). In a regular octree structure, each node represents a cubic region and these cubes attach to their neighbours. The node at the top of the structure is called the root and nodes at the bottom level of the tree are called leaf nodes or voxels. The subdivision starts from a bounding cube of the object and stops until a sufficient precision, which normally determined by the user, is attained. As a result, each node has exactly eight children, expect for those leaf nodes. When encoding an object using the octree, a primary property that describes the state of a node is to use empty or occupied, which means the node is free of the object or occupied by the object, respectively. Because as the voxel density increases, the memory used to maintain such dense data structure becomes prohibitive, an empty node needs no more subdivision. Therefore, in real practices, not all nodes have eight children and the tree structure always has a sparse hierarchical representation as shown in Fig. 2.

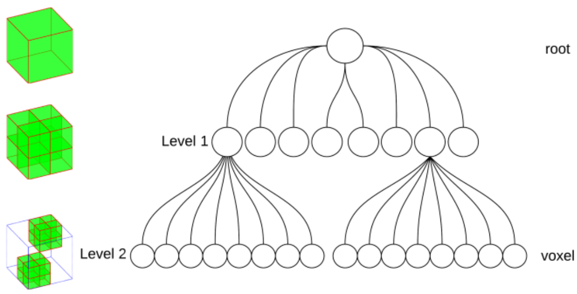

Fig. 2. A sparse octree tree structure.

In this study, the stockpile is represented as a set of points, not a surface patch or a solid object. The benefit for such representation is the state of a node can be determined straightforward. If there is no point existing in the cube, the corresponding node is at empty state and the subdivision stops. The cube itself is also deleted from the stockpile model. If point(s) does exist inside a cube, the subdivision continues until the stopping criterion the empty state is reached. However, because these points are on stockpile surface and disjoint, after the discretization, only those voxels in contact with the stockpile surface are remained and the internal space is still left empty. Furthermore, such loose representation prevents users from obtaining a high precision model. This is because if voxels are too small, they can only surround scanning points but disjoin with their neighbours. Considering the modelling procedure is a time-critical application, the following steps are proposed before the octree voxelization:

1. Determining the optimal voxel size based on users' input and the real size of the stockpile. If the side length of the voxel is smaller than the average distance between two scanning point (either in X or Y direction), a warning message will appear and the voxelization will proceed to step 2 if a confirmation is given. The side length of the l level cube is: $d_l = L_r/2^l$, where L_r is the side length of the cube at the root.
2. Increasing the resolution of the laser scanning data according to the side length. This is done by involving the previous developed modelling algorithm (Zhao et al., 2012b), which is able to interpolate more points into a single scan or simulate a scan between two laser scans with a high accuracy. This operation is optional.
3. Filling the internal space. According to octree partition strategy, if there is even one point exists inside the voxel, the voxel is considered to be occupied and will not be deleted.

Meanwhile, the voxelization procedure can be also considered as dividing an object by a sequence of planes horizontally and vertically. Therefore, if a group of points on these planes that illustrates the stockpile region can be inserted to the scanning data, a solid voxel model can be generated. This paper uses horizontal planes which are parallel with the ground as reference planes for point filling operation. Because the cutting procedure of these horizontal planes is similar to the bench reclaiming process. These planes are also called benches in this study and the bench height represents the y-coordinate of those inserted points. Using the segmentation algorithm described in previous section, the boundary of removed bench can be detected and a bonding box and a convex hull can be obtained from the detection results. The rectangular bounding box that circumscribes the stockpile boundary defines a region representing the x- and z- coordinates of the inserted point set. Hence, a set of points can be generated simply. If these points are inside the convex hull, they are also inside the stockpile, and verse viza. Points inside the convex hull are then added into the original X, Y and Z matrix respectively for voxelization. A conical stockpile after points are inserted onto the first bench is illustrated in Fig. 3. For display purpose, the inserted points are shown in blue. This operation repeats until all benches are filled with points.

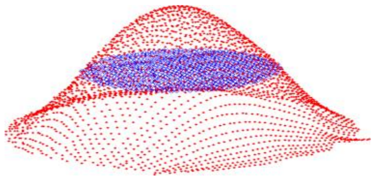

Fig. 3. Points inserted into the scanning data for voxelization.

For this specified application, the hierarchical tree structure and geometric relations between voxels may be less importation to users than the voxel itself. Hence, a reverse level-order traversal of octree is adapted. The reverse-level traversal means building the octree tree from a finest level and moving towards to the root level. The bounding coordinates of these cubes can be calculated using basic geometric relations:

$$\begin{cases} (x, y, z)_{min} = (\min(X) + i_l d_l, \min(Y) + j_l d_l, \min(Z) + k_l d_l) \\ (x, y, z)_{max} = (\min(X) + (i_l + 1)d_l, \min(Y) + (j_l + 1)d_l, \min(Z) + (k_l + 1)d_l) \end{cases} \quad (5)$$

where i_l, j_l, k_l is the index of the voxel and $i_l, j_l, k_l \in [0, 2^l]$ and l is the level of the voxel.

The coordinates of the voxel centre are:

$$(x, y, z)_{centre} = (min(X) + (i_l + \frac{1}{2})d_l, min(Y) + (j_l + \frac{1}{2})d_l, min(Z) + (k_l + \frac{1}{2})d_l) \quad (6)$$

By evaluating whether there is/are point(s) existing in these voxels, the voxel model can be obtained. Furthermore, to generate the octree, two more details are needed. The first is to identify the parents and children of these cells and the second is to detect touching and non-touching neighbours of each cell. The calculation for these two types of information is adapted from a method described by Meagher (1982). Fig. 4 shows a voxel model superimposed to stockpile surface. The upside-down building sequence reduces the computation complexity and thus saves the processing time.

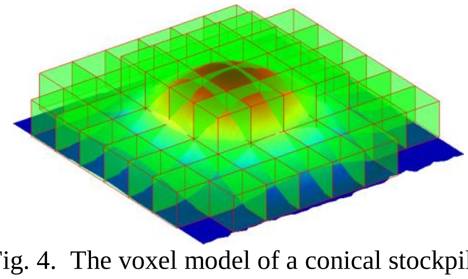

Fig. 4. The voxel model of a conical stockpile.

2. 3. Reclaiming Simulation

When a stockpile is recovered using a Bucket Wheel Reclaimer (BWR) perpendicularly to the stacking direction, a helical-shaped cutting geometry is generated by the rotation motion of the wheel and the slewing motion of the boom. Assuming that the bucket wheel is rotating at a constant speed and material is scooping evenly by the bucket during the reclaiming phase, the wheel with buckets can be considered as a circle. This circle extends together with the slewing motion of the BWR and forms a circular cylindrical surface. Under such assumption, the cutting geometry can be considered as the exterior surface of the cylindrical surface. Therefore, if the centre of a voxel is inside the surface, it is assumed to be excavated by the reclaimer. The cylindrical surface can be also represented as a set of points whose centres are in accord with the centres of the bucket wheel. Using Forward kinematic equations derived by Lu (Lu, 2009), the trajectory of the centre can be calculated. Hence, a set of points on the cylindrical surface are generated and a convex hull of this point set can be obtained using quickhull algorithm (Barber et al., 1996). Again, if centres of voxels are inside the hull, they are eliminated from the model.

3. Experiment and Results

To examine the proposed modelling algorithm, scaled down chevron stockpile model were stacked by a human operator by duplicating real stacking procedures in the laboratory environment. Material used for stacking is quartzite with a rough diameter of 7mm. These stockpiles were designed to have three layers and each layer was scanned twice by the laser after the stacking was completed (see Fig. 5). Six data sets were obtained.

Fig. 5. A stockpile stacked under the 3DOF laser scanning system.

The segmentation algorithm successfully eliminated the points outside the stockpile and detected edges of the stockpile for all data sets (see Fig. 6). Fig. 7 and Fig. 8 show two voxel modes of the stockpile.

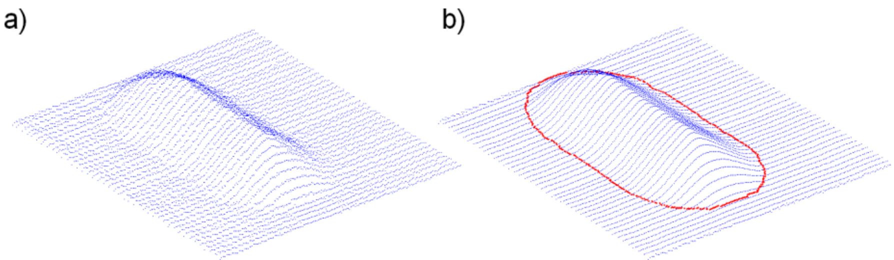

Fig. 6. Edge detected from laser measurements.

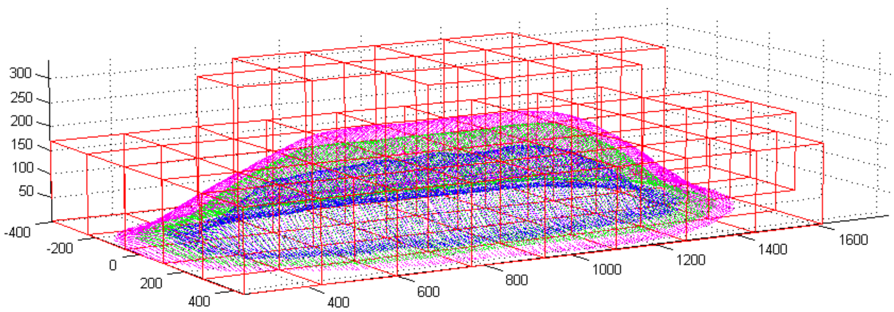

Fig. 7. A voxel model with the side length (d_{l_v}) of 162mm. Voxels are highlighted by red solid line.

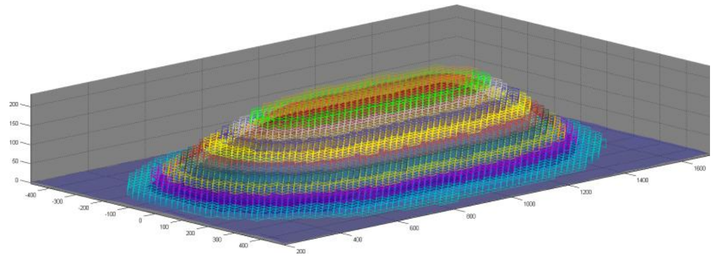

Fig. 8. A voxel model $d_{l_v} = 16.77mm$. Voxels are in different colours according to the bench height.

Table. 1. indicates the runtime of our algorithm obtained using an Intel Q9400 Quad Core CPU with 4GB Ram in the Windows 7 64-bit operation system. The side length of the voxel is 16.77mm.

Table 1. Average computation time for stockpile modelling (unit: *ms*).

	Segmentation	Point filling	Octree voxel modelling	Total
Layer 1	71.4	269.98	1955.3	2296.7
Layer 2	62.4	416.46	3323.4	3802.3
Layer 3	77.4	597.53	4622.3	5297.2

The segmentation method performed very well for the data collected in the laboratory environment. Stockpile with multiple layers was successfully separated from the ground. Because the boundary of the stockpile and the ground are connected together, this method is not able to generate very high precision results. However, these regions are considered as the 'dead storages' in real reclaiming operations. Therefore, the boundary detect results are acceptable for modelling and quality calculation purpose. The voxel model can be obtained in 5~10 second after the scanning procedure is completed. According to experiment results, the authors believe that the modelling algorithm is able to approximate the geometric shape of a real stockpile quickly and accurately.

Fig. 9 depicts a sequence of image of the reclaiming simulation using the 3D model. For display purpose, only the bench that will be recovered by the reclaimer is modelled.

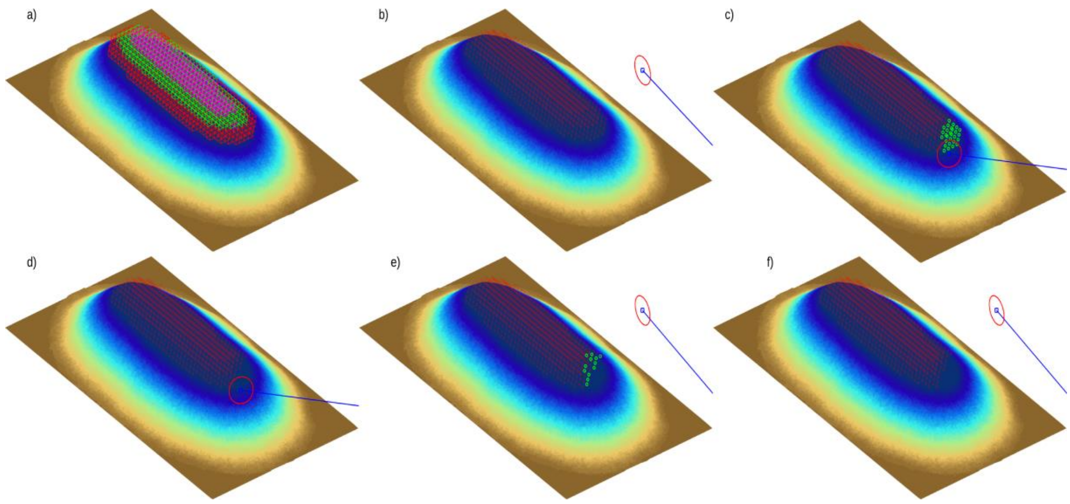

Fig. 9. Reclaiming simulation. a) A voxel model of reclaimed bench. b) Centres of the voxel c) Voxels reclaimed by the first slewing operation d) Updated voxel model e) Voxels reclaimed by the second slewing operation f) Updated voxel model.

The simulation results clear indicate that the quality of reclaimed material can be calculated if the quality of the voxel is available. The calculation of the quality inside the voxel can be achieved by a surface mode described in previous study can be used (Zhao et al., 2013). Because the quality data are defined as the weight percentage of the property in the element, if the gemetric volume of the stockpile layers inside the voxel is known, the quality is know. Given the surface function of the layer, the volume can be calculated using the double intergral.

4. Conclusion

This paper describes a 3D stockpile modelling algorithms for day-to-day material handling operations. Using image processing techniques, boundaries of the stockpile are detected from the scanning data. A voxel model is built to approximate the real stockpile. The precision of this model is adjustable according to user's requirements. Several improvements are made to the octree algorithm to reduce the modelling time. Results obtained from scale-down model indicate the modelling algorithm is applicable to full size stockpiles.

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