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ALGORITHMS AND METHODS FOR SURFACE RECONSTRUCTION OF FREEFORM SHAPE INFRASTRUCTURE OBJECTS FOR BUILDING INFORMATION MODELLING

Introduction. *The construction industry actively uses new technologies and tools, in particular, the technologies of intellectualization of management of data collection, using various types of unmanned aerial vehicles (UAVs). The development of these technologies is not an exception, on the contrary, it is actively used, both as part of the building information modeling system as well as without full integration into similar information complexes. To improve the effectiveness of quality control and monitoring, methods of using drones of various types to collect data for creating BIM (Building Information Model) models have been created. 3D models of buildings are created with the help of drones using active LIDAR (Light Identification, Detection and Ranging) sensors, which require the use of surface reconstruction algorithms from point clouds. The article provides an attempt to research algorithms, combinations of algorithms, and approaches to their combination when applied to intelligent systems based on UAVs.*

The purpose of the paper *is to investigate surface reconstruction algorithms from a cloud of points obtained using methods of laser terrain scanning and analysis of visual data obtained from an unmanned aerial vehicle and to determine the conditions for their effective combined use for building information modeling technology and approaches to their combination when applied by intelligent systems based on UAVs.*

Justification of the criteria for choosing combinations of algorithms and assessment of the perspective of their further research and improvement for tasks related to the features of the use of various types of unmanned aerial vehicles as a means of creating multidimensional models of building and infrastructure objects.

The Results. *Algorithms for the reconstruction of surfaces from a cloud of points obtained using the methods of laser terrain scanning and analysis of visual data obtained from an unmanned aerial vehicle were studied. The conditions for their effective combined use for building information modeling technology and approaches to their combination when applied to intelligent systems based on UAVs were defined.*

The criteria for selecting combinations of algorithms were substantiated and the prospects of their further research and improvement were assessed for tasks related to the specifics of using *various types of unmanned aerial vehicles as a means of creating multidimensional models of building and infrastructure objects.*

Conclusions. *The use of a single surface reconstruction algorithm to create multidimensional BIM simulation models cannot be considered optimal. The conducted review shows that for the optimal solution of this problem, it is necessary to continue research in this direction. This will avoid excessive demands on the computing power of BIM systems when modeling a geometric shape while preserving properties and details with minimal data loss.*

Keywords: *unmanned aerial vehicle, building information modeling, LIDAR, surface reconstruction, visual data, digital object models.*

INTRODUCTION

The modern world requires modern technologies in all spheres of life and industry, and not only in those that are considered innovative, such as the field of information technology, space research, and communication, but also in traditional material spheres such as, in particular, the construction sphere. It is believed that construction is a conservative branch of the economy, where changes do not occur often and do not have a profound nature. However, in reality, the construction industry actively uses new technologies and tools, in particular, unmanned aerial vehicles of various types are not an exception, but on the contrary, they are actively used as a part of the construction information modeling system, even without full integration. As a separate highly effective commercial tool, which during monitoring does not interfere with and does not disrupt technological processes at the construction site, is controlled remotely and is capable of changing viewing points, providing easy access to hard-to-reach places. The use of UAVs allows you to obtain data that in most parameters are not inferior to data obtained by traditional methods of ground information collection or aerial photography, and at the same time have the main advantages: speed, accuracy and cost.

The use of UAVs in the conditions of rapid development of information and computing technologies and the introduction of digital solutions should be considered as a part of a larger system associated with deeper automation, the introduction of a modular approach to digital technologies using artificial intelligence and augmented reality in building information modeling systems.

To improve the effectiveness of quality control and monitoring, there are methods that use the capabilities of drones to gather information to create the BIM model. Research is being conducted on the development of a fully automated and intelligent control system, one of the components of which is laser technology, as an effective means of collecting data of modeling objects.

The development of unmanned systems as carriers for transmitters requires further improvement of technologies for creating three-dimensional models. Thus, 3D models of buildings are created with the help of drones using active sensors LIDAR (Light Identification, Detection and Ranging) and passive sensors, for example, aerial cameras [1] use a number of well-known algorithms and methods to reconstruct surfaces from the collected point cloud.

The choice of a particular method depends on the requirements for accuracy, the complexity of the surface shape, the presence of noise in the data and other factors. For BIM, the best approach is usually to combine several methods and compare their results in order to choose the best one for solving a specific problem.

The article provides an attempt to research algorithms, combinations of algorithms, and approaches to their combination when applied to UAV based intelligent systems.

FORMULATION OF THE PROBLEM

BIM (Building Information Model) is a three-dimensional model of a building or other construction object. It is connected to an information database, in which additional attributes can be assigned to each element of the model. The characteristic of this approach is that the building object is actually designed as a single entity. And changing any one of its parameters entails an automatic change of others up to the drawings, specifications and calendar schedule. BIM has two main advantages over CAD (Computer Aided Design) [2].

1. BIM management models and objects are not just graphic objects, but information that allows you to automatically create drawings and reports, perform project analysis, model the work schedule, and operate objects.
2. BIM supports distributed groups, so people, tools and tasks can effectively and jointly use this information throughout the life cycle of the building, which eliminates redundancy, re-entry and loss of data, errors in their transmission and transformation.

BIM is implemented using object-oriented software and consists of parametric objects representing building components. Objects can have geometric or non-geometric attributes with functional, semantic or topological information. For example, functional attributes can be installation duration or cost, communication information, aggregation, location, or intersection. Topological attributes provide, for example, information about the location of objects, contiguity, coplanarity or perpendicularity [3].

Commercial BIM platforms offer integrated data management, component libraries, and common functions. BIM models are often described using additional "dimensions". There are widely spread BIM differentiations: 3D (spatial model with quantitative reference), 4D (plus construction planning) and 5D (plus cost calculation) BIM [4].

3D BIM is an abbreviation for three-dimensional building modeling, refers to a graphical representation of the geometric design of an asset, supplemented with information describing the attributes of individual components. Works with 3D BIM can be performed by professional disciplines such as architecture, construction and technical sciences. A three-dimensional virtual model can be created using laser scanning technology.

4D BIM is an abbreviation for 4-dimensional building information modeling, refers to the intelligent connection of individual components of systems or nodes of automated 3D CAD design with information related to time or schedule. The term 4D refers to the fourth dimension: time, i.e. 3D plus time. 4D modeling allows project participants (architects, designers, contractors, clients) to plan, sequence physical loads, visualize a series of events, mitigate risks, report and monitor the progress of activities throughout the entire project life cycle. 4D BIM allows you to visually display the sequence of events on a timeline.

5D BIM, is an abbreviation 5D Building Information Modeling, refers to the intelligent linking of individual 3D components or assemblies to schedule constraints (4D BIM) and then to cost information. 5D models allow participants to visualize construction progress and associated costs over time. This BIM-oriented method of project management has the potential to improve the management and execution of projects of any size and complexity.

BIM can be considered as a virtual process that captures all aspects, disciplines and systems of a facility in one virtual model, allowing all team members to collaborate more accurately and efficiently than using traditional methods. During the creation of the model, it is possible to constantly improve and make changes according to the project specifications and changes in the design to ensure that the model is as accurate as possible before the project is physically started.

Recently, the concept of integrated implementation of the project (IPD) was created, which appeared as a natural companion of BIM. IPD brings together construction, trade, manufacturing, supply and product management expertise with designers and owners early in the process to create a design that is optimized for quality, aesthetics, constructability, affordability, timeliness and a seamless transition to life cycle management [3]. In the United States, IPD has become the primary project delivery system for all major projects involving BIM.

The vital need for constantly improved, fast and as accurate as possible information about changes naturally leads to the choice of technologies for the use of UAVs and the reproduction of three-dimensional models with the help of laser sensors placed on them. The obtained data are used in the reconstruction and restored objects. The data collected by the LIDAR form a cloud of points where there may be objects of arbitrary shape, such as buildings with a complex surface, which are common in urban environments. Therefore, there are problems that require the selection of the optimal algorithm for their solution, namely: the presence of insufficient information, the presence of noise in the data, the need to process large volumes of data, the choice of a surface reconstruction method, work with curvilinear or uncontrolled forms.

These tasks can be reduced to the need to preserve details and complex surface shapes, while at the same time preventing an excessive increase in the requirements for volumes and means of calculation.

Application of unmanned aerial vehicles for building information modeling. BIM models are used in the construction process also for real-time quality control [5]. Early detection of defects is still the most important approach to reducing project schedule and cost overruns. Classical approaches to quality control at construction sites are time-consuming and inefficient because they provide data only at specific locations and at specific times. BIM models can also be used after the completion of construction, for example monitoring the condition or restoration of buildings. One of the modern methods for improving the effectiveness of quality control and monitoring is the use of drones to collect information to create a BIM model. This includes methods such as 3D reconstruction based on images and the use of laser scanners [6]. In order to provide a quality analysis of a construction project, it is necessary to combine data from several sources, since not all the necessary information can be collected with the help of a single data source. Drones are used in this field because they can contain a number of sensors, providing efficient and fast data collection. The ability of small drones to maneuver in a closed space allows you to explore hard-to-reach places on a construction site. The use of predetermined flight paths can ensure the autonomy of the operation.

In order to improve the current performance of quality management, a number of studies have been conducted in recent years to develop a fully automated and intelligent management system. BIM and laser scanning are effective methods of quality control. Laser scanning is an effective method of creating ready-made models, thanks to methods of automatic creation of 3D models based on laser scanner data. For the automated and efficient creation of such models, it is possible to use multi-rotor UAVs (drones) equipped with cameras and laser scanners. The drone can quickly fly over a building along a defined route, scanning from multiple points to create an accurate and detailed 3D model. The collected data is compared with the BIM model of the object [5]. The quality control system detects deficiencies and defects. Improved accuracy and responsiveness of received data on defects will increase efficiency during the construction phase.

Another area of use of UAVs and BIM is the restoration of historical objects. In this case, UAV laser scanning data is used as a basis for creating a BIM model. 3D scanning and photogrammetry technologies are especially relevant for collecting spatial data for real buildings. Laser scanners, in particular, provide accurate geometric reproduction of three-dimensional objects in a short time, in the form of millions of points, with geometric coordinates (X, Y, Z). In addition, color information can also be included or displayed using internal or external calibrated cameras. Before using the raw point cloud, a number of steps are required, such as cleaning and filtering the "noise" of the point cloud to obtain a final global cloud that aims to preserve the original complexity of the documented object. The processed point clouds can be included in BIM building information modeling platforms [7].

Using laser sensors (LIDAR) to create 3D models. The technology of reproducing three-dimensional models using laser sensors and cameras is widespread and available. 3D models of buildings can be created using drones that use active sensors for light identification, detection and ranging (LIDAR) and passive sensors, for example, an aerial camera [1]. There are a large number of commercially available UAVs of both aircraft and multi-rotor types specifically designed to work with laser sensors. Drones with connected LIDAR sensors are used for many tasks. In recent years, innovations in technology have dramatically reduced the cost and size of sensors, making it possible to attach a LIDAR payload to a drone. While drones with such equipment become more and more advanced, the data they can provide becomes more accurate and cheaper.

The data collected by the LIDAR form a cloud of a large number of points with coordinates in three-dimensional space. Point clouds can be directly visualized and are often converted to a polygonal or triangular mesh model, a non-uniform rational B-spline (NURBS) surface model, or a CAD model through a surface reconstruction process. There are many methods of converting a cloud of points to a 3D surface. Some approaches, such as Delaunay triangulation, alpha shapes, and sphere rotation, construct a network of triangles over the vertices of a scanned point cloud, while other approaches transform the point cloud into a three-dimensional distance field and reconstruct an implicit surface [8].

Objects of arbitrary shape, such as buildings with complex surfaces, are common in urban environments. Usually, general surface reconstruction algorithms such as the Poisson method can reconstruct freeform objects with acceptable accuracy. There are other methods that can access freeform objects. Most of the current surface reconstruction methods can be divided into two main categories: methods that use implicit functions to represent surfaces, and explicit methods that use triangular Delaunay–Voronoi grids to represent surfaces. In general, approaches based on Delaunay-Voronoi methods provide good approximations for dense uniformly sampled point clouds. Working on input scans without point normals often computes output meshes with complexity on the order of the size of the input point set. On the other hand, most implicit methods use derived or estimated point normals to facilitate the reconstruction process and are robust to noise. Delaunay-based methods are unable to reconstruct correct surfaces in the presence of noise. The vast majority of surface reconstruction algorithms rely on one or more parameters to reconstruct the final surface. Setting the right parameter for each model is a challenge, especially for different types of noisy and incomplete data. Since the isosurface is extracted using stepping cubes into octotrees, the corresponding depth of the octotree must be determined and set in the case of implicit methods [8]. A more detailed grid reconstruction is obtained for larger depth values, but at the expense of increased calculation time.

SURFACE ALGORITHMS FOR SURFACE RECONSTRUCTION FROM POINT CLOUDS OBTAINED FROM LIDAR SENSORS

To create a 3-D model, it is necessary to reconstruct the surface, since data from laser sensors is represented by an array of points in space. The following algorithms can be used for surface reconstruction:

- Radial basis function (RBF)
- Poisson reconstruction
- Wavelet transform
- Fast Fourier Transform (FFT)
- Multilevel Partition of Unity Implicits (MPU)
- Power Crust algorithm
- CoCone algorithms

In order to understand the typification of algorithms for the reconstruction of surfaces of arbitrary shape, it is necessary to understand the basic requirements for them. Table 1 shows four groups of requirements according to quality, limitations of computing equipment, user level and relation to possible project changes.

When scanning an object, we get a cloud of points, which is a finite set of different points P on a three-dimensional surface M. Taking this into account, we can say that implicit methods try to formulate a smooth function f: $R^3 \rightarrow R$ such that the set of zero level f is close to P.

$$Z(f) = \left\{ p \in R^3 \,\middle|\, f(p) = 0 \right\}.$$

Then the function f is determined based on the information obtained from the cloud of points P and the corresponding set of normals. Implicit surfaces can be visualized directly using a ray tracer or by polygonizing them using the marching cubes algorithm. The methods of implicit reconstruction differ mainly in the formulation of the function f. Therefore, let's move on to the algorithms themselves and their features.

Table 1. Requirements for algorithms for the reconstruction of surfaces of arbitrary shape

Requirements	Description	Priority
Quality of reconstruction		
Surface smoothness	The reconstruction should be smooth and free of artifacts.	High
Accuracy	The reconstruction must meet established standards of accuracy.	High
Detail reconstruction	It is important to reproduce details and surface features if they are present in the data.	Medium
Computational requirements		
Speed of reconstruction	Reconstruction must be carried out in an acceptable time.	High
Use of resources	The algorithm must be suitable for use on available computing resources.	Medium
Accuracy of the interface		
Compliance with standards	The algorithm interface must comply with industry standards and regulations.	High
Ease of use	The algorithm should be easy to use and have clear documentation.	Medium
Future expantion		
Scalability	The algorithm should be scalable for future expansion and development of the project.	High
Flexibility	The algorithm should be flexible to adapt to changes in project requirements and conditions.	High

Radial basis functions (RBF). It is known that radial basis function interpolation is a method of interpolating functions or data using a weighted sum of radial basis functions. Where one of the most widely used radial basis functions is the Gaussian function, which, as will be shown, is sufficiently versatile to approximate a wide range of functions. Radial basis functions are functions whose value changes only depending on the distance between the input value and some reference point — they have the following property:

$$f(x) = f\left(\|x\|\right),$$

where $\|x\|$, is some distance metric, such as Euclidean distance.

RBFs are well suited for smooth interpolation of scattered data when we estimate the function f as a linear sum of weighted and shifted radial functions, i.e.

$$p(f) = \sum_{i=1}^{n} \omega_i \left(\|p - c_i\|\right),$$

where the coefficients ω_i which are calculated by applying surface constraints at points c_i, and then by solving the resulting linear system. Selected basis functions ϕ include Gaussian:

$$(\phi(r) = exp(-cr^2)),$$

multiquadric:

$$(\phi(r) = \sqrt{c^2 + r^2}),$$

polyharmonic:

$$(\phi(r) = r \quad or \quad \phi(r) = r^2),$$

thin plate spline:

$$(\phi(r) = r^2 \log log\, r).$$

Although, compactly supported basis functions such as the Gaussian function are faster, they have been found to introduce unwanted artifacts for irregular and non-uniform data. On the other hand, polyharmonic functions are a good choice for 3D representation due to their energy minimization properties. However, since the harmonic functions are non-compact, the solution of the linear system becomes computationally complex [8]. The computational performance of RBF interpolation can be improved by using a fast multipole method for RBF estimation and a greedy algorithm for RBF fitting [9]. It is established that the method reconstructs free-form urban objects from noisy LIDAR scanning with acceptable accuracy.

It should be noted that the use of radial basis functions creates accurate and smooth surfaces from the point cloud, the disadvantage of using RBF algorithms is the high computational cost for large data sets. Applying such an algorithm to real data, which often consists of millions of points, is considered impractical in many cases. However, it is possible to use RBF in practice if you simplify the array of points beforehand, or use additional algorithms to speed up RBF calculations [9].

Poisson reconstruction. Poisson reconstruction can be applied to convert the surface points to a grid. This method states that an indicator function that determines which points in space belong to the shape surface can actually be computed based on the sample points. The key concept is that the gradient of the indicator function is 0 everywhere except at the sampling points, where it is equal to the normal to the interior surface. The Poisson surface reconstruction method solves the indicator function for a solid which gradient best approximates the normal field N, i.e.

$$F = argwin_s \left\| \nabla_s - N \right\|_2^2.$$

This minimization problem leads to a Poisson equation that is solved by a locally supported radial basis function on an adaptive octotree.

It is one of the most popular methods of surface reconstruction due to its scalability and efficiency. In addition, Poisson reconstruction gives satisfactory results, preserving even the smallest details [8]. In the published scientific works, in which the methods of improving the Poisson reconstruction were investigated, it is described that the streaming approach for the Poisson reconstruction allows the algorithm to process massive data sets of the order of hundreds of millions of point samples [10]. In other similar works, the Fourier basis and the wavelet were used to improve the computational load when solving Poisson's equations. The advantages of the Poisson method are robustness to noise and the possibility of parallel computation.

Among the disadvantages, the method requires data on the normals of the points. The reproduction of some details requires the use of additional algorithms, errors may occur when reconstructing surfaces with folds or too sharp corners.

Wavelet transform. Wavelet is a wave-like oscillation with an amplitude that starts at zero, increases or decreases, and then returns to zero one or more times. Wavelets are called "short oscillations". As a mathematical tool, wavelets can be used to extract information from many types of data, including audio signals and images.

Wavelets are an alternative to classical Fourier methods for the analysis and synthesis of one- and multidimensional data and have numerous applications both in mathematics and in fields as diverse as physics, seismology, medical imaging, digital image processing, signal processing, computer graphics and others. The main attraction of wavelets is related to their simultaneous localization in both the frequency (wavenumber) and spatial (position) domains. These properties make it possible to approximate many classes of functions with a relatively small number of wavelet basis functions, preserving most of their information content. To construct the approximation of the indicator function $\tilde{\chi}_M$ of the body M with the boundary ∂M, the input points p_i on the surface ∂M and their external normals $\vec{n}_i$ are used. The indicator function is defined as 1 inside M and 0 otherwise. Next, the approximation $\tilde{\chi}_M$ is constructed by approximating the wavelet coefficients χ_M. Then the surface $\partial\tilde{M}$ of the set of levels $\tilde{M}$ with $\tilde{\chi}_M$ is an approximation of the initial surface. The ability of wavelets to detect discontinuities naturally creates an adaptive refinement of the octotree near the boundary $\partial\tilde{M}$ of the field M. This octotree is used to construct a polygonal model of the boundary $\partial\tilde{M}$ by applying the octotree contouring method. This algorithm computes the dual cell structure of an octotree using recursive octotree traversal. The method uses the values of $\tilde{\chi}_M$ at the vertices of double cells located in the centers of the corresponding cells of the octotree. A marching cube algorithm on double cells is then used to create a coherent, adaptive contour that is guaranteed to produce topological and geometric diversity. Since the number of double cells is proportional to the size of the octotree, the execution time of this contouring method is also proportional to the size of the octotree [11]. The smoothness of the used (biorthogonal) wavelet will affect the smoothness of $\tilde{\chi}_M$ and, therefore, the smoothness of the set of levels $\tilde{M}$. Wavelets with low support yield algorithms with higher performance because fewer wavelet coefficients need to be computed and each coefficient is affected by fewer sample points. However, a smaller support negatively affects the quality of the resulting surface. Instead of increasing the wavelet support to improve the quality of the reconstructed surface, one alternative is to perform a smoothing step after feature processing.

Although, the wavelet transform is a fairly effective way of reconstructing the surface, there are also some disadvantages. For example, surfaces with sharp or thin elements are displayed inaccurately or are lost altogether. The accuracy of the reconstructed surface can vary significantly depending on the characteristics of a specific point cloud. Also, a high level of smoothing requires high computational costs.

The Fast Fourier Transform (FFT) is an algorithm that computes the Discrete Fourier Transform (DFT) of a sequence, or it's inverse. Fourier analysis transforms a signal from its original domain (often time or space) to a representation in the frequency domain and vice versa. The DFT is obtained by decomposing a sequence of values into components with different frequencies. This operation is useful in many areas, but computing it directly by the definition is often too slow to be practical. The FFT quickly computes such transformations by factoring the DFT matrix into a product of sparse (mostly zero) factors. As a result, it manages to reduce the computational complexity of DFT.

Researchers created a method that takes as input an oriented set of points taken from a model surface and returns a water-tight reconstruction of the surface using a fast Fourier transform. To calculate the characteristic function of a solid, its Fourier coefficients are calculated. According to Stokes' theorem, it is possible to express the volume integral as a surface integral using only information about the positions and normals of points on the surface. Since this is exactly the information provided as input in the case of a point cloud, there is enough information to calculate the Fourier coefficients of the characteristic function, allowing the inverse Fourier transform to be used to calculate its values. The proposed algorithm describes an efficient method of calculating Fourier coefficients and a method of choosing an iso-value that will be used to obtain an iso-surface [12]. Although the described method provides a direct way to obtain the Fourier coefficients of the characteristic function, it requires the summation of all input samples to calculate a single Fourier coefficient. Thus, in the case where both the number of input samples and the reconstruction bandwidth are large, the explicit computation of the summation becomes prohibitively slow.

One of the limitations of this method is the memory requirements. If we want to obtain a high-detail model reconstruction, a large voxel mesh must be created. In particular, to reconstruct the model on the passband b, it is necessary to perform direct and inverse fast Fourier transformation on a 2b × 2b × 2b voxel grid [12]. With large grid resolution values, the use of computer memory increases dramatically.

Multilevel Partition of Unity Implicits (MPU). The unity partition approach is commonly used to integrate locally defined approximations into a global approximation. Important properties such as maximum error and order of convergence are inherited from the local behavior. The basic idea behind the unity partition approach is to partition the data domain into multiple parts, approximate the data in each subdomain separately, and then blend the local solutions together using smooth local weights that sum to unity everywhere in the domain. More precisely, consider a bounded domain Ω in Euclidean space and a set of nonnegative compactly supported functions $\{\phi_i\}$, such as: $\sum_i \phi_i = 1 \; on \; \Omega$. Let us associate the local approximation set of functions V_i with each subdomain $supp(\phi_i)$. Now the approximation of the function *f(x)* defined on Ω is given by [13]:

$$f(x) \approx \sum_i \phi_i(x)\, Q_i(x),$$

where $Q_i \in V_i$. Having a set of nonnegative compactly supported functions $\{w_i(x)\}$ such that

$$\Omega \subset U_i\ supp(w_i)$$

partition uniti functions $\{\phi_i\}$ can be generated by:

$$\phi_i(x) = \frac{w_i(x)}{\sum_{j=1}^{n} w_i(x)}$$

Implicit MPUs are conceptually simple, easy to implement, and capable of providing fast, accurate, and adaptive reconstruction of complex shapes from sparse point data containing millions of points. The complexity of the approach is sensitive to the input data in the sense that the generation time and memory consumption depend on the complexity of the reconstructed shape and not on the number of data points. Accordingly, this algorithm may lose in efficiency if we are dealing with relatively small clouds of points. Since MPU implicits can provide high-precision shape approximation, functional operations such as shape blending, displacement, deformation can be easily applied. All of these same operations can be performed on data that was originally in parametric or polygonal form by simply converting these shape descriptions to MPU representations.

The division of algorithms into two types is illustrated (Fig. 1). Oppositely directed arrows emphasize the contradictions between different approaches, so the previous algorithms that were considered belong to implicit functions, and those that we will consider further use Delaunay triangulation. By comparing these types, we will better understand how to optimally combine them according to specific requirements.

“Power Crust” is a construction that takes a sample of points from the surface of a 3D object and creates a surface mesh and an approximate medial axis. The approach is to first approximate the medial axis transform (MAT) of the object. We then use the inverse transform to create a representation of the surface from the MAT. This idea leads to a simple algorithm with theoretical guarantees comparable to other surface reconstruction and medial axis approximation algorithms. It also does not depend in any way on the sample quality of the input point cloud. Any input gives an output surface that is the "watertight" boundary of a three-dimensional polyhedral body: a body described by an approximate MAT. This unconditional guarantee makes the algorithm quite reliable and eliminates the post-processing steps of polygonization or whole filling required in previous surface reconstruction algorithms [14].

Types of surface reconstruction algorithms from the cloud of points obtained by LIDAR laser sensors are shown in Fig. 1.

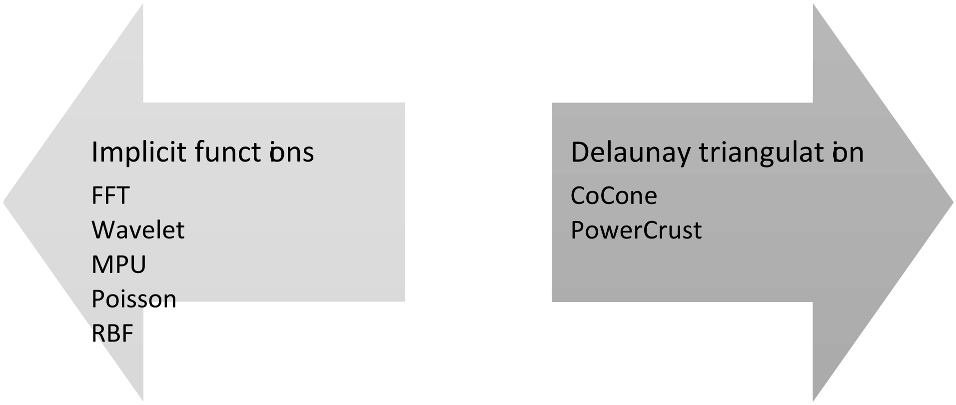

Fig. 1. Types of surface reconstruction algorithms from the cloud of points obtained by LIDAR laser sensors

The Delaunay/Voronoi model together with ε-sampling (or a related sampling model) have been widely investigated. In the ε-sampling model, the density of points depends on the size of the local feature, where the size of the local feature at the point p on the curve Σ, LFS(p) is the distance from p to the nearest point on the medial surface of the axis Σ. This sampling model is able to quantify the local LoD at each point of the smooth curve. In particular, parts of the curve that encapsulate more detail are densely sampled, while other parts are sparsely sampled. Hence, this generates an uneven sample. According to the sampling model, the first algorithm that provides theoretical guarantees for the reconstruction of smooth surfaces is crust. In two dimensions, the cortex consists of edges from the DT of the input samples, which can be enclosed by circles that have no sample points and no Voronoi vertices. Extending the crust to 3-D uses the basic idea that Voronoi cells on a surface tend to be elongated in a direction perpendicular to the assumed surface. It uses the poles that are the farthest Voronoi vertices of the sampling cell. For each sample, the algorithm selects the two furthest Voronoi vertices as poles. The surface consists of all Delaunay triangles around which there are no samples and no poles. Power crust is an extension of the crust algorithm, more robust to realistic inputs, which instead relies on a power diagram — a weighted Voronoi pole diagram [9].

One situation where the algorithm produces erroneous results is when there is significant noise in the input data, comparable to or greater than the distance between samples on the surface. This type of noise is typical when multiple laser scans are combined; although the individual scans are quite clean, alignment errors between scans cause the samples to scatter near the junction.

"CoCone" algorithms. CoCone algorithms use poles to compare face normals to point normals (the vector from the sample point to the pole). The cocoon is the complement of a double cone centered at the sample point p with an opening angle of $\frac{3\pi}{8}$ about an axis aligned with the normal at p. CoCone algorithms work as follows: each sample point p selects a set of Delaunay triangles which dual Voronoi edges intersect the CoCone defined at p. All such triangles selected by all samples represent candidate triangles, and the final manifold is extracted from the candidate triangles. Each candidate triangle has the property that its face normal is oriented approximately in the same direction as the normals at the three sampling points. Several improvements have been introduced over the base cocone algorithm. SuperCoCone uses octotree-based point cloud partitioning to reduce the computation time, thus increasing the performance of the entire cocoon algorithm. RobustCoCone generalizes the definition of poles to handle a specific noise model [8].

One of the main limitations of the cocone algorithm is the computational cost. For large point clouds, the data structures used exceed the system memory and the processing speed becomes very slow. Even if efficient and robust implementations of 3D Delaunay triangulation are used, these algorithms do not scale well and cannot accommodate large datasets containing tens of millions of points [15].

In general, the choice of surface reconstruction method should be based on the specific requirements of the project and its constraints, such as available resources and the quality of the input data. Then the optimal approach is to combine different methods to achieve the best results. BIM models are characterized by a simultaneous combination of different requirements. Therefore, when choosing a method, you need to balance the requirements and determine how each of the methods meets them (Table 2).

When choosing an algorithm or a combination of algorithms, you need to prioritize all requirements and determine how important they are to the project. In order not to carry out test reconstructions using different methods and not to waste resources on performance evaluation, according to the requirements of a separate project, you can use the comparative evaluation of surface reconstruction methods given in the article, taking advantage of the methods for different requirements.

We remember that resources are always limited. Some methods are more computationally demanding, while others do not allow reconstructing important surface details etc. Therefore, it is almost always advisable to consider a combination of methods, to combine different methods. To achieve better results, you can use one method for basic reconstruction and another for enhanced detail.

So, when it comes to the set of algorithms, it can be divided into two subsets: implicit functions and Delaunay triangulation. These groups represent two different concepts, and one cannot unequivocally say that one of them is "bad" and the other "good". Each of them has its own advantages and disadvantages.

Table 2. Subsets of algorithms for the reconstruction of surfaces of arbitrary shape based on basic properties

Algorithm	Reconstruction type	Normals	Noise reduction	Large data
RBF	Implicit function	+	+	+
Poisson	Implicit function	+	+	+
Wavelet	Implicit function	+	+	+
FFT	Implicit function	+	+	+
MPU	Implicit function	+	+	+
PowerCrust	Delaunay	-	-	slow
CoCone	Delaunay	-	+	slow

On the one hand, when reproducing a surface from a point cloud, it is advisable to try to apply algorithms that use Delaunay triangulation, because BIM modeling systems work precisely with geospatial data, and this type of algorithms was developed to solve problems related to their processing, but it is the implicit functions that are used to represent geometric objects (such as surfaces) using mathematical equations, allowing complex shapes and surfaces to be described with greater precision. And when reconstructing damaged objects, their models need accuracy for complete and correct information for analysis in automatic and semi-automatic modes using intelligent control.

Although implicit functions are widely used in computer graphics to build 3D models, as well as in computational geometry to solve problems related to collisions, motion simulation etc, we cannot ignore their shortcomings and unconditionally accept them for surface reconstruction problems. The most important among them is operation with implicit functions. Constructing and solving implicit equations is an extremely resource-intensive task that requires high computational costs. Also, it should be noted about the low tolerance of algorithms of this type to errors, the occurrence of which is related to the peculiarities of the collection of primary information by the providers during the flight. The third important drawback is the inability to model certain geometric shapes and details.

Choosing among the available algorithms for working with a point cloud obtained from laser sensors, there is a choice between those that use Delaunay triangulation and those that use implicit functions. This choice largely depends on the specific task and project requirements, but does not provide an optimal solution and together with the algorithm, the user chooses what information he will lose and what errors may appear in his project. Both approaches have their place and applications for the problems faced by BIM modeling, but it is necessary to continue the research of combinations of algorithms and approaches to their combination when applied to intelligent systems based on UAVs. Solving this problem will allow modeling of geometric shape, representation of properties and details with minimal data loss and avoiding excessive demands on computing power.

CONCLUSIONS

The use of each of the surface reconstruction algorithms considered in the article cannot be considered optimal for surface reconstruction when building 3-4-5-D BIM models. The review shows that for the optimal solution of this problem, it is necessary to choose an appropriate combination of algorithms. The optimal choice will avoid excessive demands on the computing power of BIM systems for modeling the geometric shape while preserving properties and details with minimal data loss.

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АЛГОРИТМИ І МЕТОДИ РЕКОНСТРУКЦІЇ ПОВЕРХНІ ДОВІЛЬНОЇ ФОРМИ ОБ'ЄКТІВ ІНФРАСТРУКТУРИ ДЛЯ БУДІВЕЛЬНО-ІНФОРМАЦІЙНОГО МОДЕЛЮВАННЯ

Вступ. Будівельна сфера активно застосовує нові технології і інструменти, зокрема технології інтелектуалізації керування збором даних з використанням безпілотних літальних апаратів різних типів (БпЛА). Розвиток цих технологій не стає винятком, а, навпаки, активно застосовується і як частина системи будівельно-інформаційного моделювання, так і без повної інтеграції до подібних інформаційних комплексів. Для підвищення ефективності контролю якості та моніторингу створено методи застосування дронів різного типу для збору даних задля створення будівельно-інформаційних моделей. 3D-моделі будівель створюються за допомогою дронів, які використовують активні давачі світлової ідентифікації, виявлення та визначення дальності — лідар (LIDAR — Light Identification, Detection and Ranging), потребують використання алгоритмів відтворення поверхні зі хмару точок.

Мета. Мета статті — дослідити алгоритми реконструкції поверхонь зі хмари точок, отриманих за допомогою методів лазерного сканування місцевості та аналізу візуальних даних, отриманих з безпілотного літального апарата, та визначити умови їхнього ефективного комбінованого використання для технології будівельно-інформаційного моделювання та підходів до їх поєднання у застосуванні інтелектуалізованими системами на базі БпЛА.

Результати. Досліджено алгоритми реконструкції поверхонь зі хмари точок, отриманих за допомогою методів лазерного сканування місцевості та аналізу візуальних даних, отриманих з безпілотного літального апарата. Було визначено умови їх, ефективного комбінованого використання для технології будівельно-інформаційного моделювання та підходи до їх поєднання при застосуванні інтелектуалізованими системам на базі БпЛА.

Обґрунтовано критерії вибору комбінацій алгоритмів та оцінено перспективність їхнього подальшого дослідження та удосконалення для завдань, пов'язаних з особливостями використання різнотипних безпілотних апаратів як засобу одержання інформації для створення багатовимірних моделей будівельних та інфраструктурних об'єктів.

Висновки. Використання кожного окремого з розглянутих алгоритмів реконструкції поверхні не можна визнати оптимальним для реконструкції поверхні для побудови 3-4-5-D моделей БІМ. Проведений огляд показує, що для оптимального розв'язання цього завдання необхідно вибрати відповідну комбінацію алгоритмів. Оптимальний вибір надасть змогу уникнути надмірних вимог до обчислювальних систем БІМ для моделювання геометричної форми за збереження властивостей та деталей з мінімальними втратами даних.

Ключові слова: *безпілотний літальний апарат, будівельно-інформаційне моделювання, лідар, реконструкція поверхонь, візуальні дані, цифрові моделі об'єктів.*