Visualization of UCG Process Data

Karolina Nurzyńska, Marcin Michalak, and Sebastian Iwaszenko

***Abstract*—Proper visualization of process data in underground coal gasification (UCG) may improve understanding of researched phenomena and therefore support further development of novel techniques. This work concentrates on the visualization aspects of modelled data, which describe the mentioned process. Firstly, it is presented how unorganized point cloud given as an input for the system is transformed with point extraction methods. The goal of the transformation is to diminish the number of relevant data to make the point cloud visualization clear. Secondly, the possibilities to apply surface reconstruction techniques for cavity visualization are discussed. Finally, the results of visualization are presented which support the claim that applying relatively simple techniques may provide highly functional visualization system.**

***Index Terms*—Surface reconstruction, underground coal gasification, visualization.**

I. Introduction

Recently, computer graphics finds a broad application in many domains, due to the high level of developed computer science solutions and relatively low costs of hardware. The aim of generated software is to simplify a cumbersome parts of labor and enable rapid access to information which manual acquisition is tedious and sometimes impossible to achieve without specialized equipment. The developed software aims to support employees in their duties, but also, as in this case, allows the analysis of the problem in order to research for novel technologies.

This paper presents some issues concerning a system developed to support the research on the underground coal gasification process (UCG). The process itself, although has strong theoretical background, still needs some research before it can be safely applied in industry. Therefore, the main aim of the constructed software is to provide a tool which facilitate the further research.

The UCG process is an alternative way of coal exploration. Instead of traditional ways of coal mining, which rely on excavating rocks with coal, the chemical conversion of coal filling the seams is enabled. The process takes place in situ, where the gasification of the coal in high temperatures leads to a syngas production [1]. It is assumed that the chemical composition of the resultant gas has good properties for further processing. Conducting the coal combustion process underground was firstly suggested in 19th century [2], yet the necessary technology enabled first trials to take place in the beginning of 20th century. The first recorded information about the successful UCG process described the experiment from 1934 conducted in the Soviet Union. Up till now, many experimental UCG process plants have been developed, e.g. in Russia [2], Australia [3], and in the USA [2]. During the tests it was proven that it is possible to generate a highly calorific gas, but also many troubles arising in the course of process were reported. Some of these problems were addressed in the experiments conducted in semi-technical scale [4], [5].

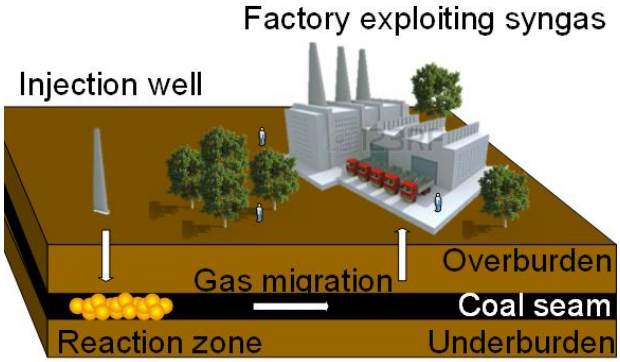

Fig. 1. Example of the UCG process schema.

There are some approaches how the process may be conducted, one of them is presented on Fig. 1. In this solution, the injection and receiving well are exploited. The injection well is used for process initialization by ignition of the coal seam, then the gasification agent (e.g. the air, steam, or oxygen) is supplied by this way to assure normal process course. The coal combustion takes place in the reaction zone, where the syngas is produced. Due to the difference in pressure between wells the resultant gas shifts in the direction of receiving well, where it may be collected or further processed, as in the case of the factory example from the Fig. 1.

The cavity forms as a result of the coal combustion in the seam. Its shape, size, and place of development are very important from the UCG process management point of view, because it influences the process itself as well as the resultant gas quality. For instance, when the void reaches the surrounding rocks, which thermal conductivity is higher than the coal, the energy achieved during the coal combustion gives away and the quality of syngas diminishes. Since the chemical reactions considered in this process have surface nature, it is better for gas quality, when the generated void is not too big, because then the amount of coal consumed from

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the seam and changed into unwanted carbon dioxide increases. Therefore, the possibility to model and visualize the cavity state became addressed in presented research.

This paper concentrates on the visualization techniques applied to the data describing UCG process. Since most of the available data base on the mathematical model, many parameters (e.g. amount of carbon, hydrogen, carbon monoxide, carbon dioxide, oxygen, gas pressure, gas temperature, etc.) are known. They are estimated in a dense three-dimensional point cloud, which visualization is considered in such a way to enable easy understanding of the current state of the process. In order to achieve this assumption, sophisticated algorithms for choosing a relevant point set are introduced in Section II. Section III presents surface reconstruction techniques applied for data visualization. The results of the work and discussion are presented in Section IV, while in Section V the conclusions are drawn.

II. Selection of Points

Generating visualization of the unorganized point cloud, which describes the values of chosen parameter in whole seam, makes the information illegible due to the big amount of data. Therefore, it was decided that only the crucial data, which describe the cavity, should be presented. In order to achieve this goal, some algorithms allowing for selection of significant data were suggested and are presented in this section.

A. Selection of Single Variable Points

The nature of the modelled process – underground coal gasification – gives the opportunity to state that values on the boundary of the modelled region can be considered as very close to the initial values and distributed more or less uniformly through the region of interest. As the process continues, values should vary (become higher or smaller – not remain on the same level). This observation leads to the definition of the point significance.

For the purpose of selecting most important points from the point cloud the notion of point significance was defined. The point is considered as significant if its value differs much from values on the boundary. The level of point significance depends on the variable distribution – to be more precise: the quantile of the distribution – and the location of the boundary value in the distribution.

The location of the boundary value in the distribution defines the location of significant points: if the border value is smaller than a median then values from the right end of the distribution are considered as significant and if the border value is greater than a median then values from the left end of the distribution are considered as significant.

The range of the significant values is determined with the significance level α. For a given α and the border value higher than a median, values smaller than the quantile of the range α are considered significant. In the opposite situation – a border value smaller than a median – values greater than the quantile of the range $1 - \alpha$ are considered significant.

For the better understanding of this mechanism see Fig. 2. The red line represents the distribution of considered variable. It is a multi-modal distribution so each locally most frequent values could be possibly admitted as interesting. When the border value is located on the distribution the global maximum of value frequency can be easily interpreted as the big amount of points close to the boundary, where nothing happens – the process does not influence their initial values. This conclusion becomes more clear when the median is marked on the distribution.

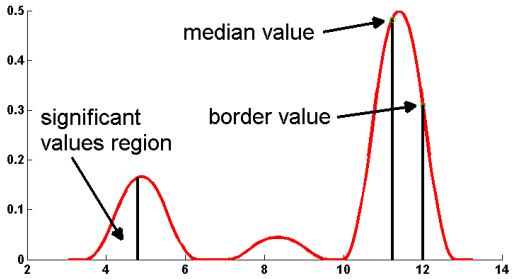

Fig. 2. Graphical explanation of significant values region.

Because border value is higher than a median it points the left end of the distribution as the region with values. All values smaller than the quantile of the range $\alpha = 0.1$ (for this distribution) are interpreted as significant.

B. Selection of Multiple Variable Points

In case when there are more than one variable measured in the point it is necessary to introduce some voting scheme that determines the point significance due to relevance of all particular variables values.

The voting scheme is as follows: each variable has a weight of its vote ([0; 1], default is 1) and the weighted average of all votes is calculated (vote = 1 when value is significant and vote = 0 in the opposite situation). If the final vote is not less than assumed level the point is interpreted as significant.

This simple scheme gives the variety of interpretable models of voting:

- logical AND: voting represents the logical conjunction for threshold = 1 and all weights equal;
- logical OR: voting represents the logical alternative for very small threshold (≈0.00001) and any weights;
- no-selection: threshold = 0 treats every point as significant.

C. Building the New Grid

The other approach to points number limitation in the unorganized point cloud assumes building a new point cloud, in which values are approximated on the basis of the values in the known points.

Since this task can be treated as the problem of nonparametric regression one of the most simple nonparametric estimator of the regression function was applied – the Nadraya-Watson kernel estimator [6], [7]. This method is developed from the task of nonparametric density estimation and gives satisfactory results in the regression problem.

The estimation of the value of the function f in the point x is given with the following formula:

$$\tilde{f}(x) = \frac{\sum_{i=1}^{n} y_i K\left(\frac{x - x_i}{h}\right)}{\sum_{i=1}^{n} K\left(\frac{x - x_i}{h}\right)}, \quad (1)$$

where $\tilde{f}(x)$ is the estimated value of the value $f(x)$, n is the number of training points (x, y), K is the kernel function and h is so-called smoothing parameter.

This equation can be interpreted as the weighted average of known observations where weights depend on the kernel function. Usually, kernel functions take positive values on the finite, zero-symmetric range (the most common exception is the Gaussian kernel, which gives positive values for every real argument). The selection of the form of the kernel does not influence on the final regression results significantly. The smoothing parameter h defines the neighborhood of the argument x. Its high values cause that values of very distant points are averaged what make the final results to be smoothed too strong. On the other hand – too small values cause that none of observations are involved in estimation of the regression function at the given argument.

This is a good practice to use the Epanechnikov kernel function [8] given in the following way:

$$K(x) = 0.75\left(1 - x^2\right) \cdot I(-1 < x < 1), \quad (2)$$

where $I(A)$ is the indicator of the set A.

According to [9] the selection of h influences more on the final results than the form of the kernel function. The simple way of finding the value of the smoothing parameter bases on the distribution of the training points and is described as:

$$h_{opt} = 1.06 \min\left(\tilde{\sigma}, 0.746 \cdot \tilde{R}\right) n^{-0.2}, \quad (3)$$

where $\tilde{\sigma}$ is the standard deviation of the variable x and $\tilde{R}$ is its interquartile range.

In case of multidimensional data a radial kernel functions are used. The only difference is that the scalar x is replaced with the scalar product of the input vector and the constant coefficient becomes dependent from the dimensionality of the input vector:

$$K(\bar{x}) = (d + 2)(2V_d)^{-1}\left(1 - \bar{x}' \cdot \bar{x}\right) \cdot I(-1 < \bar{x}' \cdot \bar{x} < 1), \quad (4)$$

where V_d is the volume of the d-dimensional unitary sphere:

$$V_d = \begin{cases} (2\pi)^{d/2} / (2 \cdot 4 \cdot \ldots \cdot d) & \text{for } d \text{ even} \\ 2(2\pi)^{(d-1)/2} / (1 \cdot 3 \cdot \ldots \cdot d) & \text{for } d \text{ odd}. \end{cases} \quad (5)$$

Also the formula for the optimal value of the smoothing parameter in the i-th dimension is modified according to the problem dimensionality as follows:

$$h_{opt_i} = \left(\frac{4}{d + 2}\right)^{1/(d+4)} \min\left(\tilde{\sigma}_i, 0.746 \cdot \tilde{R}_i\right) n^{-0.2}, \quad (6)$$

where d is the number of independent variables.

The final smoothing parameter is the multiplication of smoothing parameters values for every dimension:

$$h_{opt} = \prod_{i=1}^{d} h_{opt_i}. \quad (7)$$

III. Surface Reconstruction

Visualization of the unorganized point cloud enables tracking a parameter change during the UCG process in each measured point. Yet, it does not answer a question what is the cavity shape in a straightforward manner. Therefore, additionally a surface reconstruction techniques were applied to show the void inside the seam.

A. State of the Art

The problem of surface reconstruction from the unorganized point cloud resulting in the irregular polygonal mesh has been already studied for several years. Firstly, the static approaches were addressed, which use iterative manner to look over the point cloud in order to reconstruct a mesh. Later, the attempts to dynamically reconstruct the surface were developed. This algorithms build a surface model, which evolves to fit the point cloud as well as possible.

Among the static surface reconstruction techniques one can distinguish methods which are surface or volume oriented. The surface oriented techniques tend to reconstruct the surface directly from the point cloud. These methods use the point from the point cloud as vertices in the reconstructed mesh. Some of them need three initialization points to generate first facet, then iteratively the vertices are inserted and the edges created. The *Delaunay triangulation* [10] is the well-known example of this approach. For semi-organized point clouds, where the points are organized on the cross-sections, the *contour stitching* method [11]-[14] is exploited. In the case of volume oriented techniques, a volume enclosing point cloud is created. The volume is divided into smaller regular sub-volumes called voxels. Next, each voxel is processed separately to create a part of the surface. Finally, the patches are connected, like in the *marching cubes* technique [15].

The dynamic surface reconstruction approach started with the introduction of *active contours* [16]-[18] and its expansion in three-dimensions. In this method the model exploits external forces to drag the surface to the point cloud, whereas the internal forces take care to keep the surface's points together. This solution gives good results when the shape of the surface may change without constraints. However, when the shape variations are limited the *active shape model* [19], [20] should be taken under consideration.

B. Chosen Approach

For the visualization purposes it is important to assure the reconstruction of the surface in each measuring point, but also a smooth transition between consecutive frames is necessary. Therefore, choosing appropriate method following things one should have in mind:

- the cavity surface may lay in the neighbourhood of the points,
- the points describing the cavity may change in adjoining

frames,

- the smooth transition between surfaces found in adjoining frames should be assured.

The first assumption eliminates all statistic surface oriented techniques, because they interpolate the data, whereas in this research the approximation seems more correct. Hence, dynamic surface reconstruction method were selected. A model mesh *m*, enclosing the unorganized point cloud, is generated:

$$m(n,t) = (x(n,t), y(n,t), z(n,t)), \tag{8}$$

where *x*, *y*, and *z* are the vertex coefficients, *n* depicts the set of neighbouring vertices in the mesh, and *t* – an iteration number. The active surface model moves in the space minimizing energy equation given as:

$$E = \int_0^1 [E_{\text{int}ernal}(m(t,n)) + E_{external}(m(t))]dt, \tag{9}$$

where the internal energy is responsible to keep the mesh vertices together. In presented solution a threshold values for edge length are set and when they are exceeded additional vertex is inserted or two triangles are merged. The external energy depends from the Euclidean distance *d* to the closest point in the unorganized point cloud modified by a constant *k*, which balance the second energy:

$$E_{external} = -kd. \tag{10}$$

In order to simplify the search for the nearest point, the unorganized point cloud is enclosed in octree structure, where each cube is related to mesh vertex.

In order to meet other assumptions two solutions were considered. First of all, it is possible to evolve the surface generated for data in one snapshot using presented schema to fit the data in consecutive frames. However, this method has problem when some points of the unorganized point cloud are outside the surface. In this situation it is difficult to assure that the facets do not cross each other. On the other hand, it is possible to generate a surface for each snapshot and then interpolate the transition between them. This solution can be easily solved when assuming a known order of vertices and therefore, was implemented.

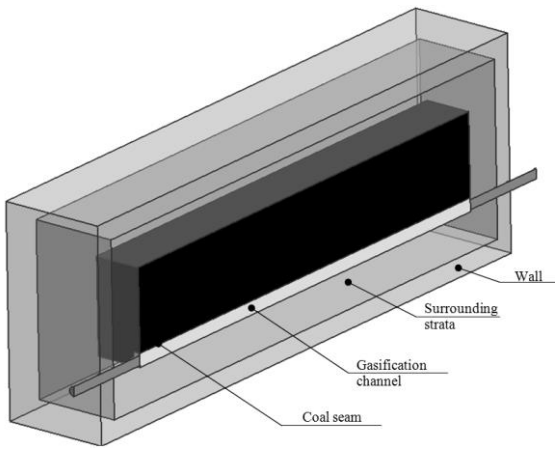

Fig. 3. The cross-section through the UCG ex-situ reactor build to observe the process and also used in mathematical model.

IV. Results

The data visualized by the described methods is generated with application of the particularly developed mathematical model for underground coal gasification process. The model assumes an *ex situ* conditions, when the block of coal was firstly extracted from the mine and placed in the reactor as it is described in [5]. The reactor length was 3 meters while its width and height were 1.5m. The dimensions of the block of coal were 1.5×0.8×0.8m (length × width × height). The gasification channel was drilled in the middle of the bottom of the block, along the longest dimension. Its cross-section had a square shape, which side equaled 0.1m. The void of the reactor was filled with sand in order to block the heat transfer. Fig. 3 presents the cross-section through the described reactor model.

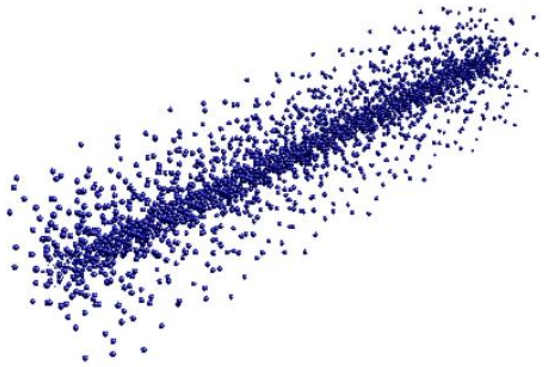

Fig. 4. Visualization of point cloud data depicting the state of CO_2 in the beginning of the UCG process.

Fig. 5. Visualization of points selected with the suggested approach in the beginning of the UCG process.

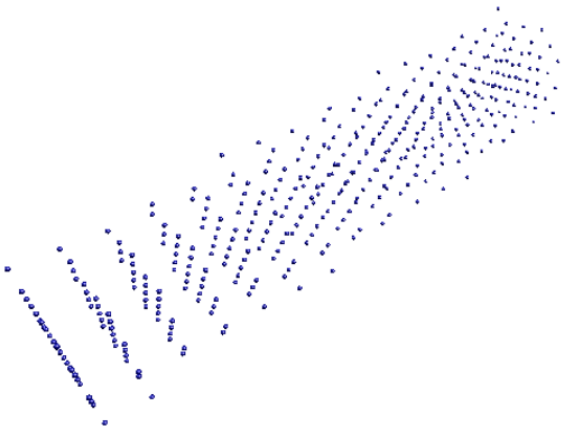

Fig. 6. Visualization of points created by the method building new mesh for data describing process.

Since the gasification channel is the most important part of

the model, regardless its small dimensions, it was described with 4173 vertices uniformly dispersed. Whereas, there were 8046 vertices in which the parameters for block of coal were estimated by the model. Fig. 4 presents visualization of all these points with point cloud visualizer. Each vertex is visualized as a sphere, which radius is correlated to the presented parameter value (in the presented case the carbon dioxide). However, in the case of the enormous amount of data, it is impossible to notice the small changes in parameter values. Yet, due to the higher concentration of vertices inside the gasification channel its placement is well visualized.

The most interesting phenomenon which is going to be observed with this software is the cavity formation in the underground gasification process. Therefore, the system applying the selection methods extracts the vertices which are valid to depict the cavity. It bases on the assumption that the values of the parameters inside and close to the neighbourhood of the cavity should vary considerably from the values in stable conditions, for instance inside the block of coal. Fig. 5 presents chosen vertices, which visualize the moment of ignition, which took place around 20 cm from the inlet of the gasification channel. This moment was chosen for tests, as the change of parameters during the ignition process is the easiest to estimate in the model, and therefore during the visualization test, the model inaccuracies could be omitted. Unfortunately, applying the second selection method based on recreating a mesh from the scratch did not bring expected results. It is due to a small changes in data values which, when averaged, disappear (please refere to Fig. 6).

Fig. 7. Visualization of surface enclosing while point cloud gathered similarly as on Fig. 4.

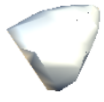

Fig. 8. Visualization of surface enclosing selected points in the same manner as those from Fig. 5.

For similar data as presented in Fig. 4 and Fig. 5 the visualization with a surface was prepared and is depicted on Fig. 7 and Fig. 8, respectively. One can see that the chosen approach well reflects the unorganized point cloud data and creates a smooth manifold.

V. Conclusions

The work presents application of computer graphics techniques for UCG process data visualization. The data pre-processing approaches, for the estimation of the most important data for the cavern presentation, were given. Then the surface reconstruction techniques were discussed. The results of data visualization show that the implemented software enables concise process data visualization, which finds application in underground coal gasification process modelling, predicting, and monitoring in the future.

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