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INTELLIGENT POINT DATA REDUCTION IN REVERSE ENGINEERING

INTELIGENTNÍ SNÍŽENÍ POČTU BODŮ V REVERSE ENGINEERINGU

Abstract

Modern systems for 3D-digitization purposed for Reverse Engineering (RE) modeling are featured by increased scanning speed and also by the possibility to generate large number of points in a short time. In general, this improves the efficiency of the RE modeling process. In practice however, a large number of points in the stage of generation of the CAD model may become a serious problem. Therefore, lately considerable attention is focused to the problem of point data reduction in the 3D-digitization results. This paper presents an approach for intelligent point data reduction based on fuzzy logic, along with the results of its practical application.

Abstrakt

Moderní systémy pro 3D digitalizaci zaměřené na moderní Reverse Engineering (RE) se zabývají zvýšenou rychlostí skenování a také s možností vytvářet velký počet bodů v krátkém čase. Obecně platí, že to zlepšuje účinnost procesu modelování RE. V praxi se však může velký počet bodů ve fázi generace CAD modelu stát vážným problémem. Proto se v poslední době zaměřuje značná pozornost na problematiku snižování počtu bodů v 3D digitalizace. Tento článek představuje přístup pro inteligentní snížení počtu bodů na základě fuzzy logiky, spolu s výsledky jeho praktického využití.

1 INTRODUCTION

Contemporary 3D-digitization systems which are applied in Reverse Engineering (RE) modelling are characterized by increased scanning speed and also by the possibility to generate large number of points in a short time. Generally, this improves the quality and efficiency of the RE-modelling process. In practice however, later in the stage of CAD model generation, a huge number of points which are generated in the stage of 3D-digitization may become a serious problem [1,2].

Considering all the above mentioned, the stage of pre-processing the results of 3D-digitization which includes error filtering, data smoothing and the most sophisticated process of data-point reduction, becomes inevitable in almost any RE system [3,4].

In the multitude of data-point reduction approaches that were developed, it is possible to identify three dominating groups of approaches for pre-processing the results of 3D-digitization: methods of point sampling, methods of polygon reduction and grid methods [5, 6].

It should be noted that there are frequent attempts to integrate the methods of artificial intelligence into the process of pre-processing, i.e. into point data reduction above all, in order to achieve better quality and process efficiency [1].

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Within the framework of this article, a novel approach for point data reduction is introduced, designated primarily for RE modeling systems based on the "cross-sectional" approach.

2 INTELLIGENT APPROACH FOR POINT DATA REDUCTION

The main features of an approach for point data reduction presented here are integrated deviation analysis and fuzzy logic reasoning. This constitutes the main difference in comparison to the approaches developed so far.

Building on the weak spots and deficiencies of current approaches to reduction of point data by sampling methods - i.e. the lack of information on the level of deviation in reduced point clouds and necessity to employ parameters which are abstract to user [4, 5] - a novel approach was developed for analysis of the level of deviation of the reduced point cloud in comparison with the initial point cloud. This novel approach introduces an additional parameter termed maximum allowed reduction error (MARE), in the reduction-related decision process with the sampling-based methods.

In order to improve the process of reduction, the novel approach was enhanced by implementing fuzzy logic in the process of reduction-related decision making. Beside the additional improvement of the deviation/mean level of reduction ratio, implementation fuzzy logic allowed a more user-friendly and intuitive application. The reduction process is controlled by simply entering the deviation tolerance, allowing the user to gain better insight into the quality of the reduced point cloud [6,7].

The key feature of the novel approach to sampling-based point data reduction, proposed here, is the procedure for analysis of deviations of cross-sectional curves, which are the result of point data reduction.

Practical realization of procedure for analysis of deviation is based on computation and analysis of maximum deviation of the resulting cross-sectional curve relative to the original cross-sectional curve generated from initial point cloud. Least squares method, modified to meet specific requirements of the problem in hand, was used to compute maximum deviation - designated MRE (Maximum Reduction Error) in this paper. In this case, the key parameter of MRE is the absolute value of maximum deviation of a cubic spline curve generated through an array of scanned and reduced points - relative to the spline curve generated through original point array. In other words, MRE is computed after each point elimination by finding maximum deviation □i(xi, yi) of the spline curve generated after elimination of j-th point Tj(xj, yj, zj) - relative to the spline curve generated through originally scanned point cloud (Fig. 1).

$$MRE = \max(\varepsilon_i) \;\; ; \;\; i = 1,2,...,n \, . \tag{1}$$

Deviations $\varepsilon_i(x_i, y_i)$ are calculated at points defined by resolution ν (Fig. 1) which can be varied to suit the length of the scanned curve, i.e. the density of scanned points within array.

Beside parameter *MRE*, the procedure also employs the *ARE* (*Average Reduction Error)* – an additional parameter which allows assessment of deviation of the resulting cross-sectional curve. *ARE is* a mean sum of deviations computed at points defined by resolution ν (Fig. 1) and can be expressed as:

$$A\mathrm{RE} = \overline{\sum_{i=1}^{n} \varepsilon_i} \, . \tag{2}$$

The methods for reduction of point data by sampling, were improved by implementing fuzzy logic into procedure for decision-making on which elimination of points is based.

To eliminate the problems which stem from the specific values of decision-critical input parameters entered by the user, and create a more user-friendly system, a new, synthetic parameter was introduced under the name reduction coefficient (RC), and its maximum allowed value was defined as maximum allowed reduction coefficient (MARC). For all three methods the RC parameter was derived based on method-specific parameters, and an additional input parameter maximum reduction error (MRE), i.e. the maximum allowed reduction error (MARE). MARE was introduced to allow the maximum reduction error to be controlled.

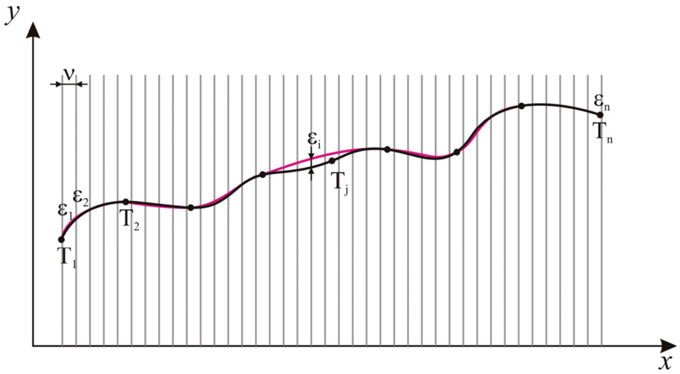

Fig. 1 Graphical interpretation of MRE and ARE

Details of the novel approach for point data reduction are presented here for the case of spatial method. The spatial method for point data reduction is based on the parameter of spatial (Euclidean) distance (d_E) [7] which, together with *MRE*, was used as input parameter for the fuzzy-logic-based decision-making system. Shown in Fig. 2 is the structure of this fuzzy system which consists of three modules – input, knowledge base and output.

The input is formed by two state variables – d_E, and *MRE*, whose values are fuzzified into fuzzy sets with appropriate input spaces, while the fuzzy sets of input values are defined by their membership functions [9]. Due to its simplicity, triangular membership function was chosen for all state variables. It should be noted that the input space for d_E (0 to 2 [mm]) was defined based on practical experience, while for the state variable *MRE,* this input space is defined on the basis of real-application experience with *MARE* = 0,05 [mm] as the pivotal parameter. The input space was segmented in the following way - for d_E it was sectioned into three segments with appropriate linguistic terms (*shorter*, *medium,* and *longer*), while for the *MRE* it was segmented into three fuzzy sets (*slight, moderate and significant*). The output from this fuzzy system is variable RC (a non-dimensional value) which, for simplicity sake, has been allotted an output space from 0 to 100, and the parameter MARC must fall within that space. To allow finer control of *RC parameter*, the input space was segmented with finer resolution, resulting in a total of nine fuzzy sets denoted with linguistic qualifiers - *minor, very low, low, medium-low, medium, medium-high, high, very high*, and *huge*.

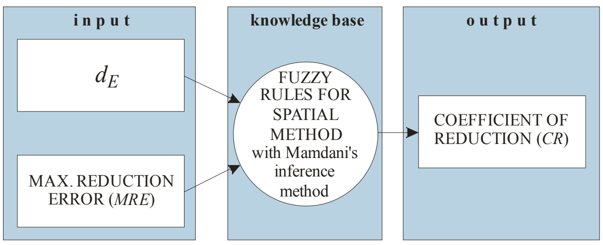

Fig. 2 Structure of fuzzy system for point data reduction using spatial method

Using the defined fuzzy variables (d_E, *MRE,* and *RC*) and their belonging fuzzy subsets with their membership functions, fuzzy control rules were defined which represent the knowledge base of the proposed fuzzy system. A total of nine fuzzy rules were defined which are presented in Table 1.

Tab. 1. Control fuzzy rules of the fuzzy system for point data reduction using spatial method

1. If (d_E is *Shorter*) and (*MRE* is *Slight*) then (*CR* is *Huge*)
2. If (d_E is *Medium*) and (*MRE* is *Slight*) then (*CR* is *Very-high*)
3. If (d_E is *Longer*) and (*MRE* is *Slight*) then (*CR* is *High*)
4. If (d_E is *Shorter*) and (*MRE* is *Moderate*) then (*CR* is *Mid-high*)
5. If (d_E is *Medium*) and (*MRE* is *Moderate*) then (*CR* is *Mid*)
6. If (d_E is *Longer*) and (*MRE* is *Moderate*) then (*CR* is *Mid-low*)
7. If (d_E is *Shorter*) and (*MRE* is *Significant*) then (*CR* is *Low*)
8. If (d_E is *Medium*) and (*MRE* is *Significant*) then (*CR* is *Very-low*)
9. If (d_E is *Longer*) and (*MRE* is *Significant*) then (*CR* is *Minor*)

The system was modelled using reference values of output variable, according to which the membership functions of input variables were adjusted. As criterion for adjustment of the membership functions, mean square deviation was adopted [8]:

$$E = \sqrt{\frac{\varepsilon_1^2 + \varepsilon_2^2 + \ldots + \varepsilon_n^2}{n}} \quad . \tag{3}$$

using the three sigma rule:

$|\varepsilon_{\max}| < 3E$ => *acceptable level of adjustment*

$|\varepsilon_{\max}| > 3E$ => *unacceptable level of adjustment*

The mechanism of fuzzy decision-making is based on the *Mamdani* method. This method uses the *minimum of operation, i.e. the minimum of* intersection, to form the fuzzy implication function [9]. The procedure of fuzzy reduction is presented in Fig. 3.

3 VERIFICATION RESULTS

The developed approach has been tested through its practical application. Here results of the application on case study of a sports glasses lens (Fig. 4) are presented.

The choice of this part, which due to ergonomic intent is of a relatively simple geometry, was motivated by the complexity of digitized data (Fig. 5) which requires adequate fixture and locating. 3D digitization was performed by a contact system Cyclone II - Renishaw, resulting in a total of 412,111 points, of which a large number represent error-points which actually belong to the fixture and measuring table.

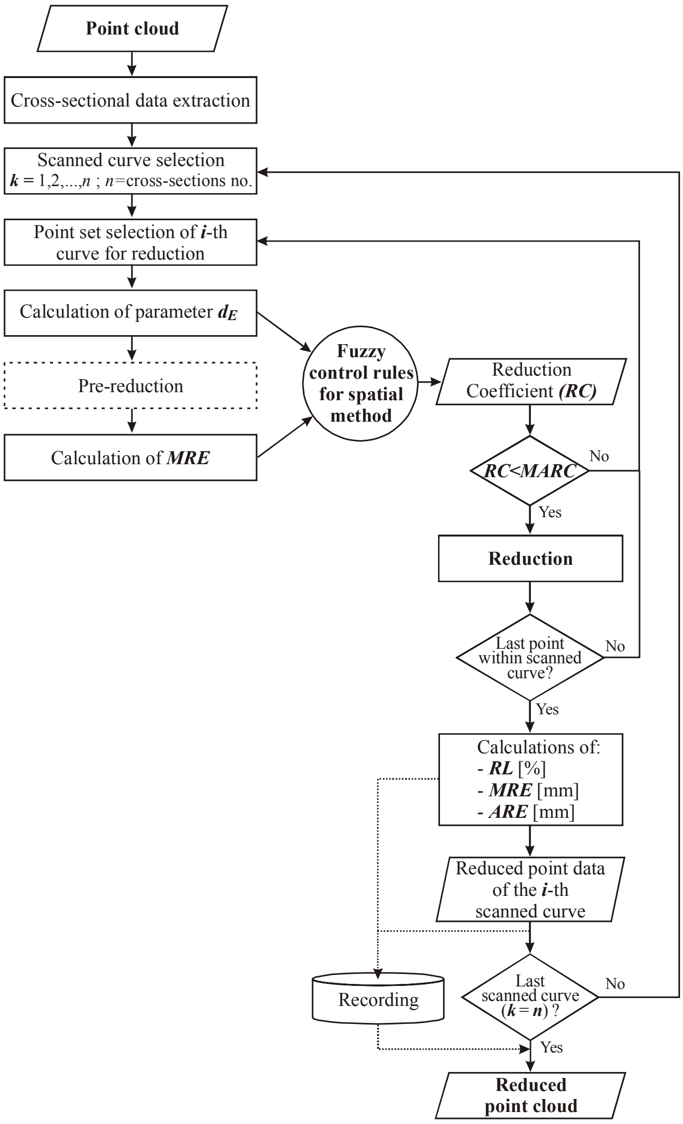

Fig. 3 Algorithm of the proposed fuzzy-logic-based software application for point data reduction by the spatial method

Fig. 4 Sports glasses and a lens

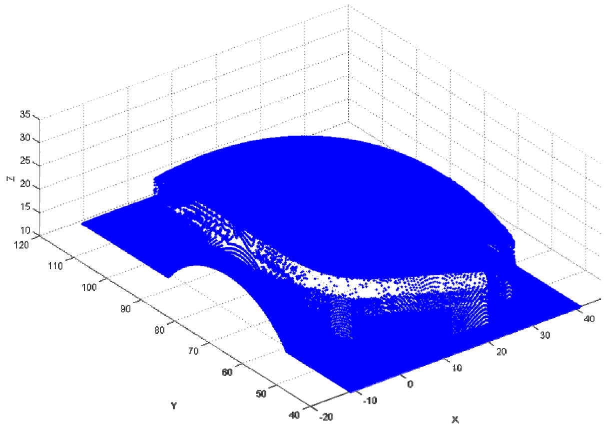

Fig. 5 The results of 3D-digitization

The pre-processing included 3D filtering (volumetric filtering, filtering by segmented line, and elimination of individual points), cross-sectional filtering/smoothing of point data (elimination of end points), change of resolution and reduction of point data. The point cloud subject to reduction, contains 109,528 points in 214 cross-sections. Fuzzy-chordal reduction method was chosen, with MAD=0.03 [mm]. The results of reduction are presented in Table 2 and in Fig. 6.

Tab. 2. Results of point data reduction

MAD [mm]	0.03
Maximum error [mm]	0.02835
Average error [mm]	0.00265
No. of eliminated points	107,466
Reduction level [%]	97.82
No. of resulting points	2,062

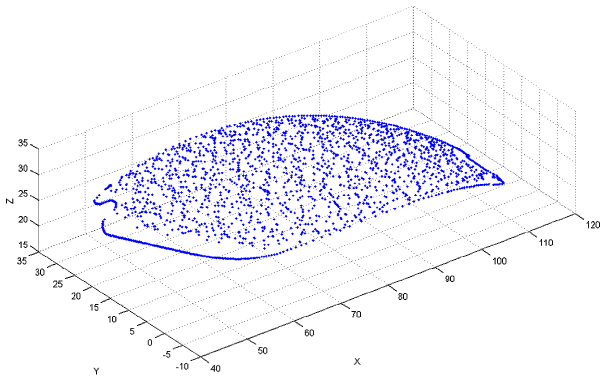

Fig. 6 Graphical representation of reduction results

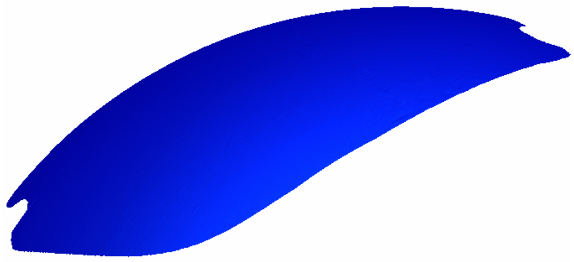

Fig. 7 Surface model generated from “reduced” point cloud

Verification of the generated surface model from “reduced” point cloud has been conducted through comparison of the deviation of the “reduced” and “original” surface models from the “original” point cloud (used as input in reduction process). Deviations have been analysed by the application of CAD inspection technique. The results are shown in Fig. 8. Numerical values for maximum positive and negative deviations are given in Table 3.

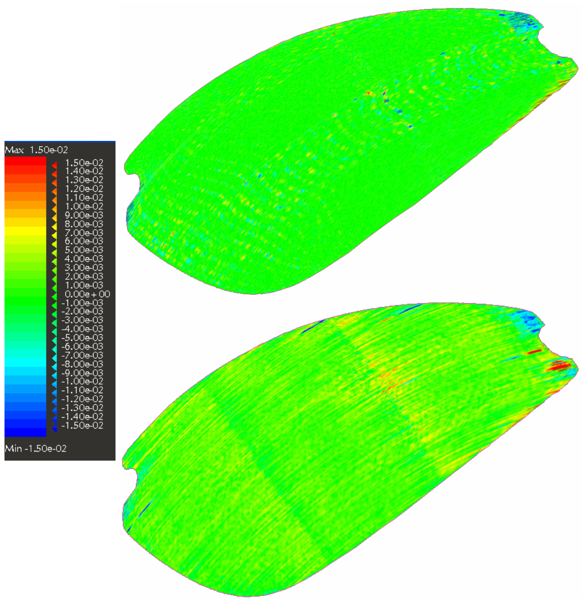

Fig. 8 Results of CAD-inspection of surface models defined by 0,015 [mm] tolerance

Table 3. Results of CAD inspection of generated surface models

Model	Deviation [mm]	
	Min.	Max.
“original”	-0.0279	0.0283
“reduced”	-0.0291	0.0280
Difference:	+0.0022	-0.0003

4 CONCLUSIONS

Within this paper a novel approach for point data reduction, designed for use in systems for Reverse Engineering modelling based on cross-sectional methodology, has been presented.

This paper also provides practical results of application of the developed approach. Judging by the graphical output from CAD inspection and the maximum values, one can conclude that the level of deviation of the “reduced” surface model is very close to that of the “original” surface model. More regions with deviations within the “reduced” surface model are direct consequences of the approximate surface generation on the bases of reduced point data. According to this it is obvious that the developed approach, although still in the experimental stage of work, shows satisfying results.

Future researches will be directed towards analyzing parameter relations, i.e. adequate functions of affiliation in fuzzy procedures with the goal of fine-tuning the performance of the reduction process.

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