http://dx.doi.org/10.5755/j01.eee.20.6.7259 ELEKTRONIKA IR ELEKTROTECHNIKA, ISSN 1392–1215, VOL. 20, NO. 6, 2014

Classification of 3D Point Cloud Using Numerical Surface Signatures on Interest Points

K. Rimkus[1], A. Lipnickas[1], S. Sinkevicius[1]
[1]*Department of Control Technology, Kaunas University of Technology, Studentu St. 48–320, LT-51367 Kaunas, Lithuania*
kestas.rimkus@gmail.com

***Abstract*—This paper describes a 3D object classification method by 3D-3D comparison using the numerical surface point signatures on interest points of 3D objects point cloud. Interest or salient points of 3D point cloud were found by Heat Kernel Signature method. The numerical point signatures used for classification were composed only on these points. To investigate the objects classification resistance to the data measurement noise, additionally to original 3D data was added 1.5 % of continuity distributed noise. Object classification was carried out using forty three 3D objects point cloud database. Study of 3D object interest points recognition has shown that the standard Surface Point Signatures methodology is sensitive to the normal vector used for signature composition as well as the object's surface normal is very sensitive to objects mesh error. In order to reduce the sensitivity to the object surface measurement error we have proposed to use one constant vector as average from all object mesh normal's. Such approach on average improved interest point's recognition rate by ~16 % and allowed to reach 95.9 % of classification accuracy on used 43 objects database.**

***Index Terms*—Classification algorithms, digital signatures, object recognition, robot vision systems.**

I. INTRODUCTION

Three dimensional object recognition by 3D-3D template matching is a young research field extensively pursued in recent decade. Only several applications have been proposed for automated object recognition task with high enough accuracy. The 2D object recognition in images has been extensively investigated with significant success [1]. Unfortunately, these methods cannot be directly extended and applied on range data for object recognition; hence new 3D point cloud data analysis techniques should be developed.

Automatic industrial sorting lines with computer vision systems are now common in food processing [2], [3], surface defect detection [4, 5], garbage recycling [6], letter sorting [7], etc. As example, 3D objects classification are successful used for produced components sorting and identification [8].

In recent years, various devices have been developed as an attempt to access the 3D information of the physical world, such as Time-Of-Flight (TOF) camera [9], stereo vision camera, laser range scanner, and the structured light camera [10]. With each new generation of these devices, they are becoming faster, more accurate and better resolution. This means more data points in each frame and longer processing time. Therefore for real time 3D point cloud processing the new 3D point cloud analysis methods should be developed and for this reason the 3D object recognition is most popular topic in recent years.

The proposed paper studied possibilities of recognition of 3D object points by comparing their numerical surface point signatures (SPS) composed on object's interest points. The matching of two SPS was done by computing Euclidian distance and correlation measure.

The composition of SPS is very sensitive to surface normal therefore we used one vector for object's signatures composition. The experimental investigation has shown that such approach improved object correct classification rate up to 95.9 %.

The paper contains five main sections. In the second Section, theoretical background is overviewed. The third Section gives more information about used data and the experiments. Experimental results are presented in Section V. Conclusions are given in Section V.

II. THEORETICAL BACKGROUND

A. Interest Points

The proposed approach is based on assumption that specific interest points of 3D object [11] can be established on 3D point cloud in order to recognise and classify objects. The comparison of two or more models of 3D objects can be done by comparing not all data of models' points, but only saliency points that have been established. If at least three equivalents of interest points were found from one object in another the correspondence could be recognized.

There are several most popular mathematical means that allow identifying interest points: Mesh saliency, salient points, 3D Harris, 3D SIFT, SD-corners and Heat Kernel Signature (HKS). The authors of the article [12] compare these mathematical methods with human-marked salient points for the same 3D objects (Fig. 1).

The authors of the research [12] conclude that human-marked salient points are individually important and they vary among individuals. The number and position of salient points depends on the model complexity and the mathematical means. One way or another, automatically found points can be used for direct comparison of 3D models, according to 3D-3D matching [11].

Manuscript received January 18, 2014; accepted April 21, 2014.
This research was funded by the European Social Fund under the project "Microsensors, microactuators and controllers for mechatronic systems (Go-Smart)" (Agreement No VP1-3.1-ŠMM-08-K-01-015).

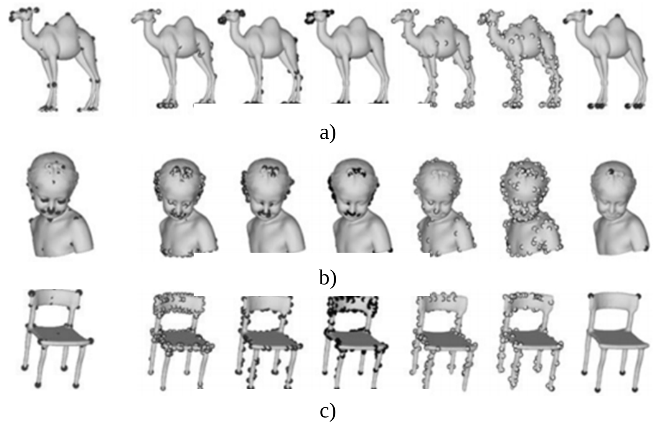

Fig. 1. Human-marked points (first column), interest points detected by the algorithms: Mesh saliency (second column), Salient points (third column), 3D-Harris (fourth column), 3D-SIFT (fifth column), SD-corners (sixth column), and HKS (seventh column) [12].

Unfortunately the amount and the order of detected interest points vary from try to try. Therefore the use of SPS is helpful in identifying interest points by comparing to stored signatures library.

B. Surface Point Signatures

A surface point signature (SPS) [13] is a two-dimensional histogram (spin-image) computed at an oriented point **P** of the surface mesh of an object (Fig. 2). The histogram accumulates the coordinates α and β of a set of contributing points *Q* on the mesh. Contributing points are those that are within a specified distance of **P** and for which the surface normal forms an angle of less than the specified size with the surface normal **N** of **P**. This angle is called the support angle. As shown in Fig. 2, the coordinate α is the distance from **P** to the projection of *Q* onto the tangent plane T_P at point **P**; β is the distance from *Q* to this plane.

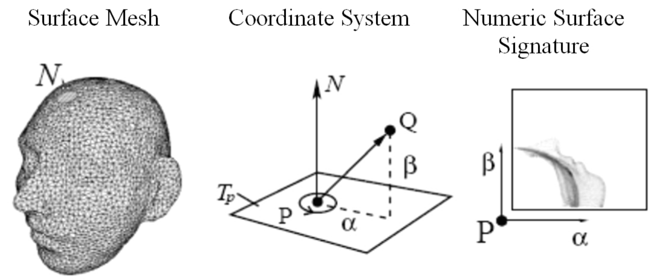

Fig. 2. The numeric surface signature for point P is constructed by accumulating in a 2-D histogram the coordinates α and β of a set of contributing points (such as Q) on the mesh representing the object [13].

By using coordinate basis, the spin image can be defined as the function S_O to project 3D points into 2D coordinate on the selected basis (**p, n**) [13]

$$\begin{cases} S_0 : \mathbf{R}^3 \to \mathbf{R}^2, \\ S_0(\mathbf{x}) \to (\sim, \quad) = \\ = \left(\sqrt{\|\mathbf{x}-\mathbf{p}\|^2 - (\mathbf{n} \bullet (\mathbf{x}-\mathbf{p}))^2}, (\mathbf{n} \bullet (\mathbf{x}-\mathbf{p})) \right), \end{cases} \tag{1}$$

where **p** – point of basis with normal **n**, **x** – mesh point. The α values are always positive, β – can be positive and negative.

Each oriented point on the object surface has its own unique spin image. The size of spin image depends on the object size and on the number of vertexes. Therefore the normalization of images is very important. It is possible to normalize the objects by its maximum length, to have scale independent matching.

In order to match and compare two spin images they are converted into non-dimensional histogramic 2D pictures with selected bins resolution [*k*,*l*]. Afterwards two images are compared by matching corresponding bins of histograms or by computing Euclidian distance or correlation.

Surface point signatures [13], [14] are attributed to the methods that have the highest level of object recognition and complexity, and their complexity is described by formula $O(n*\log_2(n))$, where *n* is number of object points.

For this reason, in order to identify an object or its specific points, it is advisable to use SPS not on all object points, but only on interest points.

C. 3D Object Point Clouds Interest Points Recognition

As mentioned above, each orientated point on the object surface has its own unique spin image, but the spin image differs for same point if they are scanned twice. This happens due to surface measurement errors. As SPS is composed around the surface normal **N** in a point, the signature is sensitive to fluctuation of surface normal vector. The small surface error significantly affects alteration of **N** angle and changes the spin-image.

Our hypothesis claims that the average of triangulated object faces normal's is less sensitive to the measuring errors and therefore the normal **N** in a point can be replaced by a single vector composed as an average of object normal's.

D. 3D Object Point Cloud Classification

3D object point cloud classification is performed by composing SPS on interest points detected by HKS method. It is assumed that the best received SPS set matching with database objects SPS sets corresponds to the wanted object class. Spin images of SPS are compared by calculating Euclidian distance or the correlation.

If for comparison Euclidian distance is used, the object is assigned to a class from a database with a minimum sum of distances counted on all interest points. If for comparison correlation function is used, the object is assigned to a class from a database with the highest sum value counted on all interest points. The algorithm for classification of 3D point cloud data using numerical surface signatures on interest point's is presented in Fig. 3.

III. DATA

A. Salient Point Recognition by Numerical Surface Signatures in 3D Point Cloud

The authors of [12] states that the interest points searching method HKS mostly corresponds to the points that were chosen by humans on the same 3D models. For this reason in this research we have adopted the HKS to identify 3D object's interest points. The 3D point cloud of a cow with detected ten interest points by using HKS method is presented in Fig. 4.

In modern 3D range measurement systems, the measurement error is ±1 % or smaller. So to investigate recognition quality by imitating the real system measurement errors, we have affect 3D object point cloud with ±1.5 % of continuous distribution noise, by claiming that available 3D space meter can have lower class of accuracy. All experiments were carried with experimentally selected discretization step for spin-image: $k = l = 15$ and limiting coefficient β to 0.5 for all experiments.

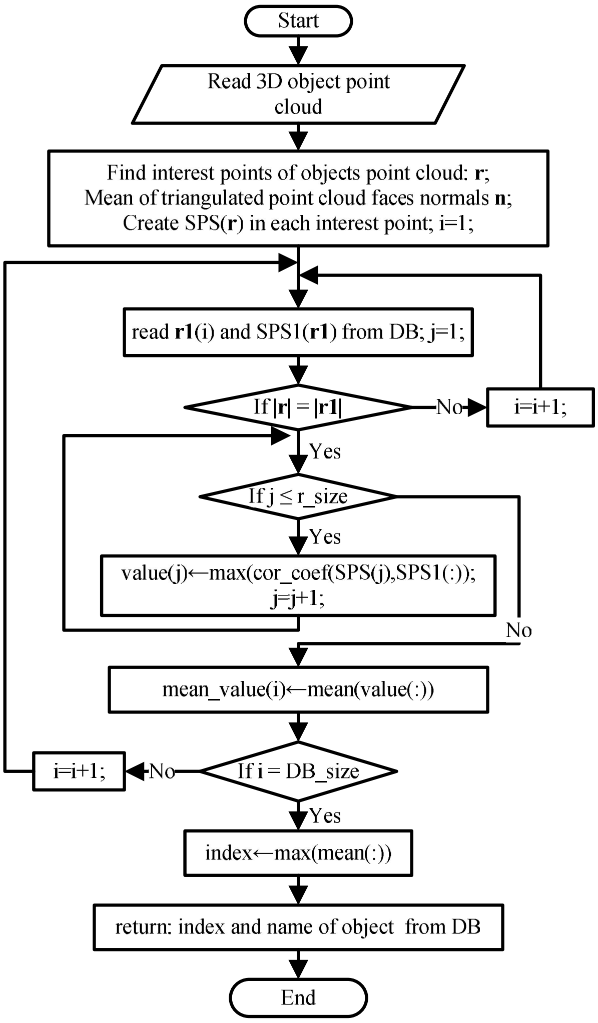

Fig. 3. Proposed algorithm for 3D objects point clouds classification.

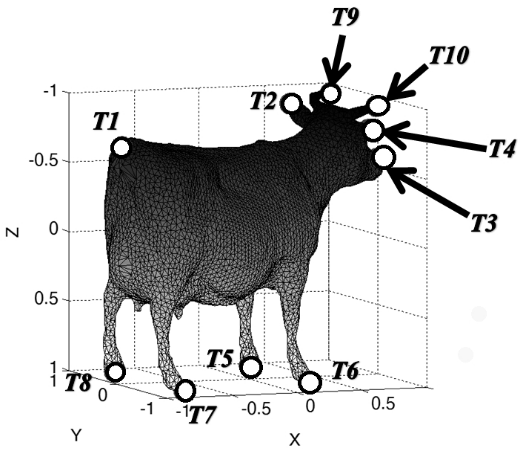

Fig. 4. 3D point cloud of cow with points that were found using HKS method.

B. Data for 3D Object Point Cloud Classification

The research of object classification uses database (first 12 elements of database are shown in TABLE I), which was also used by the authors [12]. The database consists of 43 3D object models with marked salient points.

TABLE I. FIRST 12 OBJECTS OF 43 OBJECTS POINT CLOUDS DATABASE.

Nr.	Name	Points	HKS	Nr.	Name	Points	HKS
1	airplane	7739	6	7	bust_2	8263	3
2	ant	7654	9	8	cactus	1554	4
3	armadillo	8650	19	9	camel	9757	13
4	bird_2	11790	6	10	chair_4	14052	6
5	bird_3	5970	6	11	chair_5	11421	6
6	bust	5197	12	12	cow	11610	10

IV. EXPERIMENTS

A. 3D Object Interest Points Recognition

The point cloud of Cow with detected ten interest points (Fig. 4) was used for interest point recognition analysis by numerical surface signatures. In order to cover the recognition task, the Cow point cloud was affected with ±1.5 % of continuous distribution noise. On each interest point the SPS was computed with spin-image parameters $k = l = 15$ and limiting coefficient β to 0.5. Euclidian distance and correlation coefficients were calculated between new and original SPS. The experiment was repeated 1000 times and the percentage of its confusion matrices is given in the tables (TABLE II and TABLE III. As it is seen from the tables, for the SPS method it is hard to recognize correct legs {T5-T8} and correct cow horn {T9-T10} due to object symmetry, as well as due to the fact that the object is noise-added.

TABLE II. CONFUSION MATRIX IN % OF COW INTEREST POINTS RECOGNITION USING EUCLIDIAN DISTANCE AND STANDARD SPS.

	T1	T2	T3	T4	T5	T6	T7	T8	T9	T10
T1	**97**	0	0	1	0	0	0	1	1	0
T2	0	**67**	0	0	1	0	14	16	0	0
T3	15	0	**85**	0	0	0	0	0	0	0
T4	0	0	0	**98**	1	1	1	0	0	0
T5	0	0	0	0	**73**	22	3	2	0	0
T6	0	0	0	0	15	**72**	10	2	0	0
T7	0	0	0	0	5	23	**48**	24	0	0
T8	0	0	0	0	5	18	28	**49**	0	0
T9	2	0	0	4	0	0	0	0	**72**	22
T10	0	0	0	4	0	0	0	0	33	**63**

TABLE III. CONFUSION MATRIX IN % OF COW INTEREST POINTS RECOGNITION USING CORRELATION AND STANDARD SPS.

	T1	T2	T3	T4	T5	T6	T7	T8	T9	T10
T1	**89**	0	11	0	0	0	0	0	0	0
T2	2	**84**	6	0	0	0	3	6	0	0
T3	10	0	**90**	0	0	0	0	0	0	0
T4	0	0	1	**97**	0	0	0	0	1	1
T5	0	0	0	0	**73**	21	3	2	0	0
T6	0	0	0	0	12	**73**	11	4	0	0
T7	0	0	0	0	4	21	**47**	28	0	0
T8	0	0	0	0	4	16	26	**55**	0	0
T9	4	0	0	1	0	0	0	0	**73**	22
T10	0	0	0	1	0	0	0	0	35	**63**

In order to reduce SPS sensitivity to added noise we have investigated our hypothesis described in (Theoretical background C), i.e. the spin-images of SPS were composed around the vector computed as an average of all objects' normal's. The experiment was repeated 1000 times. The results with interest point classification confusion matrixes (correlation measure case) are presented in TABLE IV (in percents).

TABLE IV. CONFUSION MATRIX IN % OF COW INTEREST POINTS RECOGNITION USING CORRELATION AND PROPOSED COMPOSITION OF SPS.

	T1	T2	T3	T4	T5	T6	T7	T8	T9	T10
T1	**100**	0	0	0	0	0	0	0	0	0
T2	0	**85**	0	15	0	0	0	0	0	0
T3	0	0	**100**	0	0	0	0	0	0	0
T4	0	14	0	**86**	0	0	0	0	0	0
T5	0	0	0	0	**84**	12	4	0	0	0
T6	0	0	0	0	2	**97**	1	0	0	0
T7	0	0	0	0	1	5	**84**	10	0	0
T8	0	0	0	0	0	0	8	**92**	0	0
T9	0	0	0	0	0	0	0	0	**84**	16
T10	0	0	0	0	0	0	0	0	9	**91**

As it is seen from, TABLE III on average the accuracy of interest points recognition using correlation method is 74.4 % with standard error of 16.1 %, and using correlation method (TABLE IV) – 90.3 % with standard error of 6.7 %. The results confirm the hypothesis that the SPS spin-images are very sensitive to added noise and in order to resist to the noise the 3D object mesh normal's could be replaced by a single vector. Such approach has gained interest point's recognition improvement by ~16 %, and individual point recognition - up to 37 % (from ~47 % to ~84 %). An finally the obtained results shows that ~90 % of interest points can by identified correctly by using proposed SPS comparison.

From this it can be assumed that such interest point's recognition rate would be efficient for the 3D object classification in big databases.

B. 3D Object Point Cloud Classification

For 3D object point cloud classification we assume that the interest point's detection methods (such as HKS) always find the same amount of interest points. The SPS of interest points are composed not around the normal of the point, but around the vector of normal average of 3D model objects points. The database of 3D object models is composed of objects SPS signatures defined on salient points.

To improve the recognition results, it is also possible to use the number of salient points as an additional measure used for classification, i.e. 3D point cloud of an object is being compared only with those objects of the database that have the same number of salient points. By applying such additional model classification not only quality of recognition is being improved, but also the speed, because it reduced the number of objects to be compared.

Naturally these salient points detected by HKS method those are not stable – will increase recognition error. It is assumed that they are defined in the neighbourhood of a "real" point – up to 20 closest mesh points. Then SPS is composed in one of 20 closest mesh points chosen randomly. Each object point cloud, with generated point cloud error and HKS interest point's detection error was searched 1000 times in whole data base. The average 95.9 % accuracy of correct classification was reached using correlation measure in SPS comparison. In the database of 43 object we have gained on average that 41 of them are classified correctly with 99 % of accuracy and only two models cow and horse were miss classified by gaining up to 20 % of correct classification.

V. CONCLUSIONS

A novel approach for classification of 3D point cloud using numerical surface signatures on interest points was presented in this paper. As well as we have proposed to use one vector for each SPS instead of meshed surface normal's. Such approach on average allowed improving interest point's recognition rate by ~17 % and worst point recognition - by 37 % (from ~47 % to ~84 %). So using same constant vector for all objects points SPS composition makes point's recognition less sensitive to added data noise. On average the classification of 43 3D object database has shown 95.9 % accuracy of correct classification.

For numerical surface signatures comparison successfully can be used booth – Euclidian distance and correlation coefficient methods. As shown by the experiments the difference between them was not statistically significant and is in the range of ~2 %.

In the future the proposed algorithm will be implemented for online object recognition with the 3D data obtained by Kinect range finder.

REFERENCES

[1] E. Rosch, C. B. Mervis, W. D. Gray, S. M. Johnson, P. Boyes-Braem, "Basic objects in natural categories", *Cognit. Psychol.*, vol. 8, pp. 382–439, 1976. [Online]. Available: http://dx.doi.org/10.1016/0010-0285(76)90013-X

[2] T. Pearson, D. Brabec, S. Haley, "Color image based sorter for separating red and white wheat", *Sensing and Instrumentation for Food Quality and Safety*, vol. 2, pp. 280–288, 2008. [Online]. Available: http://dx.doi.org/10.1007/s11694-008-9062-0

[3] M. Omid, A. Mahmoudi, M. H. Omida, "Study on fresh fish sorting techniques", *Expert Systems with Applications*, vol. 37, pp. 7205–7212, 2010. [Online]. Available: http://dx.doi.org/10.1016/j.eswa.2010.04.008

[4] W. Guifang, K. Hoonsung, J. Seyoung, X. Ke, X. Jinwu, "Design of online surface inspection system of hot rolled strips", in *IEEE Int. Con. Automation and Logistics*, 2008.

[5] J. Guzaitis, A. Verikas, "An efficient technique to detect visual defects in particleboards", *Informatica*, vol. 19, pp. 363–376, 2008.

[6] S. Shahrani, H. Aini, A. W. Dzuraidah, M. M. Mohd, R. Suzaimah, "Support vector machines for automated classification of plastic bottles", in *6th Int. Colloquium. Signal Processing and Its Applications (CSPA 2010)*, 2010.

[7] E. Normanyo, D. Ayim, A. Isaac, "Designing of a letter sorting machine for the regional post offices in Ghana", *Engineering and Applied Sciences*, vol. 4, pp. 1–13, 2009.

[8] S. Sinkevicius, A. Lipnickas, V. Sinkevicius, K. Rimkus, "Orientation invariant surface classification using uncertainty level estimation", *Elektronika ir Elektrotechnika*, vol. 19, no. 10, 2013.

[9] B. Buttgen, *et al.*, "CCD/CMOS lock-in pixel for range imaging: challenges, limitations and state-of-the-art", in *1st range imaging research day*, 2005.

[10] P. Mihelich, K. Konolige, "Technical description of Kinect calibration", ROS (Robot Operating System). [Online]. Available: http://www.ros.org/wiki/kinect_calibration/technical

[11] R. Wessel, M. Novotni, R. Klein, "Correspondences between salient points on 3D shapes", in *Vision, Modeling, and Visualization*, Aachen, 2006.

[12] H. Dutagaci, C. P. Cheung, A. Godil, "Evaluation of 3D interest point detection techniques via human-generated ground truth", *The Visual Computer*, vol. 28, no. 9, pp. 901–917, 2012. [Online]. Available: http://dx.doi.org/10.1007/s00371-012-0746-4

[13] S. Ruiz-Correa, L. G. Shapiro, M. Meila, "A new paradigm for recognizing 3-D object shapes from range data", in *ICCV, Ninth IEEE Int. Conf. Computer Vision (ICCV 2003)*, 2003. [Online]. Available: http://dx.doi.org/10.1109/ICCV.2003.1238475

[14] S. Ruiz-Correa, *et al.*, "Symbolic signatures for deformable shapes", *IEEE Trans. Pattern Analysis and Machine Intelligence*, vol. 28, no. 1, pp. 75–90, 2006. [Online]. Available: http://dx.doi.org/10.1109/TPAMI.2006.23