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Research Article

Classifying Surface Points Based on Developability Using Machine Learning

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Abstract

The classifiers K-nearest neighbor (KNN), Multiclass support vector machine (MSVM), Decision Tree (DT), Discriminate Analysis (DA), Naive Bayes (NB), Random Forest (RF), and Ensemble Tree (ET) are the most well-known methods in machine learning. They are used in many fields like pattern recognition, medical disease analysis, user smartphone classification, text classification, etc. This paper presents a new framework for 3D surface point type classification using the most known classification methods in machine learning and the principal curvatures, the binormal vector, the cosine value of the angle between the normal vector and binormal vectors. The purpose of this study is to classify data points according to their developability. Also, the comparison between these methods is given to measure developability based on the accuracy and the processing time using several 3D surface examples.

Keywords: Machine learning, classification, principal curvatures, binormal vector.

Makine Öğrenmesini Kullanarak Açılabilirliğe Dayalı Yüzey Noktalarını Sınıflandırma

Öz

Sınıflandırıcılar K-en yakın komşu (KNN), Çok sınıflı destek vektör makinesi (MSVM), Karar Ağacı (DT), Ayrım Analizi (DA), Naive Bayes (NB), Rastgele Orman (RF) ve Topluluk Ağacı (ET) makine öğrenmesinde en iyi bilinen yöntemlerdir ve örüntü tanıma, tıbbi hastalık analizi, kullanıcı akıllı telefon sınıflandırması, metin sınıflandırması gibi birçok alanda kullanılmaktadır. Bu makale, makine öğrenmesinde en bilinen sınıflandırma yöntemlerini ve asal eğrilikleri, binormal vektörü, normal vektör ve binormal vektörler arasındaki açının kosinüs değerini kullanarak 3B yüzey noktası tipi sınıflandırması için yeni bir çerçeve sunmaktadır. Bu çalışmanın amacı, veri noktalarını açılabilirliklerine göre sınıflandırmaktır. Ayrıca, bu yöntemler arasındaki karşılaştırma, çeşitli 3B yüzey örneği kullanılarak doğruluk ve işleme süresine dayalı olarak açılabilirliği ölçmek için verilmiştir.

Anahtar Kelimeler: Makine öğrenmesi, sınıflandırma, asal eğrilikler, binormal vektör.

1. Introduction

Surface normals, principal directions, and principal curvatures are utilized in 3D computer vision to find solutions for some basic tasks, such as segmentation, surface classification, surface reconstruction, and registration Krsek et al. (1998). We can use the principal curvatures to determine the characterization of a surface due to the principal curvatures' invariant properties at a surface point. Many researchers studied the Gaussian and the mean curvatures on several kinds of surfaces such as faces and human bodies.

Shape recognition from range data is studied in terms of the principal curvatures in Vemuri et al. (1986). On the other hand, the principal curvatures are utilized for object recognition in Deng et al. (2007). Darveau et al. expressed the effect of the principal curvatures 3D rendering of relatively noisy ultrasound angiograms without degrading the spatial resolution Darveau et al. (2018). Shape similarity is measured in Wang et al. (2018) in terms of the principal curvatures.

A 3D object classification method is presented based on the numerical surface point signatures on interest points of 3D objects point cloud Rimkus et al.(2014). A 3D surface object classification method based on shape description and suitable pattern classification techniques is proposed in Shen et al. (2004). They used normalization and the spherical harmonic parameterization techniques to define a surface shape and derive a dual high dimensional landmark representation. Zheng et al. presented a new deep learning method to classify surface materials according to the acceleration signal and a corresponding surface texture image using Fully Convolutional Network (FCN) Zheng, et al. (2016).

This paper provides a new perspective for 3D surface point type classification regarding developability using the most utilized classification methods in machine learning and the principal curvatures, the binormal vector of S. Frenet frame, and the angle between the surface normal, and the binormal vectors. Additionally, we compare these methods to determine the developability of surface data points in terms of accuracy and the processing time using different 3D surface examples.

The rest of the paper is given in this manner: Section 2 provides basic information about a surface and the most popular machine learning classification methods. The proposed method is given in Section 3, while Section 4 presents several experimental studies and their results. Finally, Section 5 concludes the study.

2. Preliminaries

This section briefly describes the curvatures of a surface and classification methods in machine learning.

2.1. Curvature of a Surface

A surface is a subset of $\mathbb{R}^3$ and looks like a piece of $\mathbb{R}^2$ in the vicinity of any given point. The following definitions describe the notion of a surface in $\mathbb{R}^3$.

Definition 1: If a surface patch $\boldsymbol{SP}: U \to \mathbb{R}^3$ is smooth, and the vectors $\boldsymbol{SP}_{\mathbf{u}}$ and $\boldsymbol{SP}_{\mathbf{v}}$ are linearly independent at all points $(u, v) \in U$, this surface is called a regular surface.

A normal unit vector is defined at a point $\boldsymbol{P}$ on this surface as

$$\mathbf{n}_{\mathbf{SP}} = \frac{\mathbf{SP}_{\mathbf{u}} \times \mathbf{SP}_{v}}{\|\mathbf{SP}_{\mathbf{u}} \times \mathbf{SP}_{v}\|}. \tag{1}$$

Definition 2: Suppose that $\mathbf{SP}(u, v)$ is a surface patch of a surface $\mathbf{S}$ and $\mathbf{r}(t) = \mathbf{SP}\big(u(t), v(t)\big)$ is a unit speed curve in $\boldsymbol{SP}$. The normal curvature of this curve is expressed with the following equation:

$$\kappa_n = L\mathrm{u}'^2 + 2M\mathrm{u}'\mathrm{v}' + N\mathrm{v}'^2 \tag{2}$$

in which L, M and N are coefficients of the second fundamental form and defined by

$$L = \mathbf{SP}_{\mathbf{uu}}\mathbf{n}, \quad M = \mathbf{SP}_{\mathbf{uv}}.\mathbf{n},\ and \quad N = \mathbf{SP}_{\mathbf{vv}}.\mathbf{n}.$$

Proposition 1: The principal curvatures κ_{n1} and κ_{n2} are the maximum and minimum of the normal curvature in (2) at the point $\boldsymbol{P}$. The principal curvatures can be written in the mean and Gaussian curvatures by Pressley, A. (2010).

$$K = \kappa_{n1}.\kappa_{n2}\ and \quad H = \frac{\kappa_{n1} + \kappa_{n2}}{2}. \tag{3}$$

or in a quadratic equation form

$$\kappa_n^2 - 2H\kappa_n + K = 0, \tag{4}$$

which has solutions as

$$\begin{cases} \kappa_{n1} = H + \sqrt{H^2 - K} \\ \kappa_{n2} = H - \sqrt{H^2 - K}. \end{cases} \tag{5}$$

The principal and Gaussian curvatures κ_{n1}, κ_{n2} and K have great importance in determining the shape of the surface. The classification of points on a surface in terms of the principal curvatures is presented in Table 1.

Table 1: Classification of surface points based on principal curvatures.

	$\kappa_{n1} < 0$	$\kappa_{n1} = 0$	$\kappa_{n1} > 0$
$\kappa_{n2} < 0$	Concave Ellipsoid	Concave Cylinder	Hyperboloid Surface
$\kappa_{n2} = 0$	Concave Cylinder	Plane	Convex Cylinder
$\kappa_{n2} > 0$	Hyperboloid Surface	Convex Cylinder	Convex Ellipsoid

Definition 3: Let $\boldsymbol{r}(t)$ be a non-unit speed curve. S. Frenet frame of this curve is:

$$\frac{\boldsymbol{r}'(t)}{\|\boldsymbol{r}'(t)\|} = \boldsymbol{T}\,, \quad \frac{\boldsymbol{r}'\times\boldsymbol{r}''}{\|\boldsymbol{r}'\times\boldsymbol{r}''\|} \times \boldsymbol{T} = \boldsymbol{N} \text{ and } \quad \frac{\boldsymbol{r}'\times\boldsymbol{r}''}{\|\boldsymbol{r}'\times\boldsymbol{r}''\|} = \boldsymbol{B}$$

in which $\boldsymbol{T}$, $\boldsymbol{N}$, and $\boldsymbol{B}$ are the unit tangent vector, principal normal vector, and binormal vector, respectively Kreyszig, E. (1959).

2.2 Classification Methods in Machine Learning

Machine learning is a branch of computer science and tries to obtain meaning from data. We describe objects around us according to their features (or attributes). Intuitively, a featured class is composed of similar objects. A training process is to state the connection between the output and the input features Patil and Kulkarni, (2019). Features can be determined in the form of names, categories, types of entities, etc. On the other hand, non-numerical features can be converted to numerical values. There are some basic classification methods in machine learning.

The k-nearest neighbor classifier (k-NN) is used widely since it is theoretically elegant and simple to use Duda et al. (2001). This method classifies an input in data by retrieving the k nearest prototypes from the labeled reference set.

The decision tree algorithm classifies the given data by containing the minimum number of nodes Sulaiman, M. A. (2020). It is related to knowledge of relationships that include nodes and connections Priyanka and Kumar, (2020).

An SVM model is applied to binary classification by dividing data elements either in 1 or 0. However, the same principle MSVM is utilized, and the multiclass problem is broken down into multiple binary classification cases Ahuja and Yadav, (2012).

For the discriminant analysis method, it generates classes based on the Gaussian distributions. The fitting function calculates the parameters for each class, and the trained classifier seeks the class for new data according to the smallest misclassification cost Tharwat, A. (2016).

A Naive Bayes classifier method is based on applying Bayes' theorem, so it is a simple probabilistic classifier. It assumes any class feature as independent from any other feature Berrar, D. (2018).

Like the KNN and the decision tree methods, a random forest method is also a tree-based method, and this method is based on a random vector's sampled values for each tree independently with the same distribution Breiman, L. (2001).

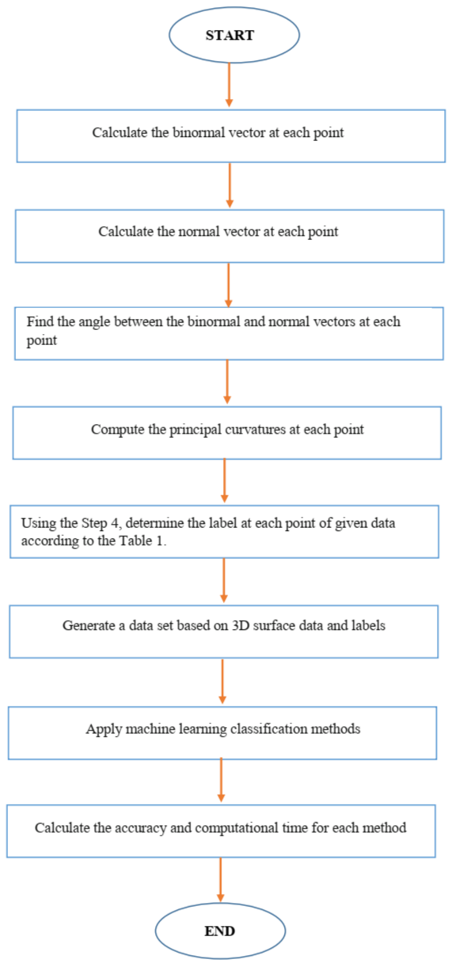
On the other hand, ensemble methods construct a classifier set and classify new data points by taking their predictions' vote Dietterich T.G. (2000).

3. Proposed Method

The principal curvatures have been used for object recognition. Therefore this study constructs a bridge between the object recognition and surface points types based on machine learning.

Assume that data points belonging to a surface are given. First, the binormal vectors, the normal vectors, and the angles between these vectors are estimated. Next, the principal curvatures are calculated at each point in the data. Moreover, some well-known classification algorithms in machine learning are used to state the best method that classifies the points without knowing the principal curvatures. The Gaussian curvature is utilized to determine the points which have developability properties. Because a surface that has zero Gaussian curvature is called a developable surface. Finally, we apply machine learning classification methods K-nearest neighbor (KNN), Multiclass support vector machine (MSVM), Decision Tree (DT), Discriminate Analysis (DA), Naive Bayes (NB), Random Forest (RF), and Ensemble Tree (ET), and obtain accuracy with the computational cost for each one, respectively. The proposed algorithm is presented in Algorithm 1.

Algorithm 1: The proposed method



4. Experimental Study and Results

In this section, as shown in Table 2, five surface examples are considered to apply the most known classification methods in machine learning. Next, the comparision between these methods is presented in Table 3 regarding the accuracy and processing time (s).

Table 2. Example Surfaces

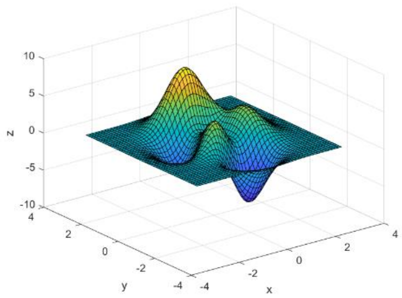
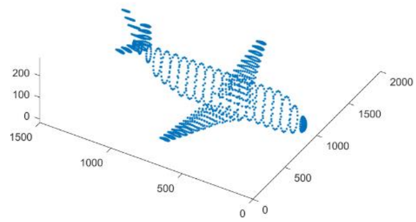
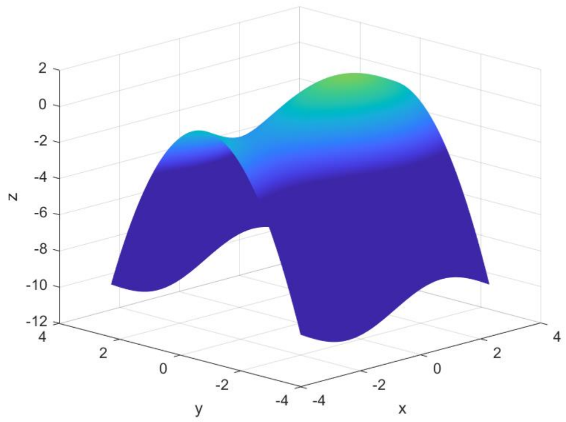
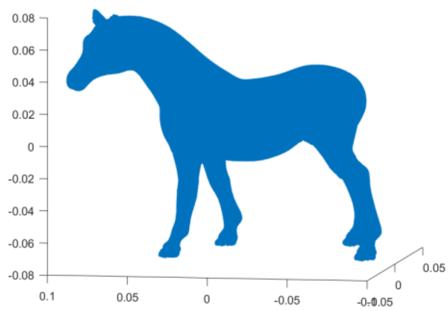
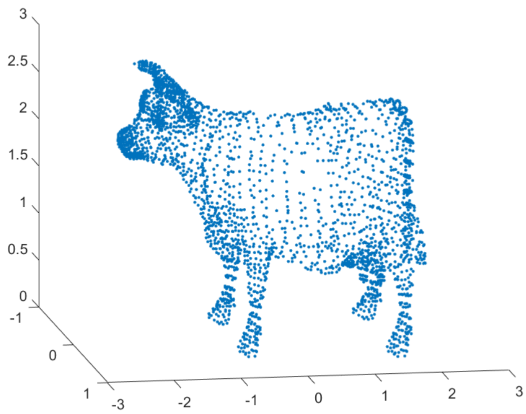
Example Surface	Data Points Number	Example Surface	Data Points Number
	2400		1296
	44100		48400
			8709

Table 3. Comparing of Classification Methods for Surface Points Types

Data Sets		#1		#2		#3		#4		#5	
		Acc.(%)	**Time(s)**	**Acc.(%)**	**Time(s)**	**Acc.(%)**	**Time(s)**	**Acc.(%)**	**Time(s)**	**Acc.(%)**	**Time(s)**
Classification Methods	**KNN**	96.9175	1.1279	65.8092	0.4183	99.941	4.5401	67.8347	4.5796	60.6905	1.1358
	MSVM	96.5278	0.4993	68.5567	0.1844	99.9169	1.6232	68.5468	56.3616	61.7577	0.5853
	DT	95.6944	0.0208	68.8185	0.6755	100	3.7776	64.6901	15.1990	59.812	1.1621
	DA	90.0048	0.4884	63.6599	0.5279	97.6916	1.0110	58.7128	0.9953	57.5299	0.5125
	NB	83.4652	0.7025	63.274	1.7716	49.9773	0.7592	49.3905	1.5157	57.6368	0.7445
	RF	97.0427	5.8494	75.6274	6.5809	100	36.2251	78.2107	191.5423	65.1418	15.6860
	ET	95.4604	23.7250	72.0697	18.9153	100	230.3312	66.5847	397.1837	59.9858	28.2437

As seen in Table **3**, the random forest (RF) method is the most accurate one among the applied methods. The RF method makes classification providing almost 100% accuracy for general 3D surfaces #1 and #3, while providing accuracies in the range 65%-80% for the surfaces with specific shapes. However, the processing time for the RF is the second most taking time to calculate the proper classes. On the other hand, the Ensemble Tree (ET) method is the one that has the most spending time even though it cannot find the accuracy with high percentages.

5. Conclusion

In this study, we utilized the most-known machine learning classification methods K-nearest neighbor (KNN), Multiclass support vector machine (MSVM), Decision Tree (DT), Discriminate Analysis (DA), Naive Bayes (NB), Random Forest (RF), and Ensemble Tree (ET) to classify 3D surface points in terms of developability. The classification is made according to the principal curvatures, binormal vector, and the angle between the normal and binormal vector features. We compared the mentioned methods using several 3D examples in terms of accuracy and computational time. Table 2 expresses that the RF method is the best classifier for surface point developability even if it takes some time to process. Also, we realized that it is more accurate for general 3D surfaces such as #1 and #3 than object surfaces.

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