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Unsupervised surface roughness discrimination based on bio-inspired artificial fingertip

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ABSTRACT

Different from texture classification, surface roughness discrimination is more challenging in the development of tactile sensing because of limited discriminative information. In recent years, it is receiving more and more attentions from researchers in various fields, most of which are based on supervised learning. But frequently all we have is unlabeled dataset with very limited prior information, i.e., labels are not available to train the discrimination models. Lacking the 'teaching' process, it becomes rather difficult to locate the boundary of different classes. In this paper, the ability of unsupervised surface roughness discrimination is explored based on our developed bio-inspired artificial fingertip. At first, the original signals are analyzed and discriminated with the most widely used unsupervised algorithm (K-means clustering). Then the technique of discrete wavelet transform and algorithm of sequential forward selection are utilized to identify the most discriminative features. The unsupervised discrimination results (K-means clustering) are presented and compared based on different distances including Squared Euclidean, Cityblock, and Cosine. The highest test accuracy reaches 72.93% ± 12.55% when the distance of Squared Euclidean is adopted with six discriminative features. Finally, another popular unsupervised algorithm, self-organizing maps neural network that is different from clustering, is also applied in discriminating surface roughness with lower accuracy. The results show that unsupervised learning algorithms with our developed tactile fingertip are capable to discriminate surface roughness, which have great potentials in robotics and autonomous applications.

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1. Introduction

Inspired by the sensing ability of human beings, artificial tactile sensing develops fast and have been widely used in a variety of applications, such as medical robotics, minimally invasive surgery and industrial automation [1]. One important task of tactile pattern recognition is to distinguish between different surface textures and materials. As a key object property, surface roughness influences many performances, such as friction characteristics and wear resistance [2], the discrimination of which thus becomes very important.

Plenty of researches have been conducted in developing tactile sensors to distinguish different surface textures by mimicking the touch capability of our fingertips. An anthropomorphic robotic soft fingertip was designed to realize the discrimination of five different materials by pushing and rubbing them with the fingertip [3]. Two kinds of receptors, including strain gauges and PVDF (polyvinylidene fluoride) films, were randomly distributed in the fingertip. A novel texture sensor containing PVDF films and force sensors was developed in [4], where a radial basis function (RBF) neural network was utilized to classify five common fabrics. By contrast, there are much less researches on surface roughness discrimination. A slender cantilever sensor integrating a piezoresistive strain gauge was designed to measure contour and roughness with a potential of high-aspect-ratio micrometrology [5]. Then a 2×2 array of four microelectromechanical system (MEMS) tactile microsensors was developed to encode surface roughness for discrimination, where a k-nearest-neighbor (kNN) classifier was constructed after an active-touch exploration of surfaces [6].

Bio-inspired by the FA-I type of mechanoreceptors in fingertips, we developed an artificial tactile fingertip including two perpendicular PVDF films, which was sensitive to the vibration stimuli [7,8]. By sliding the bio-inspired fingertip across different surfaces, roughness was discriminated based on statistical features of the raw analog signals with accuracy of 82.6% [7]. A soft neuromorphic approach was also adopted to realize the roughness discrimination in term of neural spikes [9]. Furthermore, the discrimination accuracy was improved after applying signal decomposition via discrete wavelet transform (DWT) and feature selection via sequen-

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tial forward selection (SFS). With extreme learning machine (ELM) applied, the accuracy was increased to as high as 97.88% [10].

However, all the above researches are based on supervised learning, which means a dataset containing training data and corresponding labels must be provided in advance. Actually in many circumstances, what we have is just some unlabeled data and very limited prior information, such as the number of kinds, where supervised learning is no longer applicable. By contrast, unsupervised learning is able to fully exploit as much information as possible hidden in the data even without labels. It was pointed out that a great deal of human learning might be unsupervised, which also played a critical role in the development of deep learning [11–13]. Therefore, unsupervised surface roughness discrimination becomes highly desired.

A five-finger anthropomorphic hand containing tactile sensors was developed with an incremental unsupervised learning mechanism used to classify 10 different objects [14]. The cluster number was first evaluated and then 28 kinds of surface textures was identified by employing a Pitman-Yor process and Bayesian non-parametric approach [15]. High accuracy was achieved while much computation time was required. However, these researches are all conducted for discrimination of surface texture, which consists of surface roughness, waviness, lay, hardness and a lot of other factors [16]. Discrimination of only surface roughness requires more sensitive sensor and becomes more difficult in an unsupervised way, which was rarely reported.

To fill this research gap, we employ our developed bio-inspired artificial fingertip combined with K-means clustering technique – the widely used unsupervised algorithm, to discriminate 8 surfaces of different roughness. Statistical features are extracted from original analog signals outputted by two perpendicular PVDF films when the fingertip slides across these surfaces. Similar to our previous research [10], DWT and SFS will be used to extract and select the most discriminative feature combination. With only unlabeled data, the unsupervised algorithm needs to decide the cluster center of every class and automatically assign them a unique label after training. Labels of test dataset can be easily obtained by comparing their distances to every cluster center. Three definitions of distances, i.e., Squared Euclidean (SEuclidean), Cityblock and Cosine, will be compared to find the best one for K-means clustering when applied to surface roughness discrimination. In addition, another popular unsupervised algorithm, self-organizing maps (SOM) neural network that is different from clustering in mechanism, will also be explored to compare with K-means. Our designed artificial fingertip combined with the unsupervised classification methods is shown to be successful and effective in unsupervised surface roughness discrimination.

2. Experiment and method

2.1. Bio-inspired tactile sensor

Although various kinds of tactile sensors have been developed [3–6], most of them require a complex manufacture process or multiple sensors, such as PVDF film, force sensor, strain gauge etc. To simplify the manufacture process for surface roughness discrimination, an artificial fingertip was developed as shown in Fig. 1. A polymethyl methacrylate (PMMA) bar plays a supporting role just like the bones in human fingers. Two PVDF films perpendicular to each other are attached to a polydimethylsiloxane (PDMS) cube, which is fixed to the top of the PMMA bar and enables the PVDF films to deform complying with external forces. PVDF films are sensitive to vibration stimulus and capable to mimic FA-I type of mechanoreceptors [8]. Finally, the PMMA bar and PVDF films will be surrounded by another PDMS layer, which plays a role of protection and buffering as the skin. Details of the bio-inspired fingertip can be found in [7].

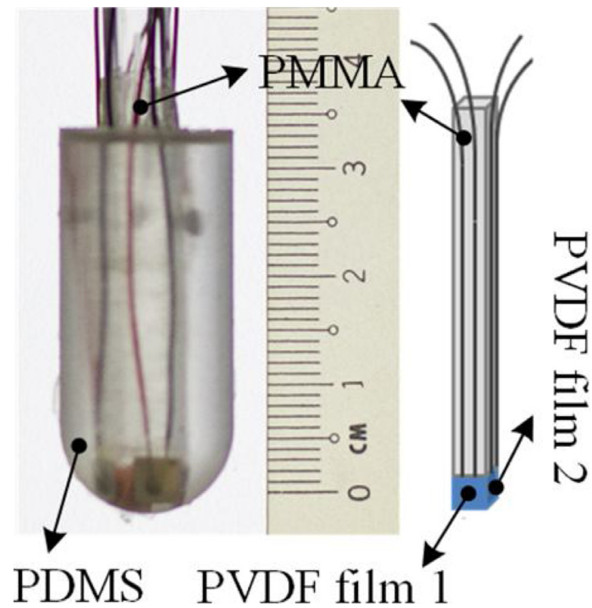

Fig. 1. Artificial tactile fingertip and its structure.

When external stimulus is imposed on the fingertip, voltage signals are generated in the two deformed PVDF films. Signals from the two films will be different due to their perpendicular orientation. The voltage signals will be amplified via an analog amplifying circuit before transformed into digital signals at a sampling rate of 1 kHz via an analog-to-digital converter. In this way, the tactile fingertip is able to ‘feel’ various vibration stimuli during sliding on rough surfaces.

2.2. Signal decomposition and feature extraction

To distinguish different surface roughness, a discrimination model should be established to determine the boundary of every class. Features including standard deviation (SD), statistical features (SF), signal roughness parameter Ra (SRa) etc. were extracted from the original signal [7]. With support vector machine (SVM) and kNN applied respectively to construct a classifier, it was shown that the kNN model ($k = 9$) with SD of PVDF film 1 inputted would achieve the highest accuracy of 82.6%. Surprisingly, discrimination accuracy was decreased by including signals from PVDF film 2.

It was hypothesized that noisy signals generated from PVDF film 2 might have a negative influence on the discrimination accuracy. Therefore, in [10], the sampled signals of both films were firstly decomposed into components in different scales and frequency bands using DWT [17] with wavelet function ‘Coiflets’ and filter function ‘coif5’. Signals in both time domain and frequency domain (transformed using fast Fourier transform (FFT)) were then decomposed into 4 layers. Every layer consisted of 4 approximation coefficients A1–A4 and 4 detail coefficients D1–D4.

Then three statistical features, including mean ($\mu(x(k))$), SD ($S(x(k))$) and energy ($E(x(k))$), given in Eqs. (1)–(3) were extracted.

$$\mu(x(k)) = \frac{1}{N}\sum_{k=1}^{N} x(k) \tag{1}$$

$$S(x(k)) = \sqrt{\frac{1}{N-1}\sum_{k=1}^{N}(x(k)-\mu)^2} \tag{2}$$

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