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Opto-tactile Sensor for Surface Texture Pattern Identification using Support Vector Machine

Abdul Md Mazid
Faculty of Sciences, Engineering & Health
Central Queensland University
Rockhampton, Australia
Email: a.mazid@cqu.edu.au

A B M Shawkat Ali
School of Computing Sciences
Central Queensland University
Rockhampton, Australia
E-mail: s.ali@cqu.edu.au

Abstract — Experimental application of a recently developed opto-tactile sensor in object surface texture pattern recognition using soft computational techniques has been successfully demonstrated in this article. Design and working principles of a number of optical type sensors have been illustrated and explained. Using the opto-tactile sensor multiple surface texture patterns of a number of objects like a carpet, stone, rough sheet metal, paper carton and a table surface have been captured and saved in MATLAB environment. The captured data have been adopted to soft computational techniques like Support Vector Machine (SVM) technique, Decision Tree (DT) C4.5 algorithm, and Naive Bayes (NB) algorithm for their learning. Testing with unknown surfaces using these techniques shows promising results at this stage and demonstrates its potential industrial use with further development. Results suggest that the methodology and procedures presented here are well suited for applications in intelligent robotic grasping.

Keywords— tactile sensor, opto-tactile sensor, robotics, classification, support vector machine, decision tree, naive bayes.

I. INTRODUCTION

Tactile sensors, by virtue of their multiple ranges of design configurations, have a large potentiality in wider applications in design and manufacturing of intelligent machines and machine units usable for different industries. The major characteristic of tactile sensors is that they provide localized information about objects by touching them physically and the information provided is about the touched area/s. The information provided is, by physical touching a real object, more reliable and realistic, and more accurate. During the past few decades many researchers reported different types of tactile sensors of different designs for various applications. In a review paper published in 2005, Daragahi and Najarian [1] attempted to categorize tactile sensors as: on-off type electro-mechanical, capacitive, magnetic, optical, piezoelectric (PZT), piezo-resistive (using strain gauges) and silicon based electromechanical tactile sensors. Recently a new opto-tactile type sensor has been reported [2] for object (non-fluidic) surface texture assessment by sliding the sensor over a static object surface and/or by moving an object while the sensor stays static in its own position.

Robots and pick and place machines are designed and manufactured as non-compliant systems. By virtue of their stiff joints, actuators and flexible control systems, robots, and pick and place machines can be used to perform repetitive superhuman-like operations. Examples of these operations are very wide spread starting from diversified materials handling in manufacturing sectors up to fruit and vegetable harvesting, as well as, in surgical operations. Another special purpose application of robots is performing humanlike operations at hazardous environment including remote area operations. Collecting the right samples of right materials or minerals from space locations, as well as, underwater areas, is a group of problems requiring humanlike intelligence. It is rather more essential for a mobile robot or autonomous system to identify where it is navigating at a particular moment. Some information like whether a mobile robot is navigating on carpeted floor or vinyl floor, or on a concrete driveway, or on soil surface or any other natural terrain is essential to learn for a robot. A newly developed opto-tactile sensor, above mentioned, is capable to discriminate objects by assessing their surface texture by touch. Hence it is anticipated robots, equipped with proposed type opto-tactile sensors, will be able to understand on what surface/floor they are navigating. This article concentrates on gathering surface texture information, then storing these information of types of surface textures in a machine memory, and then by touching a particular object to recognize the approximated type of object. For testing, storing surface textures information and recognizing a particular object surface by touching it with the opto-tactile sensor the following machine learning technology has been used successfully in this multidisciplinary research work.

More successful results have been obtained by using Support Vector Machine (SVM) computational technique by virtue of its higher computational efficiency and higher resistance to noise. SVM was first introduced [3] by Boser, Guyon and Vapnik in 1992. The other two popular techniques such as Decision Tree and Naive Bayes have also been applied for computational purposes in the current experiments and relative assessment of these three techniques has also been established.

II. OBJECT SENSING AND LITERATURE REVIEW

Human brain senses materia in the world in different ways. We can sense smell using our nose, taste using different parts of our tongue. We recognize temperature, colors, shapes and sizes, type of materia using our body surfaces and, parts of muscles and nervous systems. Human brain recognizes and determines objects by light rays reflected or emitted from/by objects. However, in popular understanding, according to some researchers, sensing could be roughly divided [4] into two types:

- Sensing by direct contact
- Sensing by indirect or non-contact

Indirect or non-contact type sensing is performed by sound wave, light rays, magnetic flux or electric field, wind flow, and so on.

Direct contact sensing is performed by physical contact of component/s of objects. This type is recognized in literature as tactile sensing. Here, it worth to recite the definition formulated by Russell [4] as "Tactile sensing covers any sensing modality which requires physical contact between sensors and an external object." Tactile sensing may extend the capabilities of robots, manipulators and other autonomous systems beyond those obtained from using other sensor models only. In robotic manipulation and navigation we are more interested in physio-mechanical properties of objects. Lee and Nicholls (1999) defined [5] tactile sensor as "a device that can measure a given property of an object or contact event through physical contact between sensor and object."

New types of tactile sensors have been offered every year and some reasonable successful applications have been achieved. Many of these tactile sensors are designed based on strain gauges applications. There are very few sensors that have used optical technology or optical principles. A finger-shaped tactile sensor based on optical technology has been offered by Lo, Shen, and Liu (2001) and it has been applied [6] to capture tactile image of the touched area of an object. This finger-shaped opto-tactile sensor was designed, based on principle of another finger-shaped tactile sensor that used optical waveguide presented [7] by Nakao, Kaneko, Suzuki and Tanie in 1990.

Figure 1 depicts the design and working principles of the given finger-shaped optical waveguide based tactile sensor (Nakao, et al), which consists of a semi-spherical optical waveguide covered with a white elastic membrane, a light source, a concave lens, and an optical detector (CCD) device connected to a computer (not shown). According to authors, the light is injected into the optical waveguide from the edge of it. If no object is in touch with the sensor, the light is reflected internally inside the optical guide and no light rays are passing on to the lens. If the elastic membrane is not in touch with the waveguide and the waveguide is surrounded by an air-sleeve, the injected light fully reflect at the boundary surface of the waveguide in a critical angle and travel inside the waveguide because of the difference of the refractive indexes between the material of the waveguide and of air. But when a part of the elastic membrane is pressed by an object, the membrane comes in contact with the surface of the waveguide. From the contact area the light rays are scattered because of the total internal reflection conditions are changed. The object contact location on the waveguide surface can be obtained by detecting the scattering light pattern. Such an image pattern (of the apex of cross-head screwdriver) displayed in Fig. 2, which was taken by Lo et al [6] using their designed finger-shaped tactile sensor based on optical waveguide.

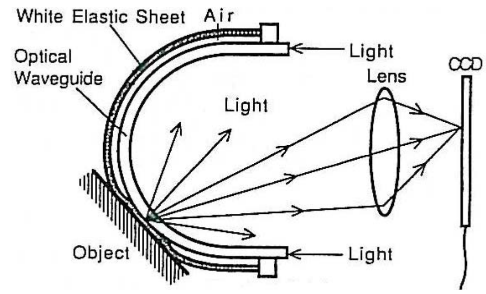

Figure 1. Design, working principle of optical waveguide based finger-shaped tactile sensor (Nakao, et al, 1990)

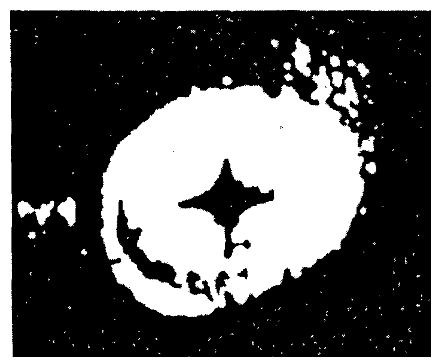

Figure 2. Image of a cross-head screwdriver apex touched by the finger-shaped tactile sensor (Lo et al, 2001)

Another tactile sensor based on strain gauge technology has been designed and published [8] in 2004 by Tsujiuchi and his fellow researchers for the purposes of slip detection in robotic grasping applications assessing the triaxial forces generated during object slippage. Previously (2001) similar principle of strain gauge application but simpler (Fig. 3), as used by Tsujiuchi, has been used by Yamada, Maeno and Yamada to design artificial finger skin having human like ridges on it. The authors proposed [9] to use the artificial finger skin with ridges and distributed sensor accommodated underneath the skin ridges to detect slippage during robotic grasping assessing tangential and longitudinal forces of grasp.

Earlier Tremblay and Cutkosky (1993) presented [10] an improved dynamic tactile sensor to detect incipient slip of grasped object, which used accelerometers.

The opto-tactile sensor proposed [2] recently has been demonstrated to assess surface texture of objects like carpet, concrete floor, timbre surface, cast iron surface, machined metal surfaces and applicable mostly for any non-fluidic surfaces. This article demonstrates a new area of applications of the opto-tactile sensor for object surface texture pattern recognition using soft computational techniques.

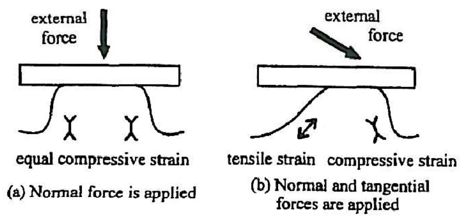

Figure 3. Schematics of a tactile unit (Yamada, et al, 2001) used to build skin ridge type distributed sensor

III. DESIGN CONCEPT AND WORKING PRINCIPLES OF THE OPTO-TACTILE SENSOR IN USE

The development and potentiality of the aforesaid opto-tactile sensor system was first reported [2] in 2006. Figure 4, a photograph of the prototype system, displays the sensor units in assembly: the transmitter and receiver connected to the diode and the phototransistor respectively, and an evaluation board. Potential application areas were also indicated including some experimental results of successfully assessing surface texture of a number of objects like floor carpet, cast iron and a table top.

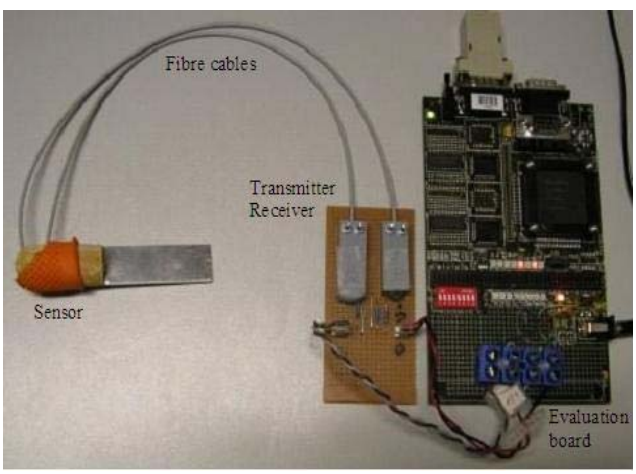

Figure 4. An Opto-tactile sensor system (Mazid and Russell, 2006)

The opto-tactile sensor consists of, as depicted in Figure 5, a small rectangular piece of full-silvered mirror, a tactile-pin, a light emitting diode (LED), a phototransistor, two pieces of optical fiber cables, and a flexible rubber body with nib / bumps / ridges. The tactile pin is perpendicularly attached to the galvanized side of the mirror and the free end of the tactile is molded into one of the ridges of the elastic body. The elastic body helps to keep the tactile pin perpendicular reducing instability and provides springy effect to the tactile. The end of the tactile is molded into a nib of the elastic skin. The tactile pin or bump which extends below the mirror has the same sensing function as the fingerprint ridges of the human hand. The pin and mirror can rotate as if hinged at the point where the bump joins the elastic body. Light from a light-emitting diode (LED), is guided down by one of the optical fibers to the mirror. Depending on the angle of orientation of the mirror, some portion of the light is reflected towards the receiving end of the second optical fiber where it is directed to the phototransistor. The ends of the optical fibers are both positioned at a distance of $\delta = 0.50mm$ from the mirror surface. The core of the sensor is made of cork and these components are embedded into it to maintain their proper relative positions. The signal from the transistor is digitized by one of the analogue to digital converter (ADC) channels in an Infineon C167 microprocessor mounted on a PHYTEC KitCON-167 evaluation board (Fig. 4). The photograph shown in Fig. 4 illustrates the major components of the opto-tactile sensor system.

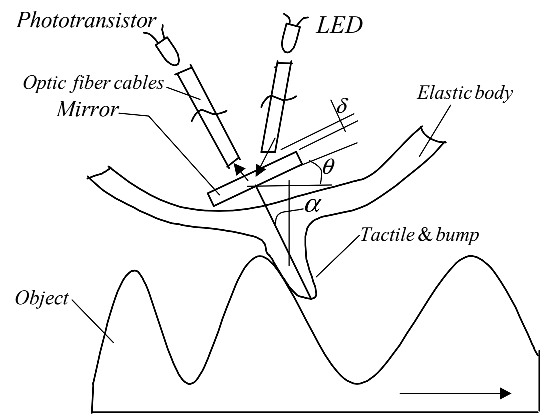

Figure 5. Schematic of an opto-tactile sensor for object surface assessment (Mazid and Russell, 2006)

During motion of the sensor relative to the surface of an object, the tactile pin is deflected by undulations in the object surface. Accordingly, the mirror secured at the top of the tactile pin changes its orientation which in turn changes the intensity (I) of reflected light beam received by the receiver – phototransistor. Thus the intensity of the light beam received by the transistor depends directly on the position of the full-silvered mirror in relation to the light ray direction. This phenomenon was used to design the sensor for assessing surface texture of different objects manipulated by a robot gripper. Envisaged, the application of the sensor can be extended for surface texture pattern recognition with the help of computational techniques.

IV. COMPUTATIONAL TECHNIQUES USED

In the current research three different soft computational learning algorithms namely Support Vector Machine (SVM) algorithm, Decision Tree algorithm C4.5 and Naive Bayes (NB) algorithms have been used to process the sensor data for learning and identifying object surface texture patterns.

A. Support Vector Machine (SVM) algorithm

The SVM algorithm, first introduced by Vladimir Vapnik [11], is one of the most successful learning and classifying supervised algorithms. It is widely used and popular in businesses, engineering, medical, and science communities [12, 13, 14]. The main function of SVM is to construct the optimal hyperplane (OH) in the training phase using the proper estimation [11, 15] of a weight vector ω and the scalar bias factor b. All of the training patterns are said to be linearly separable if there exists ω and b such that the following inequalities satisfied:

$$(\omega \cdot \mathbf{x}_i) + b \geq 1; \qquad \text{if } y_i = 1 \tag{1}$$

$$(\omega \cdot \mathbf{x}_i) + b \leq -1; \qquad \text{if } y_i = -1 \tag{2}$$

Where, $\mathbf{x}_i = x_1, x_2, x_3, \cdots, x_n$ are vectors representing the data points, and y_i are the classes attributes.

The prediction function in SVM is expressed [11] as follows:

$$\hat{f}(\mathbf{x}) = sign\left(\omega^o \cdot \Phi(\mathbf{x}) + b\right) = sign\left(\sum_{i=1}^{l} \alpha_i^o y_i \Phi(\mathbf{x}_i) \cdot \Phi\left(\mathbf{x}_j\right) + b^o\right) \tag{3}$$

Where, α is the optimization parameter, and the product of $\Phi(\mathbf{x}_i) \cdot \Phi(\mathbf{x}_j)$ is a scalar quantity. In machine learning literature this product is called *kernel function*. In our experiments we used rbf (radial basis function) kernel function with SVM.

B. Decision Tree C4.5 algorithm

Decision Tree is a member of the supervised learning algorithms, which was first used [16] by Quilan (1993) for data classification. A decision tree is a simple rule based learning algorithm which is easy to understand.

Given the similar data matrix $[x_1, x_2, x_3, \cdots, x_n]$ and a probability distribution $P = (p_1, p_2, p_3, \ldots, p_n)$ the Entropy P is expressed as follows:

$$I(P) = -(p_1 \log(p_1) + p_2 \log(p_2) + p_3 \log(p_3) + \cdots + p_n \log(p_n)) \tag{4}$$

If a set T of records is partitioned into disjoint exhaustive targets $y_1, y_2, y_3, \ldots, y_k$ based on categorical attribute, then the information needed to identify the target of an element of T is Info(T) = I(P), where P is the probability distribution of the target i.e., partition ($y_1, y_2, y_3, \ldots, y_k$) and P can be computed using the following equation:

$$P = (|\, y_1 \,| / |\, T \,|, |\, y_2 \,| / |\, T \,|, |\, y_3 \,| / |\, T \,|, \cdots, |\, y_n \,| / |\, T \,|) \tag{5}$$

Now, we can define the quantity Gain (X,T) for a variable as:

$$Gain(X,T) = Info(T) - Info(X,T) \tag{6}$$

Finally, the measure Gain to rank variables was used and to build decision trees depending on where each node is located and the variable with greatest Gain among the variables is not yet considered in the path from the root.

C. Naive Bayes algorithm

The Naive Bayes (NB) algorithm [17] based on the Bayesian theorem and is suitable for high dimensional data classification. Given a set of variables, $X = \{x_1, x_2, x_3, \ldots, x_n\}$, our aim is to construct the posterior probability for the event y_j among a set of possible targets $Y = \{y_1, y_2, y_3, \ldots, y_n\}$. Following the traditional method, X is the independent variables and Y is the set of categorical levels i.e., dependent variable. Bayes' rule can be formulated as follows:

$$\begin{aligned} & p(Y_j \mid [x_1, x_2, x_3, \cdots, x_n] \cdot [x_1, x_2, x_3, \cdots, x_n]') \propto \\ & p([x_1, x_2, x_3, \cdots, x_n] \cdot [x_1, x_2, x_3, \cdots, x_n]' \mid Y_j) p(Y_j) \end{aligned} \tag{7}$$

Where, $p(Y_j \mid [x_1, x_2, x_3, \cdots, x_n] \cdot [x_1, x_2, x_3, \cdots, x_n]')$ represents the posterior probability of class membership.

Naive Bayes algorithm considers the conditional probabilities of the independent variables to be statistically independent. Now we can decompose the likelihood to a product of terms:

$$p(X \mid Y_j) \propto \prod_{k=1}^{mm} p(x_k \mid Y_j) \tag{8}$$

Finally, with the help of Bayes' rule, we classify a new example X with a class level C_j that earns the highest posterior probability.

V. EXPERIMENTS AND RESULTS DISCUSSION

The above described three learning and classifying algorithms were used in tactile sensor data processing to learn and identify particular objects randomly amongst the objects which have been sensed. Surface texture data were recorded in MATLAB environment running the sensor on samples of carpet, rough sheet metal, paper carton, stone and table surface. After that we used data splitting approach 10 fold cross validation method as it has been suggested by Henery [18] for datasets having fewer than 1000 instances. At first we split the data set into 10 subsets of approximately the same size. The learning algorithm is then trained 10 times, each time leaving out one of the subsets from training, but using that subset as test data to compute an estimated error. Finally the average of the 10 error estimates can be taken as an estimate of the generalization [19] error of a given model.

The experimental performances of the algorithms were summarized, based on tactile sensor data, in the confusion matrix. That helps easy understanding of the sensor performances. In the confusion matrix, two attributes are more significant, namely True Positive (TP) Rate and False Positive (FP) Rate. For a two class (say, positive and negative) problem

TP is the proportion of positive cases that were correctly classified and FP is the proportion of negative cases that were incorrectly classified as positive [19]. In Table 1 sensor performances using SVM technique were not satisfactory when it tried to identify the carpet samples. The sensor move 45 times on the carpet but only 5 times it was successful to identify the carpet surface texture. On the other hand it was 100% successful to identify the stone sample. The TP and FP rate for stone was 1 and 0. For other cases metal, paper carton and table surface the success rate was 93.2%, 93.6% and 76.6% respectively. Finally we measure the accuracy for each algorithm to identify the individual performance. The overall accuracy for the sensor with SVM was 76.33%, which is reasonably a satisfactory result.

Table 1. Tactile Sensor Performances using SVM learning and classifying algorithm

SVM Classification								
	Carpet	Metal	Paper Carton	Stone	Table Surface	TP Rate	FP Rate	
Carpet	5	7	16	0	17	0.111	0.02	Accuracy = 76.33%
Metal	0	55	0	0	4	0.932	0.07	
Paper Carton	1	0	44	0	2	0.936	0.091	
Stone	0	0	0	47	0	1	0	
Table Surface	3	6	2	0	36	0.766	0.116	

Table 2. Tactile Sensor Performance using Decision Tree C4.5 Learning Algorithm

Decision Tree C4.5 Classification								
	Carpet	Metal	Paper Carton	Stone	Table Surface	TP Rate	FP Rate	
Carpet	17	4	13	0	11	0.378	0.08	Accuracy = 76.33%
Metal	1	51	0	0	7	0.864	0.038	
Paper Carton	5	0	40	0	2	0.851	0.076	
Stone	0	0	0	47	0	1	0	
Table Surface	10	3	2	0	32	0.681	0.615	

Amongst these three algorithms, the opto-tactile sensor performed better with SVM and Decision Tree C4.5. The accuracy for these both of the algorithms was 76.33%. In terms of carpet C4.5 learning algorithm performed better than SVM. But in the individual object recognition SVM was better than C4.5. Accuracy of the third learning algorithm using Naïve Bayes is 75.10%, which is less than the other two algorithms cases.

Table 3. Tactile Sensor Performance using NB Learning Algorithm

NB Classification								
	Carpet	Metal	Paper Carton	Stone	Table Surface	TP Rate	FP Rate	
Carpet	3	8	15	0	19	0.067	0.02	Accuracy = 75.10%
Metal	0	53	0	0	6	0.898	0.075	
Paper Carton	2	0	44	0	1	0.936	0.086	
Stone	0	0	0	47	0	1	0	
Table Surface	2	6	2	0	37	0.787	0.131	

Table 4. A comparison of the computational performance among SVM, C4.5 and NB algorithms

Computational Time			
	SVM	C4.5	NB
Time in Second	1.13	0.01	0

Comparatively Naive Bayes (NB) algorithm performed faster than other two algorithms used for experiments. But the computation time was not much more difference to feed the learning algorithms with the opto-tactile sensor system.

VI. CONCLUSIONS

Wider application perspectives of tactile sensing have been indicated in this article. Attempt has been made to indicate historical development of tactile sensors; particular attention has been paid to development of optical based tactile sensors and their areas of applications. Design and working principles of a number of more successful types of optical based tactile sensors have been elaborately explained with credible illustrations.

This work is dedicated to a new area of applications of opto-tactile sensors for object surface texture pattern recognition. A methodology for surface texture recognition using a recently developed opto-tactile sensor using three different soft computational techniques has been suggested. The experimental exercises have confirmed that all of the three soft computational techniques such as Support Vector Machine (SVM), Decision Tree C4.5, and Naive Bayes algorithms may be used to recognize object surface texture knowing tactile data produced by the opto-tactile sensor in robotic technology.

Results in the experiment suggest that the opto-tactile sensor performed better with SVM and Decision Tree C4.5 in surface texture recognition. The overall accuracy achieved by both algorithms (SVM and C4.5) as presented in Table 1 & 2 was 76.33%. In experiments with carpet, C4.5 learning algorithm performed better than SVM. But in the individual object recognition SVM was better than C4.5. These results also have established that the accuracy of object surface recognition using opto-tactile sensor is reasonably satisfactory. However, for better results and accuracy acceptable enough for industrial applications, the study also suggests using higher volume of sensor data until it reaches perfection.

Accuracy of the third learning algorithm using Naive Bayes is 75.10%, which is less than the other two algorithm cases. This does not confirm that Naive Bayes technique is not usable, but uses of higher volume of experimental data might get to the true credibility of the technique. Further experiments with higher volume of data and use of optimization techniques [20] to optimize SVM and kernel parameters remain the focus of future works. The methodology and procedures presented in the paper demonstrates their applicability in intelligent robotic grasping and in object texture pattern recognition in robotic manipulation.

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