CONTACT RECOGNITION USING TACTILE SENSOR

Somrak Petchartee[1] and Gareth Monkman[2]

[1]Ferderal Arms Force University Munich, Germany,
somrak.petchartee@gmail.com,
[2]University of Applied Sciences Regensburg, Germany,
gareth.monkman@e-technik.fh-regensburg.de

Abstract: The surface recognition algorithm that determines the types of contact surfaces by fusing information collected by the tactile sensor system is proposed. The tactile system will be determined from the shape of the object image which can then be characterized using the mathematical properties of Quadric surface. This algorithm can recognize 3-D objects using a 2-fingered robot gripper, on which tactile sensors are mounted. Experiments have demonstrated the reliability of the surface classification method and the accuracy of transformations independent of an object's shape, translation and rotation. *Copyright 2007*.

Keywords: multisensor integration, surface classification, surface recognition, shape recognition, shape discrimination.

1. INTRODUCTION

A number of approaches have been put forward to process the output of tactile sensors in order to yield useful characterizations of contact surfaces for applications such as characterizing the surface textures for different manipulations as well as object identification. For example, the output of a single-point sensor sliding over different textures has been used to identify surfaces based on the frequency power spectrum of the sensor response (Baglio et al. 2002). Kim et al. (2005) classified surface textures by using a polymer-based microelectromechanical systems (MEMS) tactile sensor array using a statistical approach. Five simple textures were distinguished using a 4 × 4 strain gauge sensor array serving as a transduction element. Five of the texture arrays were diagonal, enlarged diagonal, check pattern, four corner pixels, and perimeter pixels only. Texture classification was achieved by using a maximum likelihood decision rule. Their final results were analyzed by using cross validation to yield an acceptable overall performance of 68% correct classification, but the experiments cannot cope with either rotation nor translation invariants.

There also exist other techniques for contact identification based a tactile sensor. For examples, Ibrayev and Jia, (2005, 2004) proposed the recognition of low-degree polynomial curves based on minimal tactile data. In their application, Euclidean differential and semi-differential invariants were derived for quadratic and special cubic curves. Those invariants, independent of translation and rotation, were evaluated over the differential geometry at up to three points on a curve. Unfortunately, he did not present any implementation methods and experimental results.

In this study, an algorithm that can discriminate between types of contact surfaces and recognize objects at the contact stage is proposed. The type of contact surfaces obtained by the tactile system will be determined from the shape of the object image which can then be characterized using the mathematical properties of Quadric surfaces.

With resistive tactile sensor, changes in electrical resistance are detected by a tactile sensor made from electrically conductive foam.

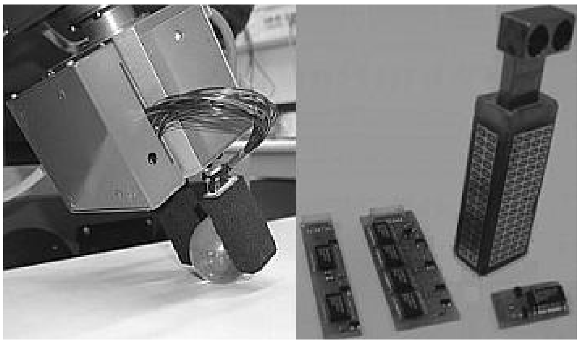

Fig. 1. Sensor Components

The electrical resistance measured between two electrodes on the same side of the conductive foam (one tactile element) is derived from electrical conductivity through a number of simultaneously conducting paths. The tactile sensors have been developed with the following specifications: One finger consists of two 16x4 cells, two 16x2 cells, and one 6x2 cells, making up the total 408 cells for the two fingers. The width of the fingers is 20 mm, their length is 55 mm excluding an aluminum core and they have a thickness of 12 mm.

Specifically in this study, the eigenvalue represents the matrix properties of the Quadric surface of object prototypes calculable from the eigenvalue trajectory of the object types. Four different shapes of objects have been used to test for the robot's ability to recognize object types. The robot makes contact with these objects, and the data from the tactile sensor is stored and analyzed. Later, one of the four objects is grasped again but with different magnitudes of forces and with different positions and rotations. The ability to distinguish between object types is calculated. The tested objects are an oval object with two major axes of 14 mm and 11.7 mm; a cylindrical object with 6.0 mm in diameter and 20 mm in length; a cube with dimensions 10 x 15.9 x 10 mm; and a ball with a diameter of 9.5 mm respectively.

2. SURFACE INTERPOLATIONS

The shape representation designed for this study is both rotation and translation invariant. The Quadric surface seems to be a simple, yet adequate, method for the proposed tactile sensor as the dimension of the tactile array (16x4) cannot represent a complex object surface. The basic way of creating Quadric surfaces uses least-squares interpolation. Considering a general 3-D surface expressed in the contact point as $f(x,y,z)=0$, the general surface function can be approximated locally at the contact point as the following second order polynomial equation:

$$ax^2+by^2+cz^2+2dxy+2eyz+2fxz+2gx+2hy+2jz+k=0 \quad (1)$$

Equation (1) can be rewritten in a quadratic form of a matrix equation: $P^T.Q.P=0$, where

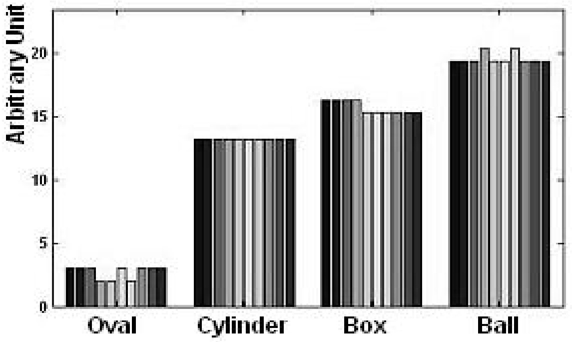

Fig. 2. Fitting Accuracy

$$Q=\begin{pmatrix} a & d & f & g \\ d & b & e & h \\ f & e & c & j \\ g & h & j & k \end{pmatrix} \text{ and } \qquad P=\begin{pmatrix} x \\ y \\ z \\ 1 \end{pmatrix}$$

The properties of the surfaces represented by Q can be translated, rotated and scaled. Given a 4 x 4 transformation matrix M of the form developed, the transformed Quadric surface Q^* is:

$$Q^*=(M^{-1})^T.Q.M^{-1} \quad (2)$$

The general transformation matrices (M) are of the Denavit-Hartenberg type combining both translation and rotation.

The least-squares problem arises when the polynomial is being fit at some data points $\{(x_i,y_i)\}$, $i = 1, \ldots, m$, where m is greater than or equal to the number of unknown variables. A further generalization of the linear least-squares problem is to take a linear combination of basic functions $\{f(x_1,y_1), f(x_2,y_2),..., f(x_m,y_m)\}$. Firstly, the c, e, f and j variables of Q are set to zero to get an explicit form as (3):

$$z = f(x,y)=ax^2+by^2+2dxy+2gx+2hy+k \quad (3)$$

z or $f(x,y)$ represents the tactile data of the tactile elements at the location (x,y). Then, the problem of fitting this polynomial can be initiated. In the matrix form $Ac \approx Z$, A is a square matrix, the unknown $\boldsymbol{c}$ is a column vector, and Z is also a column vector. The least-squares problem becomes: $\min\|z-Ac\|^2$. A solution of the least-squares problem is the solution $\boldsymbol{c}$ to the linear system: $A^T Ac = A^T z$, that is known as a *normal equation*. The solution of the least-squares problem is obtained by analyzing the singular value decomposition (SVD) of A.

We have been experimenting with Quadric surfaces with an arbitrary set of data points. The fitting accuracy evaluation is to use a simple root-mean-squared (RMS) error function where each error value is the distance from a tactile data point to the point on the interpolation surface. The bar graphs in figure 2 are grouped into four different types of object shapes and show the mean square distance deviation over 10 iterations of the experiments on different data sets. The random noise was simulated using the Matlab *'randn'* function. It generates normally distributed random numbers, whose values are in the range [1, 20] mixing with the tactile data sets.

3. MATHEMATICAL PROOF

One property of the matrices of Quadric surfaces is that they are symmetric matrices. They can always be diagonalized, and their eigenvectors can be chosen to form an orthonormal basis with respect to the canonical dot product. For example, if we form a matrix A with their eigenvectors as the columns, then we will obtain the diagonal matrix as vAv^T. Rayleigh's principle (Rayleigh, 1945) states that the smallest eigenvalue $\lambda_{\min}$ coinciding with the minimum of

$$R(v) := \frac{< v, Av >}{< v, v >}\,,\ < v, v > \text{ is inner product.} \quad (4)$$

The minimizer of R is an eigenvector with the smallest eigenvalue $\lambda_{\min}$. Likewise, the largest eigenvalue and its corresponding eigenvector can be found by maximizing R. Let the eigenvalues of A be ordered as $(\lambda_{\min})\lambda_1 \le \lambda_2 \le \lambda_3 \le ...\lambda_{n-1} \le \lambda_n(\lambda_{\max})$.

Then, we obtain $\lambda_1 x * x \le x * Ax \le \lambda_n x * x$ for all $A \in M_n$ where n is the matrix dimension, $\lambda_{\max} = \lambda_n = \max_{x\ne 0} \frac{x * Ax}{x * x}$ and $\lambda_{\min} = \lambda_1 = \min_{x \ne 0} \frac{x * Ax}{x * x}$. At this point, we aim to prove that the smallest eigenvalue can facilitate contact identification.

$$\text{In our case, } v = \begin{bmatrix} x \\ y \\ z \\ 1 \end{bmatrix} \text{ and } A = \begin{bmatrix} a & d & 0 & g \\ d & b & 0 & h \\ 0 & 0 & 0 & j \\ g & h & j & k \end{bmatrix},$$

$$Av = \begin{bmatrix} ax + dy + g \\ dx + by + h \\ j \\ gx + hy + jz + k \end{bmatrix},$$

$$< v, Av >= \begin{bmatrix} x \\ y \\ z \\ 1 \end{bmatrix} \begin{bmatrix} ax + dy + g \\ dx + by + h \\ j \\ gx + hy + jz + k \end{bmatrix}.$$

Then, we have

$$< v, Av >= ax^2 + dxy + gx + dxy + by^2 + hy + jz + gx + hy + jz + k$$

and $< v, v >= x^2 + y^2 + z^2 + 1$, which can finally be formulated as:

$$R(v) = \frac{< v, Av >}{< v, v >} = \frac{ax^2 + by^2 + 2dxy + 2gx + 2hy + 2jz + k}{x^2 + y^2 + z^2 + 1} \quad (5)$$

The next step is to minimize $R(v)$ and obtain $\lambda_{\min}$, to cope with the question of how the Quadric parameter can be used for contact classification.

In considering the problem of minimizing a polynomial fraction on R_n, it is known to be difficult even for degree-2 polynomials. Jibetean and Laurent (2005) have proposed a method for computing tight upper bounds based on perturbing the original polynomial and using semidefinite programming. Their works are on global optimization methods for multivariate polynomials and rational functions, and their method can be applied to our problem. According to their theory, it involves the following problem:

$$\inf_{x \in R^n} \frac{p(x)}{q(x)} \text{ with } p(x), q(x) \in R[x]. \quad (6)$$

Regarding the terminology, they use the infimum ($\inf$) instead of the more common minimum (min) simply to stress that the optimal value may not be attained exactly in R_n but may only be approached asymptotically.

Nevertheless, it is important to have a procedure which computes, in principle, the global optimum. Jibetean's interest is in designing algorithms which guarantee finding the global solution. Her method is based on the relation between positive polynomials and the sum of squares of polynomials. In fact, in this approach the effort is directed towards finding a real number α such that $p(x) - \alpha q(x) \ge 0, \forall x \in R^n$, where $p(x)$ and $q(x)$ are the given polynomials. Obviously the largest α satisfying the condition is the infimum of $p(x)/q(x)$.

Moreover, she rewrote the rational optimization problem into a semi-define optimization problem (SDP) which is known to have good computational complexity. Actually, in general she obtains SDP as the relaxation of the original problem, which gives a lower bound for the solution of the original problem. Firstly, she rewrote the problem as an SDP by denoting $F(x) = p(x) - \alpha q(x)$. If the total degree of F is even where the total degree is d (d; power of polynomial), she can find a matrix Q such that $F(x) = z^T Qz$, $z = \left[1, x_1, x_2, ..., x_n, x_1x_2, ..., x_n^d\right]$. The value z contains all monomials of the variables $x_1, ..., x_n$ having its degree less than or equal to d. Obviously, if such Q exists, then it is a symmetric matrix. In the conclusion, equation (6) can be rewritten as:

$$F(x) = z^T Qz = p(x) - \alpha q(x) \ge 0\ . \quad (7)$$

The matrix Q can always be constructed. If $Q \succeq 0$, then $F(x) \geq 0$, $\forall x \in R^n$. A positive semidefinite matrix, or $Q \succeq 0$, is a matrix all of whose eigenvalues are nonnegative. The Q matrix is called a positive semidefinite matrix if $x^T Q x \geq 0$. It means for every points x in the vector space introduced, $x^T Q x$ is a positive value. Referring to (5), if we define $x_1 = x, x_2 = y$ and $x_3 = z$, then we get

$$\inf_{x \in R^3} \left(\frac{a x_1^2 + b x_2^2 + 2d x_1 x_2 + 2g x_1 + 2h x_2 + 2j x_3 + k}{x_1^2 + x_2^2 + x_2^3 + 1} \right) \quad (8)$$

Using the method of Jibetean , then our problem can be arranged into

$$a x_1^2 + b x_2^2 + 2d x_1 x_2 + 2g x_1 + 2h x_2 + 2j x_3 + k - \alpha(x_1^2 + x_2^2 + x_2^3 + 1) = z^T Q z$$

, where $z = \begin{bmatrix} x_1 & x_2 & x_3 & 1 \end{bmatrix}$. (9)

Then, it can be re-arranged as:

$$\begin{aligned} &(a-\alpha) x_1^2 + (b-\alpha) x_2^2 - \alpha x_2^3 + 2d x_1 x_2 + .. \\ &2g x_1 + 2h x_2 + 2j x_3 + k - 1 = z^T Q z \end{aligned} \quad (10)$$

Based on (7), it can be observed that one solution is $x^T Q x = 0$ which is the definition of a Quadric surface.

$$Q = \begin{bmatrix} a-\alpha & d & 0 & g \\ d & b-\alpha & 0 & h \\ 0 & 0 & -\alpha & j \\ g & h & j & k-\alpha \end{bmatrix} \quad (11)$$

Introducing the Quadric parameter into Rayleigh's quotient to finding the minimization of $R(v)$ based Jibetean's method leads the result to be $\alpha = 0$, at least in one case. The conclusion of these proofs can confirm that the smallest eigenvalue of the Quadric parameter is identical with the Quadric parameter itself. This means the smallest eigenvalue of the Quadric parameter yields the identical characteristic of the Quadric shape. Every symmetric matrix has this property, including its covariance which is also a symmetric matrix. In order to achieve more noise tolerance in real applications, using covariance of Q in finding the smallest eigenvalue seems to be reasonable. Richard and Stephen (2000) also have a proof on the covariance matrix in terms of the effect of the noise rising in all the eigenvalues by σ^2, where σ is the standard deviation of a random noise. Moreover the variation of eigenvalue will coincide with $\lambda_n + \sigma^2 b_- \leq \omega_n \leq \lambda_n + \sigma^2 b_+$, where $b_\pm = (1 \pm \sqrt{y})^2$, $y = N/T$, N is the dimension of the vector space, and T is the number of samples.

In the experiment, the training procedure is done to check classification performance, as shown Table 1. The Quadric surface properties are modified by multpilying with transformation matrix for translation, rotation and scaling operations.

Table 1 Procedure for the evaluation of eigenvalue trajectories

Object				
Quadric Surface				
Scale Ratio	0.1 to 4	0.1 to 4	0.1 to 4	0.1 to 4
Translation in x-axis	-2 to 2	-2 to 2	-2 to 2	-2 to 2
Translation in y-axis	-4 to 4	-4 to 4	-4 to 4	-4 to 4
Rotation x-axis	0 to 2π	0 to 2π	0 to 2π	0 to 2π
Rotation y-axis	0 to 2π	0 to 2π	0 to 2π	0 to 2π
Rotation z-axis	0 to 2π	0 to 2π	0 to 2π	0 to 2π

For a matrix of 4x4, there are four eigenvalues, the smallest one being in the order of 10^{-3}, and the largest one in the order of 10^2. Thus, the eigenvalues in the first three columns ordered ascendingly are not used while the one in the last column is utilized because it is the smallest eigenvalue.

This experiment applies graphical techniques to study the behavior of eigenvalues after the matrix elements change. This change normally requires numerical analysis and perturbation theory, but the technique called "eigenvalue trajectory analysis", illustrated in Figure 3, is more applicable and will be adopted. This graph shows the smallest eigenvalue of the covariance matrix of the Quadric surface property independent of translations in all two axes, of rotations around any axis, and of scalable values. After the trajectory of the eigenvalue is derived, it can be used to classify to the contact surface of object by matching the level of eigenvalue of surface property matrix belonging to the object prototype.

An important tool for describing the eigenvalues of square matrices is the characteristic polynomial.

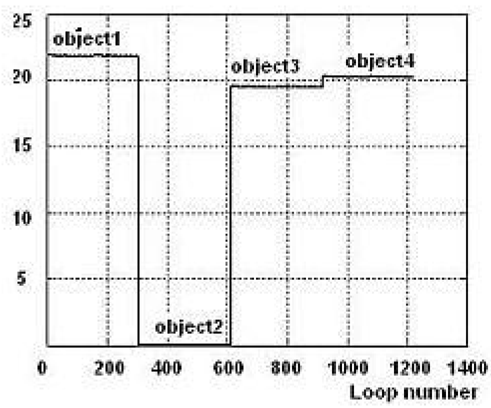

Fig. 3. Eigenvalue trajectories of Quadric parameters under different tested objects

Eigenvalues of large matrices should not be computed using the characteristic polynomial. The Abel–Ruffini theorem implies that the roots of high-degree polynomials cannot be expressed simply using n^{th} roots (Dehn,1930). Moreover, although effective numerical algorithms for approximating the roots of polynomials exist, small errors in the eigenvalues can lead to large errors in the eigenvectors. Then, the eigenvalues using the characteristic polynomial give unexpected results in our tests. General algorithms for finding eigenvectors and eigenvalues are usually iterative methods, but only a few iterative methods can provide round-off errors small enough to be useful for our purposes.

The easiest method is the power method in which a random vector is chosen and used it to comput a series of increasing power matrix. The aim of the power method is to find only the largest eigenvalue. The problem with this method is that if the data in matrix A has errors, the square of A^m will exacerbate them leading to higher round-off errors. Although the modified method enables estimation of the smallest eigenvalue, these two limitations are inevitable.

Even though the level enabling classification of objects is only in the order of 10^{-3}, the computing method to find an eigenvalue needs a very small round-off error. Powerful methods such as the QR algorithm used in the LaPACK library (Linear Algebra Software Package), have good classification ability since a precise resolution within the order of 10^{-3} is possible with very small round-off errors.

3. EXPERIMENT EVALUATIONS

The random noise associated with the interpolation in a real application can generate variations in eigenvalues. This requires an investigation into the eigenvalue trajectory under random noise.

4.1 Effects of Random Noise on Eigenvalue Trajectory

Figure 4 indicates that noise on the trajectory dampened some graph levels during the test experiments. Nonetheless, it did not reduce contact classification capability with respect to the overall error growth. Contact classification can still be achieved through level checking. Noise was simulated using a random function with a normal distribution with values in the range [1, 20]. Then, they were added to every tactile data element. All of the eigenvalue trajectories were tested with ranging noise levels, for 10 iterations. The noise levels for all tactile elements were randomly and simultaneously increased, yet only to the maximum values of 8% of ADC's maximum (255), and the performance of algorithms was demonstrated as shown in figure 4.

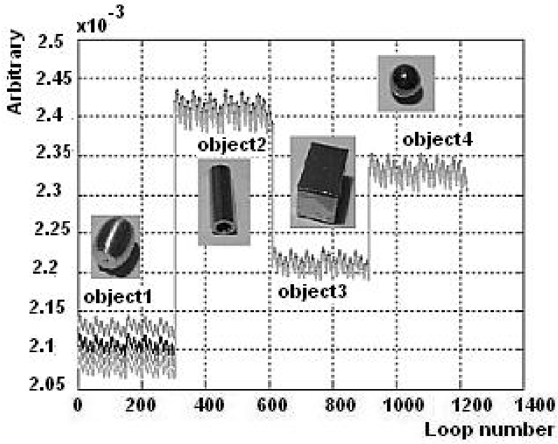

Fig. 4. Noise Tolerances

This leads to the conclusions that if the noise level is kept below 8% it will not be statistically meaningful for, nor affect, classification. By experimenting, it is also clear that classification capability is reduced if the random noise peaks are greater than 8% of the ADC's maximum value. Invalid classification was tested by increasing noise to a level higher than 8%, and consequentially, the crossing levels of eigenvalue trajectory appeared. The use of a noise filter on the tactile data reduces the effect of noise on the eigenvalue trajectory, and such a filtration must be performed before surface interpolation was applied.

3.2 Border of classification

The principal idea used to classify the contact is in the matched threshold of the eigenvalue trajectory. For example, in figure 5, the 'a' level can be used to distinguish between object A and object B; the 'b' level can be used to distinguish between object A and object C, and so on. As formerly mentioned, random noise has an effect on the eigenvalue trajectory. The windows of different sizes (A, B, C) have their uses on defining different thresholds for the eigenvalue trajectory, and classification by thresholds has to be adjusted dynamically.

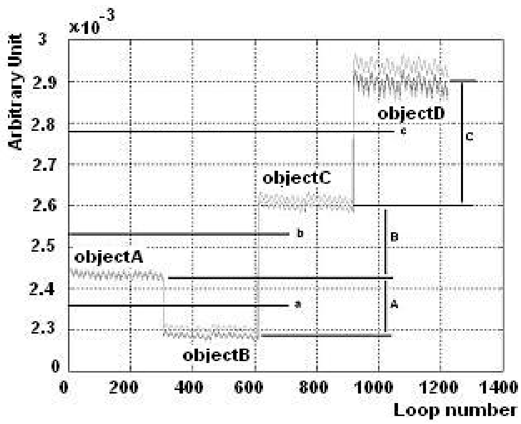

Fig. 5. Windows of Margin

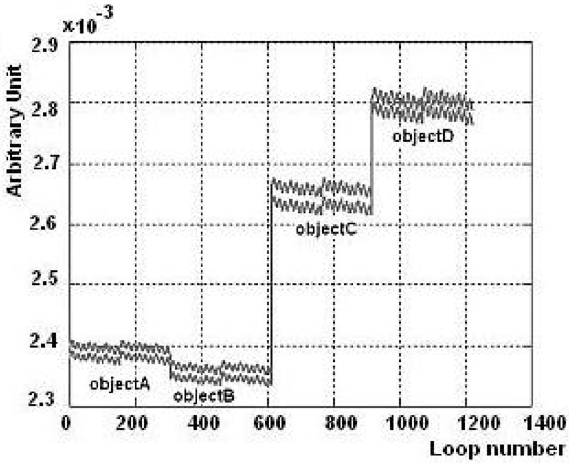

Fig. 6. Mixed threshold

Also, some object shapes are very sensitive to noise which leads them to be incorrectly identified in the interpolation process. As displayed in figure 6, object A and object B yield little difference in terms of the smallest eigenvalues, which lead to a classification failure. In reality, the noise mixed with the tactile data also has an effect on the smallest eigenvalue. If the window size is too small, then the added noise will make the classification capability approach zero.

According to figure 4, the thresholds of object 1, object 2, object 3, object 4 correspond with the oval, cylindrical, cube (box) and ball shapes, respectively. Each object has a different eigenvalue in the eigenvalue trajectory with no particular increasing or decreasing order in terms of their levels. This can lead to misclsssification in the case of two very close threshold values.

Table 2 demonstrates the test results, whose testing were repeated ten times on each object shape. The classification results reveal correct recognitions as well as misrecognitions. These differences may indicate that there are indeed limitations on the ranges of classification due to the similarity of test objects, fitting performance, and random noise.

Table 2 Statistic error of classification

Object Features	Percent of misclassify				Percent Error
	Oval	Cylinder	Box	Ball	
(1) Oval	0	0	10%	0	10%
(2) Cylinder	0	0	0	0	0%
(3) Box	10%	0	0	0	10%
(4) Ball	0	0	0	0	0%

For examples, the oval object can be misclassified as a box object by 10%. Yet, the oval may be less likely misclassified as a cylinder object, because their thresholds are not in neighbouring ranges. The experiments have also clearly shown that classification capability reduces if the random noise peaks are greater than 8% of the ADC's maximum value.

Invalid classification was achieved by increasing noise levels above 8%, and consequentially. As a result, contact classification cannot be achieved by a simple level checking.

4. CONCLUSION

A technique for recognizing objects using tactile sensor arrays, and a method based on the Quadric parameter for classifying grasped objects is described. It has been shown that the covariance matrix from the parameter of Quadric surfaces by interpolation of tactile data may be formulated by eigenvalue decomposition and can reflect under all contact geometries. The smallest component of an eigenvalue can be used to estimate and identify object shapes without using any other references, whereas classification is used as the principal indication of surface identity. The shape reflectance parameter pertaining to (unique to) each surface may be recovered and identified. It has been shown that the reliability of the surface classification method and the accuracy of transformation are independent of object shapes.

REFERENCES

Baglio, S., G. Muscato and N. Savalli (2002): *Tactile measuring systems for the recognition of unknown surfaces*, IEEE Trans. Instrument Measurement, Vol. 51, pp. 522–31.

Dorina Jibetean, Monique Laurent (2005). Semidefinite approximations for global unconstrained polynomial optimization, *the SIAM Journal on Optimization*.

Edgar Dehn (1930). *Algebraic Equations: An Introduction to the Theories of Lagrange and Galois.* Columbia University Press.

J. W .S. Rayleigh (1945), *Theory of Sound*, Dover Publications, New York.

Kim, Sung-Hoon, J. Engel, C. Liu and D. Jones (2005): *Texture classification using a polymer-based MEMS tactile sensor*, Journal of Micromechanics and Microengineering, Vol.15, p.912–920.

Richard Everson and Stephen Roberts (2000). Inferring the Eigenvalues of Covariance Matrices From Limited, Noisy Data. *IEEE transactions on signal processing*, Vol. 48(7), pp. 2083-2091.

Rinat Ibrayev and Yan-Bin Jia (2004). Tactile recognition of algebraic shapes using differential invariants. *Proceedings of the IEEE International Conference on Robotics and Automation*, pp. 1548-1553.

Rinat Ibrayev and Yan-Bin Jia (2005). Semi-Differential Invariants for Tactile Recognition of Algebraic Curves. *International Journal of Robotics Research*, Vol. 24, no. 11, pp. 951-969.