Available online at www.sciencedirect.com
SCIENCE DIRECT®

Sensors and Actuators A 105 (2003) 47–54

SENSORS AND ACTUATORS A PHYSICAL

www.elsevier.com/locate/sna

An approach to optimise the critical sensor locations in one-dimensional novel distributive tactile surface to maximise performance

P. Tongpadungrod [a,*], T.D.L. Rhys [b], P.N. Brett [c]

[a] *Department of Production Engineering, King Mongkut's Institute of Technology North Bangkok, 1518 Piboolsongkram Road, Bangkok 10800, Thailand*
[b] *Department of Mechanical Engineering, University of Bristol, Queen's Building, University Walk, Bristol BS8 1TR, UK*
[c] *Department of Mechanical Engineering, School of Engineering and Applied Science, Aston University, Aston Triangle, Birmingham B4 7ET, UK*

Received 23 August 2001; received in revised form 4 January 2003; accepted 6 February 2003

Abstract

The distributive approach to tactile sensing is a novel approach. The method relies on the distributed deformation of the surface in response to the applied load to a few sensing points within the surface area. The description of the contacting load is then interpreted into meaningful descriptors typically by using a neural network or fuzzy rules. The method has been shown to interpret descriptors such as load position, load value and load width and relies on strong coupling between the sensory data retrieved. This opposes the design aims in many alternative tactile sensing systems that formulate load description from isolated discrete data detected over an array of sensing elements, or that delineate force descriptions through a structure that minimises coupling on Cartesian axes. For distributive tactile sensors, the performance can be optimised through placement of sensing points such that the obtained information is optimal. This paper examines the effect on performance of sensor location points on an experimental one-dimensional surface designed for this purpose. The algorithm interpreting load descriptors was a back-propagation neural network. The critical parameter of sensor location is optimised using the genetic algorithm (GA) and principal component analysis (PCA) approach. It is shown that when an optimised configuration is used load position can be predicted to within 5% of the full range by using as few as two sensing elements, and that performance is improved by using additional sensor points. The results of this study are a basis for selecting sensor locations to achieve high performance with planar one- and two-dimensional distributive tactile surfaces.

Keywords: Distributive; Tactile sensing; Optimisation; Principal component analysis; Back-propagation neural network; Genetic algorithm

1. Introduction

Precise automated control of contact between surfaces can be achieved using tactile sensors are necessary, for example, in assembly and in the attachment to work pieces in robotics and in the control of process machinery such as paper manufacture and rolling steel mills. Additionally, tactile sensing is used in the form of weighing machines and keyboards to retrieve certain properties or information on the contact.

Conventional constructions of tactile sensors range from complex to simple, ranging respectively from full arrays of sensors to gather a great deal of data that can be used to derive complex properties of the contacting object, to single point measurement of force to merely determine that contact has occurred. Load plates are one example where three properties of contact may be determined such as weight, and x–y positions of the centre of load. These use a rigid surface with sensors mounted at the corners and are commercially available [1]. Computation of contacting properties is derived by a closed form solution of a set of simultaneous equations.

To obtain further properties of the contacting object, arrays of sensors are used that provide many data points over a surface corresponding with the pressure measured at those points. By monitoring these values, properties of the contacting imprints can be measured by using complex computational functions similar to that of a vision system. Examples of array sensors that emulate machine vision systems, can be found in various applications for instance force sensing for robot fingers [2], slip detection [3,4] and reconstruction of two- and three-dimensional object profiles [5–7]. By the nature of their construction, these sensors can be both complex and expensive, and suit applications needing high levels of precision in some of the data that is retrieved.

* Corresponding author. Tel.: +66-2-923-2500x8208; fax: +66-2-587-0029.
E-mail address: pensiri@kmitnb.ac.th (P. Tongpadungrod).

0924-4247/03/$ – see front matter © 2003 Elsevier Science B.V. All rights reserved.
doi:10.1016/S0924-4247(03)00059-1

There are also applications where the level of precision is not the most important parameter, but rather that the sensing system is low cost and reliable. The distributive approach offers advantages in this respect, as it requires few sensing points placed within surfaces: This can take the form of a sealed surface and may be used to discriminate many descriptors of a contacting surface, such as shape, orientation, size, position, slip and weight. The approach also introduces low computational load in the derivation of properties or the state of contact. Food processing, agricultural, domestic, leisure and medical applications can benefit from the potential low cost and physical robustness. However, the performance of such sensors is sensitive to the location of the sensing points.

Holweg and Jongkind [8] also adopted a simplified mechanical construction of tactile sensor by using an array of contact points on a substrate attached beneath a layer of conductive foam. The voltage outputs from the sensing points appear as a vector that can be related to the shape of the contacting surface. This sensor was used to control the nature of contact between the end-effector of a manipulator with a variety of objects. While the complexity of construction has been reduced by this approach, there is still a question of the number of connection points to provide the necessary large number of sensor points/values.

An alternative is to use fewer sensing points where sensor outputs are coupled by the deformation of a common contact surface. This is the 'distributive approach' and relies heavily on the correct placement of sensors computational algorithm used that relates the vector of the sensory output data to the properties of contact. Ellis et al. [9] applied a closed form approach for determining certain properties of grasped objects. A more computationally efficient approach applied to various surface shapes has been explored by Stone [10]. In this latter scheme, there is a discriminatory rather than deterministic process to determine properties of the load and state of contact. This approach is able to gather a great deal of information despite the simplicity of construction. A surface of this type was constructed and used by Stone and Brett [11] and Evans and Brett [12] to control the gripping of discrete compact shape soft objects with the aim to minimise deformation. The scheme enabled the contact force distribution to be deduced, and the deformation and slip of the object to be detected. The sensors used sensing elements placed beneath the surface and this offered the benefit of a robust construction. Although the investigation showed the potential of the method there was little understanding of the parameters that led to optimum performance. The approach is relevant to a wide range of applications and this paper reports on studies to increase performance by optimising the location and number of sensing positions.

The focus is on a one dimensional beam surface that enables 'behaviour' to be measured accurately in the laboratory under specific load conditions. The results on performance and the selection of design parameters can be used to design both one- and two-dimensional tactile surfaces, as the approach developed and the trends identified are appropriate to both. The demonstration rig uses a back-propagation neural network as a computational algorithm for the discrimination of contact conditions. To identify the optimum number of sensors as well as their positions, an optimisation technique is described. The method adopted is based on the genetic algorithms (GAs) and uses a performance evaluation function based on the principal component analysis (PCA); a well used multi-variable data reduction technique.

In Section 2, the experimental rig and complementary simulation model for an effective generation of sensory data are described. The approach taken in the application of PCA to the test data is described in Section 3. Subsequently, the optimal number of sensors for this example case is determined. In Section 4, the search algorithm is applied to optimise the sensory positions by using simulated data. Using the result as a guide to sensor locations, this is followed by the comparison between discrimination performances of the networks trained with simulated and experimental measurements with sensory positions at an equal pitch and at the optimised positions.

2. Test rig and sensing surface simulation

The single dimensional tactile surface was constructed to evaluate the performance of the sensing scheme for deflection of a simply-supported steel beam of length 400 mm when subjected to an applied load. The configuration shown in Fig. 1 illustrates that eight proximity sensors were initially positioned at equal pitch under the surface measuring deflection at these points. The advantage of using non-contact proximity sensors is that different sensed positions can be achieved readily as compared with using attached sensors such as strain gauges. The sensors were used over their linear range between 1 and 4 mm separation from the surface. A typical sensor characteristic is shown in Fig. 2 in terms of voltage output in response to the deflection of the surface. Single point loads were applied as manually positioned weights on the surface of the beam. The load position, was interpreted from the changes in the sensory data from all sensors by using a back-propagation neural net-

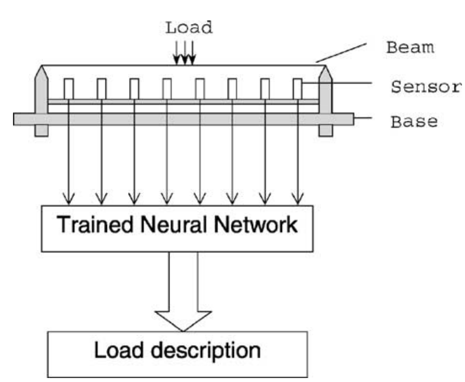

Fig. 1. The experimental rig.

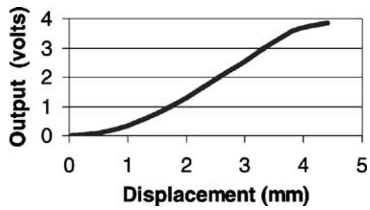

Fig. 2. A typical characteristic of the proximity sensors.

work. The back-propagation network is used in many engineering applications owing to its clear structure and robust performance [13]. The networks used in this work consisted of an input layer with the number of nodes equal to the number of sensors used, a single hidden layer with 10 hidden nodes and an output layer containing a single node outputting the estimated magnitude of load position along the beam. They were trained to achieve composite error of no more than 0.1% with the fixed learning and momentum rates of 0.9 and 0.7, respectively. In experiments of point loading, the accuracy to which position was predicted, when using equally spaced sensor positions, was to within 5% of the full range. The trends in measured performance with respect to the number of sensors used, in optimal sensor locations, is discussed later in this paper with comparison to a computer simulated study of the system subjected to the same design variations.

The network was first trained in order to derive the relationship between input and output states. Network training was carried out by giving the network vectors of input (beam deflection) and corresponding output (applied position). To explore the performance of the device efficiently, test data was generated from a simulation model in a parallel study with the experimental measurements.

A simulation of the full sensing system incorporating surface, sensor characteristics and the neural network was produced to explore characteristic behaviour of the whole system when subjected to changes in major design parameters leading to improved performance. The model was able to explore such trends more efficiently when compared to such changes made to the test rig. For the deflection behaviour of the beam surface, standard beam bending theory was applied. The bending theory is reported in most structural mechanics texts, for example [14]. The deflection y at position x in response to an applied load W at position a on a simply supported beam of length l is given by

$$y = \frac{W}{6EI}\left[\frac{(2l-a)(a-l)ax+(l-a)x^3}{l} - \langle x-a\rangle^3\right] \quad (1)$$

where E and I are Young's modulus and second moment of area of the beam, respectively. For Eq. (1), the following assumptions for the beam apply: (a) straight beam, (b) beam is constructed from a homogeneous material of constant elasticity, (c) the cross-sectional area remains planar and is uniform, and (d) the applied load will not cause permanent deformation. This equation is applicable when the responding deflections induced by the load are small with respect to the length.

3. Principal component analysis (PCA) for reduction of neural network inputs

From the viewpoints of reducing constructional complexity and unacceptably high computational loads associated with training neural networks, there is advantage in minimising the number of input nodes. This corresponds with minimising the number of sensors deployed. To achieve satisfactory performance whilst reducing the number of sensory inputs requires the strategic placement of sensing points to enable the required sensitivity in the output of the sensing system. PCA analysis has been applied to compress the real higher dimensional space into a meaningful lower dimensional space. This approach has been well applied in other applications [15,16] in conjunction with GAs to optimise system parameters against performance criteria and to enhance feature determination in data. PCA has also been widely used as a data reduction technique, for example, in process fault diagnosis [17,18] and analysis of bench-marking data [19]. In this application, it is shown that reduction can be achieved successfully when applied to this novel approach for tactile sensing. The first principal component PC lies along an axis corresponding with the direction of the largest variation in the dataset. The second PC corresponds with the next largest variance and is orthogonal, and hence, is uncorrelated with the first. The derivation of PCs continues until the number of PCs equals the number of input variables. In practice, the need to compute all components is rare since the data captured within the first few PCs are usually sufficient to explain the input variables [17].

In this example, the minimum number of PCs required to distinguish certain contact types can be determined from the minimum number of PCs that provide a unique description for selected parameters. In this process, PCs of large magnitudes (first PCs) are selected. Additional PCs above this minimum number can be introduced to allow for redundancy, however in this case, their magnitudes are insignificant when compared to sensor noise.

The derivation of PCs is carried out as follows [18]. For a dataset X, consisting of a set of N_0 applied positions measured at p sensory positions, the covariance matrix is

$$\Sigma = \frac{1}{N_0} X^{\mathrm{T}} X \quad (2)$$

The eigenvectors and eigenvalues of Σ are solved to satisfy the standard equation:

$$\Sigma U = UD \quad (3)$$

where D is a diagonal matrix with the diagonal elements equal to the eigenvalues λ_i and $U = \{U_1, \ldots, U_p\}$ is a matrix whose columns are the normalised eigenvectors such that $UU^{\mathrm{T}} = U^{\mathrm{T}}U = I$ (the identity matrix). The eigenvalues

λ_i correspond to the data variances in the directions of the eigenvectors U_i. Thus, by rearranging the columns of U in descending order of magnitude of the corresponding eigenvalues, a new matrix U_p is formed whose p columns are the p PCs of X.

To determine the minimum number of inputs required, PCA was applied to simulated beam deformation. This was computed at eight equally pitched positions for every 1 mm in applied position along the beam. The covariance of the input matrix, characterising the correlation between input channels was calculated using Eq. (2). Accordingly, the input matrix of 399 samples by eight sensors was reduced to a covariance matrix of size 8×8. From the result, eigenvalues and eigenvectors of the covariance were computed. The eigenvalues directly determine the variance of inputs whereas the eigenvectors comprised transformation matrices or direction for each PC. The transformed data obtained as a product of original beam deflection and transformation matrices were orthogonal and shown in a descendent order from the most prominent PC of which magnitude, thus, variance was the largest. The transformed inputs of the largest four magnitudes are shown in Fig. 3.

As expected, the first PC is of the largest magnitude. The magnitudes of later PCs are reduced rapidly. The magnitudes of PCs 5–8 are insignificant and their corresponding transformed inputs cannot be discerned on the same scale as the first four PCs.

The first PC is a reflection of the magnitude of deflection whereas the second PC depicts a bias of beam deformation due to load applied towards the left or the right of the beam. The influences on later PCs are less clear. By inspection, it can be suggested that at least the two most prominent PCs (PC1 and PC2) are required for determining the load position. With the first two PCs, all combinations of transformed inputs are unique.

The profile of later PCs can be corrupted by sensor noise when amplitudes become comparable. To investigate this, sensory noise at 2–10% of maximum deflection was randomly added to the theoretical deflection inputs. This was conducted in parallel with experimental measurements from the demonstration rig. Absolute differences between noisy and experimental data and transformed inputs derived theoretically were computed.

Fig. 4 shows a plot of absolute percentage errors between transformed data of theoretical inputs and those with additional noise of 2, 10% and experimental measurements. The x-axis shows the transformed feature whereas the y-axis represents an average absolute error. Trend lines were drawn through the error plots (based on $y = Ax^B$). There was an increase in error as the noise increased from 2–10%. This phenomenon was anticipated due to diminishing magnitudes of later PCs, given that the noise level remains unchanged.

4. GA for optimisation of sensory positions

To detect changes in beam deflection resulting from an applied load at different position, the sensors were initially placed at an equal pitch with respect to the beam length. To improve the accuracy of sensory information, there was a need to search for the positions, which result in the largest variance in input data. This can be accomplished by varying the sensory positions such that the magnitude of each PC characterised by the corresponding eigenvalue is optimal.

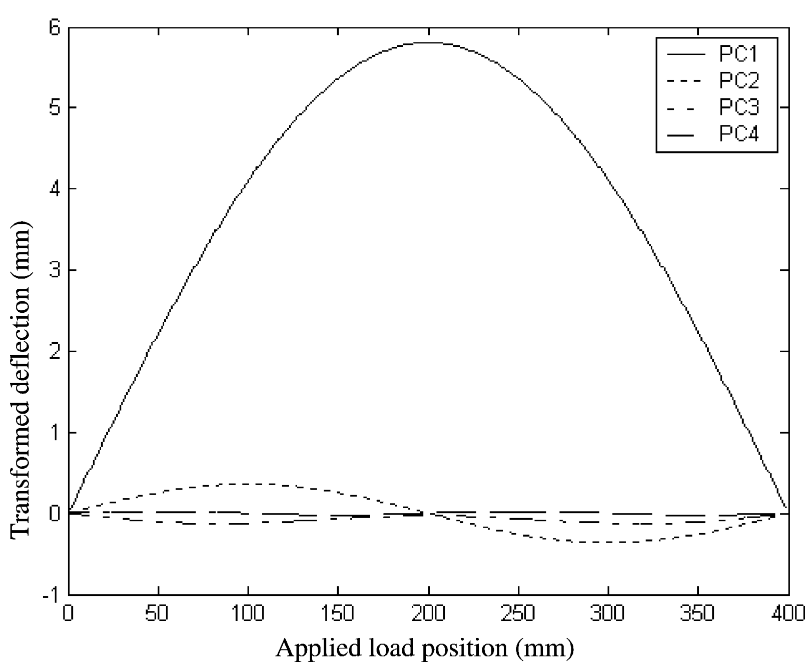

Fig. 3. Principal components.

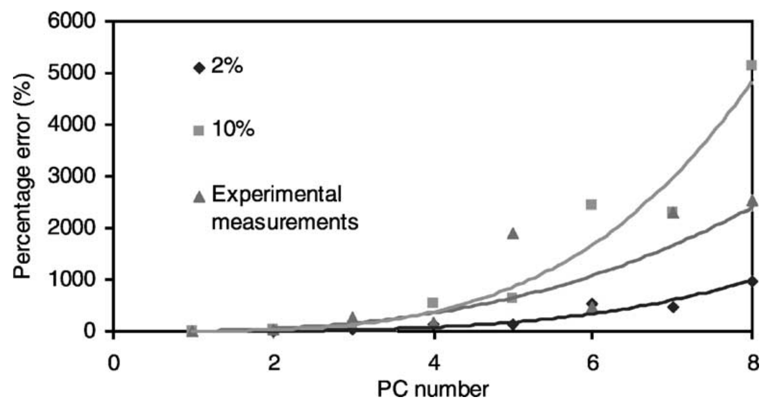

Fig. 4. Average absolute percentage errors plot between transformed features of inputs at different levels on noise and theoretical inputs.

A search algorithm based on the GA was employed as an optimisation tool.

The search algorithm was initialised with eight sensory locations separated at an equal distance. A slight variation was randomly assigned to the initial positions generating new sensory positions. This was repeated so that a population of combinations of new sensory positions was created. The performances of the new sensory locations were evaluated using an optimisation function described by a cost function shown by Eq. (4):

$$m = \frac{1}{E_1 \times E_2 \times \cdots \times E_n} \tag{4}$$

where m is the performance value, E_i the eigenvalue of the ith PC, and n is the number of features to be optimised.

The performance was evaluated by taking the product of inverse eigenvalues. With the described cost function, later PCs with small eigenvalues were given high momentum. As a result when the eigenvalues characterising magnitudes of later PCs increased, the performance value, m, reduced. To optimise the sensory positions, the algorithm searched for minimal performance value. To minimise the inputs and computational time, the number of eigenvalues considered was reduced to the optimum number of inputs determined previously with the method described in Section 3. In this particular example, a use of four sensors was identified as an optimum number for discrimination of an applied position.

Once the performances of all combinations of sensory locations in the population were evaluated, the combination with the best performance was chosen as new sensory locations for the next generation. Based on the best positions obtained from the preceding generation, the search algorithm reproduced a new set of locations. The positional variation (increment) was reduced when the best performance remained the same as the starting positions of that generation. The process was repeated until the increment converged to a specified value or when the search algorithm reached a specified maximum number of iteration.

Fig. 6 shows the convergence of sensory positions based on the described method to optimise the first four eigenvalues. The sensory positions were plotted on the x-axis and

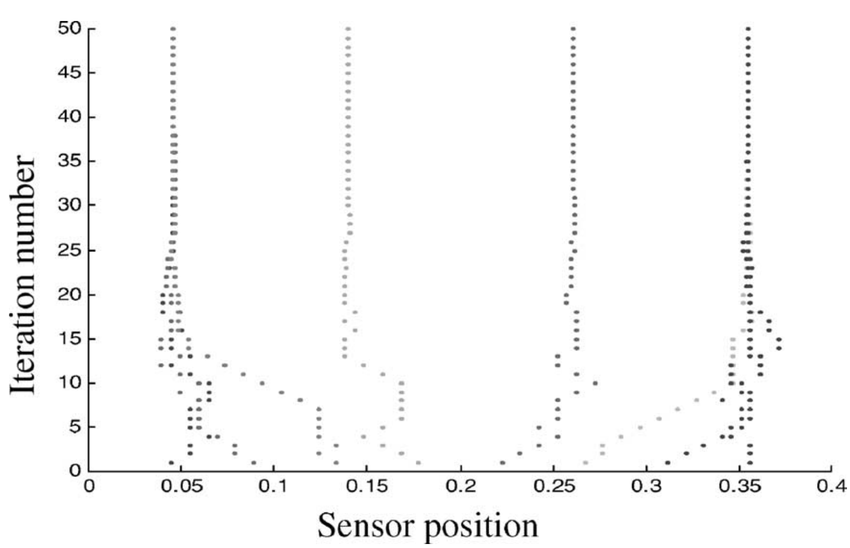

Fig. 5. Convergence of sensory positions for optimisation of the four largest eigenvalues.

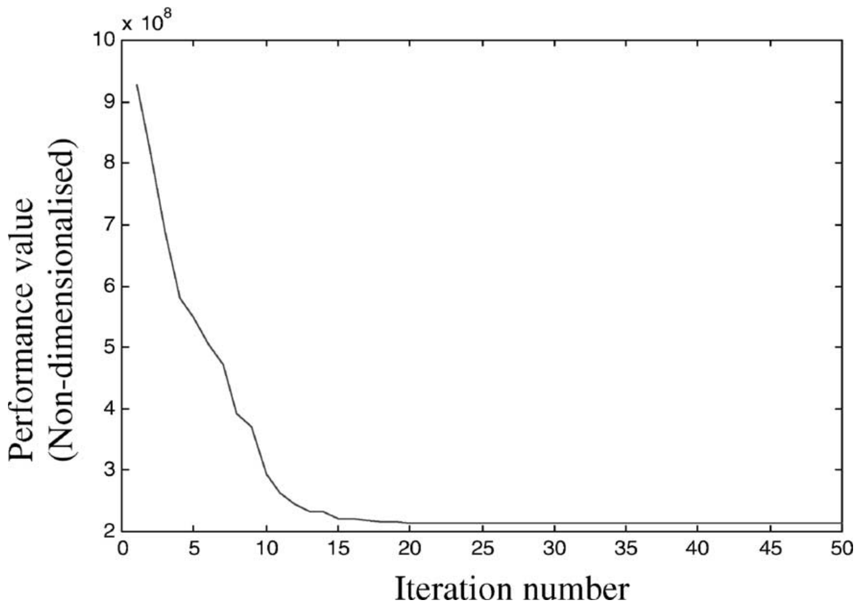

Fig. 6. Convergence of performance value.

search iterations on the y-axis. The convergence of performance value, m, is illustrated in Fig. 6. Fig. 5 clearly shows the convergence of the sensory positions from eight to four. The optimised positions were symmetrical about the beam centre. Fig. 6 demonstrates an asymptotic convergence of the performance value as the number of iterations increased. The convergence was achieved within approximately 20 iterations.

Fig. 7 enables comparison between the PCs when using equally spaced and optimised sensing positions, respectively. There was a prominent reduction in magnitude of the first. The second PC experienced a slight reduction in maximum magnitude. The maximum magnitude of the third PC also slightly decreased, but there was an increase in magnitude when load was applied near the middle of the beam. The fourth PC experienced an increase in maximum magnitude.

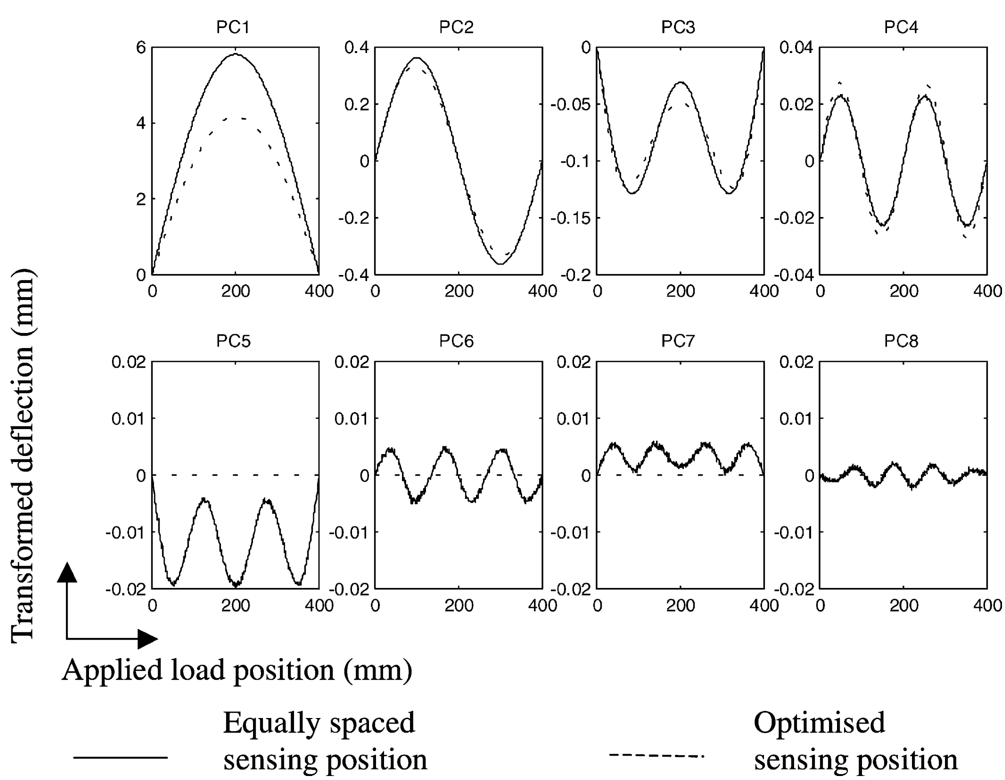

Fig. 7. Principal components when using equally spaced and optimised sensing positions, respectively.

5. Comparison of performances of optimised and equally spaced sensors

This section compares performances of optimised sensory positions for discrimination of an applied position with the initial arrangement of the rig, with sensors placed at an equal pitch (at intervals of 67, 80, 100 and 133 mm for two, three, four and five sensors, respectively). The comparison shows the effect of optimisation on the accuracy of the system. Additionally, to verify the practicality of the optimisation technique, experimental measurements of beam deformation were obtained and used as inputs.

Optimised sensor positions of two to five sensors were identified using the described method. To evaluate the performance of the optimised positions, neural networks with the number of inputs corresponding to the number of sensory positions were created and trained using inputs derived theoretically. Subsequently, these networks were used to determine an applied load position when beam deflections were derived both theoretically and experimentally. For all neural networks, the number of inputs varied with the number of sensing elements. The average positional errors (e) were evaluated using Eq. (5):

$$e = \frac{|A - P|}{l} \times 100\% \quad (5)$$

where e is the error (%), A the applied load position (mm), P the determined load position (mm), and l is the total beam length (mm).

For the cases where inputs were derived both theoretically and experimentally, Fig. 8 illustrates trends of the discrimination errors with respect to the number of sensory positions. In both cases, simulated and measured results, the discrimination errors decrease with an increase in the number of sensors. Also as the number of sensors increases the rate of error reduction is diminished. A limiting factor is noise in the sensory data. A greater number of sensors increases the tolerance of the system to error, although it was found that in the optimised case that the tolerance was greater. As expected, the difference between the errors in the case of equally spaced, as opposed to optimised positions diminishes with the increasing number of sensors used. With many sensors, there is less physical difference between optimised and equal pitch positions. It can be concluded that the optimisation method is an advantage if the aim is to reduce the number of sensing elements used.

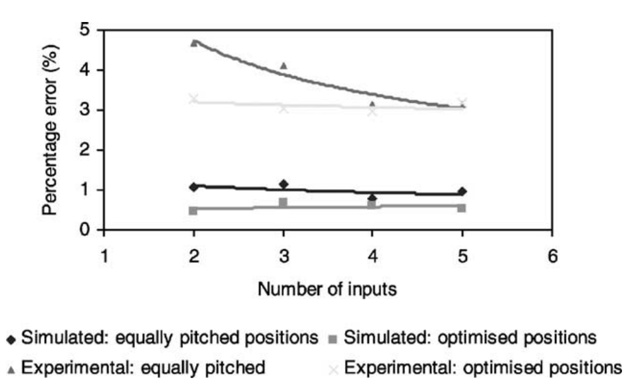

Fig. 8. Percentage errors of positional discrimination using two to five inputs at equally pitched and optimised positions with inputs derived theoretically and experimentally.

6. Conclusions

A novel distributive single-dimensional sensor for identifying the position of an applied load has been presented. The method offers a reduction in the number of transducers and the resolution achieved is higher than the number of transducers employed. The distributive approach is suited to the discrimination of states rather than to give an exact description of the contact.

To search for the minimum number of sensors required and to optimise the sensory positions, a technique for data reduction, PCA, has been implemented. With this method, the minimum number of sensors was identified by determining the minimum number of PCs needed to distinguish the parameters of load position. In this example, it was found that to discriminate the position of an applied load, at least two sensors must be employed. It can be concluded that the most prominent PCs of the data in this example are the magnitude of deflection and the bias of deflection towards the left and the right of the beam. In addition to the minimum number of sensors required, extra sensors can be employed to enhance the reliability and redundancy. The determination of the optimum number of sensors was achieved by examining the differences between PCs of the theoretical data and those with randomly added sensory noise as well as those derived experimentally.

To enhance the performance of the system, the paper describe an optimisation technique through sensor placement using a search algorithm based on the GA, using the eigenvalues derived from the PCA as the performance evaluators. The performances of the optimised and equally pitched sensory positions derived both experimentally and theoretically were compared. It was found that at a low number of sensors, the improvement in performance as a result of the optimisation technique was more pronounced, whilst the trend was the same. For example, with two sensors the average percentage positional error using inputs derived experimentally was reduced from 4.67% when the sensors were placed at an equal pitch to 3.28% when the sensory positions were optimised. With five sensors, the corresponding errors were 3.13 and 3.16%, respectively.

Potentially this optimisation technique can be applied to other sensing systems for both one- and two-dimensional surfaces. The approach is beneficial for a reduction in construction complexity and computational requirements. In addition, to enhance the sensor performance, the optimisation technique described can be used to identify the optimum number of sensors as well as their positions. Further, the work has shown that simulation is a satisfactory way to identify design trends for optimising sensor placement.

References

[1] Kistler, Force plate, http://www.kistler.com/, September 1999.
[2] R.S. Fearing, Tactile sensing mechanism, Int. J. Robot. Res. 9 (3) (1990) 3–23.
[3] G. Canepa, R. Petrigliano, M. Campanella, D. DeRossi, Detection of incipient object slippage by skin-like sensing and neural network processing, IEEE Trans. Syst. Man Cybernet. Part B: Cybernet. 28 (3) (1998) 348–356.
[4] B. Eberman, J.K. Salisbury, Application of change detection to dynamic contact sensing, Int. J. Robot. Res. 13 (5) (1994) 369–394.
[5] A.J. Harrison, P.J. Hillard, A moment-based technique for the automatic spatial alignment of plantar pressure data, Proc. Inst. Mech. Eng. Part H: J. Eng. Med. 214 (3) (2000) 257–264.
[6] A. Caiti, G. Canepa, D. DeRossi, F. Germagnoli, G. Magnenes, T. Parisisni, Towards the realization of an artificial tactile system: fine-form discrimination by a tensorial tactile sensor array and neural inversion algorithms, IEEE Trans. Syst. Man Cybernet. 25 (6) (1995).
[7] A. Leung, S. Payandeh, Application of adaptive neural network to localization of objects using pressure array transducer, Robotica 14 (4) (1996) 407–414.
[8] E.G.M. Holweg, W. Jongkind, Object recognition using a tactile matrix sensor, in: Proceedings of the EURISCON'94 Advanced Manufacturing and Automation RES 1994, August 1994, Malaga, Spain, pp. 1379–1383.
[9] R.E. Ellis, S.R. Ganeshan, S.J. Lederman, A tactile sensing-based on thin plate deformation, Robotica 12 (4) (1994) 343–351.
[10] R.W.S. Stone, A distributive tactile sensing technique for soft deformable contact, University of Bristol, 1997.
[11] R.S.W. Stone, P.N. Brett, A sensing technique for the measurement of tactile forces in the gripping of dough like material, Proc. Inst. Mech. Eng. Part B: J. Eng. Manuf. 210 (3) (1996) 261–269.
[12] B.S. Evans, P.N. Brett, Computer simulation of the deformation of dough-like materials in a parallel plate gripper, Proc. Inst. Mech. Eng. 210 (B) (1996) 119–126.
[13] H. Demuth, M. Beale, Neural Network Toolbox Technical Manual, Math Works, Inc., Natick, MA, June 1992.
[14] W.C. Young, Roark's Formulas for Stress and Strain, McGraw-Hill, Singapore, 1989.
[15] C. Guo, W. Wu, D.L. Massart, C. Boucon, S. de-Jong, Feature selection in principal component analysis of analytical data, Chemom. Intell. Lab. Syst. 61 (1–2) (2002) 123–132.
[16] A. Spalanzani, S.A. Selouani, Improving robustness of connectionist speech recognition systems by genetic algorithms, in: Proceedings of the 1999 International Conference on Information Intelligence and Systems, Cat. No. PR00446, 1999, pp. 415–422.
[17] J.F. MacGregor, T. Kourti, Statistical process control of multivariate processes, Contr. Eng. Pract. 3 (3) (1995) 403–414.
[18] J.B. Gomm, M. Weerasinghe, D. Williams, Diagnosis of process faults with neural networks and principal component analysis, Proc. Inst. Mech. Eng. Part E 214 (2) (2000) 131–143.
[19] J.A. Nickerson, T.W. Sloan, Data reduction techniques and hypothesis testing for analysis of bench-marking data, Int. J. Prod. Res. 37 (8) (1999) 1717–1741.

Biographies

P. Tongpadungrod received a PhD in mechanical engineering from the University of Britol, UK in 2002. She is currently a lecturer at the King Mongkut's Institute of Technology, North Bangkok, Thailand. Her research interests are focused on tactile sensing technology.

T.D.L. Rhys completed a masters degree in mechanical engineering at the University of Bristol in 1999. Since that time he has been researching smart sensing technology at the University of Bristol, UK, as a research assistant. Currently, he is completing his PhD studies.

P.N. Brett graduated with a PhD in mechanical engineering from the University of Bath, UK in 1986. He is currently professor of biomedical engineering systems at the University of Aston, UK where he leads a research group on advanced tool systems and sensing techniques for clinical application. He has organised international workshops in the field since 1992 and is vice chair of the Medical Engineering Division of the Institution of Mechanical Engineers, UK. His research is funded by the European Communities, Engineering and Physical Sciences Council, Ministry of Defence and Industry.