Load estimation from photoelastic fringe patterns under combined normal and shear forces

Venketesh N Dubey and Gurtej S Grewal

School of Design, Engineering and Computing, Bournemouth University
Talbot Campus, Fern Barrow, Poole, BH12 5BB, UK

E-mail: vdubey@bmth.ac.uk

Abstract Recently there has been some spurt of interests to use photoelastic materials for sensing applications. This has been successfully applied for designing a number of signal-based sensors, however, there have been limited efforts to design image-based sensors on photoelasticity which can have wider applications in term of actual loading and visualisation. The main difficulty in achieving this is the infinite loading conditions that may generate same image on the material surface. This, however, can be useful for known loading situations as this can provide dynamic and actual conditions of loading in real time. This is particularly useful for separating components of forces in and out of the loading plane. One such application is the separation of normal and shear forces acting on the plantar surface of foot of diabetic patients for predicting ulceration. In our earlier work we have used neural networks to extract normal force information from the fringe patterns using image intensity. This paper considers geometric and various other statistical parameters in addition to the image intensity to extract normal as well as shear force information from the fringe pattern in a controlled experimental environment. The results of neural network output with the above parameters and their combinations are compared and discussed. The aim is to generalise the technique for a range of loading conditions that can be exploited for whole-field load visualisation and sensing applications in biomedical field.

1. Introduction

Photoelasticity has been conventionally used for experimental stress analysis, however, use of this technique is not very well explored in sensing applications, especially by analysing the fringe patterns. The main challenge involved is to extract load information from the fringe patterns, as there may be infinite number of load settings for the same resulting patterns. This may be further compounded due to generalised loading conditions and out of plane deformation of the photoelastic material. The technique, however, looks ever more promising with the advent of high computing power and low straining photoelastic material that can lend to dynamic and wave propagation studies. Advantage of using this technique is to get whole-field visualization of the stress field, which may provide load information of the entire field as opposed to employing strain gauges, or load cells that only offer discrete load information. Photoelasticity has been used in developing a number of discrete signal-based sensors [1-3], however, as the material develops fringe patterns that contain details of the loading conditions this can be exploited for developing a whole-field sensor. If this technique is fully developed for a sensing device, it could find application in many biomedical sensing areas such as early detection of diabetic foot ulceration or assessment of pressure sores in disabled subjects, thereby enacting prevention strategies by suitable footwear or bed designs.

One of the main impediments in assessment of diabetic foot ulceration is the difficulty of resolving the forces acting on the sole of the foot during standing and walking. The shear force acting during walking is considered to be more harmful than the vertical force alone [4] as it occludes the blood flow more severely, thus resulting in tissue dystrophy and rapid ulceration. However, the mechanism of ulceration due to biomechanical forces is not very well understood [5, 6], partly due to unavailability of appropriate sensors that can resolve these forces and partly because the forces cannot be quantified. Some interesting works have been reported on the risk analysis of walking foot pressure in diabetic patients using pedobarograph [7, 8], however, they have looked at foot pressure not the components of forces under foot. This research aims to tackle these problems by analysing normal and shear force data from the image under actual condition of loading. This requires inverse problem of force extraction to be solved i.e. finding the applied force from the generated fringe patterns. In our earlier work [9] we proposed use of neural networks for extraction of vertical load using intensity information from photoelastic fringes. It was shown that in absence of analytical solutions, neural network is a better approach for such inverse problems. In this paper we consider various geometric and statistical parameters of the image to train the neural network for extracting vertical as well as shear forces under controlled experimental conditions. The results from various combinations of these parameters have been compared and discussed.

2. Experimental Setup and Loading Conditions

The setup used for this experiment is shown in Fig. 1. Vertical load was applied by directly placing the weights over the indenter disc set over the photoelastic sensor plate while the shear force was applied by pulling the disc over a pulley using weights connected to a nylon cord as shown in the figure. The optical setup used in this experiment included a digital camera (Olympus, SP500) with high image resolution of 6M, a cold cathode fluorescent tube (CCFL) as a light source and a plane polariscope constructed using linear polariser [10]. The photoelastic material used was PS-4 of 3mm thickness with suitable coatings and adhesives [11, 12].

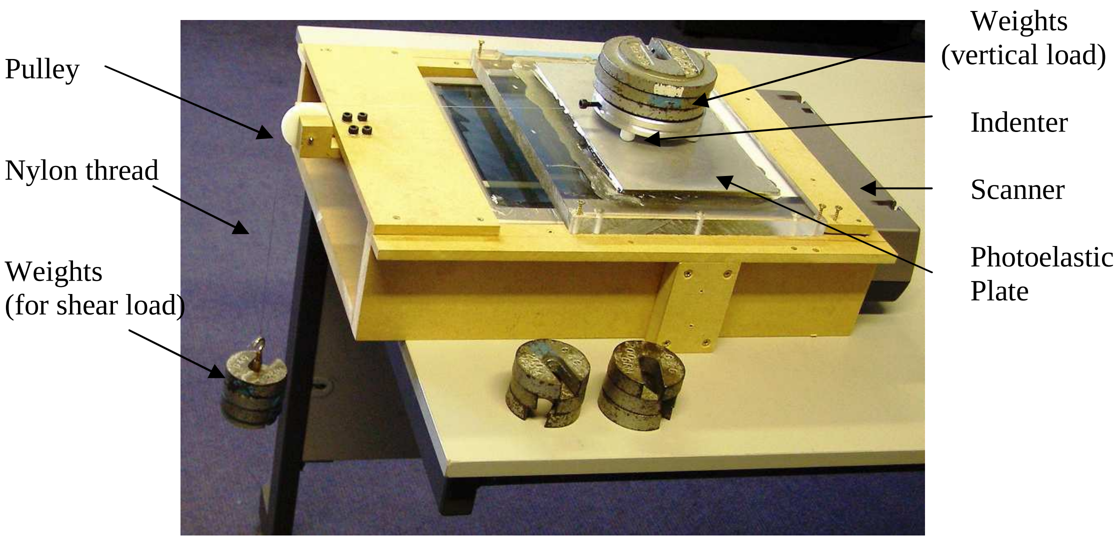

Figure 1: Experimental Setup for vertical and shear loading

Figure 2 shows fringe patterns developed on the surface of the photoelastic plate due to vertical and shear forces applied by the specifically designed indenter. The vertical force deforms the material and fringes propagate radially from point of application of load in a symmetrical way. The fringe patterns appear concentric circles of different colours under white light. When shear force is introduced in conjunction with the vertical force the fringe patterns smear in direction of application of force. This appreciable shift in the fringe pattern can be advantageously exploited for shear force sensing.

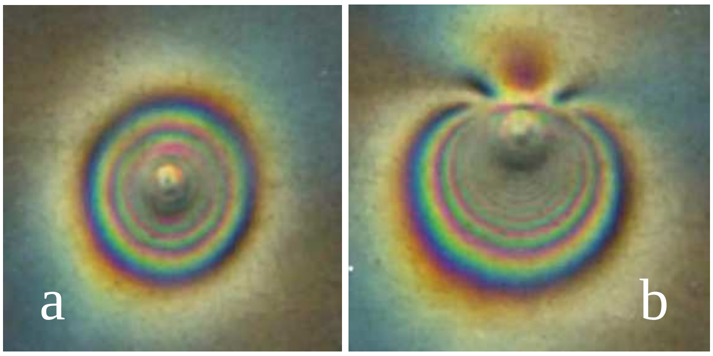

Figure 2: Fringe pattern generated on a photoelastic sensing plate due to (a) vertical force (b) due to combined vertical and shear forces. The effect of shear force results in appreciable shift in the image that can be exploited for developing a shear force sensor.

3. Fringe Characteristics

As stated earlier that it is not straightforward to extract load information from the fringe pattern hence a neural network based approach was used for normal force information [9]. In the current work to extract vertical as well as shear forces images were recorded at various combination of these forces to train the neural network. Table 1 shows a part of the range of vertical and shear forces applied on the material for this experiment. The vertical load was incremented in steps of 100g starting from 500g (excluding the weight of indenter) and the shear load was incremented in steps of 200g. The limiting value of shear at a particular vertical load was experimentally determined by estimating the co-efficient of friction between the two contacting surfaces.

Table 1: Applied Vertical loads with a range of Shear loads

Vertical force (N)	**8.68**	**9.66**	**10.64**	**11.62**	**…….**	**21.43**	**22.42**	**23.4**
Shear force (N)	1.47	1.47	1.47	1.47		1.47	1.47	1.47
	3.43	3.43	3.43	3.43		3.43	3.43	3.43
	5.39	5.39	5.39	5.39		5.39	5.39	5.39
	7.35	7.35	7.35	7.35		7.35	7.35	7.35
			9.32	9.32		9.32	9.32	9.32
						11.28	11.28	11.28
						13.24	13.24	13.24
						15.20	15.20	15.20
						17.16	17.16	17.16
								19.13

The error in loading was minimised by measuring the diameter of the circular fringe by repeating the experiment several times. For ease of implementation this was achieved by converting the images to HSV plane (this ensures that the original colour information does not change with change in fringe gradient or slight variation in light intensity) and segmenting it to measure the diameter of the outermost fringe by the developed algorithm [13]. The measured diameter for 9 sets of experiments was averaged to get as an ideal diameter (the fringe diameters are represented in pixels and for each experiment). The percentage error for all the measured diameters was evaluated against the known diameter. The average percentage error for all the vertical loads for 9 experiments was found to be 2.557%. Thus the calculated error in input data would affect the accuracy of results by a minimum of 2.557% as this much error has been added in the input at the outset inevitably. The various factors that may have contributed to this error include unsymmetrical fringe patterns due to uneven load transfer, unsymmetrical design of weights and disorientation of the indenter while shear force was applied.

3.1 Response to Vertical Force

As discussed earlier the fringe patterns pan out due to increase in the vertical load. Figure 3 shows the influence of increasing vertical load on the diameter of fringe patterns, this was obtained from 9 repeated experiments. Every point plotted in each data line is average measured diameter from 9 experiments. It is evident that the plot of averaged diameter has significant differences. This means that using just one geometric parameter in determination of load from the fringe patterns may not be a reliable method.

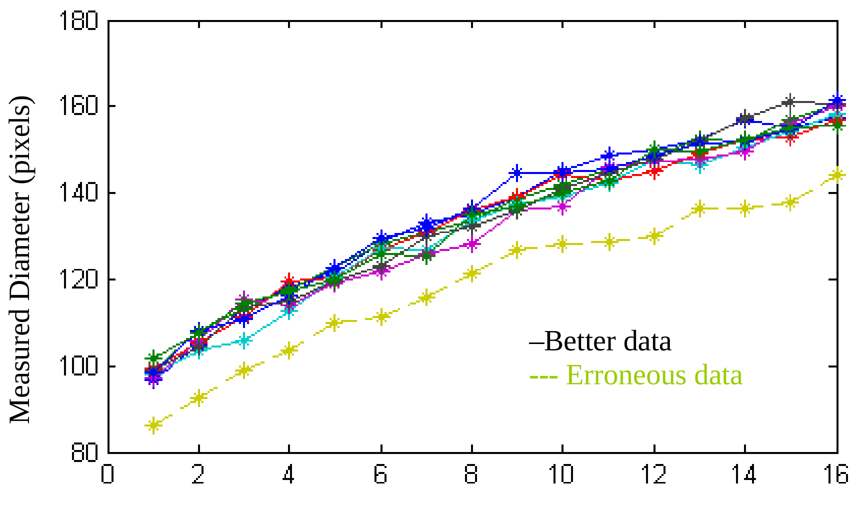

Figure 3: Influence of Vertical load on measured diameter of fringe patterns

4. Data Conditioning and Analysis

The fringe data acquired in the form of images was used for training and testing of the neural networks. Since an entire image cannot be used as input due to high input dimensionality, it was necessary to condition the data and optimise the dimensionality of input being fed to the network [14]. A large number of parameters were extracted from the fringe images that were used as input to the network. A region of interest (ROI) was selected encompassing fringe patterns and the following parameters were extracted (i) Mean pixel intensity (ii) Median pixel value (iii) Standard deviation (iv) Kurtosis (v) Skewness of data (vi) Horizontal radius- horizontal stretch in fringe from point of load (vii) Vertical radius- vertical stretch in fringe from point of load (viii) Pixel area of segmented ROI

(ix) Intensity information from region of interest. These parameters were fed in combination and individually to reach to an optimal input for network training. Principal component analysis (PCA) was used as data reduction technique [15]. Since training data is limited by the number of experiments, it was important to narrow down to an optimal dimensionality through PCA whilst maintaining subtle differences in fringe patterns under consecutive loads.

4.1 Data Analyses using Statistical Parameters

The input training data used for the network was derived from statistical analysis performed on the acquired images. Each image was stacked down to individual planes and intensity data from only one plane was used for statistical analysis. Since there is no considerable difference between fringe patterns in different planes (R, G & B), the plane with highest contrast was considered for analysis. Different statistical parameters, kurtosis, skewness, mean pixel intensity, standard deviation, median were extracted and fed as input to neural networks to map the shear force. Figure 4 shows the optimal results that were achieved using statistical parameters as input to the network with 23 random test images.

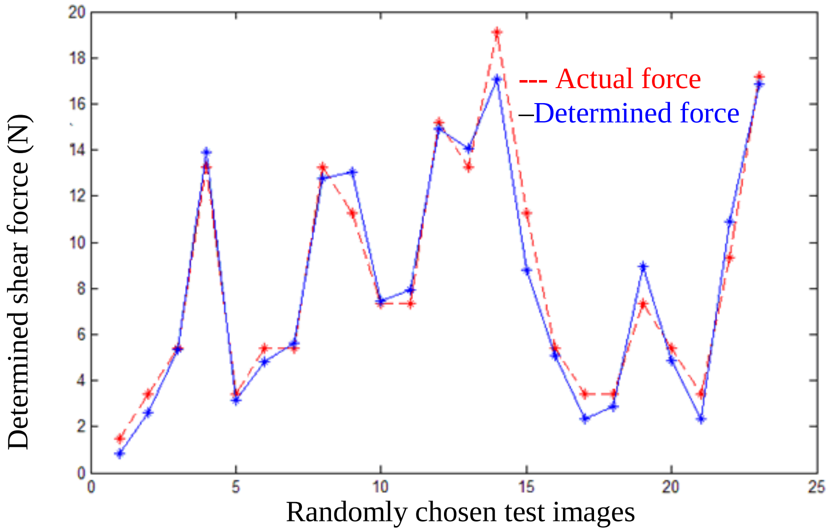

Figure 4: Determined Shear force using statistical parameters

The figure shows the actual shear force compared to the determined shear force at different vertical load values. The average percentage error found for 23 test images was 13.15% and for the entire load range (112 test images) was 13.45%. The results obtained were reasonable to continue using neural networks for force determination but were not accurate enough. As can be seen from the figure, for some test images the error is too high due to insufficient input data and training patterns. Many of the statistical parameters like mean pixel intensity and standard deviation did not show much variation with change in load values.

4.2 Data Analyses using Geometrical Parameters

As shear force smear the image in the direction of force thus measuring geometrical parameters could be a better approach that could lead to meaningful results. The measured parameters included segmented area from hue plane and radius measured in both horizontal and vertical axis since they are controlled by different forces. Horizontal radius being influenced mostly by the vertical load, whereas vertical radius is influenced by the shear load which stretches the fringe patterns in direction of application of load starting from point of loading. The results showed that the percentage error was 8.15 % for 23 test images and 11.4 % for entire range of loading (112 images). The results obtained were better than what were achieved with statistical parameters, since the geometrical parameters were influenced more significantly with the change in load. However, the accuracy desired was not achieved and thus combined statistical and geometric data was tried for training the network.

4.3 Combined Statistical and Geometric Parameters

Since the encouraging results were obtained using statistical and geometric data, it was envisaged that error would reduce if the training data was combined from the two. Thus a network was constructed and trained with combined statistical and geometric data. The results improved dramatically by almost 4% as the total averaged percentage error for the entire range was found to be 8.43% and 7.229% for 23 test images. To move a step further in an attempt to achieve higher accuracy the network was trained with intensity data extracted from load images. However, the results gave an average error of 19% for the entire range and 13.3% for 23 test images thus a lower accuracy compared to the previously fed input of statistical or geometrical values. This obviously is not a better combination of fringe parameters for load determination. The reason why intensity data came out with such a low accuracy was that the input fed as intensity from a small region of interest would not be as relevant and crisp as features extracted from geometrical and statistical parameters. To improve results the entire image was considered for extracting input rather than just a region of interest or line of interest, this however marginally improved the error by 5.99% at the cost of high dimensionality of the network [14].

5. Modified Strategy

The determination of shear force through different approaches like statistical parameters, geometric parameters and intensity data did provide clear indication for implementation of neural networks but the results desired were still not very accurate. A modified approach was adopted in order to improve the accuracy and efficiency of the system. A network was used to determine the vertical force from image data using intensity information and for the determination of shear force the data was fed to a second network as a combination of previously tested parameters and the vertical force was determined by the first network.

5.1 Determination of Vertical Force

In order to analyse the fringe patterns as accurately as possible both vertical and shear forces were determined from the same fringe patterns. This will also be the actual situation when using this technique for sensing applications. A network trained from the intensity data extracted from image was tested for optimal results for vertical force determination. Since the desired numbers of targets were considerably fewer compared to the shear force, the network was trained efficiently and it required less computational time. Figure 5 shows the results obtained for the determination of vertical load from fringe patterns.

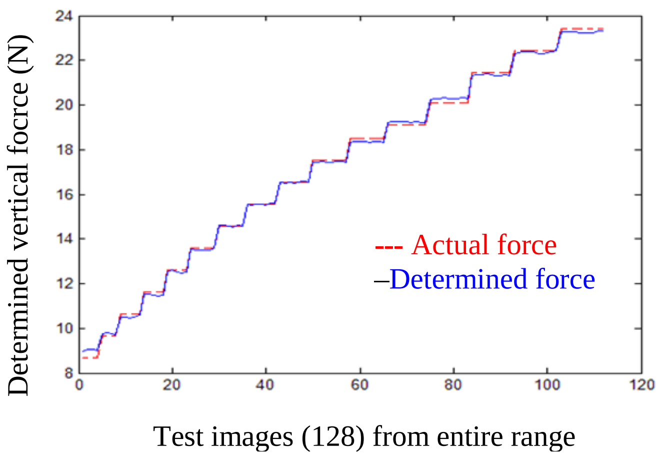

Figure 5: Determination vertical force for 128 test images

The averaged percentage error for 128 test images was found to be 0.67%, thus giving an accurate value of the applied vertical load. The results appeared stepped up in the plot because at each vertical load different shear loads were applied (Table 1). In absence of shear load the graph would be a straight line for each vertical load. The vertical load determined from the network can now be combined with other input parameters (statistical, geometric, intensity) and fed to a new network for determination of shear load.

5.2 Statistical and Geometric Parameters with Vertical Load Input

The network was trained with combined statistical and geometric parameters as input but an additional input parameter, the determined vertical load, was added as another relevant input. Figure 6 shows the results obtained from the trained network tested over 23 test images. The error was reduced drastically from averaged 8% to 5.37% for the entire range of load and 3.86% for the 23 test images as shown in the plot.

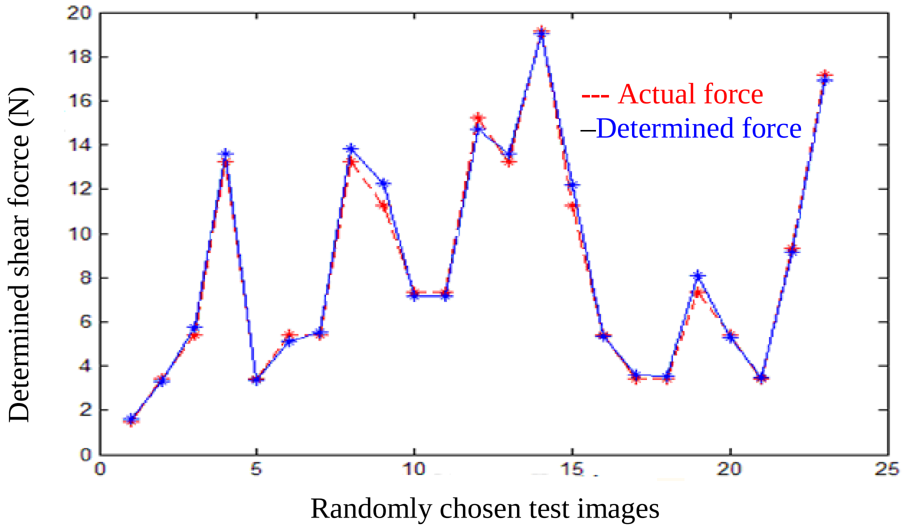

Figure 6: Determined Shear force using statistical, geometric and vertical input

5.3 Intensity Data with Vertical Input

The determined vertical force input was added to the conditioned intensity data. The results obtained improved slightly from 5.1% error to 5.08% but the network dimension increased. This option was not considered viable. The addition of determined vertical force as input improved the results significantly for the network trained with statistical and geometrical parameters and the error reduced dramatically (8% to 5%). However, for the network trained with intensity data there was no significant improvement in results (5.1% to 5%) with additional input of vertical force. This was because the intensity input was extracted by considering the entire image, thus it represented the whole image and addition of similar image data (vertical force) was unlikely to change the results. On the other hand input of the vertical force to statistical and geometric parameters was found to improve the error as it complemented the whole image. However, the network fed with intensity data from entire image also gave comparable results to this, thus the network trained with entire intensity data was considered to be optimal and efficient.

6. Conclusions

This paper focused on analysing the fringe patterns obtained under vertical and shear loads in order to determine the load characteristics. Various strategies were adopted to refine the results by taking various image parameters for implementation. Since an image has enormous data in itself it cannot be used as a whole for training neural networks of moderate size. Thus a range of data were extracted from the images including statistical, geometric, intensity and fed as training data. A mix of input parameters were also tried to achieve the best possible network with desired accuracy. The accurate results in determination of shear force from fringe patterns were found in two networks, one trained with the combination of statistical and geometric parameters with determined vertical force and second trained with intensity data from entire image. Both networks gave comparable results of 5.37% and 5.1% error respectively, however, the later was found to be the right network as it represented the image better. The training of network in this case was easy and required no feature extraction or specific processing of data. Therefore the later network was chosen to be a better choice due to most relevant input to the network with high tolerance.

Acknowledgments
This research was supported by the bursary awarded by the School of Design, Engineering & Computing, Bournemouth University.

References

[1] Dubey, V. N. and Crowder, R. M., 2006 "A dynamic tactile sensor on photoelastic effect" Sensors and Actuators, 128: 217-224.
[2] Dario, P., Fermi, D. and Vivaldi, F., 1987 "Fiber-optic catheter-tip sensor based on photoelastic effect" Sensors and Actuators 12: 35-47.
[3] Jacobsen, S. C., Wood, J. E., Knutti, D. F. and Biggers, K. B., 1986 "The Utah/MIT dextrous hand: work in progress" in D.T. Pham and W.B. Heginbotham edited Robot Grippers, pp 341-389.
[4] B. Davis, "Foot ulceration: hypothesis concerning shear and vertical forces acting on adjacent regions of the skin", Medical Hypothesis (1993), 40:44-7.
[5] P. Cavanagh, J. S. Ulbrecht, and G. M. Caputo, "New developments in the biomechanics of the diabetic foot", Diabetes Metab. Res. Rev (2000), 16(Sl)1:S6-S10.
[6] M. Curryer, and. E. Lemaire, "Effectiveness of various materials in reducing plantar shear forces: a pilot study", J. Am Podiatr Med. Assoc. (2000) 90(7): 346-53.
[7] V.J. Thomas, K.M. Patil, S. Radhakrishnan, V.B.N. Murthy, and R. Parivalavan [2003] "Diabetic feet at risk of plantar ulcers: a new method of analysis of walking foot pressure images with changes in foot sole properties" IEEE TENCON Conference on Convergent Technologies for the Asia-Pacific Region, Vol.4, 1320-4.
[8] G. Charanya, K.M. Patil, V.B. Narayanamurthy, R. Parivalavan, and K. Visvanathan [2004] "Effect of foot sole hardness, thickness and footwear on foot pressure distribution parameters in diabetic neuropathy" Proceedings of the Institution of Mechanical Engineers, Part H (Journal of Engineering in Medicine), v 218, n H6, 431-43.
[9] G. S. Grewal, V. N. Dubey, [2007] "Inverse Problem of Photoelastic Fringe Mapping using Neural Networks", Measurement Science & Technology, Vol. 18, No. 5, pp. 1361-1366.
[10] Edmund, O (2004). Determining fast axis of quarter wave plate, Edmund Optics. 2004.
[11] Vishay Measurement Groups [1992], Photoelastic Materials, Bulletin S-116-G.
[12] V. N. Dubey, G. S. Grewal [2007] "Tactile Whole-field Imaging Sensor on photoelasticity", ASME International Design Engineering Technical Conference, DETC2007-35264, Las Vegas, Nevada (USA), Sept. 4-7, 2007.
[13] G. S. Grewal, [2007] "Digital Photoelasticity in Biomedical Sensing" PhD Thesis, Bournemouth University.
[14] V. N. Dubey, G. S. Grewal and D. J. Claremont [2007] "Load Extraction from Photoelastic Images Using Neural Networks" Experimental Mechanics, Vol. 47, N0. 2, pp.263-270.
[15] C. M. Bishop, [1995], Neural networks for pattern recognition, Oxford University Press.