Computational Detection of Salient Information to Identify High Stress and Ambiguity Regions in Digital Photoelasticity Images

Juan C. Briñez de León, Diego A. Patiño, Alejandro Restrepo M, John W. Branch Universidad Nacional de Colombia, Sede Medellín, Facultad de Minas, Grupo GIDIA, Medellín, Antioquia, Colombia jcbrinezl@unal.edu.co

Abstract: Identifying ambiguities and high stress regions in digital photoelasticity is a complex process. We consider such zones as salient information, and process them through saliency algorithms. Hence, highlighted information coincided with ambiguities and stress concentrations.

OCIS codes: (100.2960) Fringe analysis; (150.1135) Machine vision; (110.2960) Image analysis

Digital photoelasticity is an experimental technique to describe the stress distributed in a model under mechanical loads. This technique is based on the processing of images with fringe patterns that wrap information about the principal stress difference (Isochromatic map), and principal stress direction (Isoclinic map) [1]. There, the main goal accounts for extracting a correct and whole stress field from fringe patterns.

There are different methods to retrieve stress fields in photoelasticity. Notwithstanding, phase shifting methods has advantages because they allow to obtain the isochromatic, and the isoclinic map. In this method, the interaction between the principal stress and its direction produces zones with wrong information, as was explained by Ramesh in [2]. Such phenomena is caused because the intensities cause undetermined operations for the isoclinic calculation (Inconsistency); and as a consequence the phase is reversed (Ambiguity). This effect makes the unwrapping algorithms be limited to obtain a continuous and whole stress field [3].

Another limitation is attributed to zones with high stress concentrations. In those regions, high stress values produce high fringe orders, which are seen as areas with high fringe densities into the photoelasticity images. This effect makes the fringe patterns do not be distinguished, and as a consequence, a correct phase delay cannot be estimated.

In order to overcome the above limitations, detecting and correcting the ambiguity zones is the solution for many authors, as was shown by Ramesh, Quiroga, Pinit, and others in [4-6]. Where, techniques based on remove the ambiguities, adaptive unwrapping, regularized phase tracking, detection of singularities, and isoclinic unwrapping have been highlighted. Notwithstanding, the zone identifications is not a simple process. There, many of them need a seed point manually placed, the gradient evaluation, or even using more images. And after that, several sub-processes are developed. This represents a restriction for the techniques when they have to be applied in situations where the stress must be evaluated automatically.

On the other hand, in [7] and [8], the authors proposed dynamic techniques to perform the automatic detection of regions with high stress concentrations. However, they were only applied for dynamic experiments, which do not match with our proposal. This mean that such techniques are not useful for situations of frozen stress.

In sight that zones with inconsistencies, ambiguities, and high stress concentrations show special characteristics, this paper evaluates them by assuming they are salient regions. For inconsistencies and ambiguities, such zones show intensities that are reversed in comparison with the rest of the map. But, for zones with stress concentrations, the fringe density tends to increase considerably.

Analysis of salient information have been used in computer vision to find regions where objects highlight in an image [13-20]. Taking advantage of this, ten standard saliency algorithms were used to calculate saliency maps of photoelasticity images. Here, the photoelasticity images were generated synthetically from the analytical model of a disk under diametral compression.

Despite from each algorithm we obtain a different result, saliency methods such as Graph-Based Visual Saliency (GBVS), and Frequency-tuned Salient regions were capable of highlighting areas with inconsistencies into the isoclinic map. On the other hand, methods based on spectral saliency were useful for accurately identifying zones of stress concentrations. The results were validated through the comparison between the saliency maps, and the stress maps obtained from the analytic model.

As a main contribution, the regions with inconsistencies, and zones with stress concentration are identified without the implementation of several procedures commonly used in conventional phase shifting techniques. We can conclude that saliency maps can be used as a new tool to process and analyze stress field wrapped in photoelasticity images.

2. Methods

2.1 Synthetic photoelasticity images

Fringe intensities in photoelasticity images are a function of the light source, the optical instruments, the mechanical model, and the environment; as is presented in (1) for a circular polarization arrangement [4].

$$I = I_m + I_v[\sin 2(\beta - \phi)\cos \delta - \sin(\theta - \phi)\cos(\beta - \phi)\sin\delta]$$
(1)

Where, '*I*' is the emergent light intensity, ' I_m ' represents the background intensity, ' I_v ' is the maxima intensity emitted by the source, ' θ ' is the principal stress direction, ' δ ' is the phase delay associated to the mechanical model (principal stress difference), ' β ' and ' ϕ ' are the rotated angles for the second retarder and polarizer, respectively [4]. For birefringent materials, the phase delay is a relation among the model thickness, its optical coefficient, the principal stress difference, and the light wavelength, as is expressed in (2).

$$\delta = \frac{2\pi h C(\sigma_1 - \sigma_2)}{\lambda} \tag{2}$$

Where 'h' is the thickness, 'C' represents the material optical coefficient, and ' $\sigma_1 - \sigma_2$ ' is the principal stress difference. For a disc under compression, the stress components are modeled. Then, the analytic stress map is used to generate synthetic images that correspond to phase shifting six images. Our model considered a birefringent material of '8mm' thickness, and '57.6e-12m²/N' stress optical coefficient, the radius was '25mm', and the load was '503N'. In this case, a '560nm' wavelength was used.

2.2 Saliency algorithms applied to photoelasticity images

A saliency map of an image is a matrix of the same size. There, every position contains a measurement of the visual saliency produced by a pixel. Hence, ten standard algorithms for saliency were used to calculate saliency maps of photoelasticity images. They were selected according to several approaches such as graph theory, spectral decomposition, feature extraction, etc. As a summarized version, the saliency algorithms will not be listed, but they can be found in [9 - 16]. The algorithm parameters were applied according to previous references.

3. Results

Disk analytical model produced a set of six images according to the phase shifting method. In addition isoclinic and isochromatic maps where generated. There, zones with inconsistencies, ambiguities and high stress concentrations can be observed, as is presented in the Figure 1.



Figure 1: Synthetic photoelasticity images. a) I1, b) I2, c) I3, d) I4, e) I5, f) I6, g) Isoclinic map ('Iso'), h) Isochromatic map, i) Inconsistencies, j) Ambiguities

Table 1: Resultant saliency maps. Top row: 'I2', Bottom row: 'Isoclinic map'

Ref [9]	Ref [10]	Ref [11]	Ref [12]	Ref [13]	Ref [14]	Ref [15]	Ref [15]	Ref [16]	Ref [16]
		\$		5 4	5 6				
$\langle \rangle$		\bigcirc		\bigcirc	\bigcirc			()	8 8 8 8

Algorithms for saliency maps were applied on the six phase shifting images, the isoclinic, and isochromatic maps. But as a summary in this document, the previous table only showed results for the image '12' and the isoclinic map are discussed, as was illustrated in the previous table. Top row is for '12', bottom row is for the isoclinic map. Above results indicate that saliency maps applied to phase shifted images tend to point areas of high-stress concentration. Those areas correspond to contact regions where the load is applied. In this case, the saliency toolbox

and Image Signature performed better than the rest of methods. For the isoclinic case, Saliency toolbox and LDRC match regions with inconsistencies. Highlighting that Achanta method was able to identify their boundaries, which is of high interest for the purpose of their correction.

4. Conclusions

Saliency maps are capable for highlighting regions with stress concentration, inconsistencies and ambiguities in photoelasticity images. In this work, images generated from a benchmark model in photoelasticity studies was analyzed through the application of ten saliency algorithms. The result of this exercise shows that the stress concentration zones and regions with inconsistencies have characteristics than can be compared as salient objects into scenes. Particularly, the algorithms of GBVS, Image Signature, and FFT-SS perform better for the analysis of stress concentration zones. Additionally, algorithms such as LDRC, and Achanta perform better for identifying regions with inconsistencies.

References

[1] Patterson, Eann A. "Digital photoelasticity: principles, practice and potential." Strain, vol. 38, no 1, 27-39, (2002).

[2] RAMESH, K.; KASIMAYAN, T.; NEETHI SIMON, B. Digital photoelasticity–A comprehensive review. The Journal of Strain Analysis for Engineering Design, vol. 46, no 4, p. 245-266, (2011).

[3] MAGALHÃES, Pedro Américo Almeida; MAGALHÃES, Cristina Almeida; MAGALHÃES, Ana Laura Mendonça Almeida. Computational methods of phase shifting to stress measurement with photoelasticity using plane polariscope. Optik-International Journal for Light and Electron Optics, vol. 130, p. 213-226, (2017).

[4] RAMJI, M.; RAMESH, K. Adaptive Quality Guided Phase Unwrapping Algorithm for Whole-Field Digital Photoelastic Parameter Estimation of Complex Models. Strain, vol. 46, no 2, p. 184-194, (2010).

[5] QUIROGA, J. A.; GONZALEZ-CANO, A. Separation of isoclinics and isochromatics from photoelastic data with a regularized phase-tracking technique. Applied optics, vol. 39, no 17, p. 2931-2940, (2000).

[6] PINIT, P.; UMEZAKI, E. Digitally whole-field analysis of isoclinic parameter in photoelasticity by four-step color phase-shifting technique. Optics and Lasers in Engineering, vol. 45, no 7, p. 795-807, (2007).

[7] DE LEÓN, Juan Carlos Briñez; MARTÍNEZ, Alejandro Restrepo; BEDOYA, John W. Branch. High stress concentration analysis using RGB intensity changes in dynamic photoelasticity videos. En Signal Processing, Images and Artificial Vision (STSIVA), 2016 XXI Symposium on. IEEE, p. 1-7, (2016).

[8] DE LEÓN, Juan C. Briñez; RESTREPO, Alejandro; BRANCH, John W. Time-space analysis in photoelasticity images using recurrent neuralnetworks to detect zones with stress concentration. En SPIE Optical Engineering+ Applications. International Society for Optics and Photonics, 99712P-99712P-10, (2016).

[9] Itti, L., Koch, C., & Niebur, E., "A Model of Saliency-based Visual Attention for Rapid Scene Analysis", IEEE Transactions on Pattern Analysis and Machine Intelligence, (1998).

[10] Harel, J., Koch, C., & Perona, P., "Graph-based visual saliency". Advances in Neural Information Processing Systems, pp. 545–552, (2006).

[11] D. Walther, "Interactions of visual attention and object recognition: Computational modeling, algorithms, and psychophysics," (2007).

[12] R. Achanta, S. Hemami, F. Estrada, and S. Susstrunk, "Frequency-tuned salient region detection," in 2009 IEEE Conference on Computer Vision and Pattern Recognition, no. Ic, pp. 1597–1604, (2009).

[13] C. Li, X. Meng, and Z. Wang, "A Visual Saliency Model Based on Local Entropy," Appl. Informatics Commun., pp. 422–429, (2011).

[14] H. Xiaodi, J. Harel, and C. Koch, "Image Signature: Highlighting Sparse Salient Regions," IEEE Trans Pattern Anal Mach Intell, vol. 34, no. 1, pp. 194–201, (2012).

[15] B. Schauerte and R. Stiefelhagen, "Quaternion DCT Spectral Saliency: Predicting Human Gaze using Quaternion DCT Image Signatures and Face Detection," Proc. IEEE Work. Appl. Comput. Vis., vol. 9, no. 11, pp. 137–144, (2012).

[16] B. Schauerte and R. Stiefelhagen, "How the distribution of salient objects in images influences salient object detection," 2013 IEEE Int. Conf. Image Process. ICIP 2013 - Proc., pp. 74–78, (2013).

Acknowledgements

We thanks to the project 'Caracterización De Dinámicas En Campos De Esfuerzos Usando Estrategias De Visión Artificial En El Análisis De Videos De Fotoelasticidad' carried out by Universidad Nacional de Colombia. We also thanks to the '647' Colciencias scholarship, the doctoral engineering program of Universidad Nacional de Colombia – Sede Medellín, and the mechanical engineering department of Universidad Nacional de Colombia – Sede Medellín, and the mechanical engineering department of Universidad Nacional de Colombia – Sede Medellín.