Expert Systems with Applications 41 (2014) 3935–3943

Contents lists available at ScienceDirect

Expert Systems with Applications

journal homepage: www.elsevier.com/locate/eswa

A decision-making algorithm for automatic flow pattern identification in high-speed imaging

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ARTICLE INFO

Keywords:
Image processing
Intelligent decision-making
Pattern recognition
Shock wave
Schlieren

ABSTRACT

A digital image processing algorithm was developed to identify flow patterns in high speed imaging. This numerical tool allows to quantify the fluid dynamic features in compressible flows of relevance in aerospace and space related applications. This technique was demonstrated in a harsh environment with poor image quality and illumination fluctuations. This original pattern recognition tool is based on image binarization and object identification. The geometrical properties of the detected elements are obtained by measuring the characteristics of each object in the binary image. In case of multiple shock waves or shock bifurcations, a "decision-making" algorithm chooses the best shock-wave path, based on the original image intensity and local pattern orientation. The algorithm was successfully used for validation on numerical Schlieren images, where the shock-wave fluctuation was triggered by vortex shedding. The applicability of the algorithm was finally evaluated in two Schlieren imaging studies: at the trailing edge of supersonic airfoils and for hypersonic research. The program correctly identified the fuzzy flow features present in all applications.

1. Introduction

In multiple engineering applications, refractive flow imaging, such as Schlieren and shadowgraphy, allows the investigation of complex flow field in a non-intrusive way. Those techniques find their application into flows in which density variations are sufficiently important such as high speed flows, but also low speed flows with natural convection. The extreme conditions in which the measurements are performed in the first case often lead to vibrations, poor image quality or illumination fluctuations, that, in turn, risk to compromise the flow pattern identification itself.

Decision making algorithms are used in a wide variety of fields, from cancer diagnosis (Wu et al., 1993) to airbag control (Mahmud & Alrabady, 1995). These programs are typically tailored *ad hoc* on the specific problem, since the creation of a computer-aided decision procedure requires the transformation of the particular phenomenon properties into measurable quantities. In order to do so, either a large dataset to train a neural network based software or a strict mathematical representation of the pattern to identify are required. Cheng, Cai, Chen, Hu, and Lou (2003) summarised and compared the methods used in various stages of the computer-aided detection systems of micro-calcifications in mammograms. In particular, the enhancement and segmentation algorithms, mammographic features, classifiers and their performances were studied and compared. In order to deal with a relatively small training dataset an Augmented Behaviour Knowledge Space method was developed (Constantinidis, Fairhurst, & Rahman, 2001) and applied to the detection of circumscribed masses in digital mammograms. This multiple expert fusion algorithm based its decisions on several classifiers (e.g. *Multivariate Gaussian*, *1-nearest-neighbour classifier*...), which were first trained and initialised, providing a more reliable method of classifier integration.

In order to avoid misclassification, Le Capitaine and Frelicot (2012) presented a family of measures for best top-n class-selective decision rules, deriving a general class-selective rule which allowed, in a single step, either to distance reject, to classify or to ambiguously reject a pattern, given only one user-specified threshold. El-Dahshan, Hosny, and Salem (2010) and later Zhang, Dong, Wu, and Wang (2011) used hybrid intelligent techniques for classification of magnetic resonance images of brain. Discrete wavelet transformation and principal component analysis were used for feature extraction, whereas neural network based classifier were used for image classification.

Textural and chromatic features were used (Bianconi, González, Fernández, & Saetta, 2012) together with several classifiers (i.e. linear classifier, support vector classifier) in order to automatically classify granite tiles, showing that classification based on both colour and texture outperformed previous methods based on textural features alone, with a limited amount of training samples.

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http://dx.doi.org/10.1016/j.eswa.2013.12.015

Intelligent decision making systems are utilised in image processing for various applications. Cena, Cardenas, Pazmino, Puglisi, and Santonja (2013) used an automated image processing algorithms for the intelligent decision making of the movement of a robotic system by multiple real time image manipulation for obstacle detection. Moreover, images of human lymphocytes were analyzed by an automated algorithm to enhance and accelerate tracing the effects of toxicity (Frieauff, Martus, Suter, & Elhajouji, 2013). Detection of the flow patterns with intelligent systems were studied for turbomachinery combustion by Bryanston-Cross, Burnett, Timmerman, Lee, and Dunkley (2000). The 3-D velocity field was quantified by integrated narrow-angle tomographic flow visualisations and intelligent software. Density gradient based techniques have been widely exploited for qualitative and quantitative analysis of flow imaging (Settles, 2001). Quantitative analysis was mainly concentrated on calibrated Schlieren, background oriented Schlieren (BOS), and rainbow Schlieren techniques. Quantitative flow field analysis through software assisted image processing compared the aforementioned methods (Hargather & Settles, 2012), concluding that the calibrated Schlieren and BOS outperformed the rainbow Schlieren method.

The improvement of reliability and efficiency in compact fluid machinery is a challenging task that requires acute understanding of shock wave interactions. Schlieren images are often used to analyse the flow topology. An algorithm able to read and analyse automatically the images needed to be designed to allow a quantitative assessment of flow features, i.e. shock waves inclination and relevant frequencies.

The main goal of the present paper is to define mathematical operations that allow shock waves identification and the correct pattern orientation measurement in case of ambiguity. When multiple shock wave paths are found, due to weak bifurcations or reflections, mathematical, geometrical or logical criteria were implemented to allow the program to take the correct decision.

The algorithm was validated on numerical Schlieren images, where shock waves were generated at a generic trailing edge of an airfoil. The system was then successfully implemented on two discrete set of raw images obtained during two different wind-tunnel experiments to trace the shock waves at the trailing edge of supersonic airfoils and to identify curved shock waves in hypersonic research.

2. Algorithms development

A Digital Image Processing algorithm was developed with Matlab® 2009b to automatically analyse the Schlieren images. Image preprocessing represents a crucial part in each feature extraction algorithm, especially when real-life, experimentally obtained images need to be analysed and poor image quality and illumination fluctuations would impede otherwise any correct pattern recognition.

In order to maximise the accuracy of the subsequent steps, each single image was read and cropped around the area of interest. According to the type of background the image was then pretreated.

In case of a uniform background texture, a local background was created and subtracted from the image to compensate for illumination variations. The background was computed row by row, by evaluating the average columns intensity. On the other hand, in case of a noisy image with smaller textures coexisting with major patterns, it was first necessary to clean the image. The image was therefore filtered, first with a flat, disk-shaped structuring element of radius *R*, to smooth out the imperfections, then with a Prewitt and a Sobel horizontal edge-emphasising filters, to enhance the edges.

The contrast of the greyscale picture was enhanced by means of a contrast-limited adaptive histogram equalisation function, *adapthisteq* (Gonzalez, Woods, & Eddins, 2009).

2.1. Vibration suppression algorithm

In order to correctly analyse Schlieren images captured in a fluctuating environment, it was necessary to suppress the vibration-induced image shift by re-centring them. A devoted algorithm named *Vibration-Suppression-Algorithm* (VSA) was developed (Fig. 1). The algorithm was tested with Schlieren images obtained in a supersonic turbine test section (Fig. 2(a)). The incoming flow accelerated to the supersonic speeds along the model surface and decelerated through the trailing edge shock waves where the strong density gradient was observed. Schlieren images were recorded through aligned optical windows.

- Each image was read from the Schlieren video. In order to re-centre the images, an object that preserves its shape and size despite vibrations and illumination inhomogeneities was required to be used as reference target. In this case two setup elements were suitable: the airfoil trailing edge and the set-up optical window. The latter was selected since its results were found to be more reliable and stable. The image was cropped around the bottom left optical window quadrant, that was the least sensitive image portion to light variation.
- The image was binarized with a modified global image threshold based on Otsu's method (Otsu, 1979). The threshold was halved respect to the default value, so that the optical window

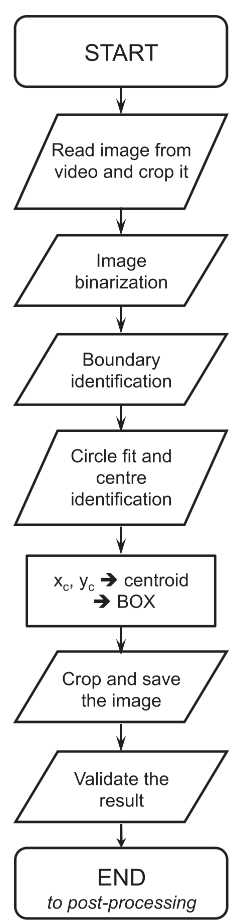

Fig. 1. Vibration suppression algorithm flowchart.