космической съемки, одной из важнейших задач которой является мониторинг территорий с целью повышения эффективности их использования.

Практическая значимость. Полученные результаты могут быть использованы для подготовки и реализации основных этапов создания Internet-центра мониторинга и анализа данных дистанционного зондирования Земли из космоса, для решения задач повышения эффективности использования земельных ресурсов Украины.

Ключевые слова: *дистанционное зондирование, космосъемка, разноуровневые и разновременные наборы данных, вегетационные индексы, Internet-центр мониторинга*

Рекомендовано до публікації докт. техн. наук В. Ф. Приходченком. Дата надходження рукопису 17.09.15.

Shuguang Wu,
Yiqing Zhou

Department of Electronics and Information Technology, Jiangmen Polytechnic, Jiangmen, Guangdong, China

NONLINEAR DYNAMICAL ANALYSIS OF ABRUPT WELDING TEXTURE CHANGE

Шугуан У,
Іцін Чжоу

Кафедра електроніки та інформаційних технологій, Цзянменьський політехнікум, Цзянмень, Гуандун, Китай

НЕЛІНІЙНИЙ ДИНАМІЧНИЙ АНАЛІЗ ТЕКСТУРНИХ ЗМІН НЕРІВНОСТЕЙ ЗВАРЮВАННЯ

Purpose. Owing to its diversity, the texton of weld image is not very salient, and weld defects are difficult to detect automatically. The goal of this work is to identify the weld image texture change for such flaw detection and to determine the optimal number of elements, in particular, in a chaotic dynamic mode.

Methodology. The texture is characterized by the approximate entropy, which is calculated in phase space. The time series are reconstructed with the entropy of sub-image values for choosing the proper texture parameters. Applying the chaotic theory, we proposed the abrupt texture change area detection method.

Findings. We first get the approximate entropy in phase space, and then by using the abrupt texture change area detection method, we obtained the abrupt texture change area.

Originality. We pursued a study of the abrupt texture change area. We discussed a reconstruction of the principle of time series, approximate entropy mutation threshold determination. The research on this aspect has not been conducted before.

Practical value. In practice, it is essential to reconstruct the time series with the entropy of sub-image values in a first step, these results of approximate entropy in phase space are much more accurate within abrupt texture change areas.

Keywords: *texton, texture change, chaotic dynamic mode, approximate entropy, time series, sub-image values*

Introduction. Quality monitoring and controlling in weld defects detection, especially electric arc and welding process stability analysis and evaluation, is an important factor in achieving higher productivity, lower cost and greater reliability of the welded equipment. Textural patterns can often be used to recognize familiar objects in an image or to retrieve images with similar texture from a database. Texture patterns can provide significance and abundance of texture and shape information. Literature depicts that previous work has been explored in huge amount on various aspects of modelling, simulation and process optimization in image texture.

Four technical components to improve graph cut based algorithms are combining both colour and texture information for graph cut, including structure tensors in the graph cut model, incorporating active contours into the segmentation process, and using a "softbrush" tool to impose soft constraints to refine problematic boundaries by Zhou [1]. The integration of these components provides an interactive segmentation method that overcomes the difficulties of previous segmentation algorithms in handling images containing textures or low contrast boundaries and producing a smooth and accurate segmentation boundary.

Asha V. proposed a new machine vision algorithm for automatic defect detection on patterned textures with the help of texture-periodicity and the Jensen-Shannon Divergence, which is a symmetrized and smoothed version of the Kullback-Leibler Divergence [2]. In order to determine the texture periodicity, the texture element size and further characteristics like the area of the basin of attraction in the case of computing the similarity of a test image patch with a reference, the presented method is proposed by Stübl G. with the properties of a novel metric, the so-called discrepancy norm [3]. Due to the monotonicity and Lipschitz property the discrepancy norm distinguishes itself from other metrics by well-formed and stable convergence areas. Considering the multi-scalar information in both vertical and lateral directions, a multi-resolution fuzzy Markov random field model for a variable scale in the wavelet domain is proposed by Chen [4].

The feature field of the scalable wavelet coefficients is modelled, combined with the fuzzy label field describing the spatially constrained correlations between neighbourhood features to achieve more accurate parameter estimation. Spampinato, C., S. Palazzo, et al. presented a kernel density estimation method which models background and foreground by exploiting textons to describe textures within small and low contrasted areas. Being compared to other texture descriptors, namely, local binary pattern (LBP) and scale invariant local ternary pattern (SILTP), they showed improved performance [5]. Kennel P., Fiorio C., Borne F. proposed a simple and efficient texture-based algorithm for image segmentation [6]. This method constitutes computing textons and bag of words (BOWs) learned by support vector machine (SVM) classifiers. Textons are composed of local magnitude coefficients that arise from the Q-Shift Dual-Tree Complex Wavelet Transform (DT-CWT) combined with colour components. Basha S. R., Reddy P. K. K. present paper divides the 3 × 3 neighbourhood into two different 2 × 2 neighbourhood grids each consisting of four pixels. On these 2 × 2 grids shape descriptor indexes (SDI) are evaluated separately and added to form a Total Shape Descriptor Index Image (TSDI) [7]. By deriving textons on TSDI image Total Texton Shape Matrix (TTSM) image is formed and Grey Level Co-Occurrence Matrix (GLCM) parameters are derived on it for efficient texture discrimination.

There have been, above all, no definitive characteristics of the complexity of weld defects. As a matter of fact, flaw detection is a so much complicated phenomenon that its nonlinear nature, i. e. its chaotic state, has been revealed quite recently. Generally speaking, in accordance with the nonlinear dynamics theory, for the purpose of studying a chaotic system, calculation of such characteristic parameters as Lyapunov exponent, correlation dimension, Kolmogorov entropy, etc., often requires a large number of data. Since the pioneering work of Lorenz in 1963, nonlinear dynamical theory has attracted a great deal of attention in the engineering society, including atmospheric studies, medicine and engineering. However, there are only few studies to our knowledge which focus on the flaw detection process stability from the viewpoint of chaos, especially the ApEn of welding image signals. Because of the nonlinear character of a welding image signal, the ApEn can be used as a powerful tool in the study of weld flaw detection. The present paper is mainly devoted to the problem of exploring arc and process stability in weld flaw detection by virtue of the chaotic parameter, ApEn. In particular, the goal of the paper is to attempt to propose a new numerical standard to accurately quantify and evaluate the arc and welding process stability in weld flaw detection.

Chaotic dynamic technologies. Image characteristic. An important approach to an area description is to quantify its texture content. The three principal approaches used in image processing to describe the texture of an area are contrast, entropy, uniformity (also called energy). One of the simplest approaches for describing texture is to use statistical moments of the intensity histogram of a welding image. Let $p(z_I)$, $I = 0, 1, \ldots, L-1$, denote the values of all possible intensities in a $M \times N$ digital image. The probability, $p(z_I)$, of intensity level occurring in a given image is estimated as

$$p(z_I) = \frac{n_I}{M \times N}. \quad (1)$$

Where n_I is the number of times that intensity occurs in the image and $M \times N$ is the total number of pixels.

Clearly,

$$\sum_{I=0}^{L-1} p(Z_I) = 1. \quad (2)$$

A measure of “uniformity”, given by

$$W_0 = \sum_{I=0}^{L-1} p(Z_I) p(Z_I), \quad (3)$$

and the average entropy measure is defined as

$$W_1 = -\sum_{I=0}^{L-1} p(Z_I) \log_2 p(Z_I). \quad (4)$$

The measure W_0 is maximum for an image in which all intensity levels are equal. Entropy is a measure of variability and is 0 for a constant image. Then, a measure of intensity contrast W_2 can be written as

$$W_2 = \sum_{I=0}^{L-1} p(Z_I) * I * I. \quad (5)$$

The Definition and algorithm of ApEn. For a better grasping of the ApEn, the definition of ApEn along with its computing procedure is described by Pincus as follows.

Step 1: Form a time series of data

$$\varepsilon(1), \varepsilon(2), \ldots, \varepsilon(N),$$

given N raw data values from measurements equally spaced in time.

Step 2: Fix m, an integer, and r, a positive real number. The value of m represents the length of compared runs (a window), and r effectively represents a filter.

Step 3: Form a sequence of vectors $\psi(1), \psi(2), \ldots, \psi(N)$ in R^m, real m-dimensional space, by

$$\psi(i) = [\varepsilon(1), \varepsilon(2), \ldots, \varepsilon(i + (m-1))]. \quad (6)$$

Step 4: Use the sequence $\psi(1), \psi(2), \ldots, \psi(N)$, if $1 \le i \le N + m - 1$, define $C_i^{m+1}(r) =$ [number of $\psi(i)$ so that

$$[d(\psi(i), \psi(j)) \le r]/(N - m + 1). \quad (7)$$

We must define d_{ij} for vectors $\psi(i)$ and $\psi(j)$.

$$d_{ij} = \max|\varepsilon(i + k - 1) - \varepsilon(j + k - 1)|, \quad (8)$$

for $k = 1, 2, \ldots, m$.

d represents the distance between the vectors $\psi(i)$ and $\psi(j)$, given by the maximum of their respective scalar components.

Step 5: Take the natural logarithm of each $C_i^{m+1}(r)$ and average it over $\varphi^m(r)$, define $\varphi^m(r)$ as

$$q = 1/(N - m + 1); \tag{9}$$

$$\varphi^m(r) = q\sum_{i=1}^{N-m+1}\ln C_i^m(r). \tag{10}$$

Step 6 (*ApEn*): Fix m and r in Eq 3; defined

$$ApEn(m, r) = \varphi^m(r) - \varphi^{m+1}(r), \tag{11}$$

for m and r fixed as in *Step 2.*

Obviously, the value of the estimate depends on m and r. As suggested by Pincus, m can be taken as 2 and r as (0.1–0.25) SD, where SD is the standard deviation from the original data sequence $\Gamma(n)$

Calculating the approximate entropy in phase space.

Step 1: Reconstruct $\Gamma(n)$ as L-dimensional of phase space with the data $f(n)$.

$$\Gamma(n) = \{f(i+1), f(i+2), \ldots, f(i+L)\}.$$

$$i = L, L+1, \ldots, N-L-1,\ L = 100. \tag{12}$$

Step 2: Calculate the *ApEn* value of $\Gamma(n)$, $n = 1, 2, \ldots, L$.

Step 3: If $i < N - L - 1$, return back to *Step 1.*

The abrupt texture change detection method.

Step 1: Crop a weld image in N equal of sub-images with column, and mark the sub-images as $\bigcup_{i=1}^{N}\varphi_i$.

Step 2: Calculating image entropy of each sub-image $\bigcup_{i=1}^{N}\alpha_i$ and $\bigcup_{i=1}^{N}\alpha_i$ is written as series A.

Step 3: Calculating the approximate entropy of series A in phase space, and the results marked as $\bigcup_{i=1}^{N}\beta_i$.

Step 4: Mutation identifier with $p(i)$, $i \in [1, N]$ according to (10).

Define the abrupt *ApEn* condition

$$Q = \begin{cases} i > L/2 \\ \beta_{i-1} > 0.2, \beta_{i+j+1} < 0.2; \\ j < L/2 \end{cases} \tag{13}$$

$$p(i) = \begin{cases} 1 & Q \\ 0 & other \end{cases}. \tag{14}$$

Results. In order to investigate the effect of the proposed approach, a weld image was selected to build our test set, see in Fig. 1. By cropping the welding image in n sub-images and calculating image entropy for each sub-image, we improve our chance to have better results compared to applying the approximate entropy in phase space methods. In conducted experiments we heuristically set $n = 800$.

For the purpose of evaluating texture change, we analysed Fig. 1 with eight pairs: (0, 100), (100, 200),

Fig. 1. The weld image

(200, 300), (300, 400), (400, 500), (500, 600), (600, 700), and (700, 800).

The time series is reconstructed with the entropy values, which is shown in Fig. 2, *a*. There is no significant correlation between the texture direction of a weld image and sub-image entropy values, which is shown in Fig. 2, *a*. The *ApEn* values which are calculated with the approximate entropy in phase space, are shown in Fig. 2, *b*. Obviously, the *ApEn* values characterize the abrupt texture change.

According to Eq. 14 calculation was done to achieve segmentation of the abrupt texture area, which was consistent with the original image, see Fig. 2, *c*.

The abrupt texture change detection is to accurately identify the texture distortion area.

Discussion and conclusion. The other approximate entropy image feature extraction as follows. A new time series is reconstructed with the energy values, which is shown in Fig. 3, *a*. However, there was no apparent association between the texture change of weld image and sub-image energy values. The *ApEn* values are calculated with the approximate entropy in phase space, which is shown in Fig. 3, *b*. It is clear that the *ApEn* values cannot characterize the abrupt texture change. According to Eq. 14 calculation was done to achieve segmentation of the abrupt texture area, which was not consistent with the original image, see Fig. 3, *c*.

Similarly, the new time series is reconstructed with the contrast values, which is shown in Fig. 4, *a*. Weather being related party or not, the texture direction of weld image and sub-image contrast value are of little significant difference. The *ApEn* values are calculated with the approximate entropy in phase space, which is shown in Fig. 4, *b*. Apparently, the *ApEn* values cannot characterize the abrupt texture change.

According to Eq. 14 calculation was done to achieve segmentation of the abrupt texture area, which was not consistent with the original image, see Fig. 4, *c*.

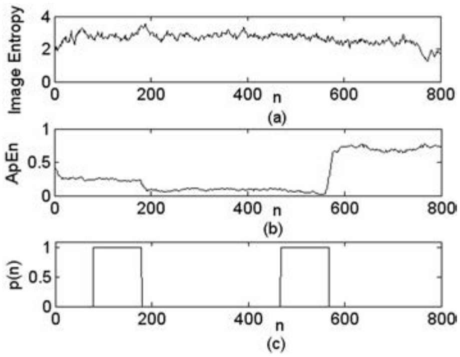

Fig. 2. The abrupt texture change detection process based on sub-image entropy values:

a — the time series was reconstructed with sub-images entropy value; b — the value of approximate entropy in phase space; c — identification of the area abrupt texture change

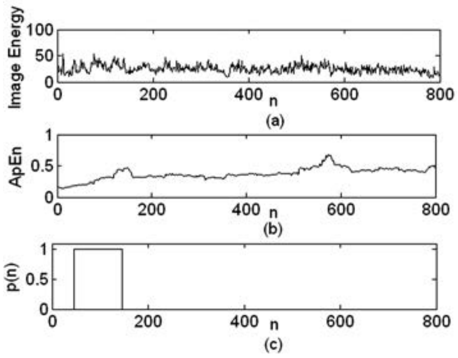

Fig. 3. The abrupt texture change detection process based on sub-image energy values:

a — the time series with image energy; b — the value of approximate entropy in phase space; c — identifying the area of abrupt texture change

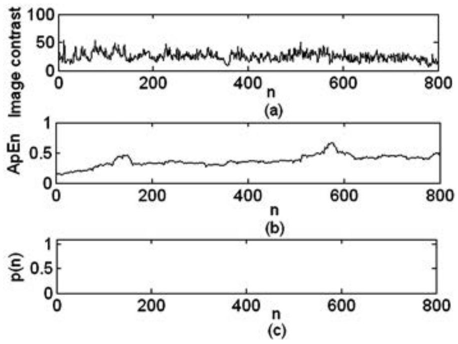

Fig. 4. The abrupt texture change detection process based on sub-image contrast values (a) The original image:

a — the time series with image contrast; b — the value of approximate entropy in phase space; c — identifying the area of abrupt texture change

In this paper, the abrupt texture change detection method has been introduced. It is important to reconstruct time series. The algorithm that defines *ApEn* does not only allow one to distinguish between such obviously different series but also to determine subtler differences in regularity. More accurately, using the property of *ApEn* which can give the robust estimate from short data and is attractive to dynamic analysis, we have shown that the welding image *ApEn* is significantly correlated with the texture change and the welding process stabilities. To sum up, the calculating of the approximate entropy of image entropy in phase space has huge potential utility to analyse the welding process stabilities due to its salient features. It can be concluded that the less value the image entropy in phase space reaches and the smaller one the oscillation amplitude (*ApEn*) attains, the more stable the arc and the welding process will be. So the approximate entropy of image entropy in phase space gives large opportunities for the quantifying and monitoring of the weld and the welding process stabilities.

Acknowledgements. This work was supported by pdjh2016b0752 and JiangKe 2016.196.

References/Список літератури

1. Zhou, H., Zheng, J. and Wei, L., 2013. Texture aware image segmentation using graph cuts and active contours. *Pattern Recognition*, Vol. 46, No. 6, pp. 1719–1733.

2. Asha, V., Bhajantri, N. U. and Nagabhushan, P., 2012. Automatic Detection of Texture-defects using Texture-periodicity and Jensen-Shannon Divergence. *Journal of Information Processing Systems*, Vol. 8, No. 2, pp. 548–553.

3. Gernot Stübl, 2013. Periodicity Estimation of Nearly Regular Textures Based on Discrepancy Norm. *Proc of SPIE,* Vol. 8661, pp. 45–78.

4. Chen, Mi and Strobl, J., 2013. Multispectral textured image segmentation using a multi-resolution fuzzy Markov random field model on variable scales in the wavelet domain. *International Journal of Remote Sensing*, Vol. 34, No. 13, pp. 4550–4569.

5. Spampinato, C., Palazzo, S. and Kavasidis, I., 2013. A texton-based kernel density estimation approach for background modeling under extreme conditions. *Computer Vision & Image Understanding*, Vol. 122, No. 4, pp. 74–83.

6. Kennel, Pol, Fiorio, C. and F. Borne, 2015. Supervised image segmentation using Q-Shift Dual-Tree Complex Wavelet Transform coefficients with a texton approach. *Formal Pattern Analysis & Applications*, Vol. 18, No. 2, pp. 1–11.

7. Basha, S. R. and Reddy, P. K., 2015. Discrimination of Textures Using Texton Patterns. *Global Journal of Computer Science and Technology*, Vol. 15, No. 3, pp. 1–7.

Мета. Завдяки своєму різноманіттю, текстон зварювального зображення мало помітний, і дефекти зварювання важко виявити автоматично. Метою даної роботи є визначення текстурних змін зображення зварювального шва задля знаходження дефектів зварювання та визначення оптимального числа елементів, зокрема, у хаотичному динамічному режимі.

Методика. Текстура характеризується ентропією подібності, що розраховується у фазовому просторі. Часові ряди реконструюються з ентропією значень субзображень для вибору з відповідних параметрів текстури. Застосовуючи хаотичну теорію, ми запропонували метод пошуку зони різких текстурних змін.

Результати. Спочатку ми отримуємо ентропію подібності у фазовому просторі, а потім, за допомогою метода пошуку зони змін текстури нерівностей, ми знаходимо область змін відповідної текстури.

Наукова новизна. Нами проведене дослідження області різких текстурних змін. Розглянута реконструкція принципу часових рядів, ентропія подібності визначення порогу мутації.

Практична значимість. На практиці, можливо реконструювати часові ряди з ентропією значень субзображень на першому етапі, ці результати набагато більш точні в зоні різких текстурних змін.

Ключові слова: *текстон, зміна текстури, хаотичний динамічний режим, ентропія подібності, часові ряди, значення субзображень*

Цель. Благодаря своему разнообразию, текстон сварочного изображения мало заметен, и дефекты сварки трудно обнаружить автоматически. Цель данной работы заключается в определении текстурных изменений изображения сварного шва для обнаружения дефектов сварки и определении оптимального числа элементов, в частности, в хаотичном динамическом режиме.

Методика. Текстура характеризуется энтропией подобия, которая рассчитывается в фазовом пространстве. Временные ряды реконструируются с энтропией значений субизображений для выбора из соответствующих параметров текстуры. Применяя хаотическую теорию, мы предложили метод поиска зоны резких текстурных изменений.

Результаты. Сначала мы получаем энтропию подобия в фазовом пространстве, а затем, с помощью метода поиска зоны изменений текстуры неровностей, мы находим область изменения соответствующей текстуры.

Научная новизна. Нами проведено исследование области резких текстурных изменений. Рассмотрена реконструкция принципа временных рядов, энтропия подобия определения порога мутации.

Практическая значимость. На практике, возможно реконструировать временные ряды с энтропией значений субизображений на первом этапе, эти результаты намного более точны в зоне резких текстурных изменений.

Ключевые слова: *текстон, изменение текстуры, хаотический динамический режим, энтропия подобия, временные ряды, значения субизображений*

Рекомендовано до публікації докт. техн. наук В. В. Гнатушенком. Дата надходження рукопису 25.10.15.

Changjiu Pu,
Fei Hu,
Jie Long

Chongqing University of Education, Chongqing, China

AN IMAGE COPYRIGHT PROTECTION AND TAMPERING DETECTION SCHEME BASED ON DEEP LEARNING AND MEMRISTOR

Чанцзю Пу,
Фей Ху,
Цзе Лун

Чунчинський університет освіти, Чунцин, Китай

СХЕМА ЗАХИСТУ АВТОРСЬКИХ ПРАВ І ВИЯВЛЕННЯ ФАЛЬСИФІКАЦІЇ ЗОБРАЖЕНЬ НА ОСНОВІ ГЛИБИННОГО НАВЧАННЯ ТА МЕМРИСТОРА

Purpose. In order to improve the effect of image copyright protection and detect whether an image is tampered illegally, we introduce an image copyright protection and tampering detection scheme of ROI (Region of interest) image based on image feature sequence in NROI (Non Region of interest) image. We have evaluated this scheme with some performance measures and the results show it is effective.

Methodology. We formulate the scheme using the copyright watermarking and the fragile watermarking. With the deep learning, memristor chaos, Arnold transform and extend zigzag transform, the watermarkings are generated and embedded into ROI image in DCT (Discrete cosine transform) domain using the feature sequence of NROI image.

Findings. We first completed the division of ROI and NROI image and get the feature sequence of NROI image using deep learning and memristor chaos. Then by using the sequence and some methods such as Arnold transform, we obtained the scrambling copyright watermarking and the new fragile watermarking of each image grouping and embedded them into ROI image.

Originality. We realize the extraction of image feature sequence in NROI image using deep learning and memristor chaos. It is applied to generate and embed the scrambling copyright watermarking and the new fragile watermarking into ROI image. The research on this aspect has not been found at present.

Practical value. We have completed some validation experiments with some performance measures. The results show it can completely satisfy the need of secure transmission. This scheme features strong robustness and security.

Keywords: *image feature, image protection, tampering detection, copyright, memristor, deep learning*