Weaving Pattern Recognition of Ancient Chinese Textiles by Regular Bands Analysis

Connie C.W. Chan¹, K.S. (Sammy) Li², Henry Y.T. Ngan¹

¹Department of Mathematics, ²Department of History, Hong Kong Baptist University, Hong Kong

Abstract

This paper aims at investigating the ancient Chinese textile in order to facilitate the growing trend of an interdisciplinary study between art history, industrial design and imaging science. This is an early attempt to study how decorative patterns of the textiles were created with various weaving techniques with the help of digital technology. Since the captured fabric image only reveals the floating varn, the combination of the underneath varns are unknown. From the mathematical point of view, the weaving technique can be regarded as a research problem of combinatorics that contains how the varns of weft and warp intersect with each other. Hence, the analysis of the weaving pattern contains two layers: (a) detection of the floating yarn and (b) estimation of the combination of the underneath yarns. Previously, the regular bands (RB) method is a tool for regularity analysis that has been successfully applied to patterned fabric inspection. This paper achieves the first layer goal, which applies computer vision technique in the imaging science through the RB method to achieve the detection of the floating varns of images of some ancient Chinese textiles. Ancient textile samples from Ming dynasty, China (ca. 1368-1644 CE) are utilized for the experiments in the paper.

Introduction

Textile is one of the earliest products in human society. Weaving techniques and woven patterns became much complicated throughout the long spans of time in Chinese history [1-4]. In Ming dynasty, textiles from China represented one of the highest and most sophisticated achievements in the world. Currently, when archaeologists and art historians attempt to study the weaving techniques of old textile pieces, they do not have many convenient tools to help recognize the woven structures. They have to invest copious time and efforts on the looms to produce replicas of old textiles. How computer science can aid in archaeology and art history will become a crucial research direction in the future. We aim at using computer vision techniques to help recognize the woven structures and patterns and store these in digital form in order to quickly produce replicas of old textiles by inserting the data to modern automatic weaving machines. This will help archaeologists and art historians to closely study the weaving techniques as well. The outcome of this research project does not only benefit the modern textile industry to imitate antique textile products and enrich weaving knowledge of textile designers, it can also enhance our understanding of the mentality of the weavers in ancient China and help us probe the history of industrial manufacturing of Chinese textiles.

We are interested in the patterned textures of the textiles. Patterned textures can be classified into 17 wallpaper groups by a fundamental unit, motif, in geometry by mathematicians [5]. Each motif is composed of a larger lattice by pre-defined symmetry rules. An ancient Chinese textile sample is assumed to be fallen under the classification of 17 wallpaper groups. The complexity of the weaving technique can be investigated in this first attempt of the study. In addition, the regularity property of the ancient textile sample will be enhanced by the regular bands analysis in this paper.

The objectives of the project include: firstly investigate and recognize the weaving pattern on ancient Chinese textile samples; secondly explore the number of yarn combinations embedded on ancient Chinese textile images; thirdly enhance the regularity property of the acquired ancient Chinese textile images for further analysis in their hidden distributions of the weaving pattern.

In this paper, an RB analysis is employed for weaving pattern recognition. The RB analysis previously was applied for modern patterned fabric inspection [6] and it achieved high detection accuracy, 100% in [6]. The RB is designed based on the statistical tools: moving average and moving standard deviation. It can effectively detect any irregularity (i.e. defects) on patterned texture. This paper will demonstrate that the RB method successfully enhances the regularity property of the ancient Chinese textile sample with uneven illumination distribution in appearance. Fig. 1 shows the image of a textile piece from Ming dynasty China, which was collected by the Seattle Art Museum, U.S. An enlarged photo of the detail of this textile piece, shown in Fig. 2, will be used throughout the paper.



Figure 1. A sample of plain compound silk fragment from 15th-16th century, Ming dynasty, China. 57.79 x 100.33 cm. Eugene Fuller Memorial Collection at the Seattle Art Museum, U.S. Accession no. 34.66. Photo courtesy of the Seattle Art Museum.



Figure 2. An enlarged region of the sample of ancient textile piece in Fig. 1 (Authors' photo).

In the textile sample, the pixel intensities of row 70 is extracted for the RB analysis, and their corresponding results by LRB on row (i.e. LRBR) and DRB on row (i.e. DRBR) are displayed under different N_r and N_c values. Throughout a preliminary study, the regularity of the textile sample can be discovered. It is believed the weaving pattern of the ancient textile sample can be re-engineered very soon in our next phase of research. In short, the contributions of the paper include several areas:

- 1. To the best of our knowledge, the project is the first attempt to study the weaving pattern of ancient Chinese textile by imaging science techniques.
- A methodology of the weaving pattern recognition of ancient Chinese textile is proposed in this paper. It includes four main steps: inputting ancient Chinese textile image, enhancing regularity property by the RB method, discovering hidden distributions, and recognizing the weaving pattern.
- 3. The complexity of the yarn combinations has also been studied in the project. It helps us to understand how complex of the research problem is.

The organization of the paper is as follows. Literature review is given in Section 2. Mathematical expressions and procedure of the Regular bands analysis are given in Section 3. Experimental results and discussions are presented in Section 4. Lastly, the conclusion is drawn in Section 5.

Literature Review

Fabric is combined by warp and weft. Warp is the vertical thread and weft is the horizontal thread in waving. Normally, the warp is fixed and the difference of each weave is on the 'up and down' of the weft, which means the wefts go through the warp or under the warp [7].

There are a number of weaves in a textile product and the most common weaves are tabby, twill and satin [8]. In tabby weave (also called plain weave), the wefts go over one warp and under the next warp, then repeat this way. Twill is done by the wefts going through two or more warps and under one or more warps. The binding points which the warp and the weft are crossed form the diagonal pattern [9]. The satin weave gives the smoothest surface and the warps go over four (as a common one) or more wefts which most likely are in an even number. The warp is usually under one weft. By combining the weaving techniques, different patterns can be created.

Ancient and modern weaving techniques



Figure. 3. Idea part of shaft loom. A: warp beam, B: back beam, C: shed rods, D: breast beam, E: knee beam, F: cloth beam, G: treadles, H: beater.

Fig. 3 shows part of a shaft loom (a re-drawn version from [8]). This demonstrates the basic idea of how to weave. First, a warp will be rolled onto a warp beam A. Then, the warp will be climbed up to a back beam B and extended to a breast beam D. Lastly, the warp will be rolled onto a cloth beam F. To give some space for a worker's legs, a knee beam E is designed. Also, between B and D, the warp ends order should be proper and shed rods C will have this use. Treadles G can open the warp for a beater H to cross the weft into it.

Computer vision inspection techniques

There are several successful computer vision techniques for fabric inspection in literature. The wavelet preprocessed golden image subtraction (WGIS) method [10] has a golden template to be performed as a sliding window on the inspected image. First, histogram equalization is used to achieve a smoothing effect to reduce noise effect. Then, processes of wavelet transform (WT) and golden image subtraction (GIS) will be applied on the image. It reaches an average 96.7% inspection accuracy for three patterned fabrics. A thresholding and smooth filtering accomplish the detection. The Bollinger bands (BB) method [11], based on the statistical moving average and moving standard deviation, measures the trend of image in a certain period by using the upper and lower Bollinger bands. Also, this is proceeded on the image into both row and column directions. Its basic structure is easy to be implemented in the real scenario. Its average inspection accuracy is 98.59% for three patterned fabrics. The Image decomposition (ID) method [12] (with 94.9%-99.6% inspection accuracies for the same three patterned fabrics) mainly decomposes into a cartoon structure (i.e. defects) and a texture structure (i.e. pattern). The WGIS, BB, ID methods can deal with the dot-, box-, star-patterned fabrics for defect detection.

Lastly, the Regular bands (RB) method [6] has a great performance in the defect detection in patterned fabric, in which the detection success rate on 60 dot-patterned fabric images is 100% and achieves an average 99.4% for three patterned fabrics [6]. It can outline a clear and clean defect in the resultant image. This means that the RB method can show a clear pattern of the ancient weaving fabric and this helps reverse engineering. If there exists a traceable concrete pattern, it has a possibility to apply reverse engineering to find out the original pattern structure [13]. As the RB method is an effective method for fabric inspection [14], it is worth applying to the ancient fabric to discover its weaving pattern.

The RB method is composed of two subbands: the light regular band (LRB) and the dark regular band (DRB). The physical meanings of the LRB is the point or area is lighter than the other will have a higher value in LRB and lower value in DRB, vice versa. As a result, it may match the value with different colors of the yarn or the floating yarn will have a higher value in LRB. This may show the number of floating yarn in a more accurate way and help discover the way of weaves in the past.

Regular Bands Analysis

Mathematical expression

Weaving pattern can be understood as a combination of yarns on different positions of a textile image. Therefore, a complexity analysis on simulated images by wallpaper group samples can help us understand how complex the research in weaving pattern recognition of ancient Chinese textile is. More specifically, this is a combinatorics problem in mathematics.

Mathematically, the number of yarn combination below floating yarns is

$$P = (n-1)^m \tag{1}$$

where n - 1 is the number of yarn combinations of each yarn (or color) under the floating yarn, m is the number of pixels of the lattice. In this paper, the research will firstly focus on two simulated samples and one real ancient Chinese textile sample.

The regularity property enhancement in the ancient textile sample is performed by the RB method. Previously, the RB method [6] has been successfully performed for patterned texture defect detection. The RB is composed of two bands: light regular band (LRB) and dark regular band (DRB). Herein, both bands consist of moving average $(u_{i,j}) = (\sum_{j=r_1}^{r_m} x_{ij})/m$ for any image $X = (x_{ij})$ and moving standard deviation $(\sigma_{i,j}) = \sqrt{(\sum_{j=r_1}^{r_m} x_{ij} - u_{i,j})^2/m}$ in definitions, where *m* can be a length of row N_r (or column N_c). The RB method can identify, locate and segment the defect (irregularity) from the regular parts of the patterned fabric image.

Mathematically, the RB is defined as

$$L_{i,j} = \left| u_{i,j} - \sigma_{i,j} \right| + u_{i,j} \text{ for the LRB}$$
(2)

and

$$D_{i,j} = \left| u_{i,j} + \sigma_{i,j} \right| - u_{i,j} \text{ for the DRB}$$
(3)

where *i*, *j* are row and column of the proceeded image. Meanwhile, $u_{i,j}$ and $\sigma_{i,j}$ require different lengths of row N_r and column N_c for computation.

Procedure



Figure 4. Flowchart of the weaving pattern recognition of ancient Chinese textile.

The procedure of weaving pattern recognition of ancient Chinese textile can be divided into four steps (Fig. 4), as follow:

Step 1: Inputting old Chinese textile image

Input an ancient Chinese textile image into MATLAB. In this research, an ancient textile sample of size 3872×2592 from Ming dynasty, China (ca. 1368-1644 CE) is used. In addition, the input image is resized as 685×1024 since the original image is too large which is computationally expensive.

Step 2: Enhancing regularity property by the RB method

Every textile image has the regularity property as it is generated by a repetitive unit, lattice [5]. If we directly input the textile image and investigate the pixel intensity, the image may display some regular patterns on two-dimensional intensity matrix, which is the regularity property. However, an input image is usually unevenly illuminated during the acquisition, the embedded regularity property is difficult to be demonstrated. As a result, the RB method is used to enhance the regularity.

Step 3: Discovering hidden distributions

After applying the RB method, the embedded regularity feature of the ancient textile sample is enhanced and prominent in the RB proceed image. For example, the light color in the original image has a higher corresponding value in the RB proceeded distributions of the LRB.

Step 4: Recognizing the weaving pattern

Based on the hidden distributions of yarns, the weaving pattern can be recognized by probability or combinatorics tools. At the current stage, only the floating yarn can be recognized in our experimental results.

Performance Evaluation

The computational times of row and column of the RB method are 36.85s and 33.65s, respectively, averagely in 100 times. The computer is equipped with a processor: 1.6GHz dual-core Intel Core i5 @ DDR3 1600MHz.

Experimental Results

Simulated and real experimental results are described below.

(a) Simulated results

Lattice							
Floating yarns					0	1]	
Number of yarn combination floating yarns	ation belo	ow		1	× 1	=	1
Possible yarn combinations					$\begin{pmatrix} 0\\1 \end{pmatrix}$		
(a) Brief summ	ary of latt	tice a	and yar	n in t D	he p	olgr 10	roup ITh
Simulated chartered box patterned texture	(c) La	yout	of yarı	n con	ibin	atio	ns in

(p1 group) unterform to cations at (b) Figure 5. Yarn combination of a simulated patterned texture sample from the p1 group. (a) lattice, floating yarn, number of yarn combination below floating yarns, possible yarn combinations; (b) Simulated chartered box patterned texture (p1 group); (c) Layout of yarn combinations in different locations at (b).

Two simulated results are offered in this part. Fig. 5 illustrates a simulation of a chartered box patterned texture sample from the p1 group. Fig. 5(a) gives a brief summary of its lattice and number of yarn combination below floating yarns and possible yarn combinations. Fig. 5(b) shows the simulated image and Fig. 5(c) offers the layout of yarn combinations in different locations at Fig. 5(b).

This basic box pattern in Fig. 5 is only woven with two colors: black and white. The lattice of this pattern with the black and white colors looks like two boxes. A lattice means the repetitive unit of the pattern and the whole patterned texture (or fabric) can be regenerated by geometrical rules based on the lattice. To simplify the expression, 0 represents black and 1 represents white. Then, the floating yarns of the lattice can represent by $\begin{bmatrix} 0 & 1 \\ 1 & 0 \end{bmatrix}$ represent the yarn combinations, such as $\begin{bmatrix} 0 \\ 1 \end{bmatrix}$ represent the floating yarn is black color and white is the under one. A matrix $\begin{pmatrix} 0 & 1 \\ 1 & 0 \end{pmatrix}$ can be used to present the possible yarn combinations of lattice. As in this case, only have two colors, there are only two possible yarn combinations.

Fig. 6 illustrates another simulated patterned texture from the p1 group. Fig. 6 is a difficult case that a pattern combines by four colors. Each color is represented by a number: 0 represents white, 0.33 represents red, 0.66 represents blue and 1 represents green. In this case, the yarn combination below a floating yarn of each color is 6 (from 3 different yarns underneath). For example, the floating

Lattice	
Floating yarns	$\begin{pmatrix} 0 & 0.33 & 0 & 0 \\ 0.66 & 0 & 1 & 0 \end{pmatrix}$
Number of yarn combination below floating yarns	$6 \times 6 = 6^8$ $= 1679616$
Possible yarn combinations	$ \begin{pmatrix} 0 \\ 0.33 \\ 0.66 \\ 1 \\ 0.66 \\ 0 \\ 0.33 \\ 0.66 \\ 0 \\ 0.33 \\ 0.33 \\ 0.66 \\ 0 \\ 0.33 \\ 0.66 \\ 0.33 \\ 0 \\ 0.33 \\ 0 \\ 0.33 \\ 0 \\ 0.66 \\ 1 \\ 1 \\ 0.66 \\ 1 \\ 1 \\ 0 \\ 0.66 \\ 1 \\ 1 \\ 0 \\ 0.66 \\ 1 \\ 1 \\ 0 \\ 0.66 \\ 1 \\ 1 \\ 0 \\ 0.66 \\ 1 \\ 1 \\ 0 \\ 0 \\ 0 \\ 0 \\ 0 \\ 0 \\ 0 \\ 0$
(a) Brief summary	of lattice and yarn in the p1 group
(b) Simulated chartered box p $\begin{pmatrix} 0 \\ 0.33 \\ 0.33 \\ 0 \\ 0.33 \\ 0 \\ 0.66 \\ 0.66 \\ 0.66 \\ 0.66 \\ 0.33 \\ 0.66 \\ 0.33 \\ 0.66 \\ 0.33 \\ 0.66 \\ 0.33 \\ 0.66 \\ 0.33 \\ 0.66 \\ 0.33 \\ 0 \\ 0 \\ 0.66 \\ 0 \\ 0.33 \\ 0 \\ 0 \\ 0 \\ 0.66 \\ 0 \\ 0 \\ 0.33 \\ 0 \\ 0 \\ 0 \\ 0 \\ 0 \\ 0.66 \\ 0 \\ 0 \\ 0 \\ 0 \\ 0 \\ 0 \\ 0 \\ 0 \\ 0 \\$	0 0 0.33 0 0.33 0 .33 0.33 0 0.33 0.33 0.33 .66 0.66 1 0.66 0.66 1 1 0 0 0.66 0 1 1 1 0 0.66 0 1 0 0.33 0.66 1 1 0.66 1 0.66 1 1 0 0 0.33 0 0.33 0.66 1 1 0.33 0.33 0.66 0.33 0.66 1 1 0 0 0.33 0 0.33 0.33 0.66 1 1 0 0 0.33 0 0.33 0.66 1 1 1 0 0 0.33 0 0.33 0.66 1 1 1 1 1 0 0 0.33 0 0.33 0.66 1 1 1 1 1 1 1 1 1 1

(c) Layout of yarn combinations in different locations at (b) Figure. 6. Yarn combination of a simulated patterned texture sample from the p1 group. (a) lattice, floating yarn, number of yarn combination below floating yarns, possible yarn combinations; (b) Simulated chartered box patterned texture (p1 group); (c) Layout of yarn combinations in different locations at (b).



Figure 7. (a) Ancient Chinese textile sample; (b) Grey-scale image of (a); (c) Specified rows and columns for the RB analysis.

yarn is white (0) will have those cases:
$$\begin{pmatrix} 0\\0.33\\0.66\\1 \end{pmatrix}$$
, $\begin{pmatrix} 0\\0.33\\1\\0.66 \end{pmatrix}$, $\begin{pmatrix} 0\\0.66\\1\\0.33\\1 \end{pmatrix}$, $\begin{pmatrix} 0\\0.66\\1\\0.33\\0.66 \end{pmatrix}$ and $\begin{pmatrix} 0\\1\\0.66\\0.33 \end{pmatrix}$. As the lattice is

composed by eight floating yarns (look like 8 boxes in Fig. 6), the number of yarn combination below floating yarns of the lattice is $6 \times 6 \times 6 \times 6 \times 6 \times 6 \times 6 = 6^8$. Imaginably, there will be a huge number of combinations when a fabric contains more than two color yarns. Hence, a grey scale version of the original ancient textile image is used (Fig. 7b) in this research for the proof-of-concept of the RB analysis.

(b) Real results

The RB analysis will be applied to enhance the regularity property of an ancient textile sample from Ming dynasty, China (ca. 1368-1644 CE) in Fig. 7. Fig. 7(a) is the original sample and Fig. 7(b) is the grey scale image from Fig. 7(a) after a preprocessing. Fig. 7(c) illustrates some rows and columns for the RB analysis in Fig. 8.

Fig. 8(a), (c) demonstrate pixel intensities of row 70 and their corresponding results by LRB on row (i.e. shorthanded as LRBR) and DRB on row (i.e. shorthanded as DRBR) under different N_r and N_c values. Fig. 8 (b), (d) show scaled up parts (columns 400-700) on the row 70 and their corresponding results by LRB on row (i.e. LRBR) and DRB on row (i.e. DRBR) again.

To show that RB method is useful in weaving pattern recognition, some rows or columns are randomly taken for the



Figure 8. (a), (c) Pixel intensities of row 70 and their corresponding results by LRB on row (i.e. LRBR) and DRB on row (i.e. DRBR) under different N_r and N_c values. (b), (d) Scaled up parts (columns 400-700) on the row 70 and their corresponding results by LRB on row (i.e. LRBR) and DRB on row (i.e. DRBR) again.

research. In Fig. 7(c), red lines represent the chosen row and blue lines represent the chosen column. As there are too many pixels for the entire row or column, this is hard to observe the differences, the row or column will be scaled up. For row, the columns from 400 to 700 are chosen, which means the yellow lines in Fig. 7(c). On the other hand, for column, the rows from 300 to 500 are chosen. The green lines in Fig. 7(c) show the range of row 300 to 500.

Fig. 8 shows the RB method can enhance the waveform in row and column so that the peaks and valleys in this waveform are evenly distributed and obvious in appearance. In Fig. 8(b), (d), the original row 70 shows chaotic patterns in intensity while the processed RB rows in the LRBR (i.e. LRB on row) and DRBR (i.e. DRB on column) demonstrate better regular patterns. Therefore, this helps us discover the hidden distribution easier. As it is easier to see the regularity property. Moreover, to optimize the solution, the sole parameter of period in the RB method is required to be tuned. Empirically, some parameters are randomly guessed in the initial step and N_r and N_c equal to 15 are the best after trials.

In Fig. 9, a matching of color and yarn is performed. As the LRB has a clearer waveform, we mainly match the LRB graph



(b) Column 493 between rows 300-500 Figure 9. (a) Scaled parts (columns 400-700) on the row 70 of LRBR. (b) Scaled parts (rows 300-500) on the column 493 of LRBC.

with the original grey scale image. To have a clear matching, a scaled LRB graph is illustrated. In Fig. 9, yellow lines with arrows match the light color (i.e. the higher value) and blue lines with arrows match the dark color (i.e. the lower value). This discovers the pattern of the floating yarns in the ancient Chinese textile sample.

Conclusion

This paper demonstrates the application of the RB analysis to enhance the regularity property of the ancient Chinese textile and to discover the floating yarn pattern. In addition, the LRB in the RB method can tackle the yarn with lighter color while the DRB can handle the yarn with darker color through a careful study. We believe that the hidden pattern of ancient Chinese textile weaving can be discovered. It helps us generate a better understanding of the mentality of the ancient Chinese textile manufacturers, artists, and industrial manufacturers in China. More old textile images can be employed for later research projects and we can further study the yarn combinations to eliminate the yarn order.

Acknowledgment

The work described in this paper was supported by a grant from the Hong Kong Baptist University (HKBU) FRG2/15-16/045 and the ancient textile sample is provided by the Seattle Art Museum, U.S.

References

- Dieter Kuhn, ed. Chinese Silks, New Haven: Yale University Press, 2012.
- [2] Angela Sheng, "The Disappearance of Silk Weaves with Weft Effects," *Chinese Science*, no. 12, pp. 56-61, 1995.
- [3] N. Huang, J. Cheng, *Zhongguo fuzhuangshi*, Beijing: Zhongguo Lüyou Chubanshe, pp. 54-69, 1995.
- [4] N. Huang, ed. Yin ran zhi xiu/ Zhongguo meishu quanji (gongyi meishu bian), Beijing: Wenwu Chubanshe, vol. 6, pp. 4-37, 1985.
- [5] H.Y.T. Ngan, G.K.H. Pang and N.H.C. Yung, "Motif-based Defect Detection for Patterned Fabric," *Pattern Recognition*, vol. 41, issue 6, pp. 1878-1894, 2008.
- [6] H.Y.T. Ngan, and G.K.H. Pang, "Regularity Analysis for Patterned Texture Inspection," *IEEE Trans. Automation Science & Engineering*, vol. 6, no. 1, pp. 131-144, 2009.
- [7] P. Collingwood, "The techniques of rug weaving," New York: Watson-Guptill Publications, 1969.
- [8] J. Becker and D. Wagner, Pattern and loom: a practical study of the development of weaving techniques in China, Western Asia and Europe, Copenhagen; Rhodos, 1987.
- [9] G. H. Oelsner, A handbook of weaves, New York: The Macmillan Company, 1915.
- [10] H.Y.T. Ngan, G.K.H. Pang, S.P. Yung and M.K. Ng, "Wavelet based methods on Patterned Fabric Defect Detection," *Pattern Recognition*, vol. 38, issue 4, pp. 559-576, 2005.
- [11] H.Y.T. Ngan and G.K.H. Pang, "Novel Method for Patterned Fabric Inspection using Bollinger Bands," *Optical Engineering*, 45(8), 2006.
- [12] M.K. Ng, H.Y.T. Ngan, X. Yuan and W. Zhang, "Patterned Fabric Inspection and Visualization by the Method of Image Decomposition," *IEEE Trans. Automation Science & Engineering*, vol. 11, no. 3, pp. 943-947, 2014.
- [13] N. Shi and R. Olsson, "Reverse Engineering of Design Patterns from Java Source Code," 21st IEEE/ACM Int'l Conf. Automated Software Engineering (ASE'06), 2006.
- [14] H.Y.T. Ngan, G.K.H. Pang and N.H.C. Yung, "Automated Fabric Defect Detection – A Review," *Image and Vision Computing*, vol. 29, no. 7, pp. 442-458, 2011.

Author Biography

Connie C.W. Chan is an undergraduate year-5 student in Mathematics at Hong Kong Baptist University, China. She is supposed to receive the B.Sc. (Hons) degree in Mathematical Science and diploma in Education in 2017. Her research interests include surface defect detection, art history, textile weaving techniques, pattern recognition and image processing.

Kin Sum (Sammy) Li holds a B.A. degree in Translation (2008) and an M. Phil. degree in East Asian Studies (2010) at the Chinese University of Hong Kong, and the Ph.D. degree in East Asian art and archaeology (2015) at Princeton University. He is currently an assistant professor at the Department of History, Hong Kong Baptist University, China.

Henry Y.T. Ngan received the B.Sc. degree in Mathematics (2001), the M. Phil. degree (2005) and the Ph.D. degree (2008) in Electrical & Electronic Engineering at The University of Hong Kong, China. He is currently an assistant professor of research in Mathematics, Hong Kong Baptist University. He was a conference chair of IS&T Electronic Imaging 2016, 2017. He is an editor of IS&T Journal of Imaging Science & Technology.