IOP Conference Series: Materials Science and Engineering

PAPER • OPEN ACCESS

Investigation the effect of weave repeat on woven fabric texture characterization using sparse representation

Investigation the effect of weave repeat on woven fabric texture characterization using sparse representation

Y Wu[1], J Wang[1,2], Z Zhan[1] and L Q Li[1]

[1]College of Textiles, Donghua University, Shanghai, 201620, China;
[2]Key Laboratory of Textile Science and Technology, Ministry of Education, Shanghai, 201620, China

E-mail: junwang@dhu.edu.cn

Abstract. A novel approach based on sparse representation is presented to investigate the impact of weave repeat on the characterization of woven fabric texture. Firstly, the test samples were represented by over-complete dictionary in the least squares sense. Secondly, the two indexes--PSNR value and RMSE were introduced to evaluate the representation performance. Thirdly, the image entropy was used to quantify the fabric surface texture, and then the samples were categorized according to the two indexes. Experimental results showed that our algorithm can approximate fabric texture very well and weave pattern has great impact on fabric texture reconstruction. Eight kinds of weaving patterns are classified into three categories, of which the basket fabric shows the best performance. The findings may be helpful in classification and automatic inspection of woven fabric texture.

1. Introduction

The quality inspection is an essential part of textiles production before sale. Normally, fabric visual inspection is performed by workers in most of the production lines. However, these manual operations are so subjective and repetitive that a reliable and accurate detection results can hardly be provided, because they are easily constrained by external factors such as tiredness, and inattentiveness. With the development of image processing and pattern recognition techniques, an automatic visual inspection, especially the surface texture representation technique is highly demanded by various industries to circumvent the shortcomings of manual inspection for more consistent and objective detection results.

Image processing methods have been widely applied in fabric texture analysis. Shih [1] proposed an automated analysis system for Tatami embroidery fabric images, where the color, pattern shape and texture can be automated analysis. For textile image analysis, Pan [2] simulated the woven fabric texture and constructed the characteristic model through a simulation method based on the gray level distribution of weave floats. Xin[3] presented a fairly new texture modelling method based on co-occurrence matrix and neural network for objective quality evaluation of fabric appearance. Liu[4] combined wavelet transform, generalized Gaussian density (GGD), defect segmentation and learning vector quantization (LVQ) neural network to identify 7 types of common defects in silk fabric. Though fabric texture is the basis fundamental research, there is no accurate characterization of texture in depth. Most researches in this area is mainly focused on their applications, such as weave structure recognition, texture classification and defects detection etc. Global texture analysis is still a challenging task in different kinds of fields ranging from fabric texture analysis, face recognition, image recognition and processing, visual art among others [5].

A woven fabric is made of the cross combination of warp and weft yarns according to weaving pattern, and it exhibits high periodicity. So, it can be inferred that the global woven fabric texture is determined by the factors of yarns, like weaving density and weave repeat. But the relative effects of weave structure, yarn type on the characterization fabric texture are not yet known. However studies on relationship between weave structure and fabric texture characterization are still rare as there is paucity of literature on this relationship. Since the weave pattern of fabric mainly consists of warp and weft yarn density, fabric structure, color, the array parameter of dyed yarn san so on[6]. Thus, the present study is therefore undertaken to investigate the effect of weave structure on the representation of woven fabric texture.

2. Methodology

In recent years, sparse representation works well in many aspects of applications, where the original signal y needs to be reconstructed as accurately as possible such as image compression [7], super-resolution and image de-blurring [8, 9], image de-noising [10, 11], face feature recognition [12]. Recent studies have achieved better signal representation using sparse approximation techniques as opposed to other methods [13]. For woven fabric texture representation, the implemented algorithm was sparse representation, while the used dictionary was over-complete.

2.1. Sparse representation

The aim of sparse signal representation is to find a linear combination with a small number basis vectors (named dictionary elements or atoms), which can approximate the signal with a minimal mean squared error. Suppose that there is $m\times n$ data matrix $Y=[y_1, y_2, ..., y_n]$, $y_i \in R^m$, which contains n vectors of their dimension m in its columns. For approximating every vector y_i in Y, we need to find a dictionary that is $D = [d_1, d_2, ..., d_k]$, $d_j \in R^m$ $(k>m)$, whose each column includes a basis vector, which can sparsely represent all y_i in Y. In the proposed approach, the dictionary was predefined, to ensure the characterization results stable.

The problem of seeking such a sparse coefficient matrix could be formulated as follows:

$$\min_{D,\alpha} \sum_{i=1}^{n} \|y_i - D\alpha_i\|_2^2 \text{ s.t. } \|\alpha_i\|_0 \le T, \quad 1 \le i \le n \tag{1}$$

Where α in R^k is the coefficient vector for y_i in Y, here denotes $\|\cdot\|_0 - l_0$ pseudo-norm, which counts the number of non-zero entries of its argument vector. While this problem is, in common, very hard to solve, matching pursuiting[14] and basis pursuit[15] algorithms can be used effectively to obtain an approximated solution. In this paper, we made use of the orthonormal matching pursuit (OMP), due to its simplicity and efficiency.

A fundamental consideration in employing the above model is the choice of the dictionary D. The majority of literation on this topic can be categorized into two approaches: the analytical approach and the learning-based means. The analytical dictionary is formulated by a mathematical model or transform. This predefined dictionaries generally are highly structured and have a fast numerical implementation[13]. Dictionaries of this type contain Curvelet[5], Bandelet[16], Discreet Cosine Transform DCT[17], and so on. The classical learned dictionary includes K-means Singular Value Decomposition KSVD[18], Double Sparse Modeling, DSM[13], and others.

2.2. Woven fabric texture characterization

Since the sparse representation can be seen as an approximation process, it can be applied to the field of image reconstruction. Thus, the woven fabric image characterization problem (1) can be solved by setting a threshold of average residual error ε:

$$\begin{aligned} &\hat{\alpha} = \arg\min \|\alpha\|_0 \; s.t. \|Y - D\alpha\|_2^2 \le \varepsilon \\ &Y = D\hat{\alpha} \end{aligned} \tag{2}$$

IOP Conf. Series: Materials Science and Engineering **254** (2017) 162012 doi:10.1088/1757-899X/254/16/162012

To find the optimal $\hat{\alpha}$, the OMP algorithm was adopted to obtain sparse coefficient matrix. However, as the large calculation costs of the sparse decomposition, and the calculation a whole is too huge. Thus, the approach of limited in handling small image blocks was to solve equation (2) in this context. The characterization process is shown as follows:

(1) Extract the 8×8 image patch from the image samples with overlaps.
(2) The dictionary is redundant DCT, the redundant of DCT is 4, and namely, it contains 256 atoms.
(3) Decompose and reconstruct all overlapping image patches based on the DCT dictionary. The appropriate sparsity value T is chosen to control the average error.
(4) For every reconstructed image patch, we replace the pixels in the overlapping region by the average.

3. Experiments

To study the impact of weave pattern on fabric texture representation, eight weave patterns were chosen, which involved 3/1 twill, plain, 2/2 basket, 8/3satin, 8/5 satin, diamond twill, honeycomb and compound twill (see figure 1 (a) to (h)). All the samples were manufactured on TNY101B-20 type Sakural brand rapier loom. The material was 20tex/2 cotton two fold yarn used both in warp and weft. The woven density was 350yarns/cm for both weft and warp. The size of image samples was 256×256 pixels with 256-grey levels, and original fabric samples are shown in figure 1.

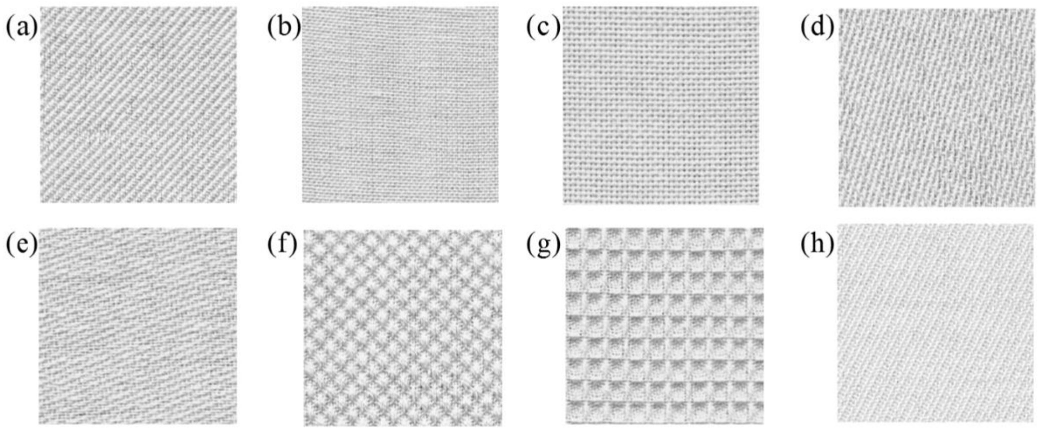

Figure 1. Original fabric samples (a) twill, (b) plain, (c) basket, (d) weft satin, (e) warp satin, (f) diamond twill, (g) honeycomb, (h) compound twill

3.1. Evaluation of the representation result

Objectively, we adopted peak signal to noise ratio (PSNR) and root mean square error (RMSE) to confirm the performance of our method. PSNR can be seen as a metric to measure the quality of the reconstructed image, and its definition is given as follows:

$$\mathrm{PSNR} = 20 \cdot \log_{10}\left(\frac{MAX_I}{\sqrt{\left\| I - \hat{I} \right\|_F^2 / MN}}\right) \tag{3}$$

In this expression, I is gray scale image, MAX_I is the maximum gray value 255, $\hat{I}$ is the approximated image, and $\|\cdot\|_F$ is F- norm. From the equation (3), it is obvious that PSNR is a positive number, and when the original image and the reconstructed image is approximately the closer, the greater the PSNR value.

$$\mathrm{RMSE} = \sqrt{\frac{\left\| X - \hat{X} \right\|^2}{mn}} \tag{4}$$

Here, X is gray scale image with m samples in n dimension, $\hat{X}$ is the approximated image.

What is more, to validate the influence of weave repeat on fabric texture characterization, the image entropy was computed to quantify the average amount of information in an image. One dimensional image entropy shows the amount of information contained in the aggregation feature of gray level distribution, which the definition is shown as follows:

$$H = \sum_{i=0}^{255} p_i ln p_i \tag{5}$$

The p_i is the proportion of the pixels whose gray value is i.

4. Results and Discussion

In this article, the offered algorithm is devised to represent texture in a fully unsupervised manner without any prior information. It attempts to represent fabric texture in patch-level with an over-complete dictionary in sense of least squared error. And then the influence of weave structure on woven fabric texture representation is investigated.

4.1. Effect of the sparsity T and dictionary size

The three foundation weave patterns--plain, twill and satin (see sample 2, 1, 5 in figure 1) samples were chosen to select the appropriate T and dictionary size. Their reconstructed versions are illustrated in figure 2. It can be obtained that there was no visual difference between original image and the reconstructed one. From the figure 3, the quality of the images is improving (PSNR value becomes higher and the RMSE turns smaller) with the sparsity T and dictionary atom, but this increase is subsiding. About PSNR, at T=30, the proposed method can approximate the fabric samples very well. Setting $T>30$, though the PSNR becomes larger, it may bring more computation burden and little difference in vision. For RMSE, the improvement performance gradually weakens and the curve turns convergence at T=60. Finally, we set T=30, which can make sure that PSNR value and RMSE of the samples are around 60dB and about 2.5 respectively. The characterization performance reaches better than the other elements, when the dictionary atom is 256, still keeping the dictionary is over-complete. So, the dictionary atom is 256.

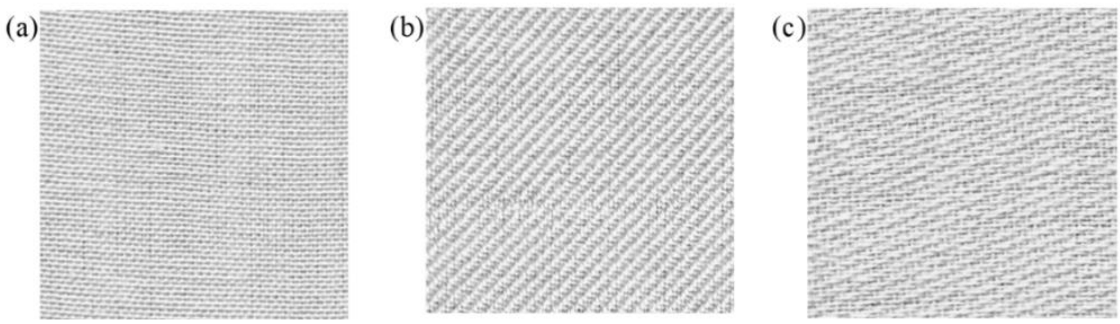

Figure 2. The reconstructed fabric image samples (a) plain, (b) twill, (c) weft satin

4.2. The impact of diverse of weave repeat

At present, we explore the difference of fabric surface texture with different structure parameters. The image entropy was calculated, and shown in table 1, which implies that the lager of the entropy value, the more complex the image surface texture. In order of most complex samples, it goes: twill, honeycomb, plain, basket, compound twill, diamond twill, warp satin and weft satin. The final characterization results have not quite the same outcomes because the every weave pattern has different organizational structures and regularity.

IOP Conf. Series: Materials Science and Engineering **254** (2017) 162012 doi:10.1088/1757-899X/254/16/162012

Table 1. The result of fabric image samples

Sample	Entropy	PSNR(dB)	RMSE
1	6.4262	57.9233	2.5652
2	6.2103	61.2406	1.8598
3	6.1706	63.9147	1.4171
4	6.0183	58.8866	2.2507
5	6.0046	60.3060	1.9409
6	6.0145	61.1927	1.1801
7	6.2447	61.8670	1.6544
8	6.1578	57.4385	2.7603

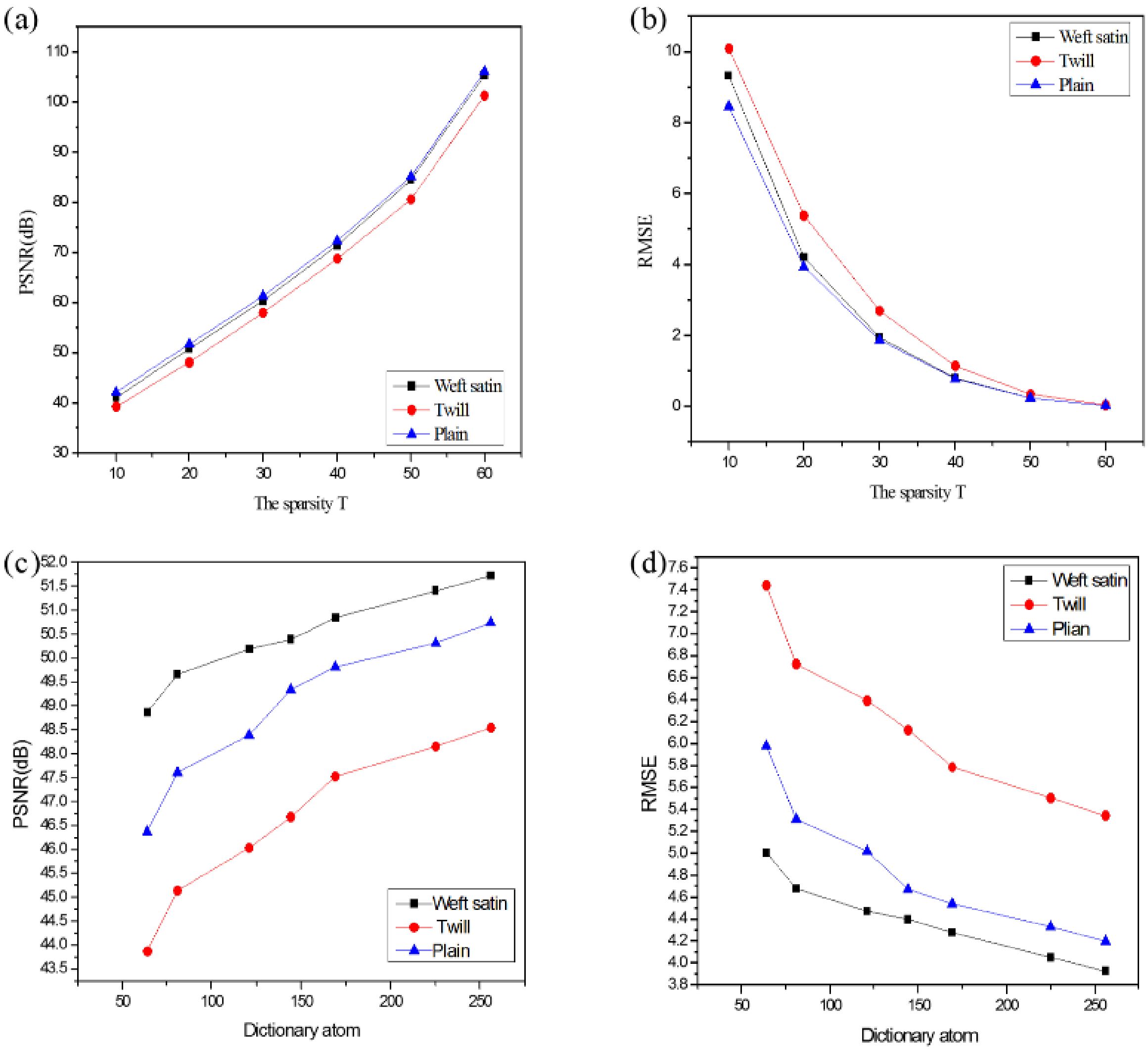

Figure 3. Illustration of the results with different *T* and dictionary size

From the table 1, we achieve that the performance results are categorized into three types, with the quality of the assessment getting worse. The surface texture of basket fabric sample is not the simplest, even a little complex. Owing to the effect of structure feature and best regularity among the text samples, the basket fabric sample had the greatest performance. The honeycomb, diamond twill, plain and weft satin samples were after the basket, which the smallest gap between the two groups is 2.1dB and 1.1, while the difference within their group is about 1dB and 0.8. Comparison with the other groups, the third group had the worst performance, which contains warp satin, twill, compound twill.

5. Conclusion

We propose an algorithm for fabric texture characterization based on sparse representation using DCT over-complete dictionary. Although the dictionary was predefined, it can effectively capture key features in the samples and obtain stable characterization result. Besides, experimental results demonstrated that different weave patterns can be approximated very well. From the perspective of the quantitative analysis, the fabric samples were classified into three categories in relation to the test results of PSNR and RMSE. Of which, the basket fabric sample has best performance. As stated by the above description, we can infer that the weave repeat has great impact on the regularity of fabric surface texture, and even can partly neglect the entropy value, which implies the complex of surface texture. In real, the woven fabric texture analysis remains a longstanding challenge from theory to application, no matter the texture definition or the woven fabric structural parameters such as materials, fabric compactness etc. or other factors, are not adequately explored. For future work, we will aim to find a discriminative dictionary, and extract more features to classify the woven fabric texture.

6. Funding

This research was supported by the National Natural Science Foundation of China (Grant Number 61379011, 61271006).

References

[1] Shih C Y, Kuo C F J and Cheng J H 2016 *Text. R. J.* **86** 1791-802
[2] Pan R R, Zhu B, Li Z J, Liu J H and Gao W D 2015 *Industria Textila* **66** 28-31
[3] Xin B J, Li Y M, Qiu J X and Liu Y 2012 *Fibres & Text. East. Eur.***20** 48-52
[4] Liu J L and Zuo B Q 2009 *Proc. 2nd Int. Congress on Image and Signal Process.* ed PH Qiu (New York: IEEE) pp 1-5
[5] Candes E J and Donoho D L 2005 *Appl. Comput. Harmon. A.* **19** 162-97
[6] Kuo C F J and Tsai C C 2006 *Text. R. J.* **76** 375-82
[7] Skretting K, Engan K and Ieee 2011 *Proc. of IEEE Int. Conf. on Acoust. Speech, and Signal Processing*, (Pargue: IEEE) pp 1517-20
[8] Jose J, Patel J N and Patnaik S 2015 *Optik* **126** 2295-9
[9] Xiang S M, Meng G F, Wang Y, Pan C H and Zhang C S 2015 *Int. J. Comput. Vision* **114** 248-71
[10] Elad M and Aharon M 2006 *IEEE Trans. Image Process.* **15** 3736-45
[11] Giryes R and Elad M 2014 *IEEE Trans. Image Process.* **23** 5057-69
[12] Zhu N B, Tang T, Tang S, Tang D Y and Yu F 2013 *Optik* **124** 6236-41
[13] Rubinstein R, Zibulevsky M and Elad M 2010 *TEEE Trans. signal Process.***58** 1553-64
[14] Donoho D L, Tsaig Y, Drori I and Starck J-L 2012 *IEEE Trans. Inf. Theory* **58** 1094-121
[15] Chen S S B, Donoho D L and Saunders M A 1998 *J. Sci. Comput*. **20** 33-61
[16] Le Pennec E and Mallat S 2005 *IEEE Trans. Image Process.* **14** 423-38
[17] Wang Y H, Shi M J, You S and Xu C 2016 *IEEE Trans. Image Process.* **25** 4406-20
[18] Aharon M, Elad M and Bruckstein A 2006 *IEEE Trans. Image Process.* **54** 4311-22