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A Fully Automatic Adjacent Key-points Localization Framework for Minimal Repeated Pattern Detection in Printed Fabric Images

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Qiyan Zang designed the research. Jian Zhang, Liling Bo, Yuchen Xiao and Guangwei Gao processed the data. Qiyan Zang drafted the manuscript. Jian Zhang helped organize the manuscript. Heng Zhang, Hongran Li, Zhaoman Zhong and Yan Ren revised and finalized the paper.

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Abstract

The printed fabric images usually contain a large number of minimal repeated patterns (MRPs), which are of great value for the color separation, plate-making and other related applications in the textile industry. The key-points localization is a well established and effective manual method to detect the MRPs by finding a number of identical key-points. Recently, computer-aided automated key-points localization techniques have shown great potential and attracted considerable interest. Nevertheless, most of the available subtle and ad-hoc strategies are poorly generalized to complex situations due to a lack of systematic formulation. In this study, we endeavor to automate and theorize this manual detection method, aiming to enhance its accuracy, robustness, and efficiency. Specifically, we delineate related concepts and systematically formalize the minimal repeated pattern (MRP) detection problem, thereby establishing a theoretical groundwork for the manual method's viability. Then, we present an effective and robust adjacent key-points localization (AKL) framework by automating manual detection method of MRP in printed fabric images. This framework is further developed into a comprehensive automated image retrieval system, complete with detailed implementation techniques. We also create a printed fabric dataset named PFI-10K containing approximately 10,000 images to test corresponding methods. The experimental results demonstrate the effectiveness and robustness of the proposed AKL framework.

Keywords: Automatic detection system, minimal repeated pattern detection, texture feature extraction, pattern recognition

1. Introduction

Over the past few decades, the development of textile industrial automation has given rise to a large number of requirements for new computer technologies [20, 1, 21, 3]. As an indispensable ingredient of the computerized color dividing and plate-making system, the automatic detection of minimal repeated patterns (MRPs) from printed images has aroused widespread concern in the textile industry [10, 6, 16]. The significance of MRPs detection in the printing industry lies in its ability to significantly reduce the difficulty and workload associated with color separation and plate-making processes. Additionally, the detected MRPs serve as a compact description for building printed image retrieval, texture image analysis, and other printed image application systems [7, 22].

Some related works on detecting repetitive structures in images have been explored in recent years [27, 19, 12, 14]. Pattern periodicity analysis for mining visual characteristics of textile appearance could be seen as early automatic MRPs detection studies. Wood [26, 25] employed Fourier and associated transforms to characterize carpet patterns exploiting the fabric surface's periodic nature. In [25], the periodicity of weft and warp yarns (yarn spacing) in plain-weave cotton fabric was analyzed via an angular Fourier power spectrum and autocorrelation function. While these techniques could handle repeating patterns, detecting repeating features from spectrograms still required manual intervention. In addition, because the early work focused on spectral analysis of weave fabric rather than printed fabric, it was difficult to apply them to the detection of minimal repeated patterns in printed fabric images.

Kuo et al. [11, 8, 9, 7] conducted a systematic study on the problem of automatic detection and identification of repeated patterns in printed fabric. They proposed a framework for automatic repeated pattern detection that involves sub-pattern image clustering and geometric segmentation. Specifically, they first apply fuzzy C-means clustering and specific cluster validity criteria to obtain pattern images from gray printed fabric, then segmented the

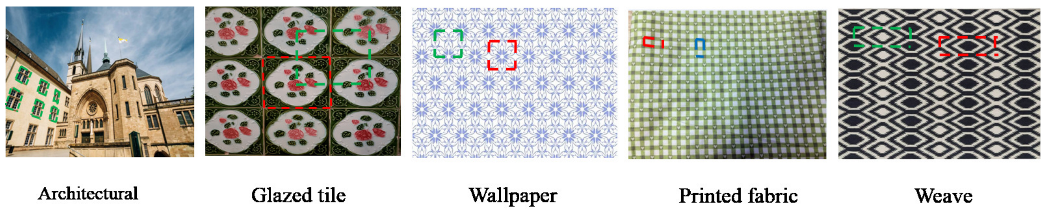

Figure 1: An intuitive illustration of the repeated patterns in difference scene images.

repeated pattern via Hough transform. In [11], they extended their framework to color images of printed fabric adopted genetic algorithm and template matching fusion. In [8], Kuo et al. created an image database of printed fabric with repeating dot patterns to alleviate issues in managing and searching numerous dot-printed fabrics in the printed industry. Recently, they proposed a complete, fully-automatic extraction, classification and image registration framework for repeating printed fabric patterns involving grayscale image transform, 2D discrete wavelet transform, fast Fourier transform, and adaptive K-means clustering methods [7]. Undoubtedly, their efforts greatly facilitated the automatic MRPs detection problem research. However, the repeated patterns detected via periodic variation of frequency in frequency domain are usually not the minimal as desired.

Besides textile research, identifying repeated structures in images of man-made objects has important implications for applications like scene perception and model-based learning. In [15], Liu et al. utilized mathematical Frieze and wallpaper groups to extract visually meaningful repeated structures from printed patterns. They adopted a peak detection algorithm based on regions of dominance to automatically detect underlying lattices. The main drawback is assuming a single, large repeated pattern. In [24], S. Wenzel et al. presented a symmetry detection method based on feature matches' localization, orientation, and scale properties to find repeated structures in facade images. However, the procedure is sensitive to regular repeated objects in facades due to generous matching criteria. In [13], Li et al. provided a novel method for detecting repeat patterns on fabrics by analyzing different lighting conditions. Deep learning approaches are used to study repeat patterns on fabrics in [5, 17].

To our knowledge, labor-intensive, time-consuming and low-accuracy manual inspection methods remain predominant in the textile industry, even though considerable academic research exists on MRPs or similar issues. We attribute this dilemma to the large gap between academia and industry. On the one hand, most studies do not target automatic MRPs detection in actual printed fabrics. And existing automatic methods have struggled to meet increasingly complex pattern detection needs (e.g., noise interference, complex patterns, colors). On the other hand, traditional industry has developed effective manual MRPs detection methods in practice. Despite inefficiency and low accuracy, these manual methods could handle most simple-to-complex patterns.

The manual key-points localization method, as a mature technique utilized for detecting the minimal repeated patterns within images, has been extensively applied across various domains. This method primarily relies on the human visual capability to recognize identical key-points within images, a skill derived from intuitive rules refined through extensive practical experience. Specifically, its operational principle involves identifying at least two adjacent points displaying the same pattern within an image and constructing a rectangular area with these points as vertices to delineate the boundaries of the repeated pattern. However, despite the widespread application of the manual key-points localization method, its efficacy and interpretability remain under scrutiny.

The primary challenge lies in the lack of a precise definition for minimal repeated patterns and the unclear explanation of the detection process. Additionally, manual detection methods are commonly seen as complex and not transparent, making their automation a significant hurdle. In [28], Zhang et al. presented a minimal repeated pattern detection problem and provided a preliminary definition of MRP, but did not achieve fully automatic MRP detection. These issues not only impede the technique's further development but also limit its potential for broader applications. Therefore, in-depth research and improvement of the manual key-points localization method, especially in terms of its precise definition, interpretability, and automation, are crucial for enhancing its overall performance and application scope.

Our Contributions This paper endeavors to automate and provide a theoretical framework for the manual detection method, aiming to enhance its accuracy, robustness, and labor efficiency. To this end, we initially formalize the problem of detecting MRPs and elucidate related concepts, thereby establishing a solid theoretical foundation that validates the feasibility of the key-points localization approach. Subsequently, we transition to automating the manual process for identifying MRPs within printed fabric images, employing a robust and effective adjacent key-points localization (AKL) framework.

This framework is then translated into a fully automated image retrieval problem, for which we delineate a concrete implementation strategy.

The contributions of this work are summarized as follows:

1. We define related concepts and formalize the minimal repeated pattern detection problem, which laid the foundation for subsequent research in this area.
2. We propose an effective adjacent key-points localization (AKL) framework for automatically detecting the minimal repeated pattern from printed fabric images. Theoretical and empirical analyses demonstrate the efficiency and robustness of the designed method.
3. We contribute the PFI-10K dataset, addressing the scarcity of recognized public datasets in the field. The dataset, comprising 11,592 printed fabric images, is designed for diversity and complexity. Extensive experiments with the AKL on this dataset showcase its advantages in detection accuracy, efficiency, and robustness in real-world scenarios.

Roadmap Section 2 presents related concepts of MRPs and formalizes the MRPs detection problem. Section 3 details the proposed AKL and its implementation. Section 4 presents experimental details, including dataset information, settings, and metrics used for evaluation. Section 5 concludes the paper.

2. Problem formalization

In this section, we first present related concepts of MRPs in textile printed and then formalize the minimal repeated pattern detection problem.

2.1. Related Symbols and Concepts

As illustrated in Figure 1, the concept of repeated patterns appears across various fields, albeit with conceptual variations that introduce research dilemmas. For example, any semantically repeated elements are termed repeated patterns in scene perception. Yet, not all such elements construct a printed pattern through duplication and stitching in fabric printed.

Generally, designing repeated pattern elements demands meticulous attention to ensure continuity at stitching points. Therefore, we present a specific definition of the minimal repeated pattern by means of pixel sets, image patterns and set relationships, tailored to the actual detection needs of printed fabrics.

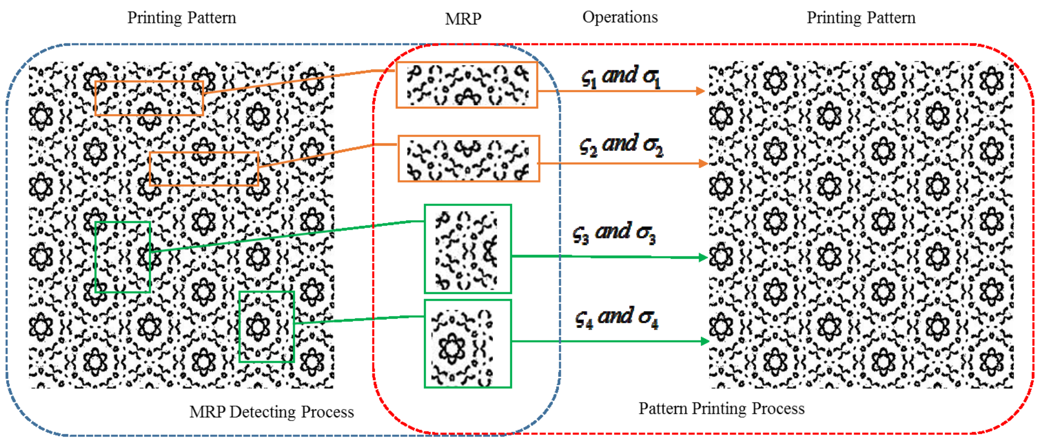

Figure 2: An intuitive illustration of the pattern printed process signed by the red dashed box and the MRP detection process signed by the blue dashed box.

In the field of fabric and wallpaper printed, patterns on printed image are typically created by duplicating and stitching a designed repeated pattern onto carriers such as fabrics and paper, using printed equipment. For simplicity, we use a grayscale image as an example and let $\boldsymbol{I} \in \mathbb{R}^{m \times n}$ and $\boldsymbol{M} \in \mathbb{R}^{p \times q}$ denote the printed pattern and repeated pattern, respectively. The pattern printed process can be formalized as:

$$\boldsymbol{I} = \varsigma(\sigma(\boldsymbol{M})), \tag{1}$$

where σ represents the stitching operation, which generally involves horizontal, vertical, and jump stitching between repeated patterns in the printed pattern process. ς denotes the cropping operation on the stitching pattern, and $\boldsymbol{M}$ is the MRP in industry terms which could not be divided into smaller repeated patterns. The intuitive illustration of this process is shown by the red dashed box in Figure 2, which shows the same printed pattern $\boldsymbol{I}$ can be obtained by applying different operations (σ and ς) on different $\boldsymbol{M}$. In other words, depending on the starting position and operation, a printed pattern can contain multiple types of minimal repeat patterns.

For convenience, we describe the pattern image in the form of the point set with the 2-dimension structure. At this point, the printed pattern $\boldsymbol{I}$ is denoted as $\{\boldsymbol{I}_{i,j} \mid 1 \leq i \leq m, 1 \leq j \leq n\}$ where $i \in \mathbb{N}$ and $j \in \mathbb{N}$ are the coordinate indicators, and the $\boldsymbol{I}_{i,j}$ represents one pixel in the printed pattern

$\boldsymbol{I}$. Noted that the values of i and j are both adjacent for one pattern and the repeated pattern $\boldsymbol{M}$ is expressed as $\{\boldsymbol{M}_{i,j} \mid 1 \leq i \leq p, 1 \leq j \leq q\}$. Although we establish the correspondence between patterns and sets, there remain some differences in their similarity expression. In general, the positional relationship of elements need not be considered in measuring sets similarity, but be involved in measuring patterns similarity. To distinguish between patterns and sets, we adopt capital letter and the letter with brackets to represent the pattern and its corresponding two-dimensional set respectively, e.g., the printed pattern $\boldsymbol{I}$ and its corresponding set $\{\boldsymbol{I}\}$. We also adopt $|\boldsymbol{I}|$ to represent the number of elements in the printed pattern. In this paper, we specify $|\boldsymbol{I}| \geq 3$ because the value of $|\boldsymbol{I}|$ is far greater than 3 in reality. In addition, the printed process will be simplified to the copy of pattern only with one or two pixels when $|\boldsymbol{I}|$=1 or 2.

Based on the above symbols and concepts, we define the MRP from the perspective of the pattern printed process as follows.

Definition 1. Minimal Repeated Pattern (MRP): Given two patterns $\boldsymbol{M}$ and $\boldsymbol{I}$, the $\boldsymbol{M}$ is defined as the minimal repeated pattern of $\boldsymbol{I}$ if $\boldsymbol{M}$ and $\boldsymbol{I}$ satisfy the following conditions:

(i) The $\{\boldsymbol{M}\}$ is the subset of the $\{\boldsymbol{I}\}$, i.e., $\{\boldsymbol{M}\} \subseteq \{\boldsymbol{I}\}$.

(ii) $\boldsymbol{I} = \varsigma_{\boldsymbol{M}} \left(\sigma_{\boldsymbol{M}} \left(\left\{ \boldsymbol{M}^{(1)}, \boldsymbol{M}^{(2)}, \ldots, \boldsymbol{M}^{(N)} \right\} \right) \right), N \geq 1$, where $\sigma_{\boldsymbol{M}}$ and $\varsigma_{\boldsymbol{M}}$ are the stitching and clipping operations on pattern $\boldsymbol{M}$ in the pattern printed process and N indicates the number of $\boldsymbol{M}$.

(iii) If $\boldsymbol{I} \neq \boldsymbol{M}$, each sub-pattern $\boldsymbol{Q}$ of the pattern $\boldsymbol{I}$ satisfying $\{\boldsymbol{Q}\} = \{\boldsymbol{M}\}$ makes $\boldsymbol{I} = \varsigma_{\boldsymbol{Q}} \left(\sigma_{\boldsymbol{Q}} \left(\left\{ \boldsymbol{Q}^{(1)}, \boldsymbol{Q}^{(2)}, \ldots, \boldsymbol{Q}^{(N)} \right\} \right) \right), N \geq 1$ valid.

(iv) For any sub-pattern $\boldsymbol{P}$ of $\boldsymbol{I}$ and $\boldsymbol{I} = \varsigma_{\boldsymbol{Q}} \left(\sigma_{\boldsymbol{Q}} \left(\left\{ \boldsymbol{Q}^{(1)}, \boldsymbol{Q}^{(2)}, \ldots, \boldsymbol{Q}^{(N)} \right\} \right) \right)$, $N \geq 1$ holds, if $\{\boldsymbol{P}\} \neq \{\boldsymbol{M}\}$, then $\{\boldsymbol{P}\} \not\subset \{\boldsymbol{M}\}$.

The conditions (i) and (ii) indicate that $\boldsymbol{I}$ can be generated by operating its sub-pattern $\boldsymbol{M}$. The condition (iii) further implicitly imposes constraints on the operations and the repeated pattern to guarantee the continuity of the printed pattern $\boldsymbol{I}$ in its any local pattern. At the same time, the condition (iii) also shows that if $\boldsymbol{I} \neq \boldsymbol{M}$, there exists other MRP of printed pattern $\boldsymbol{I}$. The condition (iv) ensures that $\boldsymbol{M}$ could not be divided into smaller repeated pattern. Based on the definition of MRP, we have the following corollaries.

Corollary 1. For any pattern $\boldsymbol{I}$ that follows the fabric pattern printed process, there is at least one MRP.

Proof: By definition of MRP, the $\boldsymbol{M}$ is the sub-pattern of the $\boldsymbol{I}$, i.e.,$\{\boldsymbol{M}\}$

$\subseteq \{\boldsymbol{I}\}$, so we can always find at least one MRP to ensure that the **Corollary 1** holds.

The corollary 1 ensures that we can always find the MRP from the printed patterns.

Corollary 2. For any printed pattern $\boldsymbol{I}$ constructed by $N(N \geq 2)$ minimal repeated pattern $\boldsymbol{M}$, if $\{\boldsymbol{M}\} \subset \{\boldsymbol{I}\}$, there are at least two identical sub-patterns in $\boldsymbol{I}$.

Proof: By definition of MRP and $N \geq 2$, we can always find one sub-pattern $\boldsymbol{P}$ in the pattern $\boldsymbol{M}$ and the remaining pattern $\boldsymbol{I} - \boldsymbol{M}$ respectively. According to the condition of $\{\boldsymbol{M}\} \subset \{\boldsymbol{I}\}$, so there are at least two identical sub-patterns $\boldsymbol{P}$ in $\boldsymbol{I}$ to ensure that the **Corollary 2** holds.

This corollary indicates that one printed pattern can contain multiple identical sub-patterns. In addition, **p**attern **s**ize **r**atio (PSR) is defined as $PSR = \frac{p \times q}{m \times n}$ to represents the proportion of sub-pattern size to original image size.

2.2. MRP Detection

Unlike the pattern printed process, the MRP detection problem requires that $\boldsymbol{M}$ be obtained from $\boldsymbol{I}$ in cases of σ and ς are unknown (See the blue dashed box of Figure 2). The detection of MRP can be treated as the inverse process of the pattern printed process. At this point, we should solve the following problem:

$$< \varsigma, \sigma, \boldsymbol{M} >= f(\boldsymbol{I}), \tag{2}$$

This represents a classic case of an ill-posed inverse problem, inherently complicating solution finding. Despite human processes' inherent inefficiency, our ability to discern MRPs in complex fabric images stands out. This observation suggests a promising strategy: mapping specific operations to their MRPs to effectively address the challenge. This method leverages human cognitive strengths, suggesting a pathway to develop algorithms that replicate this pattern recognition capability computationally.

As we have reviewed, the predominant body of existing research is focused on harnessing the intrinsic characteristics of pattern recurrence to derive MRP, predominantly through the application of clustering methodologies and image processing techniques. It is noteworthy, however, that the vast majority of these scholarly efforts have been predominantly oriented towards the techniques and methodologies devised to address the problem at hand, rather than venturing into a more profound and nuanced theoretical analysis of the MRP detection challenge itself. This stark emphasis on the solution, rather than the problem, might perhaps lead to a certain degree of constraint in terms of the specific applicability and versatility of the methodologies and techniques proposed by these studies.

Driven by advancements in computer performance and the availability of various intelligent optimization methods, we have identified the possibility of emulating the manual key-point localization technique. This is achieved by reformulating the problem into a quest for a model that meets the rigorous definition of MRP from an extensive solution space. In the next section, we will further elucidate this innovative approach, promising a viable solution for the aforementioned model. Given the inherent traits of the fabric printing process, our methodology is expected to yield not just one, but multiple solutions to Equation 2, each representing a distinct potential MRP.

3. Adjacent Key-points Localization Framework

Key-points localization methods in the field of MRP inspection of printed fabrics are summaries of human experience and lack relevant conceptual definitions and formal representations. In this paper, key-points are defined as pixels whose belonging sub-patterns have multiple identical sub-patterns in the image space based on the specific manual detection process. Initially, key-points within the pattern are determined through visual inspection. Subsequently, sub-patterns are manually cropped along these key points, and the cropped sub-patterns are concatenated in all directions from their initial positions in the image to confirm their repetitiveness.

Having established **Corollary 2**, it is evident that the printed image, composed of $N(N \geq 2)$ minimal repeated patterns, contains at least two similar local regions. Consequently, we can adapt the key-points localization method for MRP detection into a fully automatic sub-image search framework, termed adjacent key-points localization (AKL), within the single image space.

The AKL framework comprises four essential modules: seed sub-pattern selection, robust pattern representation, similar sub-pattern matching, and non-maximum suppression. Upon completing the above modules, key-points are accurately obtained. Subsequently, by utilizing these key-points as vertices, a meticulous construction of a rectangular region representing the MRP is achieved. Figure 3 illustrates the intuitive pipeline of AKL, with the detailed algorithm outlined in Algorithm 1.

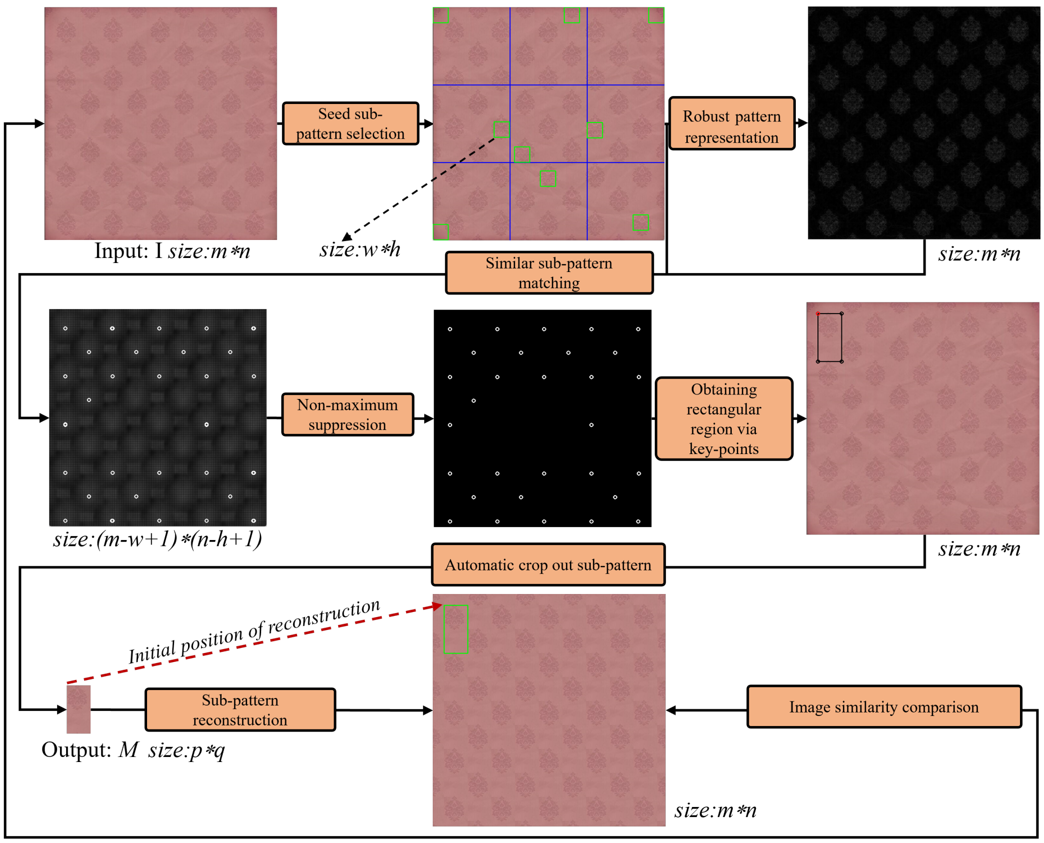

Figure 3: The pipeline of AKL framework illustrates the sequential process from seed sub-pattern selection through to the construction of the rectangular region representing the MRP.

3.1. Seed Sub-pattern Selection

Both for the manual key-points localization method and the AKL presented in this paper, the initial search sub-pattern named seed sub-pattern of the entire printed fabric image must be ascertained initially. Selecting an appropriate seed sub-pattern is paramount for accurate key-points localization, different seed sub-patterns can generate divergent minimal repeated patterns. However, an image usually contains an overwhelming number of sub-patterns, posing a formidable challenge for both manual key-points localization and AKL. Thus, we propose an automated seed sub-pattern selection method, which consists of two different but closely related sub-strategies as follows:

Selecting the initial size of the seed sub-patterns. Generally, it is understood that seed sub-patterns that are too small can result in various issues, the most notable of which are an excessive number of candidate key-points and a marked decrease in detection accuracy. Conversely, seed sub-patterns that are too large can induce another problem: the failure to detect certain key-points, which can have a negative impact on the overall performance of the system. Let the size of the printed fabric image be $m \times n$, and the size of the seed sub-pattern be $w \times h$, where $w = \lfloor \frac{m}{a} + \frac{1}{2} \rfloor$ and $h = \lfloor \frac{n}{a} + \frac{1}{2} \rfloor$, a represents the scale factor and $a \in \mathbb{N}(a \geq 2)$. We will adjust the value of a by the number of similar sub-patterns obtained subsequently, N. If N is too small, the value of a will be increased, and thus the size of the sub-pattern will be reduced, and vice-versa. In this paper, we set the initial value of a to 15, and the range of N to $[3, 8]$, if $N > 8$, then execute $a - 1$, if $N < 3$, then execute $a + 1$.

Pinpointing the initial position of the seed sub-patterns. The image is segmented into nine equal sections. Upon determining the seed sub-pattern's dimensions, our search begins from the top-left corner of each section. Adhering to a precise pixel selection sequence, we proceed from left to right, then downward. Within this grid, numerous seed sub-patterns of dimensions $w \times h$ are generated, with the current target pixel positioned at the upper left corner of the sub-pattern. However, this method results in an excessive creation of seed sub-patterns, substantially increasing computational load and straining system resources and processing capabilities.

Our approach to this challenge combines two key steps: calculating the sub-patterns' information entropy to gauge their informational complexity and assessing their connectivity to understand how well the objects within are interconnected. Only sub-patterns exhibiting both high connectivity and information entropy are chosen as seed sub-patterns. We employ a depth-first search (DFS) algorithm, a staple in computer science and artificial intelligence, to assess the connectivity of a specific sub-pattern P and then quantify its information content using a designated formula:

$$H(P) = -\sum_{i=0}^{255} p_i \log_2 p_i, \tag{3}$$

where p_i is the probability that the pixel value in the image is i.

3.2. Robust Pattern Representation

A key aspect of automating the manual method with the proposed AKL is its ability to detect MRP in complex patterns and in poorly conditioned images. This capability is essential for AKL's successful implementation and for automating what has traditionally been a black-box manual method. Therefore, we have integrated a robust, plug-and-play pattern representation module into the AKL framework to address issues with fabric images, including poor lighting and wrinkles.

Over the past few decades, robust feature extraction has significantly evolved, moving from manual designs in frequency-domain features (like Gabor, Wavelet, FFT) and spatial-domain features (such as LBP, SIFT, HOG, Haar) to automated feature learning, where deep learning has become a pivotal methodology. To balance efficiency, robustness, and accuracy, it's crucial to note that for most fabric images, opting directly for simple HOG features is often enough to achieve desired results. However, for a minority of images with complexities like lighting changes, it's advisable to use features like FFT that offer greater robustness. Upon determining the position and size of the seed subgraphs, the AKL extracts various features from both the original image and the seed subgraphs. These features are then used as input for the subsequent module, enhancing the method's robustness.

3.3. Similar Sub-pattern Matching

After identifying the seed sub-patterns and their robust representations, we retrieve similar sub-patterns across the image space with a template matching algorithm to pinpoint the exact localization of key pixels (i.e., keypoints). The algorithm slides a small template image, which represents the desired sub-pattern, over the larger target image. Various similarity metrics, such as mean squared error, correlation coefficient, and normalized cross-correlation, are computed at each position of the sliding window to quantify the resemblance between the template and the local region of the target image. The algorithm finally outputs a similarity result matrix and its dimensions are $(m - w + 1) \times (n - h + 1)$.

Algorithm 1 AKL Framework

Input: Printed fabric image $\boldsymbol{I}$
Output: Key-points kps

Preprocess the image $\boldsymbol{I}$
Initialize size scaling factor $a \leftarrow 15$, number of similar sub-patterns $N \leftarrow 0$, Iteration count $t \leftarrow 0$, $Tmax \leftarrow 12$, similar-points $sps \leftarrow []$, key-points $kps \leftarrow []$, seed sub-pattern $\boldsymbol{S}$
while $t < Tmax$ and $a > 1$ **do**
    $size \leftarrow$ calculate_seed_size(I, a)
    $positions \leftarrow$ calculate_seed_positions$(\boldsymbol{I}, size)$
    for $i \leftarrow 1$ to n **do**
        $\boldsymbol{S} \leftarrow$ extract_subpattern$(\boldsymbol{I}, positions[i], size)$
        $\boldsymbol{I}', \mathbf{S}' \leftarrow$ extract_robust_representation$(\boldsymbol{I}, \boldsymbol{S})$
        $sps \leftarrow$ similar_pattern_matching$(\boldsymbol{I}, \boldsymbol{S}, \boldsymbol{I}', \boldsymbol{S}')$
        $kps \leftarrow$ non_maximum_suppression(sps)
        $N \leftarrow$ calculate_similar_sub-patterns_number(kps)
        $N\_array.append(N)$
    end for
    $N \leftarrow$ mean(N_array)
    if $N > 8$ **then**
        $a \leftarrow a - 1$
    else if $N < 3$ **then**
        $a \leftarrow a + 1$
    end if
    $t \leftarrow t + 1$
end while
return kps

A carefully set similarity threshold is used to identify matching regions, distinguishing them from non-matching areas. Regions that exceed this threshold are identified as matches, providing an accurate indication of where the template pattern is present in the target image. However, applying a fixed similarity threshold to various printed fabric images fails to achieve satisfactory results due to factors such as image distortion caused by noise. A higher threshold may lead to the loss of similar sub-patterns in the immediate neighborhood, while a lower threshold may significantly increase the number of sub-patterns and lead to incorrect matching results. To address this issue, we develop an adaptive threshold adjustment strategy that balances these two factors, which improves the accuracy and robustness of matching.

3.4. Non-maximum Suppression

The meticulous selection of the similarity threshold and the distinctive properties of the image local patterns exert a significant influence on the designation of sub-patterns in the immediate vicinity of the seed sub-patterns as similar sub-patterns. Nonetheless, it is crucial to emphasize that these sub-patterns, which are immediately adjacent to the seed sub-patterns, do not present any utility for our specific objective: the construction of MRP. In this paper, our primary aim is to meticulously deploy the non-maximum suppression algorithm [18]. This algorithm serves a dual purpose: firstly, to curtail the non-local maximal sub-modes, and secondly, to ensure that our findings are more precise and coherent. The pseudocode of Non-Maximum Suppression in similarity result matrix is given in Algorithm 2.

Algorithm 2 Non-Maximum Suppression

Input: Similarity result matrix $\mathbf{A}_{x \times y}$, threshold φ, step λ ($\lambda \in \mathbb{N}$)
Output: Similarity result matrix after non-maximum suppression $\mathbf{A'}_{x \times y}$

for $i \leftarrow 0$ to x **do**
  for $j \leftarrow 0$ to y **do**
    $\mathbf{B}_{(2\lambda+1)\times(2\lambda+1)} \leftarrow \mathbf{A}[max(0, i-\lambda) : min(x, i+\lambda+1), max(0, j-\lambda) : min(y, j+\lambda+1)]$
    if $\mathbf{A}_{i,j} \geq \max(\mathbf{B})$ **and** $\mathbf{A}_{i,j} \geq \varphi$ **then**
      $\mathbf{A'}_{i,j} \leftarrow \mathbf{A}_{i,j}$
    else
      $\mathbf{A'}_{i,j} \leftarrow 0$
    end if
  end for
end for
return $\mathbf{A'}$

3.5. Computational Complexity Analysis

In the context of AKL, it is pertinent to note that its computational complexity is predominantly evident across three principal stages: the automatic selection of seed sub-patterns, the process of identifying similar patterns through pattern matching, and finally, the non-maximum suppression phase.

Firstly, recognizing that for a printed fabric image of dimensions $m \times n$, there exist approximately mn distinct sub-patterns, the task of isolating seed sub-patterns from this vast array of sub-patterns, guided by considerations of connectivity and the volume of information they embody, proves to be a complex undertaking intrinsically characterized by a sequencing problem. This problem is essentially computationally intensive, with a computational complexity approximating $O(mn \log mn)$. Secondly, we have demonstrated that the computational complexity of similar pattern matching method, which we have adopted, is $O((m-w+1)(n-h+1)wh)$. Moreover, the computational complexity of the classical non-maximum suppression (NMS) algorithm can be clearly defined as $O(s^2)$. Within this formula, s represents the number of similar sub-patterns, which are derived from the previously described process and is less than mn.

In our proposed algorithm, the seed sub-pattern auto selection process, a significant step, is inherently an iterative process. Thus, the total computational complexity of the proposed AKL can be meticulously calculated as $O(t(mn \log mn + (m-w+1)(n-h+1)wh + s(s+1)/2)$, where the variable t symbolizes the number of iterations that the algorithm must complete before achieving its desired result. The algorithm under consideration appears to exhibit a higher level of complexity, a trait that may initially deter potential users due to the perceived challenges associated with understanding and implementing it. However, a significant reduction in the values of and can be achieved through the judicious adjustment of two key hyperparameters: the similarity threshold and the scaling factor of the seed sub-patterns. This process of parameter tweaking could be likened to a delicate balancing act, whereby minute changes could have a profound impact on the algorithm's overall performance. Once these adjustments have been made, the computational complexity of the algorithm drops to $O(tmn \log mn)$.

4. Experiments

4.1. Datasets

To evaluate the proposed method's performance and consider the current lack of recognized public datasets in the field of printed fabric images, we create a comprehensive and challenging test dataset named PFI-10K. We collect a large number of printed fabric images from various sources, including public databases on the internet, online commercial platforms, and relevant studies published in academia. These images cover a wide range of styles, colors, textures, and sizes, encompassing different types of fabrics from traditional to modern, simple to complex. After careful filtering and deduplication, the PFI-10K dataset is formed which containing 11,592 images of printed fabrics with a variety of unique patterns and styles. We emphasize diversity to ensure that the dataset has sufficient complexity and challenges, aiming to test the algorithm's robustness in real-world scenarios. Figure 4 shows some examples of the PFI-10K dataset.

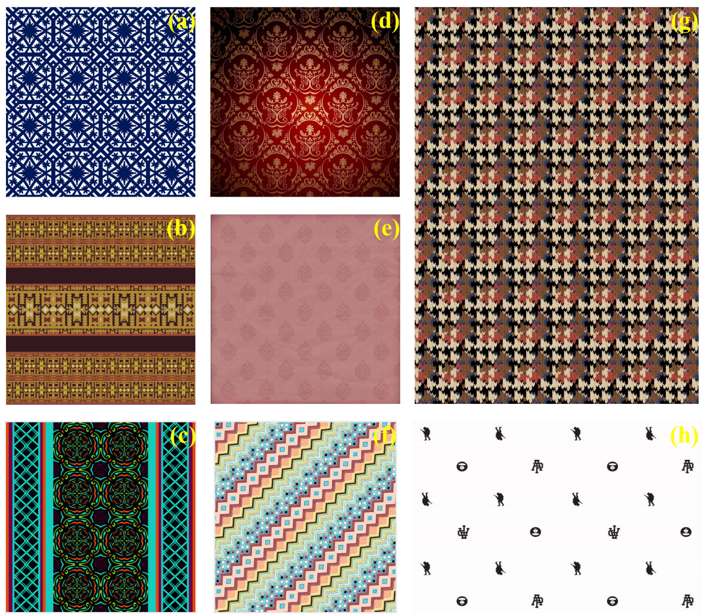

Figure 4: Examples of the PFI-10K dataset. (a) Printed fabric digital composite image with expandability on all sides. (b) Printed fabric digital composite image with horizontal expansion only. (c) Printed fabric digital image with vertical expansion only. (d) Printed fabric digital composite imatge affected by lighting conditions. (e) Realistic printed fabric image with pleats. (f) Printed fabric digital composite image with unfolded in an oblique manner. (g) Printed fabric digital image with dense sub-patterns. (h) Printed fabric digital image with sparse sub-patterns.

4.2. Experimental Setup

The experimental setup use computer hardware with the following specifications: CPU - AMD Ryzen 7 5700X 8-Core Processor (4.6GHz Turbo boost) and RAM - 32GB DDR4 2400MHz. All experiments used Python and its corresponding libraries, implementing multiprocessing and multithreading methods to improve efficiency.

We employ several metrics, including Structural Similarity Index Measure (SSIM) [23], Peak Signal-to-Noise Ratio (PSNR) [4], Normalized Mutual Information (NMI) [2], Pattern Size Ratio (PSR), computational efficiency measured in Times(/s) and the rate of successfully processing images(SIPR). The metrics together present a thorough evaluation of the AKL, offering insights into its structural, fidelity, distributional, and computational performance.

4.3. Experimental Results Analysis

Table 1: Experimental results on the PFI-10K dataset. The results of the proposed AKL are marked in **bold**.

Method	SSIM ↑	PSNR ↑	NMI ↑	PSR ↓	Times(/s) ↓	SIPR↑
Kuo's [7]	0.3692	12.3283	0.1814	0.2334	0.32	0.9857
AKL	**0.9655**	**30.899**	**0.5166**	**0.016**	**4.05**	**0.9972**

We apply AKL and existing methods to the PFI-10K dataset and reconstructed the obtained sub-pattern to original image size so as to compare it with original image to evaluate the performance of the methods. In this paper, we analyze from the following two perspectives:

Effectiveness Analysis. Table 1 presents a overview of the experimental results obtained on the PFI-10K dataset, highlighting the performance of the proposed AKL compared to existing techniques. Compared to the AKL method, Kuo's[7] method use two-dimensional discrete wavelet transform reduces computational load, which lead to the loss of information and then affect the accuracy of pattern extraction and analysis. Although FFT is effective in handling the spectral features and repetitiveness of patterns in images, it struggles to capture image details and complex patterns accurately. In addition, the adaptive K-means clustering adopted in Kuo's method does not precisely differentiate complex and subtle differences in fabric patterns due to frequency grouping errors, which directly affects the precision of pattern extraction. The SSIM, PSNR, and NMI metrics indicate that the MRP reconstructed by the AKL exhibit high consistency with the original images in terms of structure, quality, and information integrity. The high similarity metrics, along with the low PSR values, indicate the algorithm's performance in effectively identifying MRP within the images. In addition, the algorithm achieves an average processing time of 4.05s per image, significantly faster than manual detection. These results indicate the effectiveness performance and practical utility of the AKL for MRP detection. Figure 5 illustrates a qualitative visualization of the intermediate processes contained in the AKL. It is evident that AKL produces favorable outcomes for printed fabric images across various conditions.

Ablation Experiment. We conduct a series of ablation experiments to assess the contribution of different modules in AKL. By removing specific components in AKL alternately, the effect on the algorithm's performance is comprehensively analyzed. Table 2 presents ablation experiments about seed sub-pattern selection (SSPS), robust pattern representation (RPR), adaptive threshold strategy (ATS), and non-maximum suppression (NMS) on the PFI-10K dataset.

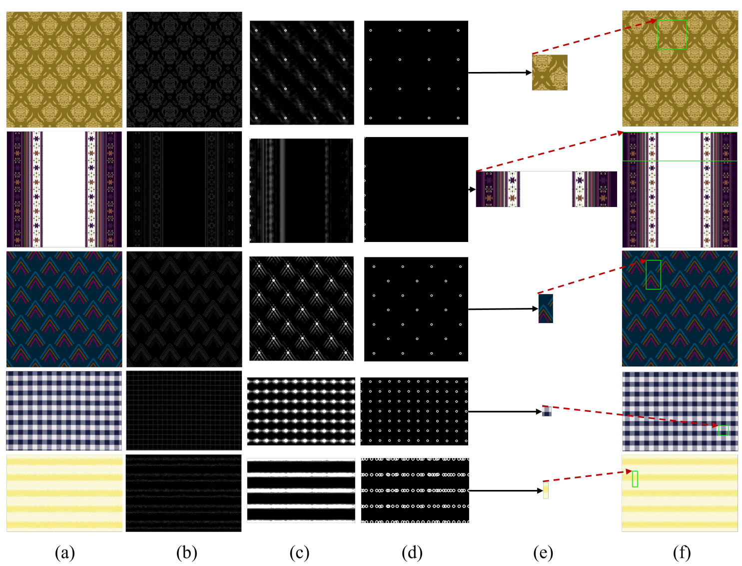

Figure 5: Visual results of AKL on the PFI-10K dataset. (a) Original image. (b) Image after robust pattern representation. (c) Similarity result matrix. (d) Similarity result matrix after non-maximum suppression. (e) MRP. (f) Image reconstructed via MRP.

(a) Effectiveness of seed sub-pattern selection: The elimination of the seed sub-pattern selection module forced the algorithm to depend on a predetermined set of seed sub-patterns for pattern matching. We designated the starting pixel in the image's upper left corner as the seed sub-patterns' localization, with a size scale factor of 15. This change resulted in signifi-

Table 2: Ablation experiment on the PFI-10K dataset.

No.	SSPS	RPR	ATS	NMS	SSIM ↑	PSNR ↑	NMI ↑	PSR ↓	Times(/s) ↓	SIPR ↑
1		✔	✔	✔	0.9277	28.5389	0.4446	0.0433	1.82	0.9474
2	✔		✔	✔	0.9573	29.941	0.5096	0.0233	3.21	0.953
3	✔	✔		✔	0.962	30.6547	0.5123	0.0192	2.77	0.9132
4	✔	✔	✔		0.9574	29.7705	0.4881	0.3626	3.84	0.7974
5	✔	✔	✔	✔	**0.9655**	**30.899**	**0.5166**	**0.016**	**4.05**	**0.9972**

cantly diminished versatility in pattern matching, evidenced by a decline in accurately identifying diverse pattern variations. The results of our experiments Table 2 (No. 1 and No. 5), illustrate the impact of seed sub-pattern selection on the performance of the algorithm.

(b) Effectiveness of robust pattern representation: With the removal of the robust pattern representation module, the algorithm relies only on the original printed fabric images to perform pattern matching. This change significantly affects the detection accuracy of the algorithm when dealing with images that are disturbed by external factors such as illumination and wrinkles (see Figure 4 (d) and (e)), thus reducing the overall robustness of the algorithm.

(c) Effectiveness of adaptive threshold strategy: Unlike the fixed threshold approach, the adaptive thresholding strategy adjusts thresholds based on local image features. This enhances the precision in distinguishing matching from non-matching regions, thereby improving accuracy. Its adaptability ensures robustness against variations in fabric patterns, noise, and distortion. This strategy's flexibility negates the need for manual threshold adjustments for every new image or pattern. Setting the similar sub-pattern matching threshold to 0.9 resulted in a notable performance decline, as evidenced by our experimental results in Table 2 (No.3 and No.5).

(d) Effectiveness of non-maximum suppression: Disabling non-maximum suppression (NMS) leads to excessive similarities in localized image regions, significantly degrading algorithm accuracy and causing a notable performance drop. The comparison between Figure 5 (c) and (d) highlights the impact of NMS, enabling precise pixel-level detection of keypoints. Table 2 (No.4 and No.5) illustrate the critical role of NMS in enhancing detection precision.

5. Conclusions

In this study, we present a robust and fully automatic framework for detecting minimal repeated patterns, automating what was once a manual process. To initiate, we rigorously formalize the concept of minimal repeated pattern detection and its associated concepts. These concepts serve as tangible computational entities, thereby facilitating a profound theoretical analysis of the manual method. Subsequently, we furnish empirical proof of the viability of the key point-based detection scheme, which is pivotal in the manual detection method. The analysis shows that at least two identical sub-patterns need to be identified in the printed fabric image in order to determine the minimal repeated patterns. Based on this, we fine-tuned the sub-pattern search framework to achieve precise and robust localization of key-points. Using these precisely localized key-points, we construct rectangular regions containing the sought-after minimal repeated patterns. Experimental results on the PFI-10K dataset further validate the effectiveness and robustness of our method. However, minimal repeated pattern detection is a pathological inverse problem with multiple solutions that satisfy the definition, so determining an optimal pattern that meets the needs of the initial design still requires further research.

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Declaration of interests

☒ The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

☐The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: