ABSTRACT: Accurate and robust tracking of defect targets in dynamic ink-jet printing videos is a huge challenge in ink-jet printing technology for digital fabrication, and becomes a popular topic for digital information applications in ink-jet printing industry. Recently, particle filters have drawn a significant amount of interest because of their robust tracking performance. In this paper, a robust defect tracking algorithm for ink-jet printing fabric products was proposed in a particle filter framework. First, the ink-jet printing defect tracking was regarded as a Bayesian estimation problem, and a representative dynamic state model was then defined prior to processing the video data. Second, an observation model based on color histogram was introduced to calculate the likelihood of sample particles. Finally, a new motion constrained resampling rule was designed by which the proposed algorithm can track defect targets undergoing abrupt motion conditions and background changes. Experimental results demonstrate the effectiveness and superiority of the proposed algorithm on tracking defect targets undergoing various challenging conditions.

Subject Categories and Descriptors
I.2.10 [Vision and Scene Understanding]: Video analysis;
I.4.10 [Image Representation]

General Terms: Video frame processing, Defect tracking

Keywords: Ink-jet Printing, Defect Tracking, Particle Filter, Color

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1. Introduction

The rapid increase of contemporary ink-jet printing fabric products over the last two decades has raised the need for monitoring and management of weaving process. Digital information methodology for automated monitoring of ink-jet printing behaviors has evolved dramatically in the past decade. Visual tracking is one of the most important problems in a wide range of digital information applications in ink-jet printing industry, such as surveillance, human computer interaction, augmented reality, and so on[1]. An accurate tracking of defect patterns from ink-jet printing videos promises reliability for ink-jet printing fabric CAD[2]. Ink-jet printing video is composed from a sequence of ink-jet fabric texture images that contain elaborate figured design with geometric motifs. Ink-jet printing image differs from traditional fabric images in that it contains many serpentine curves, regular or irregular geometric shapes, and symmetrical or unsymmetrical patterns.

Defect tracking methods are the most important preliminary steps for ink-jet printing video analysis applications. To date, manual defect tracking remains a common
method of choice for analyzing ink-jet printing patterns within these time-lapse videos[3-4]. However, in addition to being very labor-intensive and time-consuming, results of manual defect tracking may be subjective. With the development of digital information technology in the field of ink-jet printing, many researchers have designed various systems to automatically observe, control and analyze ink-jet printing behaviors based on visual inspection. In automatic visual inspection systems for real-time detection of ink-jet printing defects, obtaining a shape feature of a moving texture pattern may be necessary to enable tracing of the movement of a particular printing fabric. Tracking of a moving texture pattern from a fabric video sequence helps in determining the position of defects at different points. However, ink-jet printing imaging imposes certain challenges, such as low signal-to-noise, complicated background, and lack of a priori information. Another challenge of ink-jet printing images is the redundancy of irregular edges and boundary information in ink-jet imagery, making tracking of defect targets from the printing image a very complex task.

A robust defect-tracking algorithm is essential in solving these problems. Over the past several decades, numerous kinds of tracking algorithms have been proposed[5-10]. Generally, tracking algorithms can be divided into two major categories: (1) deterministic and (2) stochastic methods. Deterministic methods that segment images first and build associations between data points of consecutive frames in a second step require sophisticated approaches for object linking. Mean shift is a typical algorithm in the class of deterministic approaches that defines an objective function to transform tracking into an optimization problem[5]. Leichter et al. presented a modified adaptive mean shift-tracking algorithm that integrates a combination of texture and color features for robust real-time object tracking[6]. Other deterministic methods are based on target appearance, such as local features, contours, and color, which aim to correlate targets among the video sequence. However, such methods have failed to discriminate targets adequately against the background during tracking[7].

Different from deterministic methods, stochastic methods are based on Bayesian estimation theory. In such cases, visual tracking is transformed into a problem of estimating the probability density function of the state vector, which contains the target positions. Kalman filter has been proven successful in solving linear problems, and uses a series of measurements of observed overtime to estimate the status of the object in the future. However, the assumption of Gaussian is difficult to meet the needs of real scenarios, and thus Kalman filter based applications are quite limited[8]. With advances in computational ability, the particle filter has been deemed an efficient model for a non-linear, non-Gaussian, and multi-model state space. Kilic et al. proposed adaptive particle filtering for tracking multiple-moving speakers in indoor environments[9]. Zhang et al. proposed a sparse representation particle filter framework for object tracking[10]. The particle filter has been proven to exhibit excellent performance and computational efficiency.

The overall objective of this paper is to address the issue of accurate tracking of ink-jet printing defect targets generated by the weaving process. To achieve this objective, a particle filter is applied to obtain the position of defect targets on a frame-by-frame basis, thereby providing a pathway for the defection overtime. First, ink-jet printing defect tracking is regarded as a Bayesian estimation problem, and a representative dynamic state model is defined prior to processing the video data. Second, an observation model based on color histogram is built, which is adopted to calculate the likelihood of particles. Finally, a new motion constrained resampling rule is designed by which the proposed algorithm can track defect objects undergoing abrupt motion conditions and background changes.

The remainder of this paper is organized as follows: Section 2 briefly reviews the particle filter tracking framework. The proposed defect tracking algorithm is introduced in Section 3. Experimental results are provided in Section 4. Section 5 concludes the paper.

2. Particle Filter Framework

Particle filter is a well-known Bayesian sequential importance sampling technique used for posterior distribution estimation of state variables in a dynamic system[9-11]. In this paper, ink-jet printing defect tracking is regarded as a Bayesian estimation problem, and a representative dynamic state model needs to be defined. The main objective of the tracking problem is to determine the most likely target states given the set of all observations.

To formalize this goal, $X_t$ and $Z_t$ can be regarded as target state and observation at time $t$, respectively. Moreover, $Z_{1:t} = (Z_1, ..., Z_t)$ denotes all observations from the first frame up to the $t$th frame. In the recursive Bayesian estimation approach, we attempt to model a belief on the current state of the target $X_t$. This belief is expressed as a probability distribution called the posterior distribution $p(X_t | Z_{1:t})$. As a result, the goal is to find

$$\arg \max_{X_t} p(X_t | Z_{1:t})$$

(1)

The posterior distribution can be expressed recursively via the Chapman–Kolmogorov equation as

$$p(X_t | Z_{1:t}) \propto p(Z_t | X_t) \prod_{t=i} p(X_t | X_{t-1})p(X_{t-1} | Z_{1:t-1})dX_{t-1}$$

(2)

where $p(X_t | Z_{1:t-1})$ is the posterior distribution from the previous frame, $p(X_t | X_{t-1})$ is the motion model, and $p(Z_t | X_t)$ is observation likelihood.

Sequential Monte Carlo (SMC) technique is used to approximate the distribution of (2). This technique uses a set of discrete weighted particles $(X_t^{(n)}, w_t^{(n)}), n = 1, ..., N$, where $X_t^{(n)}$ and $w_t^{(n)}$ denote the $n^{th}$ particle and its asso
associated weight at time $t$. Note that $w_i^{(n)} \in [0, 1]$, and sum of the weights over all particles sums to unity. Given the weighted particle set $\{X_{t-1}^{(n)}, w_i^{(n)}\}_{n=1}^{N}$, and approximation of the posterior at previous time step $p(X_t \mid Z_{1:t}) \approx \sum_{n=1}^{N} w_i^{(n)} \delta(X_t - X_{t-1}^{(n)})$, the SMC approximation of (2) after some simplification is written as follows:

$$p(X_t \mid Z_{1:t}) \approx C \times p(Z_t \mid X_t) \sum_{n=1}^{N} w_i^{(n)} p(X_t \mid X_{t-1}^{(n)})$$  \hspace{1cm} (3)$$

where $C$ is a normalization constant.

3. The Proposed Tracking Algorithm

In this paper, we use particle filter framework for the problem of defect tracking, which can deal with non-Gaussian motions from an ink-jet printing video. For tracking defect targets based on video surveillance system, first we need to construct a motion model and calculate an observation likelihood probability. We then apply color histogram to represent the observation model and calculate the importance weights based on the observation model. Finally, the state of object is estimated using weighted sum of all particles states, and weights of particles are reinitialized for estimation of new state of target.

3.1 Target State Definition

A state at time $t$ is a target configuration defined by $X_t$, which is a mathematical description of the target. In the proposed algorithm, the target state vector $X_t$ is defined by four parameters in the non-linear dynamic state space:

$$X_t = (x_t, y_t, W_t, H_t)$$  \hspace{1cm} (4)$$

The term $(x_t, y_t)$ denotes the middle point coordinate of the defect target region where the target’s color histogram is computed. The terms $W_t$ and $H_t$ denote the width and height of the track region, respectively. The target region is in rectangular shapes. Thus, rectangular bounding boxes are utilized to approximate shape and location of the defect target. An updated bounding box is returned with the new location of the target on each subsequent frame.

3.2 Motion Model and State Estimation

The motion model governs the evolution of the state between consecutive frames. For example, if the prior distribution is available, then the predictive distribution is $p(X_{t-1} \mid Z_{1:t-1})$ determined by motion model $p(X_t \mid X_{t-1})$, which evolves the target candidates between time steps. Recently, different motion models for object tracking have been introduced by many authors, such as constant velocity model, random walk model, and adaptive motion model. Our approach adopts a random walk model based on a uniformly distributed density of the previous target state, $X_{t-1}$ as

$$X_t = 2X_{t-1} - X_{t-2} + \varepsilon$$  \hspace{1cm} (5)$$

where $\varepsilon$ is a zero-mean Gaussian noise.

3.3 Observation Model

The observation model is required for update of predicted states. Thus, changes in the motion of target are catered faithfully. For visual tracking, the observations consist of information extracted from a video sequence. In this paper, the observation model is established to describe the correlation between the observation and the state of the object. The weights of the particles are updated subsequently.

The observation likelihood $p(Z_t \mid X_t)$ measure shows how well the current observations support the predicted target state. $X_{t-1}$ is assigned a weight $w_i^{(n)} = p(Z_t \mid X_{t-1}^{(n)})$ according to the evaluation of the observation likelihood at its configuration. In this paper, the particles are initialized on target and passed through the observation model.

To date, most of observation likelihood models are based on color histogram because it can cater to small changes in appearance of target. In our work, the color histogram is chosen as the observation model for measuring the appearance similarity of ink-jet printing patterns. The color histogram has been proven to be one of the most efficient features for tracking. Here, we use a RGB color model for our experiments with 8*8*8 bin histogram. A fitness function is formed to measure the observation distance between the target and candidate. The Bhattacharyya coefficient is used to measure the similarity between two histograms, which is defined as

$$B(h_i \mid h_2) = \sum_{i=1}^{M} \sqrt{(i)(i)}$$  \hspace{1cm} (6)$$

where $M$ is the number of bins in the histograms, $h_i$ and $h_2$ are the histograms being compared. $B(h_i \mid h_2)$ is large when the histograms are similar, and is small when they are very different.

We consider the difference in color histogram between the initial target region and the tracker region as value of the weight. The difference is

$$d = \sqrt{1 - B(h_i^{(n)} \mid h_i^{(n)})}$$  \hspace{1cm} (7)$$

where $d$ is the distance between two histograms derived from the Bhattacharyya similarity coefficient, $h_i^{(n)}$ is the histogram of the target to be selected initially, and $h_i^{(n)}$ is the histogram extracted at the current location of the particle $X_{t-1}^{(n)}$.

The observation likelihood of the $n^{th}$ particle is defined as

$$w_i^{(n)} = p(Z_t \mid X_i^{(n)}) \propto \exp(-\lambda d^2(h_i^{(n)}, h_i^{(n)})) \hspace{1cm} (8)$$

where $\lambda$ is a small positive value and controls the sensitivity of the goodness value to the change of the weighted norm.

An updated distribution is achieved after applying the observation model to the set of particles. The newly weighted particle set represents the new posterior
distribution, which in turn represents the updated belief on the state of the defect target. The number of effective particles is calculated, and resampling is performed if this number is less than the threshold value to reduce particle degeneracy.

3.4 Motion Constrained Importance Resampling
The most important step of particle filter is importance resampling. The process of importance resampling from the weighted particle set involves removing particles not very representative of the target state and producing multiple copies of more representative particles. Abrupt motion, such as inconsistent speed and high frame-rate videos, may lead to drastic and unpredictable target motion in ink-jet printing imagery. Under these circumstances, the standard importance resampling cannot ensure that the samples cover and converge at the real state, eventually resulting in tracking failure.

In this paper, a novel motion constrained resampling rule is proposed in which the filter can detect the above situations. This criterion is defined by an abrupt indicator value (AIV) of the defect movement, which returns to one if the abrupt motion can be detected. Otherwise, it is zero. Before resampling, the AIV value is calculated using Eq. (9). Taking into account the sorting of normalized weights and AIV values, the particles are resampled, and particles with both higher weight and AIV obtain additional new sub-particles.

\[
\text{AIV}(\{X_t^{(i)}\}_{i=1}^N, D) = \begin{cases} \frac{\sum_{i=1}^N d(h_t^{(i)}, h_t^{(s)})}{N \times D} & \text{if } T_o < 1 \text{ \text{ (9)}} \\ 0 & \text{otherwise} \end{cases}
\]

where \( T_o \) is a threshold.

In this step, \( N \) new particles are drawn from the previous set \( \{X_t^{(i)}\}_{i=1}^N \), \( \{w_t^{(i)}\}_{i=1}^N \), according to their weights \( \{w_t^{(i)}\}_{i=1}^N \), \( \{\text{AIV}_t^{(i)}\}_{i=1}^N \), with replacement. New particles are then assigned uniform weights to prevent degeneracy problem.

Thus, the number of meaningful particles can be increased, and the particles can approximate the true state of the defect target more accurately.

In summary, the details of the proposed algorithm are summarized as follows:

**STEP 1.** Let \( t = 1, n = 1, N = 50, T = 500, T_o = 0.8 \)

**STEP 2.** Initialization. If \( t < T \), then randomly sample PDF \( p(X_{t-1} | Z_{1:t-1}) \) to select \( N \) particles on detected object and \( \{X_{t-1}^{(i)}\}_{i=1}^N, \{w_{t-1}^{(i)}\}_{i=1}^N \) set initial weights \( w_{t-1}^{(i)} = 1/N \), otherwise go to Step 7

**STEP 3.** Evaluate observation model. For each particle \( X_t^{(i)} \), assign an importance weight \( w_t^{(i)} \) by evaluating the observation likelihood \( w_t^{(i)} p(Z_t | X_t^{(i)}) \) and normalizing the weights. In this manner, \( \sum_{i=1}^N w_t^{(i)} = 1 \)

**STEP 4.** Resample. Calculate \( R_{eff} = \frac{1}{\sum_{i=1}^N (w_t^{(i)})^2} \). If \( R_{eff} \) is below a user-defined threshold, perform motion constrained resampling to generate new samples \( \{X_t^{(i)}\}_{i=1}^N, \{w_t^{(i)}\}_{i=1}^N \) based on \( \{w_t^{(i)}\}_{i=1}^N \) and \( \{\text{AIV}_t^{(i)}\}_{i=1}^N \)

**STEP 5.** Estimate the state by \( X_t = \frac{1}{N} \sum_{i=1}^N w_t^{(i)} X_t^{(i)} \), and return to the weighted particle set approximating the posterior distribution of time \( t, p(X_t | Z_{1:t}) \approx \{X_t^{(i)}\}_{i=1}^N, \{w_t^{(i)}\}_{i=1}^N \)

**STEP 6.** Set \( t = t + 1, n = n + 1 \), go to Step 2

**STEP 7.** Stop

4. Experimental Evaluation
In this section, we present experimental results to verify the effectiveness and efficiency of the proposed algorithm. The proposed algorithm was implemented in C++ and tested on a 2.93 GHz PC with 4 GB memory. We processed 50 particle samples in the experiments. In our experiments, we compare the tracking results of the proposed algorithm with two popular tracking algorithms qualitatively and quantitatively: mean-shift (MS) algorithm [5] and color-based adaptive particle filter (CPF) algorithm [11]. The tracking results for the three algorithms are highlighted by bounding boxes in different colors over representative frames of the test video sequence. In all compared algorithms, the target is initialized by using ground truth information in the first frame.

We show some representative frames of the tracking results of three different algorithms in Figure 1. A defect target labeled by a rectangle border in the first frame is tracked throughout the sequence. In the test ink-jet printing sequence, different challenges exist, such as motion speed change, background clutter, partial occlusion, etc. The six representative frame indices are 1 (normal), 106 (ink-jet drop defect), 235 (background clutter), 351 (partial occlusion), and 460 (partial missing). From the qualitative results shown in Figure.1(a)”(b), we observe that the MS and CPF algorithm are not robust and do not cope well with accurate tracking. The MS algorithm loses the defect targets because of background changes and color similarities. The CPF algorithm has lower position deviation than the MS algorithm when defect targets appear to have motion change in position between adjacent frames. However, the CPF algorithm cannot resample sufficient searching space to guarantee adequate samples to represent the motion probability of the defect targets. Most particles are concentrated around several unimportant points, thereby losing sample diversity and causing high detection error to occur. In contrast, Figure.1(c) shows that the proposed algorithm can obtain good tracking results and track the target robustly because
of the motion constrained resampling between particles, which provides a way to track defect targets undergoing abrupt motion conditions and background changes.

Figure 1. Results given by three algorithms on an ink-jet printing sequence. (a) MS algorithm; (b) CPF algorithm; (c) proposed algorithm. From left to right, the frame number is 1, 106, 235, 351, and 460

One of the goals of this work is to demonstrate that the proposed algorithm is robust and stable. Some quantitative results are summarized in Table 1. The metrics used in the quantitative evaluation include Precision Ratio (PR), Recall Ratio (RR), and \( f_{\text{measure}} \) metrics, which are formulated as follows:

\[
PR = \frac{TP}{TP + FP}, \quad RR = \frac{TP}{TP + FN}, \quad f_{\text{measure}} = 2 \cdot \frac{PR \cdot RR}{PR + RR}
\]

where TP, FP, and FN are true positive, false positive, and false negative pixels detected in the evaluation sequences. Table 1 shows that the MS algorithm achieves the lowest \( f_{\text{measure}} \), in part because of the motion effects and the vulnerability in front of foreground-background color similarities. Because the CPF algorithm is combined with efficient color histogram information, better precision and recall rates are obtained, which allow an \( f_{\text{measure}} \) of 0.79. The proposed algorithm increases the precision and maintains the recall values in most frames from Figure.1, as compared with other algorithms. The proposed algorithm achieves an \( f_{\text{measure}} \) of 0.89, solving the problem that motion effects and color similarities produce. The reason for the superior performance lies in the ability of the proposed algorithm to handle ambiguous training examples, which are provided by the motion-constrained resampling rule. From the analysis of results, we can observe that the proposed algorithm performs better than the MS algorithm and the CPF algorithm in terms of \( f_{\text{measure}} \).

We show the performance on two defect frames (Frame 106 and 235) from the same video sequence with noise added to demonstrate further the robustness of the proposed algorithm. We use white Gaussian noise with two different configurations, and the noise scales \( \sigma \) are 10 and 20, respectively. Figure 2 shows several snapshots of the tracked results for the three compared algorithms. Figure 2 shows that the MS algorithm is easily impacted by noise and exhibits many tracking failures. The estimated positions of defect targets by the MS algorithm are distant from the ground truth. When the noise level is low (\( \sigma = 10 \)), the CPF algorithm works better with more accurate tracking. However, the tracking accuracy of the CPF algorithm drops considerably once the noise becomes heavier (\( \sigma = 20 \)). The proposed algorithm is robust to heavy noise in most scenarios and can still keep the track because the target is distinguished from its background by the proposed color histogram observation model. As shown in Figure 2, the proposed algorithm demonstrates its robustness to low SNR, indicating its potential to apply the proposed algorithm in real ink-jet printing application scenarios.

<table>
<thead>
<tr>
<th>Metric</th>
<th>The MS algorithm</th>
<th>The CPF algorithm</th>
<th>The proposed algorithm</th>
</tr>
</thead>
<tbody>
<tr>
<td>Figure 1 (a)</td>
<td>Figure 1 (b)</td>
<td>Figure 1 (c)</td>
<td></td>
</tr>
<tr>
<td>Precision Ratio</td>
<td>0.42</td>
<td>0.73</td>
<td>0.86</td>
</tr>
<tr>
<td>Recall Ratio</td>
<td>0.54</td>
<td>0.85</td>
<td>0.92</td>
</tr>
<tr>
<td>( f_{\text{measure}} )</td>
<td>0.47</td>
<td>0.79</td>
<td>0.89</td>
</tr>
</tbody>
</table>

Table 1. Comparison Results of Performance Measure

Figure 2. Defect tracking comparison among three algorithms when noise is added. (Two different levels of noise with \( \sigma = 10 \) and \( \sigma = 20 \)).
5. Conclusion

Emerging digital information technologies are giving ink-jet printing industry more opportunities to boost product quality. In this study, we focus on a digital information research for quantifying defect target tracking difficulty of the ink-jet print image sequence. This paper presents a defect-tracking algorithm under a particle-filtering framework for ink-jet printing videos, which can provide robust and accurate target localization and tracking. An observation model based on color histogram is built and adopted to calculate the likelihood of sample particles. A motion constrained resampling method to guide particles to appropriate states is then proposed. This method helps to solve the unpredictable abrupt motion efficiently and suppress the cluttered background properly. Experimental results on real ink-jet printing videos and comparisons with state-of-the-art algorithms demonstrate that the proposed algorithm delivers more accurate tracking performance and is robust to abrupt motion, low SNR, as well as background changes.

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