Research Article

Image Stitching Technology in 3D Film Production Based on Digital Image Processing

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Image stitching in 3D film production synchronizes multiple independent frame images as a single high-resolution output. The stitching process is common for displaying a large coverage or shot in a single frame containing distinct images. For improving the realistic accuracy of 3D film images, this manuscript introduces an Itinerant Pixel-Matching-based Stitching Process (IPMSP). The proposed stitching process relies on cross-sectional pixels identified in merging two or more images. Based on the linear cumulative distribution in augmenting images, the homogeneity feature is identified. If the homogeneity is high then the stitching for linear pixels occurs increasing the frame resolution and size. The cumulative distribution is determined using the recurrent neural network in verifying homogeneity and contrast. For the contrast pixels identified, the cross-sectional matching is performed for substituting similar pixels in the missing sections. The process is repeated until the stitching region is the same based on the homogeneity feature and increased dimensions. Therefore, this process is capable of improving accuracy, precision, substitution, and reducing errors and complexity.

1. Introduction

Image stitching is a combination of images that contain an overlapping section to create a single panoramic image. Image stitching is an important task in computer vision and image processing systems. Image stitching or photo stitching is a process that creates a high-resolution image by combining multiple images [1]. Image stitching technology is widely used for photo editing processes that contain certain camera features. Expensive cameras and lenses are not needed for image stitching technology that improves the cost-effectiveness of the system [2]. Image stitching technology provides various sets of services to create panoramic images for an application. Computer-based applications mostly use image stitching technology to get seamless images [3]. Processes such as image registration, image calibration, and image blending have come off the steps that are available in image stitching technology. Identifying matching features and patterns are done by the image registration process. The image calibration process reduces the difference between lens and lens models. The calibration process performs alignment and composting that provide an appropriate set of details for the blending process. The image blending process combines every detail of images and creates finalized high-resolution images. Several algorithms are used in image stitching technology to get an appropriate panoramic image [4,5].

Image stitching for 3D videos is a complicated task to perform in an application. Image stitching needs an appropriate set of details when it comes to 3D videos. 3DmmC3 videos contain actual details about an event that reduces the latency rate in the searching process [6]. Image stitching produces certain templates and patterns that find out the exact pixel of an image. Images are stitched based on templates and patterns. Field of view (FOV) is a problem in 3D videos that cause troubles in the image stitching process [7]. The image stitching process finds out the relationship among multiple overlapping images and provides the necessary set of data for further process. In 3D videos, the Image stitching process blends the overlapping images and creates
a new aligned image [8]. FOV limitations are reduced by the image stitching process. Image stitching is more complicated in 3D videos due to moving objects and frames. Panoramic stitching is mostly used in 3D videos to that reduce the shakiness, blurriness, and fadedness of an image [9]. The foreground technique is used here to reduce the blurriness in the stitching process. Panoramic stitching maximizes the resolution of an image in 3D videos that enhance the feasibility of the system. The image stitching process achieves low texture problems and low-resolution problems in 3D videos [10].

Machine learning (ML) techniques are most commonly used in various fields to improve the performance rate. ML techniques provide various methods to perform particular tasks. Image stitching technology uses ML techniques and algorithms for the stitching process [11]. The convolutional neural network (CNN) approach is a commonly used ML technique for the image stitching process. CNN approach uses a feature extraction process to get a feasible set of data for the stitching process [12]. The feature extraction process extracts important features that are presented in an image. CNN approach maximizes the efficiency rate in the image stitching process that enhances the performance of an application. The deep feature extraction method is used for the panoramic image stitching process [13]. The deep feature extraction method increases the matrix among the images that provide necessary information for the stitching process. The deep feature extraction method provides high-resolution panoramic images that improve the effectiveness of the image processing system. Speeded up robust feature (SURF) algorithm is also used in the image stitching process that classifies the metric of an image. The classification process is performed to detect the important structures of an image by using the image registration process [14, 15].

2. Related Works

Li et al. [16] introduced a deep stitching approach for the image quality assessment (IQA) process. Omnidirectional images are used here to find out the effective contents that are presented in an image. IQA validates the high-resolution images and produces an optimal set of data for further process. The recurrence module is used in the stitching approach to improve the occurrence of a high-resolution image. The proposed approach increases the quality of assessment that improves the performance of the system.

Hu et al. [17] proposed a feature-matching score-based approach for continuous point cloud stitching. The main of the proposed method is to find out the actual time and energy consumption rate of the stitching process. Feature matching calculates the scores and patterns of an image by identifying the frames of an image. The feature matching approach produces scorecards for an image that provide the necessary set of data for the stitching process. The proposed approach increases the accuracy rate in the stitching process which enhances the efficiency of the system.

Pham et al. [18] introduced a fast-adaptive stitching algorithm for large-scale aerial image stitching. Feature extraction and feature matching method is used in the stitching process that finds out the important features of an image. An adaptive selective algorithm is used here to eliminate the optimization problems in the unmanned aerial vehicle (UAV). The proposed method increases the accuracy rate in the image alignment process. Experimental results show that the proposed method reduces the time consumption rate in the computation process.

Cui et al. [19] proposed an unmanned aerial vehicle (UAV) thermal infrared remote sensing (TIRS) for the image stitching process. The global similarity prior (GSP) model is used here for the remote image stitching process. TIRS finds out the important features of an image that provide an optimal set of data for the stitching process. The proposed method improves the image alignment ability which enhances the efficiency rate of the system. The proposed TIRS method increases the feasibility and effectiveness of the system.

Xue et al. [20] introduced a longitude-based interpolation algorithm (LLBI) based on fisheye images for the image stitching process. LLBI is used here to find out the problems that are presented in an image. A weighted fusion algorithm is used in LLBI to identify the important features of an image. LLBI analyzes the patterns and features of an image that establish information to perform a particular function. The proposed method improves the quality of an image through the image stitching process.

Dai et al. [21] proposed an edge-guided composition network (EGCNet) for image stitching. Perceptual edges are used here to provide better structure consistency for the stitching process. The proposed approach reduces the blending problems that are available in an image. A real image stitching dataset (RISD) is used here to train the stitching images for the stitching process. The proposed EGCNet improves the performance rate and efficiency rate of the image stitching process.

Chen et al. [22] introduced a new angle-consistent warping technique for the image stitching process. Angle-consistent is used here to find out the problems that are presented in the stitching process. Feature points are identified by angle-consistent that train the necessary dataset for image stitching. The warping technique is mainly used to find out important regions of an image that provide an optimal set of data for further process. The proposed approach improves the performance and reliability of the image stitching process.

Zhao et al. [23] proposed a deep neural network-based homography estimation method for image stitching. Key components and features are identified by the feature extraction process. A synthesized training dataset is used here to train the data that are necessary for the stitching process. The proposed method estimates the accurate homography of an image that improves the effectiveness of the system. The proposed estimation method reduces the computation cost, time, and energy consumption rate in image stitching.

Youssef et al. [24] introduced a geometric matrix relation-based smart multi-view panoramic imaging integrating stitching (SMPI) for image stitching. The main purpose of the proposed SMPI method is to reduce the storage space of data. The feature extraction process is used here to extract
the important key features from an image and produce a feasible set of data for the stitching process. The proposed method increases the accuracy rate in image stitching which enhances the efficiency and robustness of the system.

Cao [25] proposed an image registration algorithm using a convolutional neural network (CNN) for video image stitching. The proposed method is mostly used in UAVs that enhance the performance rate of video image stitching techniques. The homography estimation process is also done by the CNN approach uses the feature extraction technique to find out the key factors in an image. The proposed method identifies every feature in video image stitching that improves the reliability and effectiveness of the stitching process.

Shi et al. [26] introduced a misalignment-eliminated warping image stitching method using a grid-based motion statistic (GMS) matching technique. GMS is used here to find out the accurate emotional features of an image that produce an optimal set of data for stitching. The proposed warping technique reduces the error rate in image stitching which enhances the efficiency of the stitching process. The proposed method achieves a high accuracy rate in the homography estimation process.

Wan et al. [27] proposed an aggregated star group-based image stitching algorithm. The proposed algorithm is mainly used to compress the dataset which reduces the storage space of image stitching. Aggregated star group is used here to find out the accurate relationship of local stars that produce necessary details for the image stitching process. Star group improves the effectiveness rate in the data transmission process. Experimental results show that the proposed method maximizes the efficiency rate of image stitching.

Grover et al. [28] introduced a large-baseline deep homography module-based image stitching framework. The feature extraction technique is used here to find out the key components and scales of an image. Extracted features are used in the image stitching process that estimates the homography of the stitching process. When compared with traditional methods, the proposed method improves the performance, scalability, and feasibility of the image stitching process.

3. Itinerant Pixel-Matching-Based Stitching Process (IPMSP)

The image stitching process is designed to synchronize multiple independent frame images as a single high-resolution output based on the different feature verification. Based on the input image stitching is to improve the realistic accuracy due to cross-sectional pixels and missing section identification in merging two or more images. In 3D films to viewers, the stereoscopic input images have an additional dimension, and the homogeneity feature of disparity does not be taken care of a large coverage or shot in a single frame containing distinct images refers to independently stitching the two or more views. The features such as homogeneity and contrast are verified and check similarities between the input image features. The feature verifications are processed based on the linear cumulative distribution in improving images. Then the homogeneity feature is identified based on LCDF analysis required from the features. Therefore, the linear cumulative distribution based on input images is observed at different instances through the recurrent neural network. This process is used to detect the cross-sectional pixels and homogeneity features based on the stitching of two or more images. In particular, the cumulative distribution based on homogeneity and contrast verification is used to increase the frame resolution and size depending on the previous image features verification with the pursued input image. The single frame includes distinct images and multiple independent frame image analyzes based on sectional homogeneity verification. According to the stitching of linear pixels occurrence, the input image is verified with two features, namely, homogeneity and contrast. In Figure 1, the proposed process functions are illustrated.

The feature verification based on homogeneity and contrast analysis depends on 3D film images on a recurrent neural network. This image stitching process aims to improve realistic accuracy and reduce errors at the time of identifying contrast pixels. The challenging role in this proposed process is identifying the missing pixels at the time of the image stitching process based on the 3D images with the pursued input image. The stitched image is verified in the form of linear pixels from the previous image stitching based on 3D representation. The sectional homogeneity verification requires three sections such as cross section, linear matching, and substitution analysis is performed. The input image analysis based on feature verification through linear pixels in 3D film production is processed for homogeneity feature and contrast pixels verification. This consecutive process relies on their similarity check and is analyzed with the LCDF method through the recurrent neural network. The single high-resolution linear pixels are distributed for augmenting the pixels. The similarity analysis reduces the pixels missing and increases the accuracy through even pixel verification. The proposed process performs pixel matching and stitching to increase homogeneity features and contrast pixels in the pursued input image. Based on 3D representation, the pursued new input image relies on performing dimension verification through digital image processing based on RNN. The consecutive process of the recurrent neural network, the image feature, and dimension verification has been further analyzed with the linear pixels accurately and the stitching region is the same in the output image for more accuracy.

3.1. Feature Verification. The collection of pixels in 3D film production based on digital image processing assists to provide homogeneity and contrast analysis through feature verification. This verification is common for displaying a large coverage or shot in a single frame, preventing the complexity at the time of image stitching. The feature verification of input images provides a precise output of high-resolution images through merging two or more images. The feature verification process is shown in Figure 2.

The $H$ and $C$ from the input images are extracted from all possible dimensions. This relies on the cross-sectional
input segregation across the edge pixels. A DCF for $H$ and $C$ is cumulatively constructed for the segregated dimension using linear pixels. If both the CDF and linear representation are nominal, then this verification is disparity less (Refer to Figure 2). IPMSP considers image stitching in 3D film production and serves as the single frame containing distinct images. Let $Image_1(x, y)$ represents the first input image from 3D film production. The sequence of input images is represented as $Image_2(x, y)$ and is given as follows:

$$Image_1(x, y) = \frac{Fp}{St_1St_2} * f_\gamma * \left(\frac{Fp}{St_1} x' + \frac{Fp}{St_2} y'\right).$$ (1a)

$$Image_2(x, y) = \frac{Fp}{St_1St_2} * f_\gamma * \left[Fp \left(\frac{x'}{St_1} + \frac{y'}{St_2}\right)\right] * 3xx'. $$ (1b)

In equations 1a and 1b, where $Fp$ is the variable used to denote 3D film production, $St_1St_2$ are image stitching along with the distinct images, and $f_\gamma$ represents the feature verification based on homogeneity and contrast analysis, the image stitching is computed as follows:

$$Image_{St} = \sum_{D} \sum_{\Pi} \left\|H_i - C_j\right\|^2,$$ (2)

where

$$f_{ij}^\gamma = \begin{cases} H_i - H_j, & i f L = 1 \\ C_i - C_j, & i f L = 2 \end{cases}$$ (3)

In the above equations (2) and (3), the variable $D$ represents the disparity at the neighboring image pixels with $i$ and $j$ of the right panorama. The $H$ and $C$ are the homogeneity and contrast features based on previous image pixels and $n$ is the four connected stitching of image pixels $i$ and $j$ inappropriate input stereoscopic image. If the input image pixel $i$ in the right panorama comes from the input image $Image_1(x, y)$, which is indicated by its label $L = 1$. Where $H$ and $C$ are the features verified for the 3D film production $Image_2(x, y)$. This feature verification serves as the input to the similarity verification for digital image processing $Image_3(x, y)$ follows to consider image stitching in 3D films. The feature verification is to perform the stitching based on the image homogeneity and contrast relying on cross-sectional pixels. The remaining images can be correctly positioned and then the stitching process can be done. Therefore,

$$Image_d(x, y) = \exp \left[ \frac{x^2 + D^2y^2}{3HC} \right] \sin \left(3H \frac{x}{C} + n\right).$$ (4)

Figure 1: IPMSP illustration.

Figure 2: Feature verification process.
In equation (4), \( \Delta \) represents the feature verification associated with \( \text{Image}_1(x, y) \) through \( \text{Image}_2(x, y) \) and \( \text{Image}_3(x, y) \). Based on the feature analysis, image stitching is important in determining the homogeneity feature of the input images. Therefore, the computation is carried out for the homogeneity feature is identified based on cross section, linear matching, and substitution verification and whose \( n \in [(\pi/2),-(\pi/2)] \). The stitching of the image undergoes feature and similarity verification using the condition \( \text{Image}_2(x, y) = \text{Image}_1(x, y) \) based on linear cumulative distribution. The homogeneity and contrast are shown in equation (4) for the single frame containing distinct images and performs stitching of the image through RNN for \( n \times n \) image pixels using equation (5)

\[
\text{Image}_2 = \text{Image}_1 = \sum_{i=1}^{n} \sum_{j=1}^{n} S_{ij} [H_{ij} C_{ij} + H_{ij} C_{ij-n} + H_{ij} C_{i-nj}],
\]

(5)

where the input image feature is verified based on \( H_{ij} \) and \( C_{ij} \). In the above equation (5), the image stitching through similarity is verified for processing LCDF. This LCDF state is not performing the different pixels in the 3D representation-based input image in any \( n \) or \( n \times n \) undergoes high homogeneity. Then the stitching for linear pixels occurs in the input image for performing the LCDF function based on the feature. Based on the feature verification of image pixels, the above equation is used to analyze the cumulative distribution of uniformity and contrast, so as to verify the cross-sectional uniformity of uniform pixel verification. In a 3D film production-based digital image processing, the feature and similarity verification is performed by processing linear cumulative distribution from the neighboring image pixels. The assisted image stitching process takes place based on the linear pixels occurrence in the 3D representation. The LCDF for similarity verification using even pixels is shown in Figure 3.

The linear pixels are induced for \( \rho(cr, \text{lm}) \) such that linear and cumulative representations from the image \( \Delta \) are made. Based on the error interrupt, the linear cumulative modifications (without \( E \)) are performed. From this point, the matching linear and cumulative pixels are alone represented for \( f_v \). This provides for mitigating \( D \) and hence the \( M_{\text{pixels}} \) (Refer to Figure 3). The LCDF consists of even pixel verification to identify the resolution and size of the images. The homogeneity features output and linear distribution as in equations (1a) and (1b). The probability of accumulated linear distribution images and neighboring image pixels at different time intervals \( t \) without errors and complexity \( \rho(cr, \text{lm}) \) is given by

\[
\rho(cr, \text{lm}) = \frac{- (x'/S_{t1} + y'/S_{t2})}{Fp}.
\]

(6)

In Equation (6), the variable \( E \) denotes the errors at the time of the image stitching process based on similar pixels with the same frame size and resolution through similarity verification. The LCDF depends on image pixels of 3D film images at different time intervals \( t \). In the LCDF process, the horizontal, vertical, and diagonal lines of the image can be expressed as \( 1 - [(H_{ij}) \sum (S_{1} + S_{2})] \) and estimated using contrast pixels identification. The condition for maximizing LCDF is \( n = 1 \) as the even verification for the pixels. This is the cross-sectional pixel identification based on the homogeneity feature. Hence, the missing pixel is identified in the \( \forall (H_{ij}, t) \), \( t \in n \) condition. Linear matching is the process based on the homogeneity feature being high in the input 3D film image for \( x \) and \( y \). If the cross section and the linear distribution of 3D film images at different intervals are calculated, output for both cross-sections is matching with linear pixels of \( cr \) and \( lm \). Therefore, the contrast pixel identification performs; the pixel substitution based on similar cross-sectional and linear pixels is evaluated as

\[
(cr + \text{lm}) \forall t \epsilon n = \left(1 - C_{ij}\right) \left(\frac{(x'/{S_{t1}} + (y'/{S_{t2}}))}{S_{t1} + S_{t2}}\right)
\]

(7)

In equation (7), the similarities in cross-sectional and linear pixels of the input image pixels are identified. Then pixel substitution is performed for verification time. If this \( (H_{ij}, t) \forall t \epsilon n \) exceeds, then missing pixels are identified. An error occurs in a 3D film image maximizes \( H \), defacing the contrast pixels and matching based on cross section and linear matching. The learning for \( D \) based errors is shown in Figure 4.

The input \( \bar{C}_r \) is analyzed \( \forall \) for possible combinations of \( D \) and \( lm \) across the extracted linear pixels. If \( f_v \) is true then \( M \) pixels are extracted for \( E \) and \( S^b \). An \( f_v = \text{false} \) pixel is considered an error and the process in Figure 3 is pursued from this. From the extracted \( C_{ij} \) and \( H_{ij} \), the assimilation is further mapped with \( lm \) (alone) for \( f_v \) assessment (Figure 4). This process is repeated until the stitching region is the same based on the available homogeneity feature of \( E \) as \( [n, H, H_n, \rho(cr, \text{lm})] \) post the image stitching at different \( T \) intervals. The output for the error in 3D film images is based on cross section and linear matching verification, the condition \( (H_{ij}, H_{ij}) \forall n \epsilon E \) is substituting similar pixels in the missing pixels. Based on the matching process if the cross section pixel and linear pixel are matched then it is processed. Whereas, if the cross section pixels and linear pixels are unmatched then substitution is performed with the missing pixels identification. At this time, dimensions are increased. The outputs are addressed for final verification and accumulated linear pixels in the previous image stitching. For instance, the errors and complexities are identified using different pixels in the section and it depends on homogeneity and contrast verification based on the condition \( \rho(cr, \text{lm}) \) for the differing pixels in equations (1a) and (1b). Let \( S^b \) and \( M_{\text{pixels}} \) represent the substitution and missing pixels identification functions in both the instance in the above equations (1a) and (1b). It refers to the error-less and realistic accuracy output for the 3D film image-based digital image processing. Therefore, the final verification \( (F_{\text{Verify}}) \) is computed as follows:
\[ S_b = \sum_{m \in E} (cr + lm)_i = n + \sum_{m \in E} (cr + lm)_{i,j} = n + \sum_{i \in E} C_i, \quad (8) \]

where

\[ M_{\text{pixels}} = \sum_{m \in E} \sum_{i \in C} (cr + lm)_{i,j}(1 - C_i) = \sum_{i \in E} (H_n - H_f)_i (cr + lm)_n. \quad (9) \]

In the above equations (8), and (9), final verification is computed as an instance of \((cr, lm)\) for \(H\) and \(C\) features to evaluate the error-less and realistic image stitching in 3D film production. Therefore, \(S^b\) relies on \(H\) and \(n\) whereas \(M_{\text{pixels}}\) depends on \(cr\) and \(lm\). Based on the condition missing pixels identification and \(n\) need not be the same but also not different provided pixels and frames at a different time interval can be achieved successfully. In this condition, if \(F_{\text{Verify}} = M_{\text{pixels}}\) then substitution and missing pixels detection do not occur. The similar pixels in that region are analyzed and verified based on equations (1a) and (1b) does not represent 3D for further film images in a single frame containing distinct images. This final verification depends on \(n = 1\) and \(H_n \forall t \in n = H_f \forall n \in E\) for which the causing errors in the image stitching process based on the different intervals \(t\). The complex problems of \(0 < n < 1\) are detected for the missing pixel checking of \(F_{\text{Verify}} = S^b + M_{\text{pixels}}\) that is processed in different time intervals of \(F_{\text{Verify}}(t) = S^b(t - (H_n/H_f)) + M_{\text{pixels}}(t) \forall t \in n \) and \(n \in E\), respectively. The cross section and linear pixels in the previous image stitching instance equate to a recurrent neural network. In this performance, the dimension is increased based on 3D representation for providing precise output in the digital image processing \((t - (H_n/H_f))\) in the following region. This is the image stitching based on input image pixels at different times \(t\) where \(H_n \neq H_f\). The first input image based on sectional homogeneity-based similarity verification assisted matching \(\rho(cr, lm)\) is computed through \(S^b(t - (H_n/H_f))\) based on \(n\).

\[
F_{\text{Verify}} = n \star \left[ \frac{\min_{n \in E}(cr + lm)_n}{\max_{n \in E}(cr + lm)_n} \right]^{C} * \rho(cr, lm). \quad (10)
\]

In the above equation (10), the final verification output based on the cross section and linear matching process provides increased dimension based on the homogeneity feature. The solution based on the stitching region requires similar pixels for substituting the missing pixel outputs in 1 as \(n = 1\) and \(lm = 0\). Therefore, it is considered as \(F_{\text{Verify}} = \sum_{n \in E} \min_{n \in E}(cr + lm)_n\) for \(x(or)y\) until \([1 < t - (H_n/H_f) < t]\) it is
stitched. The final verification post the stitching process is shown in Figure 5.

The $C_{ijr} \oplus H_{ij}$ (discarding $D$ and $E$) is analyzed as $(cr + lm)$ is identifying $M_{\text{pixels}}$, such pixels are $S_{\text{pix}}$ using linear extractions, and however, the $\rho_{(cr, lm)}$ positions are alone substituted. The further sectional segregation permits $f_{\nu}$ assessment for ensuring less $D$ (Refer to Figure 5). In particular, the consecutive image stitching analysis based on even pixel verification is analyzed. Where the probabilistic image-stitching and feature verification based on causing the error are identified. Hence, the maximum image stitching is performed, and therefore the substitution and matching increase through cross-sectional pixels. It identifies the complexities in that image stitching and reduces the error through final verification. This image stitching technology in 3D film production based on digital image processing under RNN is used to reduce the complexity and error for $x$ and $y$. In Figure 6, the analysis for $\Delta$ (%) and LCDF are presented.

The self-analysis for $\Delta$ (%) and LCDF by varying $D$ is shown in Figure 6. The proposed process achieves fewer $\Delta$ (%) for $D < 0$ as its impact is mitigated using $F$ features. The $C$ based features are alone analyzed $\forall D < 0$ such that $\rho_{(cr, lm)}$ reduces the need $\Delta$. In the $D > 0$ case, $C$ impacts $H$, and hence cross-sectional validation is performed as $(cr + lm)$ and therefore $S_{\text{pix}}$ is less. In the consecutive recurrent process, the CDF with linear pixels is verified. Therefore, the LCDF hikes and gradually falls for linear and cumulative outcomes with $E$. Therefore, the recurrent learning process identifies $C_{ijr}$ and $H_{ij}$ for preventing further CDF drop. This is pursued from the next alternating $f_{\nu}$ for improving the LCDF concentration and therefore, the accuracy is improved. The analysis for error, $M_{\text{pixels}}$, and $S_{\text{pix}}$ is shown in Figure 7.

In Figure 7, the analysis for error, $M_{\text{pixels}}$ and $S_{\text{pix}}$ for the varying $\rho_{(cr, lm)}$ is presented. The proposed process identifies the missing pixel based on $D$ and $E$ detection. Depending on the $f_{\nu}$ such that $D$ is mitigated $\forall \Delta$; based on which linear pixels are organized. Therefore, the error reduction is achieved by overcoming $H$ other than $C$. In the $M_{\text{pixels}}$ identification, $S_{\text{pix}}$ is provided for $\Delta$ such that $(cr + lm)$ is jointly provided. Therefore the stitching process $St_{1}$ $St_{2}$ in $F_{\nu}$ $\forall$ $H$ and $C$ is prevented with $D \in E$. This is recurrently analyzed $\forall \Delta$ such that it is identifying $E$ with similar $f_{\nu}$. Therefore, the substituting process ensures maximum precision without disturbing the learning iteration.

4. Discussion

This section presents the comparative analysis of the proposed process using the images from [29]. A brief explanation of the dataset is given later after the comparative analysis. In this analysis, 24 joint $H$ and $C$ features are considered with a maximum of 140-pixel substitutions. The input images vary from $2 \times 2$ to $8 \times 8$ by size for which stitching is performed. The metrics accuracy, precision, substitution, error, and complexity are analyzed and compared with ISLF [28], EGCNet [21], and LLBI-AW [20] methods.

4.1. Accuracy. In this feature analysis, image stitching achieves high realistic accuracy based on digital image processing required for identifying cross-sectional pixels at different intervals. Through recurrent neural network is used for identifying the error and complexity (Refer to Figure 8). The identification of error and complexity is mitigated based on realistic accuracy. 3D film images rely on features analysis and synchronize multiple independent frame images as a single high-resolution image output. The linear distribution pixels are based on horizontal, vertical, and diagonal line analysis for $x$ and $y$. The consecutive linear pixel occurrence is matched for their similarity analysis. Based on the feature analysis through LCDF, the homogeneity feature is identified for detecting error and addressing pixel matching based stitching process at different instances. The homogeneity features are analyzed by cross-sectional pixels through final verification in a 3D representation $(x'/St_{i} + (y'/St_{j})$ that requires dimension verification at the neighbor image. Similarly, feature verification is performed for increasing the accuracy and addressing errors in image stitching relying on different region. Therefore, the realistic accuracy is high in image stitching.

4.2. Precision. This proposed process achieves high precision for image stitching and error identification based on a recurrent neural network (Refer to Figure 9). The linear cumulative distribution for pixels occurs based on homogeneity feature identification is based on the condition $\sum_{D \in \text{ LCDF}} (H_{i} - C_{j}) - f_{\nu}^{\text{LCDF}}$. Similarity verification is performed through LCDF and verifying contrast pixels for substituting similar pixels in the missing sections. The 3D representation-based film image increases through homogeneity feature analysis based on RNN. The error identification is addressed based on similarity verification and merging of two or more images. The feature analysis based on the previous image-stitching and linear pixel occur in input images verifying for homogeneity and contrast reducing the cumulative distribution through the recurrent neural network. Therefore, the $St_{1}$ $St_{2}$ is computed for improving the homogeneity feature along with image stitching at different intervals. Therefore, the sectional homogeneity based on linear cumulative distribution is to be identified as missing pixels depending on cross-sectional pixels, this error has to satisfy conditions for performing the image stitching for time. In this proposed process, the contrast pixel is identified for addressing error and increasing precision.

4.3. Substitution. This feature and similarity verification process-based substitution are high in this proposed process for increases realistic accuracy and precision compared to the other factors in image stitching (Refer to Figure 10). In this process, the contrast pixel identification is used for cross-sectional matching for substituting similar pixels in the missing pixels through RNN for analyzing $n \in [(\pi/2), -(\pi/2)]$. In this condition, the increasing error and complexity are due to even pixel verification [as in equation (4)], and then the condition $n \in [0, 1]$ is achieved. The feature analysis is computed for horizontal, vertical, and
Figure 5: Final verification process.

Figure 6: Analysis of $\Delta$ (%) and LCDF.

Figure 7: Error, $M_{\text{pixels}}$ and $S^b$ analysis.
In this method, error and complexity are identified for obtaining the maximum substitution of similar pixels due to missing sections is occurred. This error identification requires increasing complexity, preventing the linear cumulative distribution of pixels. Hence, the image stitching based on different input images performs cross section, and linearity matching is administered as in equations (6) and (7) for their similarity analysis. In this proposed process, the stitching region depends on feature analysis and therefore the errors identified from the image stitching process with other cross-sectional pixel is less.

4.4. Error. This proposed image stitching process is a single high-resolution output based on homogeneity feature identification as it does not detect 3D representation for different linear pixels processed through RNN. The addressing of error based on the cross-sectional pixels and linear pixel analysis is calculated from the previous stitched

![Figure 8: Accuracy analysis.](image8)

![Figure 9: Precision analysis.](image9)

![Figure 10: Substitution analysis.](image10)
images for similarity analysis. The substitution and missing sections at different intervals are identified for increasing the precision. The error can be identified in performing the similarity verification through LCDF. From this output error in the image, stitching is identified as the instance of homogeneity feature identification based on the matching process through RNN, preventing errors. The stitching region can be verified with homogeneity and contrast verification is performed without increasing cross-sectional pixels. Instead, the conditions rely on feature analysis based on the linear cumulative distribution in 3D film images. In this proposed process, the linear distribution is used for increasing final verification and achieves less error as shown in Figure 11.

4.5. Complexity. This proposed process of image stitching technology in 3D film production achieves less complexity based on digital image processing compared to the other

Table 1: Comparative analysis for varying \((H + C)\).

| Metrics          | ISLF | EGCNet | LLBI-AW | IPMSP | Findings  |
|------------------|------|--------|---------|-------|-----------|
| Accuracy (%)     | 65.77| 72.25  | 82.05   | 91.574| 9.11% high|
| Precision        | 0.711| 0.815  | 0.894   | 0.9436| 13.69% high|
| Substitutions    | 32   | 72     | 102     | 141   | 8.55% high|
| Error            | 0.243| 0.189  | 0.149   | 0.0934| 10.03% less|
| Complexity (s)   | 0.229| 0.182  | 0.113   | 0.0838| 8.65% less |

Table 2: Comparative analysis for varying \(S^b\).

| Metrics          | ISLF | EGCNet | LLBI-AW | IPMSP | Findings  |
|------------------|------|--------|---------|-------|-----------|
| Accuracy (%)     | 69.41| 78.48  | 85.24   | 91.501| 6.89% high|
| Precision        | 0.722| 0.818  | 0.896   | 0.9456| 13.36% high|
| Error            | 0.251| 0.199  | 0.132   | 0.0933| 10.07% less|
| Complexity (s)   | 0.202| 0.153  | 0.109   | 0.0822| 7.79% less |
### Table 3: Input and feature verification.

| Input | Contrast | Homogeneity | Verification |
|-------|----------|-------------|--------------|
| ![Input](image1) | ![Contrast](image2) | ![Homogeneity](image3) | ![Verification](image4) |
| ![Input](image5) | ![Contrast](image6) | ![Homogeneity](image7) | ![Verification](image8) |
| ![Input](image9) | ![Contrast](image10) | ![Homogeneity](image11) | ![Verification](image12) |
| ![Input](image13) | ![Contrast](image14) | ![Homogeneity](image15) | ![Verification](image16) |

### Table 4: Cross-sectional analysis.

| Feature verified input | Cross-sectional representation | Linear matching | Similarity |
|------------------------|--------------------------------|-----------------|------------|
| ![Feature verified input](image17) | ![Cross-sectional representation](image18) | ![Linear matching](image19) | ![Similarity](image20) |
| ![Feature verified input](image21) | ![Cross-sectional representation](image22) | ![Linear matching](image23) | ![Similarity](image24) |
| ![Feature verified input](image25) | ![Cross-sectional representation](image26) | ![Linear matching](image27) | ![Similarity](image28) |
| ![Feature verified input](image29) | ![Cross-sectional representation](image30) | ![Linear matching](image31) | ![Similarity](image32) |
factors as shown in Figure 12. The realistic accuracy increases in 3D film images, whereas the missing pixels decreases, and then error occurrence based on cumulative linear distribution through cross-sectional pixels is identified. The feature analysis is based on 3D representation; the error and complexity are identified and then controlled through the proposed IPMSP method. This is important to preventing realistic accuracy and homogeneity feature identification at different instances is used for decreasing error. The pursued image stitching through feature verification is computed for identifying errors at the time of similarity analysis, preventing missing sections. The feature verification ensures cross section and linear matching based on substitution and missing pixels in the occurrence of linear pixels. It is retained using homogeneity feature analysis as in equations (8) and (9). Therefore, the error is identified in the image stitching process with LCDF through RNN and sectional homogeneity at different time intervals used for even verification. Thus the proposed image stitching process verifies 3D film image pixels. Therefore, complexity is less in this process of identifying missing pixels. Tables 1 and 2 present the comparative analysis result for varying \((H + C)\) and \(S^6\).

4.6 Experimental Results. This section presents the experimental analysis using the dataset [29] for analyzing the efficiency of the proposed process. From the given 3163 input images, 1500 images are used for testing and 1428 images are used for training the learning network. The proposed process is analyzed using a single input image for the different steps discussed. The experimental analysis results are given in Tables 3, 4, and 5.

5. Conclusion

This manuscript introduced a novel process for improving the image stitching accuracy and precision of single frame inputs. This proposed itinerant pixel-matching-based stitching process relies on cross-sectional verification for reducing errors. The proposed process performs a linear cumulative distribution of the cross-sectional pixels for feature verification during the stitching process. Prominently, the homogeneity and contrast pixels are extracted from the varying image dimensions. The cumulative distribution output is verified using a recurrent neural network for disparity and substitution analysis. Depending on the sectional homogeneity, the need for missing pixel replacement is analyzed. The substitution follows verified linear pixels for preventing additional complexity. The recurrent learning process is repeated through different iterations for leveraging the pre-sectional feature extraction and verification. From the increasing image size, the sectional verification is performed and thus the proposed process achieves 6.89% high accuracy, 13.36% high precision, 10.07% less error, and 7.79% less complexity for the varying substitutions.
Data Availability

The data that support the findings of this study are available from the corresponding author upon reasonable request.

Conflicts of Interest

The authors declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

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