Dynamic Healing Process Analysis: Image Morphing with Warping Technique for Nose and Esophagus Studies

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Abstract: *In this study, image morphing technology is harnessed to investigate the dynamic processes of healing in both the nose and esophagus. The researchers employ a computer-assisted morphing approach to dynamically analyze mucosal processes during the healing study. The focal point of the proposed image morphing method is a specified warping technique that transforms the first image into the second, and vice versa. The metamorphosis unfolds with the first image initially completely deformed toward the second, gradually fading in, while the current image simultaneously becomes progressively distorted and fades out. This results in an initial series of photographs closely resembling the original. The pivotal middle image is crafted through the averaging of the first source image altered halfway toward the second and the second source picture deformed halfway away from the first. The subsequent images in the series resemble the second source picture. The significance of the center picture is underscored, as its visual appeal ensures the overall aesthetic quality of the entire animation sequence. To facilitate seamless transitions between frames, intermediate frames are generated. The proposed technique is substantiated through the use of realistic datasets for testing and validation, demonstrating its superior performance compared to state-of-the-art studies in the field. This comprehensive approach to image morphing not only advances our understanding of healing dynamics in the nose and esophagus but also presents a novel and effective methodology with broad applicability, surpassing the capabilities of current leading-edge studies. The proposed approach showed best performance against state-of-the works.*

Keywords: *Computer vision, image morphing, warping, face matching, forward algorithm, backward algorithm*.

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1. Introduction

Image morphing finds applications across various domains such as in the health industry, it is utilized to examine cell changes, in forensic science, it aids in identifying the potential physical alterations a criminal might undergo over time, the film industry employs it to craft unique animations, and environmental science benefits from it by facilitating the analysis of environmental changes [27]. Image morphing could offer physicians an extra resource for illustrating the physiological reactions to various treatment possibilities. It’s conceivable that planned variations in treatments for fractures, plastic surgery, burn recovery, or dermatological infections could be observed, studied, and visualized.

The problem at hand involves addressing the need for a robust and efficient image morphing solution that can seamlessly integrate into healthcare applications, providing real-time transformations of medical images. The current challenges include the demand for on-the-fly morphing capabilities to enhance visualization and analysis of medical data, such as monitoring dynamic physiological changes or facilitating comparative analyses for diagnostic purposes. The research will explore methods to optimize computational efficiency without compromising image quality, ensuring that the morphing technique aligns with the stringent time constraints inherent in healthcare workflows. Additionally, the study will consider ethical and privacy implications, seeking to establish a framework that adheres to regulatory standards while advancing the utility of image morphing in healthcare systems. The ultimate goal is to contribute to improved medical imaging techniques, fostering better real-time visualization and analysis for enhanced decision-making in clinical environments. An illustrative example of image morphing in the healthcare context can be seen in Figure 1.

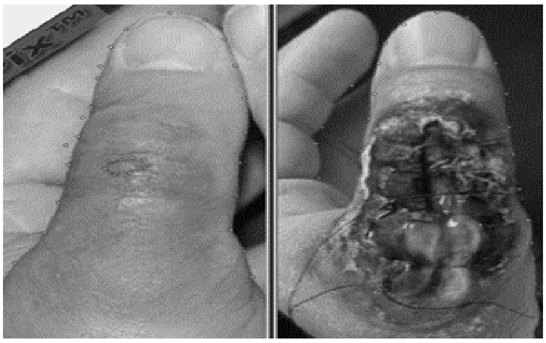


Figure 1. The importance of the image morphing in healthcare [26].

Morphing is an influential implementation which might enhance various multimedia plans, demonstrations, schooling and computer-based exercises. Face morphing is an image transformation that entails both cross-dissolving between image parts and generic image warping. Face altering or morphing is a kind of digital manipulation of the face, which is a method that may be employed to produce fake biometric face illustrations that mimic the biometric data of couple of people [34, 43]. This poses a major threat to face recognition systems [9, 17] since the new morphing face image would successfully be checked using facial instances of couple of people. It's important to keep in mind that face morphing focuses mostly on producing bogus instances at the image level rather than video, as with individuality exchange operations [30].

Generally speaking, the creation of face morphing images involves the following three steps in order: The first step is to determine which facial photos of the various subjects coincide. Typically, to do this, landmark features like the mouth, nasal tips, eyes, and so forth are extracted. Second, the individuals' actual face images are warped until the associated sample elements (landmarks) are geometrically aligned. The third stage is blending, which is the merging of the color values of the warped images. Last but not least, postprocessing methods are frequently utilized to remove odd artefacts brought on by pixel/region-based morphing [42, 46].

Artificially created facial photos that pass for real-looking can undermine trust in digital content and harm users by disseminating incorrect details [39]. Additionally, the automatic processing of altered facial photos may result in incorrect judgments, for example, in a biometric system. The aforementioned changes, for instance, may have an effect on facial recognition performance. Face recognition systems are used in many application domains, such as mobile devices, access control, forensics, or surveillance [18, 41], for identity management. Face picture alterations may be used for a variety of purposes, such as beautifying, by unintentional users who are not trying to compromise the concern of a face identification system. However, they might also be used maliciously by those who want to obstruct the functioning. They might, however, potentially be used maliciously by individuals to obstruct a facial recognition system's functionality. Presentation attacks are the name given to such attacks [3, 22]. Digital facial image alteration can be thought of as digital presentational attacks. 1 Face recognition systems have been demonstrated to be especially susceptible to presentation attacks [28], such as printing out facial photos or 3D masks. Presentation assaults are either carried out with the intention of identity concealment, in which the attacker attempts to avoid detection, or impersonation, in which the attacker attempts to be identified as someone else (target subject). The feasibility of both sorts of attacks with the aid of digital face image alteration has already been demonstrated by Tolosana *et al*. [39]. Often, startlingly high attack success rates can be achieved with simply minor changes to the original facial photos. Face recognition systems face major security vulnerabilities as a result of this.

A state-of-the-art algorithm was developed by Scherhag *et al*. [33] for the detection of face morphing attack in realistic domains. They calculated and measured the metrics of the face and respectively compared their significance against comprehensive datasets and realistic image post-processing. Similarly, a conditional Generative Adversarial Network (GAN) morphing framework was designed by Fish *et al*. [7] that operated a pair of input images, and validated their approach against synthesized images along with the temporal samples. They provided the fair comparison between the classic and latent space morphing methods. They validated that the provided set of images for self-supervision, their framework agreed to produce visually attractive morphing effects. Likewise, a latest morph attack detection algorithm was proposed by Chaudhary *et al*. [5] that was based on discrete wavelet transform which further identified a morphed face image. In their approach, the artifacts are not visible due to which the domain of the images are easily determined. After this stage, the mid and high sub-bands are emphasized through multilevel wavelet transform and the respective entropy is calculated for each sub-band and morph images [29]. The framework has been tested and validated against publicly dataset of face images. On the other hand, Kelly *et al*. [16] presented a comprehensive algorithmic fairness analysis of the existing face morphing approaches. For better justification, they validated their approach on newly generated dataset that contained four various ethnic image groups. They claimed better detection performance against the dataset through extensive experiments under the presence of static environment. However, most of these approaches were tested and validated on synthesized images under static environments. Their performances are respectively decreased against realistic images and naturalistic domains.

Therefore, we have proposed a new face morphing technique that is based on the fields of effects nearby 2D control primitives, which is known as field morphing.

The proposed face image morphing method, incorporating elements like warping, face matching, forward algorithm, and backward algorithm, adds significant value to the current understanding of facial image manipulation. The warping technique introduces a novel spatial transformation approach, allowing for precise deformation and reshaping of facial features. Face matching contributes by ensuring accurate alignment of facial features, enhancing the fidelity of morphed images. The forward algorithm facilitates a seamless transition from the initial to the target image, creating a visually coherent morphing sequence. Conversely, the backward algorithm ensures the reverse process, maintaining consistency and integrity in both directions. Together, these components synergistically improve the accuracy, realism, and versatility of facial image morphing, addressing challenges associated with distortion, feature misalignment, and visual artifacts. The proposed method advances the current state of the art by providing a comprehensive solution that excels in both forward and backward transformations, making it a valuable contribution to the field of facial image morphing with potential applications in computer graphics, entertainment, and biometrics.

We have already provided some introduction along with the importance of the face morphing in section 1. The rest of the paper is arranged as: In section 2, we have presented some state-of-the-art approach along with their respective limitations. Section 3 presents a comprehensive description on the proposed methodology. While, the validation and discussions are provided in section 4. Finally, the proposed approach is concluded with some future directions in section 5.

2. Related Work

Morphing is the transformation of images which describes the combination of generalized image warping with a cross-dissolve between image elements. Huge number of systems have been developed in literature for image morphing; however, everyone has its own limitation.

A state-of-the-art facial morphing system was proposed by Kelly *et al*. [16] where the authors introduced a theoretical concept of worst-case morphs which is considered as one of significant concerns in face recognition systems. They generated images which estimated such worst-case morphs against mapping from embedding space back to image space. However, this system was tested and validated on few images due to which its performance decreases against various images. Similarly, Sarkar *et al*. [31] provided an association between four various types of morphing attacks using novel dataset. They utilized WebMorph, FaceMorpher, and OpenCV for such association due to which they created the original face from the state-of-the-art dataset, and the experiments were performed using ArcFace, VGG-Face, and FaceNet. Their system was compared against existing works of morphing attacks. However, at some points of morphing, the performance percentage of these techniques degrades at some levels [4]. On the other hand, Ivanovska *et al*. [12] explored the effectiveness of the detection methods which were validated on state-of-the-art dataset along with their respective morphs. They employed style Generative Adversarial Network (styleGAN) in order generate the corresponding face morphs. Then, they utilized a binary classifier for the purpose of classification. However, styleGAN has a common limitation which sometimes produces abnormal artifacts on the processed images [25].

A novel fused classification approach was designed by Medvedev *et al*. [23] for the detection of face morphing, which was based on deep facial learning model. They introduced a new deep learning scheme for face morphing detection which further utilized the discrimination of morphed face images coupled with a cultured face detection task against a dynamic recognition domain. This approach further directed onto learning the deep facial features that convey information about the legitimacy of such features. However, this approach might not be used in naturalistic domains because of the complexity of deep facial learning model. Similarly, a state-of-the-art morphing attack detection technique was proposed by Fu and Damer [8] that was based on quality scores. They compared the detectability and generalizability of into-intra and inter-dataset in order to assess the performance of the proposed detection concepts against various morphing approaches and bona fide sources. However, this approach might not completely exploit the image information which is pertinent for the perception of the quality [45]. Moreover, in this approach, when image information is inattentive by deeper, then the spatial information may be lost [45]. Likewise, a face morphing method was designed by Lu *et al*. [21] and Yılmaz and Nabiyev [44] which was based on convolutional neural network-based multi features coupled with color and micro-texture features. They utilized local binary pattern, HSV color space, and histogram-oriented gradient for color features. These techniques also employed for the enhancement of image morphing attacks. However, this approach needs extra memory, computational cost, and training time [36] and also it does not provide the spatial information of the image [40].

A novel detection method was proposed by Long *et al*. [20] for face morphing that was based on lightweight networks and patch-level features. They utilized the three blocks association for learning, which further used for the face recognition along with the integrated face features. However, speed and control are the two major limitations for patch-level features because in this approach, for each pixel, all line segments require to be referenced that may produce speed problems [24]. Also, this integration may generate unwanted and unanticipated interpolations, due to which the additional fixing effort may be caused [24]. Similarly, a latest detection method for facial morphing was developed by Hamza *et al*. [10] that was based on deep-learning features and a classifier. This approach delt with the distinctions of age, lightings, eye, and head postures. Moreover, an image enhancement method coupled with the feature associations are presented for the detection that has been tested and validated on versatile dataset. However, in this approach, the inappropriate features are described which may cause incorrect decisions for training data [1]. Apart from that, a robust and comprehensive evaluation was performed by Scherhag *et al*. [32] against various datasets under the presence of four different techniques of morphing and postprocessing. Then they employed local binary pattern on this fused approach in order to improve the significance and robustness of the system. However, this approach does not provide the spatial information of the image [40].

On the other hand, a robust deep neural network-based morphing method was developed by Ferrara *et al*. [6] and Li *et al*. [19] for the attack detection. In this method, a comprehensive examination of the network behavior with regard to bona fide and digital scanned images are utilized for classification that permits a deeper understanding of the most applicable features of the image. However, this method suffers from lack of texture details, shape alterations, and high computational complexity [13]. Similarly, a MATLAB-based morphing tool was developed by Shirore and Baji [35] which was based on mesh warping technique. In this approach, the authors create a framework for image-based morphing against facial animation on low complexity. However, mesh warping-based approach has a difficulty to fit the mesh inside the corresponding images that the landmark of the current and targeted images might not lie under the joint of the grid lines [38]. Likewise, Huber *et al*. [11] presented a new method for detection of face morphing attack that was based on privacy-aware synthetic training data. They claimed significant performance against publicly available dataset of faces. However, this approach suffers from cryptographic limitations, communication and computational overheads which are highly associated with the network of deep learning [2]. Furthermore, most of the aforementioned approach showed better performances against static domain; however, their accuracies are respectively degraded against dynamic and naturalistic domains.

Therefore, we have proposed a robust method which uses feature-based morphing, where the feature lines are chosen in turn. The two images are first warped to have the similar picture, and then the subsequent pictures are cross-dissolved. The main requirement is to warp the photos. Either forward mapping or reverse mapping can be used to warp data.

3. Proposed Methodology

Two photos with nearly identical shapes are warped throughout the morphing process, and the resulting images are then cross-dissolved. Cross dissolving is straightforward; the main challenge is warping an image. The suggested method dissolves the source picture into the targeted picture to create a gradual transition between the two (as shown in Figure 2).

a) Source image. b) Targeted image.

Figure 2. The embedding of source image in targeted image.

The flowchart for the proposed approach is given in Figure 3.

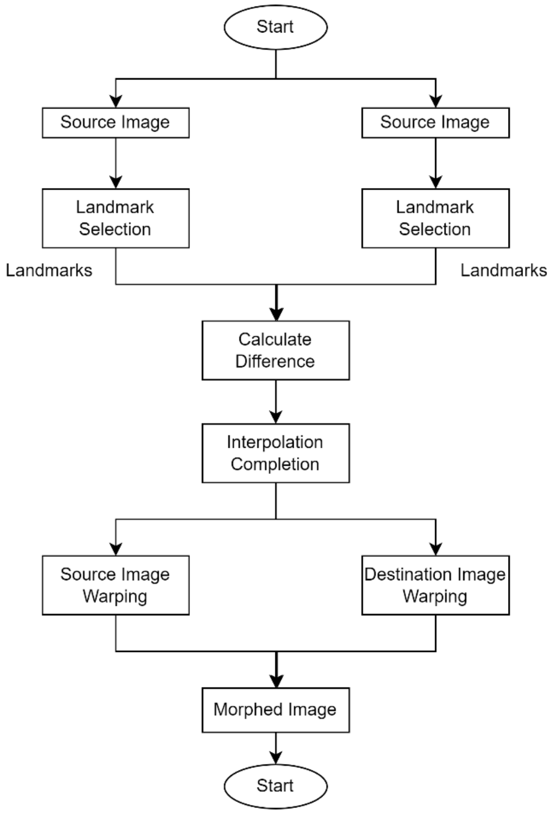
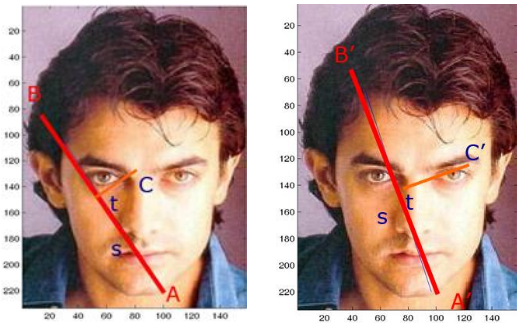


Figure 3. Working flow diagram for the proposed approach.

3.1. Transformation with Single Pair of Lines

The animator in the two photos interactively selects feature lines in the basic concept. By sampling the right pixel from the source image and applying it to the destination image, these feature lines enable reverse mapping.

A mapping from one image to the next is described by a pair of lines, one specified in relation to the source image and the other defined in relation to the destination image. Figure 4 depicts the lines as being formed by the sets of pixel coordinates (*AB*), scalars as courageous lower-case italics, and clued-up variables as values determined in relation to the source picture (*C'*, *s'*). A directed line segment is what we refer to as a line.



a) Destination image. b) Source image.

Figure 4. Transformation with single pair of lines.

In order for a line *AB* in the targeted picture and *A'B'* in the base picture, there must be two conforming outlines in both the source and targeted pictures that form a synchronize plotting from the targeted picture pixel position *C* to the base image point coordinate *C'*, as represented in Eqations (1), (2), (3), and (4).

$$s = \frac{\overrightarrow{AC}.\overrightarrow{AB}}{\overrightarrow{AB}.\overrightarrow{AB}} = \frac{(C-A).(B-A)}{|B-A|^2} \tag{1}$$

$$t = \overrightarrow{AC}.\frac{Perpendicular(\overrightarrow{AB})}{|\overrightarrow{AB}|} = (C-A).\frac{Perpendicular(B-A)}{|B-A|} \tag{2}$$

$$C' = A' + s.(A'B') + \frac{t.Perpendicular(A'B')}{|A'B'|} \tag{3}$$

$$C' = A' + s.(B'-A') + \frac{t.Perpendicular(B'-A')}{|B'-A'|} \tag{4}$$

where, perpendicular (*A'B'*) gives a vector with the similar dimension to the input vector and that is vertical to it. As long as it is employed consistently throughout, either of the two vertical vectors such as right or left might be utilized.

The length from the line and the value *s* represent the position along the line, respectively. As the pixel transitions from *A* to *B*, the value *s* increases from 0 to 1, and outside of that range, it decreases or increases from 0 to 1. The perpendicular length from the line, measured in pixels, is the value for *t*.

The corresponding correlation of the source and targeted images at pixel at *C* and *C'* is respectively shown in Figure 4. The location is at a proportion *s* along the line *A'B'* and at a distance *t* which is the length from the line to the point in the source or base image.

The algorithm modifies the image as a whole by rotating, translating, and/or scaling each pixel's coordinate. The image is scrambled on the track of the lines through the ratio of the length of the lines since the value of *s* is normalized by the length of the line. Describe a translation if the two lines have the similar distance and direction but will be at various places. The single pair of line transformation's pseudocode is as follows:

- For every pixel *C* of the targeted image
- Locate the corresponding *s*, *t* and then locate the *C'* in source picture for that *s*, *t*
- TargetedImage(*C*)=SourceImage(*C'*)

As a result, the warped image is blended with the destination image to get a morph (as shown in Figure 5).

Figure 5. The resultant warped image.

3.2. Transformation with Multiple Pairs of Lines

More complicated transformations are specified by many pairs of lines. Each line's coordinate transformations are given a weighted average. Each pair of lines has an associated location C_i'. The variance among the location of the in source and targeted images is known as the displacement $D_i = C_i' - C$, and a weighted average of those displacements is computed. The weight is determined by the distance from *C* to the line. The position *C'* to the ample in the source image is calculated by adding this weighted average to the location of the present pixel *C*. If the weight never drops to zero anywhere in the image, the single line scenario fails to hold up as a specific circumstance of the numerous line circumstance. According to the Equation (5), the weight (*W*) given to every line might be sturdiest when the pixel is accurately on it and feebler as the pixel moves away from it.

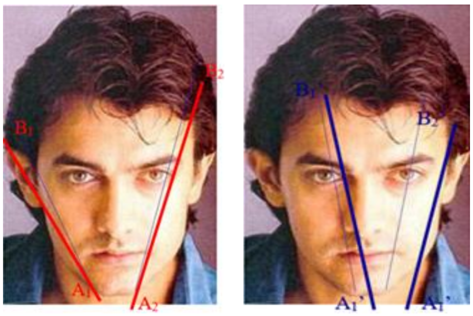
$$W = \left(\frac{L^P}{a+D}\right)^b \tag{5}$$

where, *D* is the distance between the pixel and the line, *L* is the length of the line, and *a*, *b* and *P* are the constants that can be used to alter the relative impact of the lines.

- The length strength value is "a". More local control is provided with a smaller value of "a", which affects pixels near the line more than pixels far from it. Greater values have an effect on both nearby and distant pixels. The warping will be smoother, but the control will be less exact.
- Similarly, "b" represents the reduction in value. According to this "b", the relative strength of various lines varies with distance. Only the line nearest to a pixel will be impacted if the value is high. If "b" is

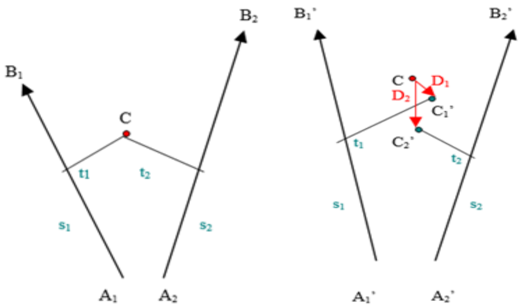
zero, all lines should have an equal impact on each pixel, and the range should be [0, 5, 2].

- The line length value is "P". "P" normally has a value between [0, 1]; if "P" is zero, all lines are equally weighted. Longer lines are given more relative weight when the value is larger than zero. Figures 6 and 7 respectively provide a description of this kind of change and image warping with multiple lines.



a) Targeted image. b) Source image.

Figure 6. Multiple pair of lines transformation.



a) Destination image. b) Source image.

Figure 7. Image warping with multiple lines.

Images with many lines can be warped similarly to those with a single line. On the final image, *C* is picked to stand in for an undetermined pixel. Calculating s1, s2, t1, t2 and the pixel C's location in the target image is necessary. These values are provided in Equatios (6) and (7).

$$s_i = \frac{(C - A_i).(B_i - A_i)}{|B_i - A_i|^2} \tag{6}$$

$$t_i = (C - A_i).\frac{Perpendicular(B_i - A_i)}{|B_i - A_i|} \tag{7}$$

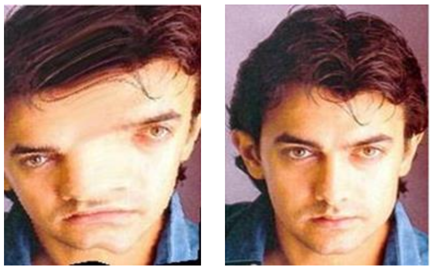
Finding C1' and C2''s locations in the source image is the next step. This can be accomplished by moving out the specified distance *t* computed in the destination image and up the line *A'B'* by the similar fraction *s* as in the targeted picture.

Then every pixel color at the source image must be computed and dispensed into every pixel at the targeted picture when a numerical image is converted into another image. C' describes the pixel color in source image; while, *C* represents the pixel location in the targeted image. The weighted average must be computed and subtracted from C to obtain the pixel color C' in the source image. Figure 6 displays the overall process. In the source picture, each pixel is represented by *C'* that has a matching pixel in the targeted picture *C* must be calculated in Equations (8) and (9).

$$D_i = C'_i - C \tag{8}$$

$$C' = C + \frac{\sum_{i=1}^{n} W_i D_i}{\sum_{i=1}^{n} W_i} \tag{9}$$

Figure 8 illustrates the warped image produced by the corresponding algorithm for the transformation of many pairs of lines, which is described in Algorithm (1).



a) Destination image. b) Source image.

Figure 8. The resultant warped image of the multiple pair of lines.

Algorithm 1: Algorithm for Transforming Several Pairs of Lines.

for every pixel of C in the targeted image
 $D_{Add} = (0, 0)$
 $Weight_{Add} = 0$
 for every line A_i, B_i
  Estimate s, t using A_i, B_i
  Estimate C_i' *using s, t and* A_i', B_i'
  Estimate movement D_i
  Dist = shortest path from C′ to A_i', B_i'
  Estimate weight
 End
 $D_{Add} = D_{Add} + D_i * weight$
 $Weight_{Add} = Weight_{Add} + weight$
 $C' = C + D_{Add} / Weight_{Sum}$
 TargetedImage(C) = SourceImage(C′)
End

4. Validation of Proposed Approach

Generally, there are numerous steps in image morphing that convert one image into another one. It is necessary to respectively select a source and targeted images first, then respectively draw lines on source and targeted images. It is a good idea to use the initial lines you draw to frame both photos. This stops any pixel in the source image from having its color determined outside of the image. Next lines might be pinched on each image's distinctive features as shown in the Figure 9.

a) Destination image. b) Source image.

Figure 9. Extraction of distinct features.

In order to warp the lines of the source image into the lines of the targeted image and vice versa, it is important to outline the features on each image. The characteristics of the character will enlarge to the size of loin's face's outlined features. Additionally, the reverse is true. The warping of the character's lines to the loin's lines is depicted in Figure 10. The progression of lines on the character's face demonstrates how its features change to take on the appearance of a loin. A series of images should be created slowly, frame by frame.

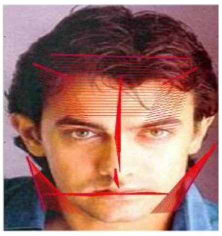


Figure 10. Warping of the character's lines to the loin's lines.

Similarly, Figure 11 shows the character's original traits, frame by frame the character's features grew to fit the lion's original features while the character's features shrunk to represent the lion's highlighted features.

The two photos are combined in the last phase to create a morph. The two image sequences need to be combined in order for one image to correctly morph into another. The destination image's reverses sequence must be mixed with the source image's forward sequence. It is necessary to blend the middle image in the sequence to make it 59% of source picture and 41% of targeted picture. Consequently, there is a seamless transition between the two images as shown in Figure 12.

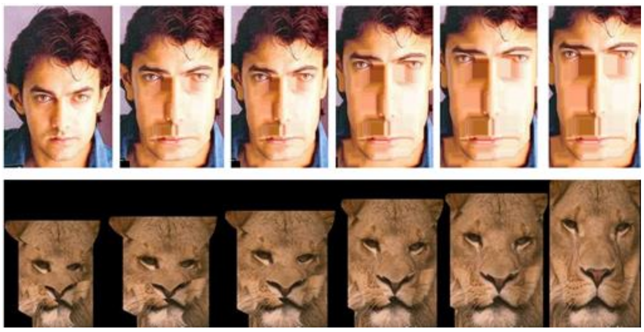


Figure 11. Features shrinking to represent the lion's outlined features.

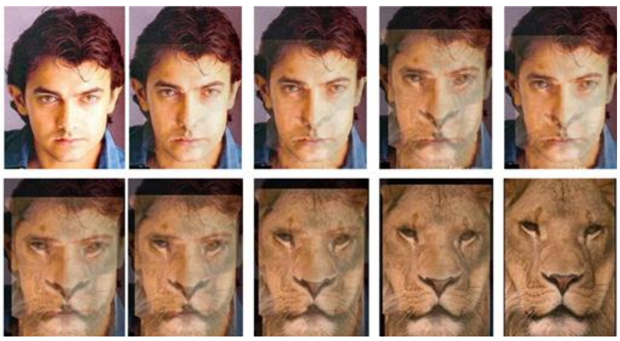


Figure 12. Blending the morph.

The proposed approach has been tested and validated on various images. The corresponding results are shown in Figures 13, 14, 15, 16, 17, and 18.

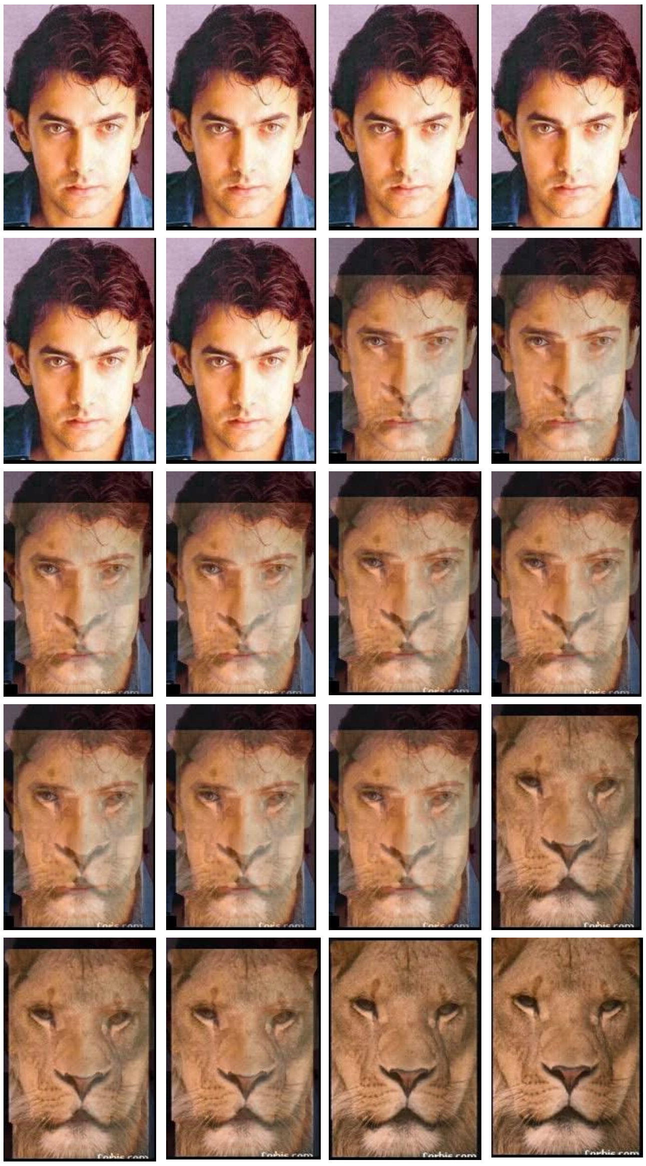


Figure 13. Morphing of Amir Khan and loin (starting from left to right).

Figure 14. Morphing of Britney and Madonna (starting from left to right).

Figure 15. Morphing of Madonna and Rani Mukarji (starting from left to right).

Figure 16. Morphing of Pretty Zenta and Britney (starting from left to right).

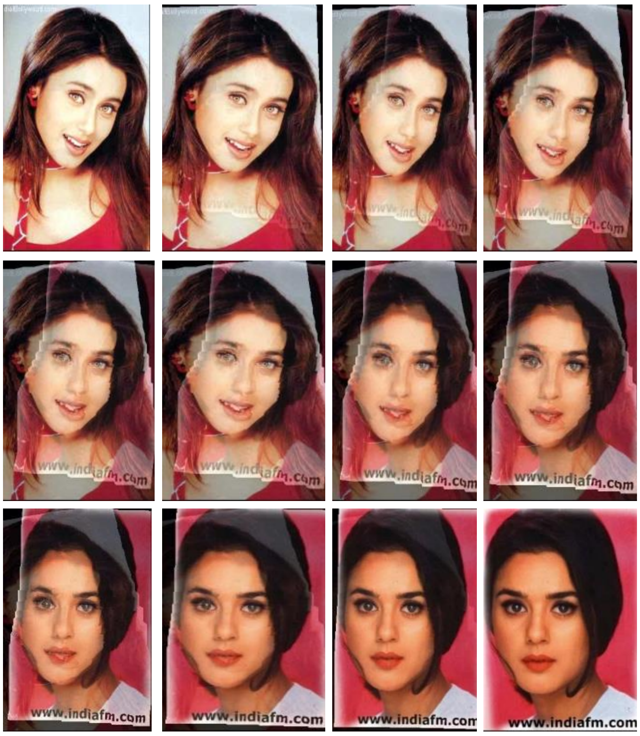


Figure 17. Morphing of Rani Mukarji and Pretty Zenta (starting from left to right).

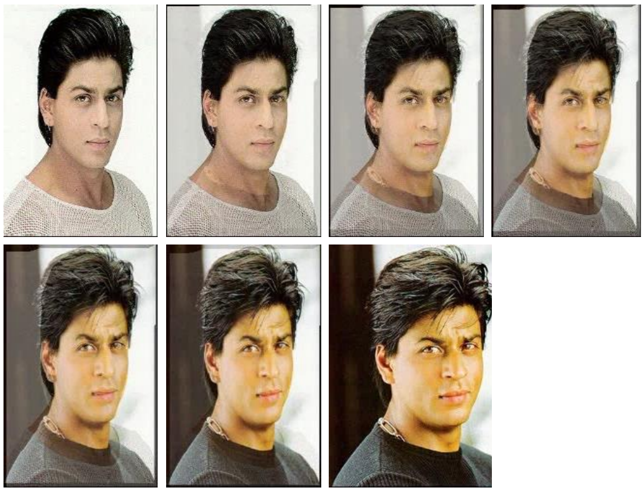


Figure 18. Morphing of two different pictures of Shah Rukh Khan (starting from left to right).

As can be seen, the proposed approach performed admirably when tested against a variety of image types, demonstrating its robustness. This is due to the fact that the suggested method uses a feature-based morphing technique in which the feature lines are individually chosen. The two images are first warped to have the similar picture, and then the subsequent pictures are cross-dissolved. The main requirement is to warp the photos. Either forward mapping or reverse mapping can be used to warp data. Forward mapping involves scanning the source image pixel-by-pixel and copying the pixels to the destination image in the proper places. In reverse mapping, each pixel of the destination image is examined, and the appropriate pixel from the source image is sampled. The reverse mapping's most crucial characteristic is that each point in the final picture is set to a suitable value. We perform a reverse mapping to determine the image deformation.

In order to show the performance of the proposed face morphing approach, we have also presented the quantitative comparison against state-of-the-art studies. The comparison results are represented in Table 1.

Table 1. Comparison results of the proposed face morphing approach against existing studies.

Existing studies	Accuracies	Efficiency	Standard deviation
[8]	85.4%	985 msec	±14.6
[37]	81.3%	771 msec	±19.7
[47]	93.9%	1004 msec	±6.1
[15]	87.0%	1125 msec	±13
[14]	91.6%	547 msec	±8.4
Proposed approach	97.2%	204 msec	±2.8

As can illustrated in Table 1 the proposed face morphing approach showed significant performance against the existing works this is because the suggested method uses feature-based morphing, where the feature lines are chosen in turn. The two images are first warped to have the similar picture, and then the subsequent pictures are cross-dissolved. The main requirement is to warp the photos. Either forward mapping or reverse mapping can be used to warp data. Forward mapping involves scanning the source image pixel-by-pixel and copying the pixels to the destination image in the proper places. In reverse mapping, each pixel of the destination image is examined, and the appropriate pixel from the source image is sampled. The reverse mapping's most crucial characteristic is that each point in the final picture is set to a suitable value. We perform a reverse mapping to determine the image deformation.

Security challenges faced by proposed face morphing systems within facial recognition systems stem from the increasing sophistication of adversarial attacks aimed at deceiving these systems. One primary challenge is the development of advanced morphing techniques that create realistic and difficult-to-detect manipulated facial images. Attackers may leverage these techniques to produce morphed faces that can successfully bypass facial recognition systems, leading to security vulnerabilities. Potential solutions and countermeasures to address these challenges include the implementation of robust anti-morphing algorithms that can identify subtle artifacts or inconsistencies introduced during the morphing process. Employing deep learning models trained on diverse datasets, including morphed examples, can enhance the system's ability to recognize sophisticated manipulations. Additionally, the integration of biometric features, such as liveness detection or 3D facial recognition, adds an extra layer of security by assessing the physiological aspects of the presented face. Continuous updates and improvements to face morphing detection algorithms, coupled with regular evaluations against evolving adversarial techniques, are essential to stay ahead of potential security threats. Collaboration between researchers, industry stakeholders, and regulatory bodies is crucial to developing standardized approaches for robust face morphing detection, ensuring the security and reliability of facial recognition systems in the face of emerging challenges.

Furthermore, achieving real-time performance for morphing on different hardware platforms involves a combination of parallel processing, memory optimization, hardware-specific tuning, model simplification, and parameter fine-tuning. By tailoring the implementation to leverage the strengths of GPUs or embedded systems, developers can optimize the morphing process for real-time applications across a variety of hardware environments.

5. Conclusions

Morphing is a method for presenting sequential radiological images. It is applicable to all types of radiological imaging, provided that the two reference images share similarities in terms of location, position, and contrast. Using the movie format is more intuitive than showcasing a sequence of static images. Additionally, morphing enhances the understanding of concurrent pathological developments that could be challenging to distinguish on still images. Image morphing is an image transformation that entails both cross-dissolving between image parts and generic image warping. Face altering or morphing is a kind of digital manipulation of the face, which is a method that may be employed to produce fake biometric face illustrations that mimic the biometric data of couple of people. We have provided a new face morphing technique that is based on the fields of effects nearby 2D control primitives, which is known as field morphing. The suggested method uses feature-based morphing, where the feature lines are chosen in turn. The two images are first warped to have the similar picture, and then the subsequent pictures are cross-dissolved. The main requirement is to warp the photos. Either forward mapping or reverse mapping can be used to warp data. Forward mapping involves scanning the source image pixel-by-pixel and copying the pixels to the destination image in the proper places. In reverse mapping, each pixel of the destination image is examined, and the appropriate pixel from the source image is sampled. The reverse mapping's most crucial characteristic is that each point in the final picture is set to a suitable value. We perform a reverse mapping to determine the image deformation.

As can be seen that the proposed approach has been tested and validated in offline lab. Therefore, in the future, we will implement the proposed framework in healthcare in order to facilitate the physicians for the elderly patients using smartphone.

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