# Morphing Detection using Local Spectra

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Abstract-Face recognition systems are used in a variety of applications such as automated border control. Recently, it was demonstrated that such systems are highly vulnerable to presentation attacks using a morphed image based on two bona fide images. This has as consequence that illegitimate sharing of biometric passports has been made possible. For proper border security, and many other applications, it is therefore necessary to find a successful morphing attack detection system which can classify between bona fide images and morphed images. Some progress has been made already in several studies. However, a proper morphing attack detection system which performs well across different databases of images and morphing pipelines has not been found yet. In this research, the effect of face morphing on local stretches and compressions of frequencies is investigated. The focus of this research is to investigate whether Affine transformations have a traceable effect on the frequency domain. This was done in two steps. Firstly, a homogeneous and a white noise image was used in the morphing pipeline to inspect distortions made by Affine transformations. A 2-D continuous wavelet transform was applied to both images. Secondly, 1-D continuous wavelet transformations have been used on skin textures to find out whether there is a substantial shift in scales (frequencies) due to the different Affine transformations. Experimental results show a remarkable pattern appearing in the homogeneous, white noise and morphed image. However, it is found that the 1-D continuous wavelet transforms used in this research are not able to differentiate bona fide images and morphed images.

## I. INTRODUCTION

Face morphing is the act of seamlessly transforming an image of a face into another face. Two (bona fide) images can be used to construct a new face which contains the features of both contributors, see figure 1. Morphed images form a threat to automated face recognition systems, which have a wide range of applications including Automatic Border Control (ABC) systems. ABC systems compare a live image of a person's face with a supplied face image in an electronic Machine Readable Travel Document (eMRTD). Morphed images could set an ABC on the wrong foot, as shown by Ferrara et al. in [2]. More than one person can namely be identified with a single morphed image. Furthermore, Robertson et al. showed in [11] a poor performance of human inspectors with

distinguishing between morphed and bona fide images. This is problematic because morphed images can be used for passport or ID card requests unnoticed. This poses a threat for border security. Ferrara et al. explain this with a nice anecdote [2]. Imagine being a criminal wanting to flee the country, the only thing you would need is an accomplice for creating a morphed image based on the criminal's and accomplice's faces. The accomplice can now request eMRTD using the morphed image and hand it over to the criminal. The ABC compares a live image from the criminal to the eMRTD and concludes that the eMRTD belongs to the criminal. The criminal can now pass through the ABC to another country with a fake identity.

To combat this problem several morphing attack detection (MAD) algorithms have been investigated already. MAD algorithms can be roughly divided into two groups: with a live image reference (D-MAD) or without (S-MAD). So far, a robust algorithm which performs well across different databases and morphing pipelines has not been found yet.



Fig. 1. Two bona fide faces can be used to create a morped image (right).

This paper focuses specifically on detecting a successful morphing strategy which makes use of Delaunay triangulation and Affine warping, see section III-A. Due to the alterations in the image created by this morphing strategy, it is expected that local frequencies within such Affine warped area of neighbouring Delaunays triangle experience a different measure of compression or stretching which should be detectable. Those sudden stretches and compressions should only be present in morphed images. This research investigates whether transformed white noise images, on which the exact same morphing strategy is performed, can be used for characterizing the frequency domain of morphed images. White noise images initially contain no information in the frequency spectrum which makes it a good reference. Next, a simple homogeneous

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pattern will be used for illustrating the effect of Affine transformations and possible interference patterns resulting of it. The frequency domain will be investigated with a 2-D continuous wavelet transformation. Furthermore, this research explores whether the frequency contents of skin textures near the border of different Affine warped areas in a morphed image have a more sudden change when compared to a morphed image. The following sections in this paper will describe related works (section II) and some theoretical background knowledge (section III); after which the method (section IV), results (section V), discussion (section VI) and conclusion (section VII) will be explored.

## II. RELATED WORK

Before moving on to the background theory for this paper, a short summary is given of previously done work to put this research into perspective. An early study for S-MAD [9] investigates the textures in morphed images. The algorithm uses Binarized Statistical Image Features (BSIF) and a linear support vector machine to classify the images. This resulted in a False Acceptance Rate (FAR) of 3.46% and a False Reject Rate (FRR) of 0%. FAR and FRR describe the percentage of the morphed images falsely accepted and bona fide images falsely rejected respectively. It is demonstrated in [12] that printing and then scanning a morphed image reduces the performance of the MAD of [9] significantly. To prevent this problem of printing and scanning, two deep convolutional neural networks were trained using transfer learning with both genuine images and morphed printed images. This algorithm works better than the morphing detection in [9] for printed and scanned images. Research that uses the 2-D discrete Fourier transform (DFT) have also been performed. Neubert et al. used in [7] a 2D-DFT for classifying between morphed and bona fide images. In their research, the frequency domain was divided in 25 windows of which the average magnitude was taken for their classifier. This resulted in an accuracy of 75.2 % for classifying between morphed and bona fide images.For D-MAD, some significant progression has been made in [3]. Their algorithm is able to 'demorph' the morphed image, by subtracting the live image from the subject from the image and the resulting image is compared to the subject. If the face is not similar, there is a low similarity score and the image is classified as a morph. This method requires an assumption for the value of the so called alpha blending factor which is used to blend the images of two contributors. None of the studies so far have resulted in a robust algorithm for morphing detection. The main focus of this research is demonstrating if the Affine transformations cause a measurable difference in the frequency domain for classifying between morphed and bona fide images.

# III. GENERATION OF MORPHED IMAGES AND TRACING ARTEFACTS

To understand how frequencies are stretched out or compressed, it is helpful to grasp the fundamentals of the face morphing technique which are used in this research. In this section, the morphing pipeline will be discussed first. Next, we will have a glance at frequency alterations due to morphing transformations and a related theorem is described. Lastly, prior knowledge of frequency transformations will be discussed which will be used in this paper.

# A. Morphing Pipeline

The initial step in face morphing is to detect facial landmarks in both (aligned) bona fide faces, see figure 2. This is realized using the Stasm library in Python. Next, average coordinates are calculated for each facial landmark of the morphed image using the corresponding coordinates of the landmarks of the two contributors. Those points are used for Delaunay triangulation, see figure 2. Subsequently, the facial landmarks belonging to each triangle in the morphed image are found in the contributing faces and the contributing faces are triangulated based on those points. In order to create a high quality morph, splicing is used. Splicing only transforms certain areas of the face, leaving out areas such as your hair which cause clear ghost artifacts in the morphed image. Through the use of Affine transformations each triangle of both contributors is being mapped to its corresponding triangle in the morphed image, see image 2. Alpha blending is then used to blend the textures of both contributors. Finally, the image is post processed such that the colours of the two contributors are mixed seamlessly.



Fig. 2. Left two images show aligned bona fide faces with dots representing certain landmarks. Right pictures shows Delaunay triangulation based on the average coordinates of those points.

## B. Affine Theorem

Now you might wonder how this morphing strategy could leave behind local compressions and stretches of frequencies, and the answer lies in the previously discussed Affine transformation. Affine transformations are transformations which preserve parallel lines and it can be described by equation 1 [1]. They map the location of pixels from one space to a new space.

$$\mathbf{y} = A\mathbf{x} + \mathbf{b} \tag{1}$$

Here the vector  $\mathbf{y}$  contains the transformed coordinate values of a pixel from the contributing face;  $\mathbf{x}$  being the value of the coordinates of the same pixel in the original face; A being a transformation matrix and  $\mathbf{b}$  a translation vector. The Affine theorem offers a clear description of the effect of Affine warping on the (Fourier) frequency domain by formula 2 [8].

$$g(A\mathbf{x} + \mathbf{b}) \xrightarrow{F} \frac{1}{|A|} * e^{2i\mathbf{b}^T A^{-T}\mathbf{u}} G(A^{-T}\mathbf{u})$$
 (2)

Here the right-hand side describes the Fourier transform of the left-hand side. It is visible that frequency domain is transformed with the transpose of the inverse of the transformation matrix and scaled by the one over the determinant of the matrix. This is directly related to the scaling property of the Fourier transform. Furthermore, the frequency domain gets modulated which is a result of the shifting property of the Fourier Transform. You can imagine that different triangles have different transformation matrices corresponding to each triangle. Therefore, frequencies can suddenly jump from amplitude, phase and orientation. This effect would be more gradual in bona fide images but could be sudden in face morphs. Note, however, that the face morph has two contributors. Therefore, the frequency spectrum will become a combination of compressed frequencies from one contributor and stretched frequencies from the other. Besides, an image is not a continuous signal which can cause a small discrepancy in the expected frequency domain, for example, due to interpolations when the pixel's transformed coordinate falls on the border of two pixels.

## C. DFT and Wavelet Transform

The frequency content of a signal can be described using the discrete Fourier transform (DFT) and the wavelet transform. For this paper some previous knowledge about those topics is required. Images consist of pixels and are discrete by nature. A discrete Fourier transform can be used for transforming an original finite signal into its complex (normalized) frequency representation. In this paper the energy of signals will be investigated. Equation 3 describes the relation between the energy of the signal x[n] in the spatial domain and frequency domain. The right-hand side describes the frequency domain representation of the (total) energy of a signal.

$$\sum_{n=0}^{N-1} |x[n]|^2 = \frac{1}{N} \sum_{k=0}^{N-1} |X[k]|^2$$
(3)

The wavelet transform can also be used for representing frequencies in a signal. The main difference between the DFT and the wavelet transformation is that the wavelet transformation is a function of both space and frequency, bounded by Heisenberg's uncertainty principle. The continuous wavelet transform used in this research is described by equation 4 [10] and one can see in figure 3 a shift in frequency of a transformed periodic function. The wavelet is part of the so called Morlet family. Such representation of the absolute value of the wavelet coefficients in terms of scale and position is called a scalogram.

$$CWT(\tau, s) = \Psi(\tau, s) = \frac{1}{\sqrt{|s|}} \int x(t)\psi^*\left(\frac{t-\tau}{s}\right)dt \quad (4)$$

$$\psi(t) = \frac{1}{\sqrt{\Pi f_b}} e^{2i\pi f_c t} e^{\frac{t^2}{f_b}}$$
(5)

Note that the variable 's' can be related to the frequency of the signal. High values of s correspond to low (normalized) frequencies. Equation 5 [6] describes the wavelet function of the so called complex Morlet wavelet. Another major



Fig. 3. Wavelet transform of cosine. Function changes from frequency at position 100.

difference is that the continuous wavelet transform is localized in space by a Gaussian window. This has as effect that different frequencies are analyzed with different time resolutions. Although the equations given seem to suggest that the continuous wavelet transform is a continuous function, this is not true. The continuous wavelet transform can be implemented as a convolution using discrete samples. The name continuous is used to differentiate between the discrete wavelet transform which has different properties concerning the scale factors for example.

#### IV. METHOD

## A. Database Face Images

The database for the face images used in the experiments were acquired from the PUT database [4]. In this database, around 100 different people were gathered and of each person 100 images of the face in different postures were taken. The database intends to create reliable data for evaluating the performance of face recognition systems. The quality of the images retrieved from the database have a relatively high resolution of 1511x1943 pixels which is of higher quality than numerous other databases [4]. High quality is needed for inspecting local changes in frequency content. For example, pores, which introduce high frequencies in an image, can become more or less visible depending on the quality of the image. All bona fide images of faces in this paper were derived from this database. All the images were converted first to grayscale before further experimenting was done.

#### B. Morphing noise images and homogeneous patterns

1) White Noise and homogeneous pattern: To experiment what the effect is of the morphing pipeline on the frequency content of the morphed image, two patterns will be morphed.

Firstly, a white noise pattern will be used. Secondly, an homogeneous pattern will be used to investigate possible interference patterns in the spatial domain which might be traceable in the frequency domain. This pattern will consist of black and white pixels alternating repetitively. Morphing such patterns can be implemented fairly easily. A normal morphing process is performed on two bona fide images. However, this time pieces of a bona fide face will not be Affine warped to its corresponding Delaunay triangle, but the noise pattern will be used. The transformed patterns can now be compared to a morphed image and a bona fide image using a frequency representation. In figure 4, the image of the white noise and the homogeneous pattern can be found.



(a) White noise image(b) Image with alternating pixelsFig. 4. Images of pattern and noise used in experiment.

2) 2-D Continuous Wavelet Transform: Next to the one dimensional wavelet transform, it is possible to perform a 2-D continuous wavelet transform as well. In this experiment a 2-D continuous Morlet wavelet will be used. An interesting property of the transform is that it can detect singularities within an image remarkably well. The local maxima of the wavelet transform correspond to those singularities which are in turn created by edges [5]. Because the images consist of different Delaunay triangles, it is expected that this transform could make transitions between the different areas visible. The resulting image in the results will show the absolute value of the wavelet coefficients at a particular scale, center frequency and bandwidth frequency which will have been optimized experimentally. The Morlet wavelet itself is also defined in the frequency domain and the transformation is also performed in the (Fourier) frequency domain. Equation 6 [10] illustrates the Fourier transform of this wavelet which is used for this experiment.

$$\widehat{\psi}\left(\omega_x, \omega_y\right) = e^{-\sigma^2 \left((\omega_x - \omega_0)^2 + \frac{(\varepsilon \omega_y)^2}{2}\right)} \tag{6}$$

The parameters will be optimized experimentally.

## C. 1-D continuous wavelet transform

In this section the method for the experiment with the 1-D continuous wavelet transform will be discussed. This transform was chosen because it is able to illustrate local frequencies as opposed to the regular DFT which gives a frequency representation of the signal in its entirety. A sudden change in the frequency domain is expected because different stretched and compressed images are warped to a new Delaunay triangle which possibly introduces new frequencies depending on the triangle as discussed in III-B.

1) Skin texture: For the experiment with the 1-D wavelet transformation, it is necessary to find a proper position in the face for extracting skin textures. The decision was made to use the cheek, because this area is less prone to shadows as compared to the side of the face. Furthermore, the cheek contains relatively less hair which can have considerable influence on the frequency spectrum. Lastly, the Delaunay triangles in the morphed image are big enough here for investigating the effect of two specific Affine transformations located next to each other without any (possible) interferences related to the warps of other triangles. Two skin textures are extracted for both bona fide and morphed images. In total 200 samples will be taken over a length of 200. Those skin textures are extracted from the cheek parallel to the border of two Affine warped areas, both laying in different Affine warped regions, see figure 5.



(a) Delaunay triangles

(b) Skin textures extracted (blue lines)

Fig. 5. Skin textures were extracted parallel to the borders of Affine warped areas (green lines).

2) Interpolation: In order to extract proper data from the skin texture along a certain line, it is necessary to use interpolations. Pixels are namely discrete and when the skin textures are extracted from the face, it might be possible that the location you want to extract falls exactly on the corner of four pixels. There are various interpolation methods such as nearest neighbor, bilinear and bicubic. The latter was chosen for this experiment. It is expected that this strategy returns more accurate extracted samples as compared to nearest neighbor.

3) Scales, Center Frequency and Bandwidth Frequency: As explained in section III-C, the continuous wavelet transform is a function of three adjustable variables: scale, center frequency and bandwidth frequency. In order to investigate the energy shift in the scalogram, a proper choice needs be made first for those parameters. The center frequency will be set to 0.5. Next, a choice for the scales can be made. Because the affine theorem suggests that all frequencies are changed with a similar amplitude and frequency, it is expected that all frequencies will undergo a change. In this experiment a set of frequencies with scales between 1 and 64 are chosen. The frequency bandwidth should be wide enough to capture interesting local spectra, without capturing any noise. It is not yet known which bandwidth will be most successful. In this experiment 3 frequency bandwidths are tried out: 5, 10 and 20.

4) Energy Differences: The scalogram has dimensions of 64x200, which is related to the amount of scales used and the length of the signal. The scalogram is divided up into windows of 8 by 25 coefficients, creating in total 64 windows. From those windows the average energy of the coefficients are calculated. Finally, the difference in energy for is calculated by comparing the corresponding windows of energy of the extracted skin features.

## V. RESULTS

#### A. White noise and homogeneous pattern

Firstly, the result of the morphing process on image 4b will be investigated. In figure 6, the results of the morphing process is illustrated when image 4b is used, instead of two bona fide images.

There is a very remarkable interference pattern visible for the highly oscillating pattern. Furthermore, it can be seen that the structure of those patterns resemble (Delaunay) triangles. It must be investigated whether those Delaunay triangle patterns are also traceable in the white noise image and morphed images. Therefore, the result of the morphing pipeline on the white noise pattern will be presented now. In figure 7 the effect of the morphing pipeline on the image is visible. It is hard to see any significant changes in the white noise image. If you look closely to figure 7, you can see that a part of the image has become of darker color. When the contrast with the background is increased and this image is darkened, this area is well visible (see figure 7, right). The



Fig. 6. Morphed homogeneous pattern.

area is surrounded with blue lines for clarification. When we now perform a continuous 2-D wavelet transformation on the same noise pattern, a pattern appears which which resembles the Delaunay triangulation of the face. The chosen parameters for the wavelet are:  $\sigma = 0.5$ ,  $\omega_0 = 6$  and  $\epsilon = 1$ . It has been found that the 2-D Morlet wavelet with a scale of 1 was most effective in finding traces of the morphing pipeline. In figure 8, two images are visible. On the left the 2-D continuous wavelet transform performed on a morphed image can be found, and on the right the transform of the white noise can be found. A similar structure of white lines can be found in both images when observed carefully. The morphing pipeline therefore leaves behind remarkable traces in both the white noise and the morphed image. However, a clear pattern is lacking in the skin content of the morphed image.



Fig. 7. The result of performing the morphing operations on white noise.



Fig. 8. Wavelet transformed noise on the right and wavelet transformed morphed image on the left.

## B. 1-D continuous wavelet

In this section the results of the 1-D continuous wavelet transform will be discussed. In table I, one can see the energy differences between a morphed image and the bona fide image. Note how the energy is not represented with any physical unit. In the table the energy differences for each frequency bandwidth  $f_b$  is given. Although this table is only a representation of one image, it is found that other

 TABLE I

 ENERGY DIFFERENCES MORPHED AND BONA FIDE IMAGE.

Energy differences	morphed image	bona fide image
Fb = 5	0.1136	0.6040
Fb = 10	0.0975	0.0860
Fb = 20	0.0604	0.0549

images behaved in a similar manner. Changing the frequency bandwidth does not help amplifying energy differences in a morphed image as compared to a bona fide image. Futhermore, it can be noted that sometimes the energy difference between the skin contents of a morphed image is even lower than that of the a bona fide image.

## VI. DISCUSSION

To start off, the results of the 2-D continuous wavelet transform will be discussed. Affine warping two images had a more radical effect on the spatial domain than expected, see figure 6. Especially those features became visible in the spatial and frequency domain representations. Although some patterns, which resemble the Delaunay triangulations, were found after performing the 2-D continuous wavelet transform, the expectations were that also in the skin content those structures would have become visible, however, this is not the case; neither in morphed or morphed noise images. The patterns might be masked by various other processes which are solely performed on this part of the face in the morphing pipeline. When the 1-D wavelet transformations were taken along a border of an Affine warped area, the results did not show sudden shifts in frequency and amplitude as it was expected. Changing the bandwidth frequency did not cause a (structural) increment or decrement of energy difference as compared between the morphed image and the bona fide image. Furthermore, for future experiments another optimization should be made. Increments in low scales (such as from scale = 1 to scale = 2) is related to halving the frequency, however, an increment of a much higher scale is related to a much lower shift in frequency. To see the frequency being halved for example, it would be wise to use scales related to an exponential with a basis of two. Like this it is expected the scales will represent expected shifts in frequencies more effectively. Another alternative could be to use a different frequency representation such as the short-time Fourier transform.

## VII. CONCLUSION

Face morphing, the act of seamlessly transforming two faces into a new face, has posed a big threat for facial recognition systems. A proper algorithm for classifying bona fide and morphed images with a high accuracy has not been found yet. In this paper a morphing strategy was discussed which uses Delaunay triangulation and Affine warping. This morphing method created a remarkable interference pattern in the spatial domain. It was found that those patterns were traceable using a 2-D continuous wavelet transform. However, further experiments need to be performed to investigate whether those traces can also be found using a different morphing pipeline and databases of faces. Furthermore, processes like printing and scanning the image can possibly erase those traces significantly. The experiments were unsuccessful in proving the expectation that the frequency content would change from frequency and amplitude significantly near the border of two Affine warped areas. Future research could perform different types of frequency transformations such as the Short Time Fourier Transform for investigating local stretches and compressions of frequencies.

#### REFERENCES

- George Bebis, Michael Georgiopoulos, Niels da Vitoria Lobo, and Mubarak Shah. Learning affine transformations. *Pattern recognition*, 32(10):1783–1799, 1999.
- [2] Matteo Ferrara, Annalisa Franco, and Davide Maltoni. The magic passport. In *IEEE International Joint Conference on Biometrics*, pages 1–7. IEEE, 2014.
- [3] Matteo Ferrara, Annalisa Franco, and Davide Maltoni. Face demorphing. *IEEE Transactions on Information Forensics and Security*, 13(4):1008–1017, 2017.
- [4] Andrzej Kasinski, Andrzej Florek, and Adam Schmidt. The put face database. *Image Processing and Communications*, 13(3-4):59–64, 2008.
- [5] Stephane Mallat and Wen Liang Hwang. Singularity detection and processing with wavelets. *IEEE transactions on information theory*, 38(2):617–643, 1992.
- [6] Mathworks. cmorwavf.
- [7] Tom Neubert, Christian Kraetzer, and Jana Dittmann. A face morphing detection concept with a frequency and a spatial domain feature space for images on emrtd. In *Proceedings of the ACM Workshop on Information Hiding and Multimedia Security*, pages 95–100, 2019.
- [8] Heechan Park, Graham R Martin, and Abhir Bhalerao. Local affine image matching and synthesis based on structural patterns. *IEEE transactions on image processing*, 19(8):1968–1977, 2010.
- [9] R Raghavendra, K Raja, and C Busch. Detecting morphed facial images. In Proceedings of 8th IEEE International Conference on Biometrics: Theory, Applications and Systems (BTAS-2016), pages 6–9.
- [10] Vijaya Kumar Reddy, Kiran Kumar Siramoju, and Pradip Sircar. Object detection by 2-d continuous wavelet transform. In 2014 International Conference on Computational Science and Computational Intelligence, volume 1, pages 162–167. IEEE, 2014.
- [11] David J Robertson, Andrew Mungall, Derrick G Watson, Kimberley A Wade, Sophie J Nightingale, and Stephen Butler. Detecting morphed passport photos: a training and individual differences approach. *Cognitive research: principles and implications*, 3(1):1–11, 2018.
- [12] Ulrich Scherhag, Ramachandra Raghavendra, Kiran B Raja, Marta Gomez-Barrero, Christian Rathgeb, and Christoph Busch. On the vulnerability of face recognition systems towards morphed face attacks. In 2017 5th International Workshop on Biometrics and Forensics (IWBF), pages 1–6. IEEE, 2017.