A Face Morphing Detection Concept with a Frequency and a Spatial Domain Feature Space for Images on eMRTD

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ABSTRACT

Since the face morphing attack was introduced by Ferrara et al. in 2014, the detection of face morphings has become a wide spread topic in image forensics. By now, the community is very active and has reported diverse detection approaches. So far, the evaluations are mostly performed on images without post-processing. Face images stored within electronic machine readable documents (eMRTD) are ICAO¹-passport-scaled to a resolution of 413x531 and a JPG or JP2fi lesize of 15 kilobytes. This paper introduces a face morphing detection concept with 3 modules (ICAO-aligned pre-processing module, feature extraction module and classification module), tailored for such images on eMRTD. In this work we exemplify design and evaluate two feature spaces for the feature extraction module, a frequency domain and a spatial domain feature space. Our evaluation will compare both feature spaces and is carried out with 66,229 passport-scaled images (64,363 morphed face images and 1,866 authentic face images) which are completely independent from training and include all images provided for the IHMMSEC'19 special session: "Media Forensics - Fake or Real?". Furthermore, we investigate the influence of different morph generation pipelines to the detection accuracies of the concept and we analyse the impact of neutral and smiling genuine faces to the morph detector performance. The evaluation determines a detection rate of 86.0% for passport-scaled morphed images with a false alarm rate of 4.4% for genuine images for the spatial domain feature space.

KEYWORDS

Face Morphing; Image Forensics; Morphing Detection; eMRTD

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¹International Civil Aviation Organization

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1 INTRODUCTION

Face image based authentication scenarios are well-accepted and widespread. In 2014 Ferrara et al. present an identity theft scheme for those scenarios in [8]. They describe an approach allowing two or more persons to pass a face image based authentication scenario with only one artificially weakened Photo-ID template. For the presented attack, a so called face morphing is created, which melts two or more face images of different persons. This morphed face image is used for the document creation performed by a corresponding authority. This Photo-ID document is able to successfully pass all subjective and biometric checks in a boarder control scenario [9]. An example is presented in Figure 1.

Figure 1: An example of a morphed image on a Photo-ID document template. The images are based on [6]

Because of the simplicity of this attack and the chance for an attacker to easily bypass a boarder control scenario, the forensic community has published different detection approaches such as [7, 14, 18, 22, 25, 28]. A survey about recent works and detection approaches concerning the face morphing attack is given in [20]. A challenge for all of these detectors are images with an ICAO-compliant *passport-scale* which is compatible for electronic machine readable travel documents (eMRTD). It means a resolution of 413x531 pixels and a lossy JPEG (.jpg) / JPEG2000 (.jp2) compression with a file size of only 15KB [29]. For example, nowadays, a standard photo taken by a Canon EOS 1300D has a native resolution of 18 megapixels (3456x5184) [3] and a .jpg-filesize of around 5 MB. This means a downscaling of 98.84% and a file size reduction of circa 99.7%. So, the post-processing (cropping, scaling and compression) leads to a significant loss of image information. This increases error rates of morphing detectors because expected morphing artifacts (e.g.:

blending artifacts) could be obscured by this processing operations [24].

Our work addresses the research gap to detect *passport-scaled* morphed images stored within eMRTD. Our main scientific contribution is a novel face morphing detection concept especially for passport-scaled images on eMRTD. The concept includes 3 modules: an ICAO-aligned pre-processing module, a feature extraction module and a classification module. We exemplarily present two different feature spaces for the feature extraction module designed for the challenge to detect passport-scaled images. The first feature space is designed with frequency domain features as discussed in the information hiding community since the mid-1990s for the detection of the artifacts introduced in digital images by watermarking embedding techniques, see [4]. The second presented feature space is based on spatial domain keypoint features as presented in [14]. The evaluation will compare the performance of the concept with these two different feature spaces and is carried out with 66,229 passport-scaled images (64,363 morphed images and 1866 authentic face images containing neutral and smiling faces) which are completely independent from the training data. Additionally, we compare the detection performance of our concept with .jpg and .jp2 files.

2 STATE OF THE ART

In this Section, we introduce the morph generation pipelines we have used to create our evaluation data sets. Furthermore, we describe one concept for the feature space module we modify for our purpose to detect passport-scaled morphed images with our detection concept.

2.1 Morph Generation Pipelines

For our paper, we use three state-of-the-art morph generation pipelines (MGP) to create three different types of face morphing for our evaluation data sets from two related works [19, 24]. As mentioned in [30], all morph pipelines are based on alpha-blending and warping. For our evaluation the alpha-blending parameter is set to 0.5 to build an average between both input images. The warping process is realized with a triangulation which uses 68 facial landmarks, localized by the dlib shape predictor ([www.dlib.net](http://dlib.net)). All presented MGP are completely automated processes to create statistically significant data sets for training and testing.

- The first MGP creates a so called *complete morph*. Here, additionally to the steps above, 20 landmarks on the image borders are added on the image borders to cover the complete image [21]. Due to this, a *complete morph* has an average texture and a average geometry of the original faces and is introduced in [19]. This leads to a high biometric quality [19] but also to clearly visible ghosting artifacts as a result of a blending operation, visualized in Figure 2.
- The second morph generation pipeline creates *splicing morphs* and is introduced in [19] too. The appearance of *splicing morphs* is more realistic than the appearance of *complete morphs*, because they are designed to avoid ghosting artifacts. The facial region is cut, warped and blended to a mutual

face and stitched back (seamlessly) into one of the input images. This leads to a lower biometric quality and to fewer visible artifacts [19].

- The *combined morph* is the third MGP used and combines the aforementioned pipelines to avoid shortcomings. The pipeline is introduced in [24] and aligns the original images prior to the warping process to ensure that warping does not lead to a distortion of the face geometry. This MGP has the best visual quality of the three mentioned pipelines as well as a high biometric quality [24].

The 3 MGP are visualized in Figure 2.

Figure 2: Morph Generation Pipelines (MGP). The images are based on [6]

2.2 Keypoint Feature Space for Morph Detection

In [14] a feature space for morph detection is presented, based on the idea that the blending operation in morphing pipelines causes a reduction of face details, especially on images with a resolution with more than 2 megapixels. The reduction of face details is quantified by the number of keypoints and edges in the face region. Here, the authors assume that the number of keypoints and edges become lower after a blending operation. As pre-processing, prior to feature extraction, the authors segment the face region as a convex hull of the 68 facial landmarks localized with the shape predictor class from the dlib programming library version 19.2 (<http://dlib.net/>). The authors use several keypoint and edge detectors, because they assume that the impact of blending operation is different for each detector, some of them will react more sensible than others. The following keypoint and edge detectors were used as features for the detector in [14]: SIFT [15], SURF [1], ORB [27], FAST [26], AGAST [17], CannyEdge [2], SobelX and SobelY [13]. These eight features were extracted with functions implemented in the OpenCV programming library version 3.0 with contributions (<http://opencv.org>). They normalize the number of detected keypoints and edges for every feature with the natural logarithm of the image size (in pixels), because of the different face sizes from different image resolutions. Furthermore, the authors build a lossy JPEG compressed self-reference (quality level: 75%) and extract the same features. Subsequent they build the ratio between features from the original image and the lossy self-reference image. So, it results in a 16 dimensional feature space.

The work in [24] shows that this detector is not suitable for passport-scaled images, because the reduction of the image size and the down-scaling also lead to a reduction of keypoints and edges. So, the detector delivers a reasonable high false alarm rate (ca. 42%) for genuine images. Furthermore, this rate is complementary, because the same passport-scaled images but without JPEG compression to 15kB were involved into training.

In this paper we selected this feature space for our face morphing detection concept and suggest a modification (see Section 3.2.2).

3 OUR MORPH DETECTION CONCEPT FOR PASSPORT-SCALED IMAGES ON EMRTD

The chapter introduces our morph detection concept for passport-scaled images stored within eMRTD. It includes 3 modules:

- an ICAO-aligned pre-processing module *PPM* (Section 3.1),
- a feature extraction module *FEM* (Section 3.2) and
- a classification module *CM* (Section 3.3).

We introduce in this paper two exemplary designed feature spaces for *FEM* to detect passport-scaled morphs. The first feature space works in frequency domain FS_{Freq} and second feature space in spatial domain FS_{Spat} . We will compare the results in our evaluation. The concept is visualized in Figure 3 and the modules will be briefly described in the following Subsections.

Figure 3: Face Morphing Detection Concept for passport-scaled Photo-ID images

3.1 ICAO-aligned Pre-Processing Module (PPM)

For our detection concept we only use passport-scaled images because they have completely different characteristics than native images caused by the downscaling to 413x531 pixels and the compression of the image file size to 15kB. So, *PPM* checks first if the input image *Img* is passport-scaled (1). If the image complies with the requirements from [29], *PPM* proceeds with the face segmentation (2), if not, the image is converted into a passport-scaled image before the face segmentation. We segment the face region with the help of the 68 facial landmarks from the dlib programming library version 19.2 (<http://dlib.net/>) and its shape predictor². For the face segmentation, the input image is converted in .pngfile format, because dlib does not support .jpg files. With the landmarks we create a bounding box around the face region (region of interest ROI). This region is our new image matrix for processing (3) and it is scaled to a constant resolution of 200x200 pixels, similarly as proposed in [28]. We choose a constant image size to normalize the face size for the feature extraction module and it results in a normalized feature spaces. The image processing pipeline for the *PPM* is visualized in Figure 4.

Figure 4: Image Processing in PPM

3.2 Feature Extraction Module (FEM)

The input of the *FEM* is a 200x200 pixels face image Img_{PPM} derived from *PPM*. We have exemplarily designed two feature spaces (FS_{Freq} and FS_{Spat}) for *FEM*, described in the following subsection. In our evaluation we compare the performance of our detection concept with FS_{Freq} and FS_{Spat} in *FEM*.

3.2.1 Frequency Domain Feature Space (FS_{Freq}). The idea to transform images into the frequency domain to detect artifacts is well known. It is used since the mid-1990s for detection of artifacts created by watermarking embedding techniques as described in [4] and also for a morph detection approach in [5]. We adapt this idea to create a feature space to detect morphings on passport-scaled images. FS_{Freq} is based on the assumption that the blending operation in the face region during the morphing process causes a reduction of high frequencies (high frequencies contain edge informations) in frequency image domain after a discrete fourier transformation (DFT), even on lossy passport-scaled images. The image processing for FS_{Freq} starts with the transformation of the image into the frequency domain with a DFT. We perform the DFT with OpenCV version 3.2 and default parametrization as described in their documentation³. The *DFT* of an image *I* results in a matrix

²http://dlib.net/files/shape_predictor_68_face_landmarks.dat.bz2

³https://docs.opencv.org/2.4/doc/tutorials/core/discrete_fourier_transform/discrete_fourier_transform.html

of complex numbers with a real part Re and a complex (imaginary) part Im . So, we transform the real and complex (imaginary) parts to magnitude M with

$$M = \sqrt{Re(DFT(I))^2 + Im(DFT(I))^2}.$$

After M is calculated, we re-arrange the quadrants of the magnitude M (1) to set the origin to the image center (see Figure 5). We assume that the blending operations during the morphing process results in a reduction of high frequencies caused by the reduction of edge informations. We try to measure this reduction by separating M in 25 blocks with 40x40 pixels (2). In this blocks we calculate the mean magnitude values as features (3). So, FS_{Freq} results in a 25 dimensional vector.

Figure 5: Image Processing for FS_{Freq}

3.2.2 Spatial Domain Feature Space (FS_{Spat}). As mentioned before, FS_{Spat} is based on the work of Kraetzer et al. in [14]. The approach is thoroughly described in Section 2.2. Basically, we primarily modify the feature normalization and the feature selection compared to [14]. The number of detected keypoint and edge features from 8 detectors (SIFT, SURF, ORB, FAST, AGAST, CannyEdge, SobelX and SobelY, see Section 2.2) are extracted on the normalized face image derived from PPM. Hence, no more feature normalization is required and we extract a 8 dimensional feature vector.

3.3 Classification Module (CM)

CM is based on feature vectors generated by FEM to train a statistical model. We train overall 4 statistical models in this work, two for each feature space (FS_{Freq} and FS_{Spat}) with each one for the allowed image datatypes (.jpg and .jp2) [29]. Hence, we get 4 the statistical models $M_{FS_{Freq}JPG}$, $M_{FS_{Freq}JP2}$, $M_{FS_{Spat}JPG}$ and $M_{FS_{Spat}JP2}$, were the models with .jpg files ($M_{FS_{Freq}JPG}$, $M_{FS_{Spat}JPG}$) were used to classify only .jpg test datasets and those with .jp2 files ($M_{FS_{Freq}JP2}$, $M_{FS_{Spat}JP2}$) to classify .jp2 test datasets. All models have 2 classes (*Morph* and *NoMorph*). The training data consists of self acquired authentic images (*NoMorph*) and morphs which are created based on these authentic images. We use images with neutral face expression to train the statistical models, a detailed description of the training data is given in Section 4.1. The statistical models are trained with WEKA 3.8 [11] and its SMO classifier. CM decides whether an image is morphed or not.

4 EVALUATION SETUP

Our face morphing detection concept is evaluated with two different feature spaces FS_{Freq} and FS_{Spat} (see Section 3.2). Therefore, we create statistical models with self-acquired training data (Section

4.1). We evaluate our concept with both feature spaces and with independent free available test data and define our test goals in Section 4.2.

4.1 Training Data

Our training data includes 12,500 images (4,234 *NoMorphs*; 8,266 *Morphs*) based on 90 different persons for all trained models. The 90 subjects have a neutral face expression and were acquired mostly with 3 different cameras and two instances of each camera model including 3 different resolutions and 3 different ISO-values per camera, based on the ICAO-requirements (see Table 1).

Table 1: Used cameras and acquisition parameters for the training data. *Resolution before the passport-scale.

Camera	Resolution*	ISO-value
2 * Canon EOS 1200D Lens: EF28-1005 f/4-5.6	3456x5184	100,400,800
	2304x3456	100,400,800
	1728x2592	100,400,800
2 * Nikon D3300 Lens: AF-S 50mm f/1.8G	4000x6000	100,400,800
	3000x4496	100,400,800
	2000x2992	100,400,800
2 * Nikon Coolpix A100	3834x5152	100,400,800
	1703x2272	100,400,800
	1200x1600	100,400,800

Morphings in our training dataset are based on those 90 persons and are created with the three used morph generation pipelines presented in Section 2.1. The dataset includes 8,266 morphs in which the three generation pipelines are nearly equal distributed (2,995 *complete morphs*, 2,637 *splicing morphs*, 2,634 *combined morphs*). These attack types represent realistic attacks with a nearly faultless visual quality of the face region. As mentioned before, all 12,500 samples in the training dataset are post-processed with the passport-scale and are stored in .jpg and .jp2 file format. So, our four statistical classification models are all build from 12,500 feature vectors resulting from one of the two detection approaches and include only vectors either from .jpg or .jp2 files as mentioned in Section 3.3.

4.2 Test Data and Goals

Our morph detection concept is evaluated with test datasets which are not included into training. Therefore, we create multiple test datasets with the 3 different morph generation pipelines and genuine images (neutral and smiling expression, *NoMorphs*). We are aware that smiling faces are not ICAO-compliant, but we evaluate them to analyse the robustness of our detection concept for genuine faces. Furthermore, we use the test datasets provided at IHMMSEC2019 Special Session: Media Forensics - Fake or Real? All test samples in all test datasets are created in both file formats .jpg and .jp2 (except the provided morph test dataset from IHMMSEC). The datasets are listed in Table 2. Hence, our tests are carried out with 66,229 passport-scaled images (64,363 morphed images and 1,866 authentic face images).

We define 5 test goals to evaluate our detection concept with both presented feature spaces.

- **G1:** Determine the detection performance of the detection concept with FS_{Freq} and FS_{Spat} .

- **G2:** Determine the impact of different morph generation pipelines (*complete*-, *splicing*-, *combined morph*) for the detection concept with FS_{Freq} and FS_{Spat} .
- **G3:** Determine the impact of a neutral and smiling face expression for genuine images to the false alarms of the detection concept with FS_{Freq} and FS_{Spat} .
- **G4:** Determine the impact of the file format .jpg and .jp2 for the detection concept with FS_{Freq} and FS_{Spat} .
- **G5:** Compare the performance of the detection concept with FS_{Freq} vs. FS_{Spat} (See Section 5.3).

The detection performance is measured with the detection accuracy ACC, which is presented in chapter 5.

Table 2: Overview of used test datasets for evaluation of morph detection approaches. *Resolution before the passport-scale. ** Morphs are based on this databases

Test Dataset	Format	Resolution*	Files	Data Ref
CombinedMorphsIHMMSEC19	jpg	1350x1350	2,175	[10]
CompleteMorphsLondon	jpg jp2	1350x1350	2*5,050	[6]**
SplicingMorphsLondon	jpg jp2	1350x1350	2*9,352	[6]**
CombinedMorphsLondon	jpg jp2	1350x1350	2*10,100	[6]**
CompleteMorphsUtrecht	jpg jp2	900x1200	2*1,326	[12]**
SplicingMorphsUtrecht	jpg jp2	900x1200	2*2,614	[12]**
CombinedMorphsUtrecht	jpg jp2	900x1200	2*2,652	[12]**
NoMorphs-neutralIHMMSEC19	jpg jp2	1350x1350	2*102	[10]
NoMorphs-smilingIHMMSEC19	jpg jp2	1350x1350	2*102	[10]
NoMorphs-neutralUtrecht	jpg jp2	900x1200	2*74	[12]
NoMorphs-smilingUtrecht	jpg jp2	900x1200	2*58	[12]
NoMorphs-neutralCFD	jpg jp2	2444x1718	2*597	[16]

5 EVALUATION RESULTS

This section presents the evaluation results for our test goals (**G1** to **G5**, see Section 4.2). We show the results for **G1** to **G4** of the concept with FS_{Freq} in Section 5.1 and with FS_{Spat} in 5.2. The results for test goal **G5** are presented in Chapter 5.3. We simply measure the detection performance of the concept with the accuracy of the detectors with $ACC = \frac{CCI}{IN} * 100$ where CCI is the number of correct classified instances in the test dataset and IN is the total number of instances in dataset.

5.1 Evaluation Results of Detection with FS_{Freq}

The results of our detection concept with FS_{Freq} are listed in Table 3. It shows that the concept is able to detect 75.2% (48,427 samples out of 64,363) of passport-scaled morphed images correctly (**G1**). Furthermore, it has an accuracy of 95% for genuine images (5% false alarms), where especially the images from the UtrechtDB [12] trigger most false alarms. Indeed, these error rate is too high for a real world application, but it can be reduced by a multi-level-detection process, as described in [23]. The morph generation pipelines have a not negligible influence to the detection performance of the concept with FS_{Freq} , especially the performance for the *splicing morph* varies in comparison to the other pipelines (**G2**). Furthermore, the results indicate that it has no influence on the detection performance

Table 3: Detection results of the concept with FS_{Freq} .

Morph Test Dataset	ACC JPG	ACC JP2
CombinedMorphsIHMMSEC19	80.9	-
CompleteMorphsLondon	78.1	70.7
SplicingMorphsLondon	65.1	62.5
CombinedMorphsLondon	75.5	68.1
CompleteMorphsUtrecht	95.9	93.7
SplicingMorphsUtrecht	97.7	99.4
CombinedMorphsUtrecht	96.0	96.0
Total Morphs	77.5	72.8
	75.2	
NoMorphs-neutralIHMMSEC19	100.0	98.0
NoMorphs-smilingIHMMSEC19	99.0	99.0
NoMorphs-neutralUtrecht	70.3	68.0
NoMorphs-smilingUtrecht	70.7	68.5
NoMorphs-neutralCFD	100.0	98.2
Total NoMorphs	95.7	94.2
	95.0	
Total	78.5	73.3
	75.8	

if a person is smiling or not (**G3**). The detection accuracy for .jpg files (78.5%) is significant higher than for .jp2 images (73.3%) (**G4**).

5.2 Evaluation Results of Detection with FS_{Spat}

The detection concept with FS_{Spat} is able to detect 86.0% (55,373 out of 64,363 samples) morphed passport-scaled images correctly and triggers a false alarm rate of 4.4% for genuine images (**G1**). The results for all test datasets are shown in Table 4. We can assert, that the detection accuracy for the morph generation pipeline *splicing morph* also varies for the concept with FS_{Spat} (**G2**). Besides, the concept with FS_{Spat} is less robust for smiling faces as with FS_{Freq} , we notice a varying detection accuracy for these test samples (**G3**). The detection accuracy for .jpg files (86.7%) over all datasets is higher than for .jp2 files (85.9%) (**G4**).

5.3 FS_{Freq} vs. FS_{Spat} (**G5**)

In this section, we compare the detection accuracies of concept with the both exemplary designed feature spaces. The first view, shows better results for the detection concept with FS_{Spat} because it classifies more morphed (+14.3%) and more genuine (+0.6%) samples correct. We assume this depends on the training data. The dimensionality of the feature space of FS_{Freq} is higher than the dimensionality of the feature space of FS_{Spat} and as a result it needs more training samples to deliver more accurate results. But, the detection concept with FS_{Freq} shows more robust results for neutral and smiling faces in our evaluation. Furthermore, FS_{Freq} has more accurate results for the "IHMMSEC'19 special session: fake or real" test data with 80.9% of detected morphs.

6 CONCLUSION

This paper introduces a detection concept for face morphings on passport-scaled images on eMRTD. The concept is evaluated with two different feature spaces (FS). The concept is able to detect morphed images with an accuracies of 86.0% by a false alarm rate

Table 4: Detection results of the concept with FS_{Spat} .

Morph Test Dataset	ACC JPG	ACC JP2
CombinedMorphySIHMMSEC19	77.7	-
CompleteMorphyLondon	86.5	81.3
SplicingMorphyLondon	81.2	81.7
CombinedMorphyLondon	86.4	84.1
CompleteMorphyUtrecht	95.9	95.0
SplicingMorphyUtrecht	97.7	99.5
CombinedMorphyUtrecht	95.5	95.6
Total Morphs	86.4	85.7
	86.0	
NoMorphs-neutralSIHMMSEC19	99.0	98.0
NoMorphs-smilingSIHMMSEC19	99.0	98.0
NoMorphs-neutralUtrecht	89.2	60.0
NoMorphs-smilingUtrecht	79.3	63.8
NoMorphs-neutralCFD	100.0	99.8
Total NoMorphs	97.0	94.1
	95.6	
Total	86.7	85.9
	86.3	

(FAR) of 4.4% with a spatial domain FS and with an accuracy of 75.2% by a FAR of 5% with a frequency domain FS. The used morph generation pipelines have a not negligible influence to the detection performance of the concept. The frequency domain FS delivers a lower error rate for genuine image with smiling face expression than the spatial domain FS. The concept has a higher detection accuracy for .jpg files than for .jp2 files with both FS. In future work, it would be helpful to create bigger training datasets with an extended variety, this could increase the detection accuracy. It would be interesting to see how the concept works with other FS and to analyse the influence of anti-forensics to the concept.

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