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Cycle-consistent generative adversarial neural networks based low quality fingerprint enhancement

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Abstract

Distortions such as dryness, wetness, blurriness, physical damages and presence of dots in fingerprints are a detriment to a good analysis of them. Even though fingerprint image enhancement is possible through physical solutions such as removing excess grace on the fingerprint or recapturing the fingerprint after some time, these solutions are usually not user-friendly and time consuming. In some cases, the enhancements may not be possible if the cause of the distortion is permanent. In this paper, we are proposing an unpaired image-to-image translation using cycle-consistent adversarial networks for translating images from distorted domain to undistorted domain, namely, dry to not-dry, wet to not-wet, dotted to not-dotted, damaged to not-damaged, blurred to not-blurred. We use a database of low quality fingerprint images containing 11541 samples with dryness, wetness, blurriness, damages and dotted distortions. The database has been prepared by real data from VISA application centres and have been provided for this research by GEYCE Biometrics. For the evaluation of the proposed enhancement technique, we use VGG16 based convolutional neural network to assess the percentage of enhanced fingerprint images which are labelled correctly as undistorted. The proposed quality enhancement technique has achieved the maximum quality improvement for wetness fingerprints in which 94% of the enhanced wet fingerprints were detected as undistorted.

Keywords Cycle-consistent adversarial neural network · Low quality fingerprint · Fingerprint quality enhancement · Biometric

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1 Introduction

Fingerprints are one of the physiological characteristics of a human for verifying and identifying. Along with them, a human has other distinctive features: face, ear print, iris and retina, palm print, vein map, voice, signature [2, 9, 19, 24, 28]. Due to its uniqueness, high recognition accuracy, and existence of low-cost devices, fingerprints are one of the most reliable biometric characteristics used in human authentications and textural structures such as ridge frequency, orientation field (OF), and minutiae distribution were commonly used for that purpose [7, 10, 29, 30, 36, 37]. Jianjiang et al. [11] presented a novel minutiae-based fingerprint matching algorithm using texture-based and minutiae-based descriptors and support vector machine (SVM) [21, 25]. Cappelli et al. [6] used minutiae cylinder-code (MCC) [5] to improve the minutiae pair selection.

The attempt to improve the accuracy of fingerprint recognition using textural structures still continues. Cao et al. [4] proposed a method that effectively detects minutiae clusters, which tend to overrate the similarity and reduce corresponding minutiae similarity. Nandakumar [27] proposed a localized minutiae phase spectrum that encodes the local minutiae structure in the neighborhood of a given minutia point as a fixed-length binary code. Some researchers have tried to reduce the complexity of the matching process. For instant, Barman et al. [1] used spatial information (distance) of minutiae points only to perform the matching in order to reduce the computational complexity of fingerprint recognition.

In the recent years many researchers are using deep neural network in biometric recognition [14, 32, 34]. Cao and Jain [3] proposed an automated latent fingerprint recognition algorithm using Convolutional Neural Networks (ConvNets) for ridge flow estimation and minutiae descriptor extraction. Zhang et al. [43] proposed Deep Dense Multi-level feature (DDM), which is a representation for partial high-resolution fingerprint. Discriminative features inside any local fingerprint block were extracted using deep ConvNets. The showed that DDM contains multi-level information, which can be utilized for partial-to-partial matching.

Although fingerprints theoretically can identify people with high accuracy, the real-world performance of the systems highly depends on the condition of the finger's surface, i.e., humidity, dust, temperature, etc., which can drop the identification accuracy [35]. Features such as OF, which is representing the trend of the ridge flow of fingerprint [16, 42], are usually used for low-quality fingerprint segmentation. However, this task is usually either computationally expensive or is time-consuming [20, 44]. Tertychnyi et al. [35] have proposed a ConvNets based technique which can identify the type of low-quality fingerprints. However, the challenge of improving the quality of fingerprints is still open. This is the main motivation of this research work to propose a methodology, which can be used to improve the low quality of fingerprints.

Even though fingerprint image enhancement is possible through physical solutions such as removing excess grace on the fingerprint or recapturing the fingerprint after some time, these solutions are usually not user-friendly and time consuming. In some cases, the enhancements may not be possible if the cause of the distortion is permanent. The objective of this research is to develop deep neural network generators that will improve the quality of distorted low quality fingerprint images digitally without requiring recapturing of the fingerprint.

The rest of the paper is organized as follows: Section 2 reviews the studies related to low quality fingerprint recognition. Section 3 describes the problem definition which contains the details of the proposed deep neural network algorithm used for the restoration of the quality of the low-quality fingerprint. The experimental results and discussions are provided in Section 4, and finally, the work is concluded in Section 5.

2 Related work

Most current approaches extract minutiae from fingerprint images and perform fingerprint matching based on the number of corresponding minutiae pairings [3, 8, 33, 35]. Shell et al. [33],questions regarding human fingerprint orientation and found that expertise in fingerprints increases the accuracy of marked-up orientation field, which is a characteristic feature. More recently, to represent the latent, Cao et al. [3] proposed an automated latent fingerprint recognition algorithm using ConvNets for ridge flow estimation and minutiae descriptor extraction. Experimental results show that their algorithm performs significantly better than published algorithms on two benchmark databases. In addition, Michelsanti et al. show that transfer learning can be used to achieve high accuracy in fingerprint classification. Chung et al. [8] also performed a benchmark study for minutiae extraction by presenting a controlled and repeatable evaluation of one open-source and three commercial-off-the-shelf minutiae extractors.

Recognition performance of the fingerprint recognition algorithms significantly influenced by fingertip surface condition, which may vary depending on environmental or personal causes [26, 35, 41]. Tertychnyi et al. [35], for instance, developed an efficient, yet high accuracy, deep neural network algorithm to recognize low quality fingerprints. Their proposed algorithm based VGG16 deep network which achieves the highest performance for dry and the lowest performance of the blurred fingerprint classes.

Zaixing et al. [15] developed a limited ellipse-band-based matching algorithm for fingerprint recognition. The method utilized the Fourier-Mellin transformation method and ellipse band on the frequency amplitude to suppress noise. Willis et al. [39] developed a threshold fast Fourier transform approach to simultaneously smooth and enhance poor quality images. After enhancing the quality of the images, feature extraction was applied to extract the required features for classification. Neural net and statistically based classifiers were evaluated for the recognition task.

Further, early research work by Ito et al. [18] presented an algorithm using phase-based image matching which used the phase components in 2D discrete Fourier transforms of fingerprint images and showed highly robust performance for low quality fingerprints recognition. An effective two-stage enhancement scheme was proposed by Yang et al. [40], where the spatial and the frequency domain were learning from the underlying images. In their work, the authors first enhanced the fingerprint image in the spatial domain with a spatial ridge-compensation filter by learning from the images and then a frequency band-pass filter was employed. The experimental results showed that their proposed algorithm was able to handle various input image contexts and it improved the performances of fingerprint-authentication systems.

3 The proposed method

3.1 Problem definition

Our research work inspired by a solution developed for GEYCE Biometrics [12] company whose main clients include Spanish and Portuguese Ministries of Foreign Affairs. The

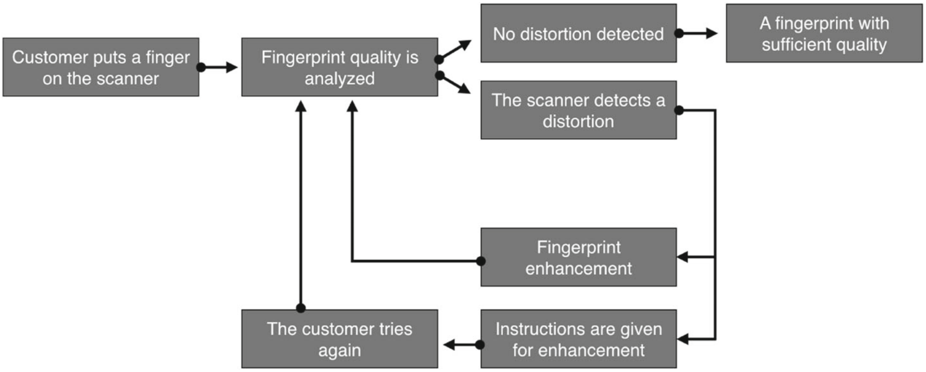

Fig. 1 A scenario of the integrated solution

company developed a tool to find the origin distortion of a low-quality fingerprint to integrate into the fingerprint scanners of consular posts. Previous ideal scenario of the solution lies in detection of the type of the distortion in order to give the customer instructions for enhancement and recapturing of the fingerprint after trying a temporary fix. However, this solution has several drawbacks. Some of the distortions cannot be compensated by recapturing the fingerprint if the distortion is caused by a skin tissue damage or a permanent cause. Moreover, recapturing process is time-consuming and not very user-friendly. We propose an alternative fingerprint enhancement method based on deep-neural networks in order to enhance the fingerprint to a sufficient quality for enabling an identification without requiring recapturing of the fingerprint. Please see the schema in Fig. 1 for the improved scenario.

3.2 Database

The database consists of low quality fingerprint images which has several long-familiar distortions such as dryness, wetness, blurriness, physical damages and presence of dots. Each fingerprint can have more than one type of distortion. In this case, most of the samples have around two-three different types of distortions, even though same very rare samples may carry all types or none.

All images were captured by visa application centres in South America countries via real life applications. The database is provided for this research by GEYCE Biometrics [12]. Each fingerprints image was analyzed and labelled by experts from GEYCE Biometrics. Due to privacy concerns, this dataset is not open for public access.

The classes used to label the fingerprint samples are listed below:

Fig. 2 Some dry fingerprint examples

Fig. 3 Some wet fingerprint examples

Dry fingerprint This type of fingerprints have a low contact area with the surface of the scanner. Since the finger skin is dry, the ridge pattern cannot be fully captured due to low contact of ridges. A potential enhancement of the fingerprint lies in rubbing the finger to forehead or nose where there are big number of sweat and grease pores. Figure 2 shows some examples.

Wet fingerprint This type of fingerprints have high contact area with the surface of the scanner. Because of large amount of grease and sweat on the finger, valleys also contact with the surface together with ridges. A potential enhancement of the fingerprint lies in removing extra grease and sweat from the finger. Figure 3 shows some examples.

Damaged fingerprint This type of fingerprints have some scars or problematic tissues such as a burn and cut. An instant solution for enhancement of the fingerprint does not exist in this case. If the problem is temporary, the fingerprint can be captured later when the wounds are healed properly. If the problem is permanent or inborn, enhancement is not possible. Figure 4 shows some examples.

Dotted fingerprint This type of fingerprint demonstrate some easily distinguishable black dots on fingerprint images. These dots occurs because of excessive sweating caused by nervousness or some other problems that can be associated with excessive sweating. The dots are located around swear pores on the skin. It is not necessary for the fingerprint to be dry in order to observe these dots. A potential enhancement is to capture the fingerprint later when the person is not nervous. Figure 5 shows some examples.

Blurred fingerprint This type of fingerprints have some regions where the ridges are not easily distinguishable. This problem usually occurs when the finger is not stable during the capturing process. Another reason can correspond to the case when the person puts too much pressure on the finger that fingerprint valleys also contact to the surface. The fingerprint image can be enhanced by recapturing when the finger is stable and pressed to the surface

Fig. 4 Some damaged fingerprint examples

Fig. 5 Some dotted fingerprint examples

appropriately. If the cause of this problem is a burned tissue, an instant solution is not possible. Figure 6 shows some examples.

3.3 Methodology

In order to address the aforementioned problems we apply a state-of-the-art Generative Adversarial Networks (GANs) [23] based unpaired image-to-image translation network, also known as Cycle-Consistent Adversarial Networks (Cycle-GAN). The network is used to translate images from distorted domain, namely, dry, wet, dotted, damaged, blurred, to undistorted domain, namely, not-dry, not-wet, not-dotted, not-damaged, not-blurred.

Our model is based on GANs introduced in [13]. A Vanilla GAN consists of two deep neural networks: a generator G and a discriminator D. The objective of the generator is to generate synthetic images indistinguishable from real images using a given random noise. On the other hand, the discriminator tries to distinguish the synthetic images generated by the generator from real images. Both G and D are trained iteratively in a minimax manner. As we want to transfer real fingerprint images from distorted domain to undistorted domain, the generator does not get noise as the input. Instead it is given a distorted real fingerprint image.

Even though CycleGAN provides symmetric transfers from one domain to the other and vice versa, translation from undistorted fingerprint images to distorted images is unwanted and hence its results are not demonstrated in this paper. However, this translation is also necessary for obtaining cycle consistency loss that is used for training of the generator network that will transfer distorted fingerprints to undistorted fingerprints. It is shown in [45] that both the adversarial loss and the cycle consistency loss have critical roles for obtaining high-quality results.

3.4 Model architecture

Our model follows the same structure as CycleGAN [45]. CycleGAN consists of two GANs in a cyclic fashion and trained in accordance. One generator ($G_{A \to B}$) transfer images

Fig. 6 Some blurred fingerprint examples

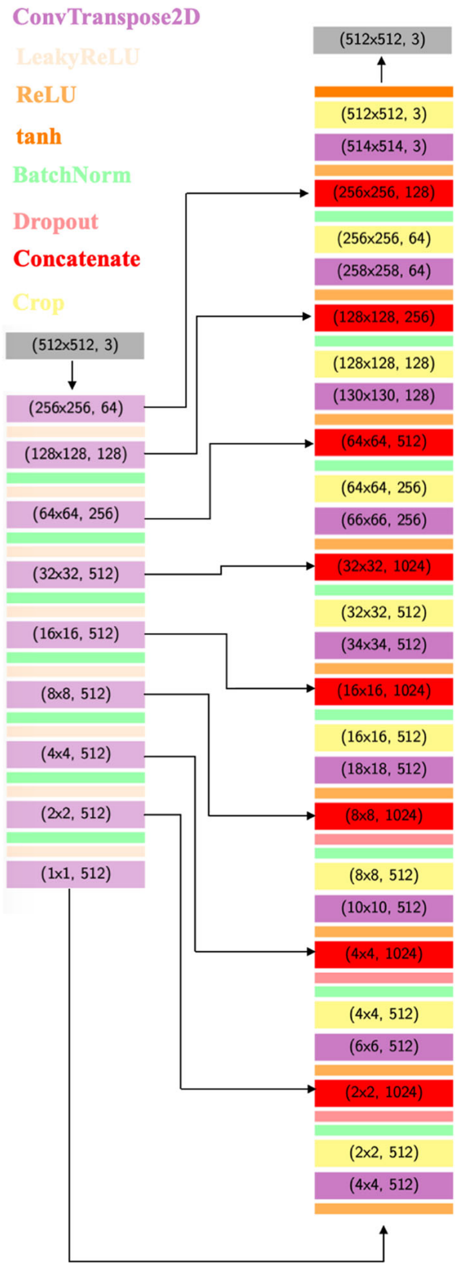

Fig. 7 Generator model architecture

from domain A to B and the other ($G_{B \to A}$) transfer from domain B to A. Discriminators D_A and D_B distinguish if the images are real or synthetic. x_A denotes a real image from domain A. $\widehat{x}_B$ is the same image after being translated to domain B, i.e., $\widehat{x}_B = G_{A \to B}(x_A)$. $\widetilde{x}{\sim}_A$ is the same image after translated back to domain A, i.e, $\widetilde{x}{\sim}_A = G_{B \to A}(\widehat{x}_B)$. Equivalently an image is also transferred from domain B to A and back to B and denoted in the same manner.

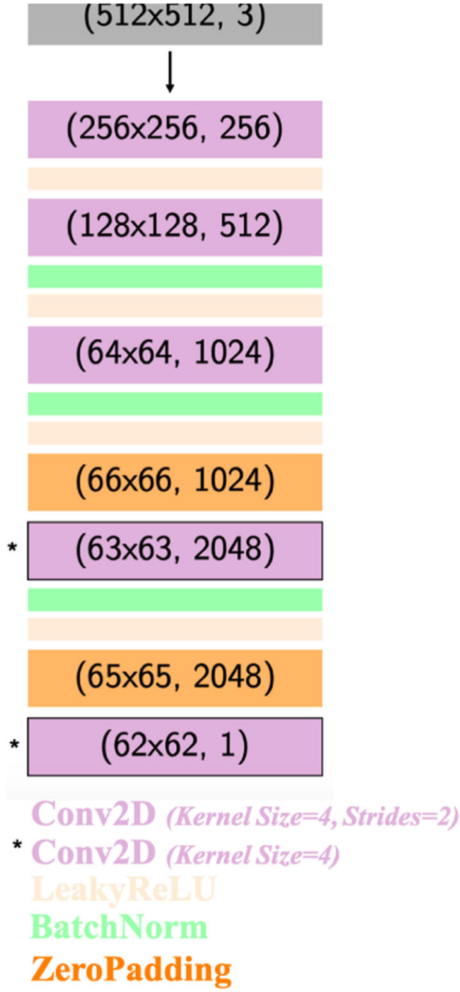

Fig. 8 Discriminator model architecture

For the generators, a U-Net-based architecture, which enables low level information to shortcut across the network [38] was used. As a good amount of low level information is shared between the input and the output for a wide range of image translation applications, it is wise to add skip connections in order to transfer low level images across the network [17]. The architecture of the generators is presented in Fig. 7. For the generators, the input size is 512 × 512. Conv2D is a 2D convolution layer with a filter size of 4 × 4 and a stride of 2 × 2. ConvTranspose2D is a transposed convolution layer (sometimes referred as deconvolution) with a filter size of 4*x*4 and a stride of 2 × 2. The weights of the this layer are initialized with a normal distribution of mean 0 and a standard deviation of 0.02. LeakyReLU (with a negative slope coefficient of 0.2), ReLU, and *tanh* are activation layers. BatchNorm is a batch normalization layer. Dropout applies dropout to its input with a rate of 0.5. Concatenate layer concatenates a list of inputs in order pass low level information along the network. Crop layer crops the image 1 pixel along both spatial dimensions.

Table 1 Classification performance of different classes

Classes	Percentage of images labelled as undistorted
Dry	86
Wet	94
Dotted	87
Damaged	88
Blurred	64

For the discriminators, we use a standard DCGAN-based architecture [31]. The model architecture is presented in Fig. 8. *Conv2D* is a 2D convolution layer with a filter size of 4 × 4 and a stride of 2 × 2. LeakyReLU is an activation layer. BatchNorm is a batch normalization layer. The last two Conv2D layers have a stride of 1 × 1. ZeroPadding layer adds 1 row and 1 column of zeros at the top, bottom, left and right side of the image tensor.

3.5 Training details

The loss function of the generators is

$$L_G = L_{G_{A\to B}} + L_{G_{B\to A}} + \lambda L_C \tag{1}$$

Fig. 9 Several selected examples of dry to not-dry translation

Fig. 10 Several selected examples of *wet* to *not-wet* translation

where the least squares loss is used as in [45]

$$L_{G_{A \to B}} = ||D_B(\widehat{x}_B) - 1||_2 \tag{2}$$

$$L_{G_{B \to A}} = ||D_A(\widehat{x}_A) - 1||_2 \tag{3}$$

λ is used to weight L_C and L_C is the cycle consistency loss defined as in [45]

$$L_C = ||\widetilde{x}\sim_A - x_A||_1 + ||\widetilde{x}\sim_B - x_B||_1 \tag{4}$$

The loss function of the discriminators is the same as standard GAN discriminators

$$L_{D_A} = \frac{1}{2}\left(||D_A(x_A) - 1||_2 + ||D_A(\widehat{x}_A)||_2\right) \tag{5}$$

$$L_{D_B} = \frac{1}{2}\left(||D_B(x_B) - 1||_2 + ||D_B(\widehat{x}_B)||_2\right) \tag{6}$$

Fig. 11 Several selected examples of damaged to not-damaged translation

Vertical flipping and rotation ($\pm 35^{\circ}$) are used for data augmentation. We set $\lambda = 10$ for training. We adopted the Adam optimizer [22] with a initial learning rate of 0.0002 and momentum decay rates $\beta_1 = 0.5$ and $\beta_2 = 0.999$ for both D and G. The batch size is 1.

As the loss curve does not reveal much information in training GANs, we periodically translated fingerprint images and tested the results in order to check convergence.

4 Experimental results and discussion

4.1 Evaluation

In order to obtain quantitative results, a low quality fingerprint classifier based on deep neural networks proposed in [35] is used. The classifier is trained using a different subset of the same database and achieved high performance [35]. Therefore, it is an appropriate choice in order to evaluate the performance of the proposed method.

We used trained generators to translate images from a test set of distorted domain to undistorted domain (*dry* to *not-dry*, *wet* to *not-wet*, *dotted* to *not-dotted*, *damaged* to *not-damaged*, *blurred* to *not-blurred*). Images in test set are not used for the training. After translating distorted fingerprint images to undistorted fingerprint images, we used the classifier

Fig. 12 Several selected examples of dotted to not-dotted translation

to evaluate the percentage of images that is labelled as undistorted. Table 1 presents the classification results of each class.

4.2 Discussion

Figure 9 presents several selected examples of dry to not-dry translation. The generator network fills small discontinuities along the ridges caused by small contact area between the fingerprint and the scanner surface. After translation, the ridge pattern of dry fingerprints are enhanced and more distinguishable.

Figure 10 shows selected examples of wet to not-wet translation. For this type of distorted fingerprint images, the generator network enhances the ridge pattern by removing the unwanted density in pixels caused by the contact of valleys in fingerprints to the scanner surface. The output images demonstrate less valley-contact, and higher contrast between ridges and valleys. This class has the highest classification performance (see Table 1).

Example damaged to not-damaged translation results are shown in Fig. 11. This type of distorted fingerprints have some scars or other problematic tissues. After translation the scars and cuts in the images are filled by the generator with respect to the original ridge pattern. While the generators correct relatively small cuts completely, a good improvement on relatively bigger cuts and gaps are obtained as well.

Fig. 13 Several selected examples of blurred to not-blurred translation

For *dotted* to *not-dotted* translation, example results are shown in Fig. 12. The generator improves the visibility of the ridge patterns and makes the dots caused by excessive sweating much less visible. It is also worth to note that the obtained results shows that the generators also fixes some issues caused by dryness in dotted fingerprint images. The presence of dots is also possible in not-dry fingerprints and our trained generator performs well in enhancing not-dry samples as well. As one might expect the dots are almost indistinguishable in a well enhanced ridge pattern.

Several example *blurred* to *not-blurred* translation results are presented in Fig. 13. This class has the lowest classification performance. As it can be seen from Fig. 13, due to the nature of CycleGAN which still produce smoothed output, the blurred fingerprint are not necessarily enhanced and this is also reflected in Table 1.

5 Conclusion

In work proposed an unpaired image-to-image translation using CycleGAN for translating images from distorted domain to undistorted domain, namely dry to not-dry, wet to not-wet, dotted to not-dotted, damaged to not-damaged, and blurred to not-blurred. In this work, a real low quality fingerprint images collected at VISA centres were used, hence the represented experimental results are reflecting the real-world performance of the proposed algorithm. In order to illustrate the effect of the proposed CycleGAN based fingerprint image undistortion, a VGG16 based convolutional neural network was adopted to evaluate the correct score of images that is labelled as undistorted. The highest and lowest quality improvement was achieved for wetness and blurred fingerprints, respectively.

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Joan Valls is an expert in face biometrics. He started at GEYCE BIOMETRICS in 2006 and participated in PLANSIC which involved Spanish Consular Post migration to new platform. He also leaded working team dedicated to maintain solutions for Spanish Ministry of Foreign Affairs. In 2017 he joined BioIdenti-Cell, where he is responsible for biometric software integration on back-end systems.

Joan Vilaseca is a Software Engineer and BioIdenti-Cell managing director, former known as GEYCE BIOMETRICS. As GEYCE BIOMETRIC director he worked in cross-platform software technologies as well as code generator engineering for user interface frameworks (JEDIFC). He also leaded biometric projects involved in borders services, issuing of passports and visas, Consular Post Management and European VIS project and National Interfaces. He is responsible for BioIdenti-Cell expansion and internationalization, changing GEYCE from a software engineering company to a biometrics engineering company. In 2017, he created BioIdenti-Cell company and is currently the owner. This company has a catalog of products related to fingerprint, facial identification, verification systems, quality analysis of acquired multi-geographical biometric data and document reader devices data acquisition. He is responsible of developing current AFIS in Catalonian prisons, enrolment of population, migration of old sheet form data and identification for access control purposes.

Thomas B. Moeslund received his PhD from Aalborg University in 2003 and is currently head of the Visual Analysis of People lab at Aalborg University: www.vap.aau.dk. His research covers all aspects of software systems for automatic analysis of people. He has been involved in 14 national and international research projects, both as coordinator, WP leader and researcher. He has published more than 300 peer reviewed journal and conference papers. Awards include a Most Cited Paper award in 2009, a Best IEEE Paper award in 2010, a Teacher of the Year award in 2010, and a Most Suitable for Commercial Application award in 2012. He serves as associate editor and editorial board member for four international journals. He has co-edited two special journal issues and acted as PC member/reviewer for a number of conferences. Professor Moeslund has co-chaired the following eight international conferences/workshops/tutorials; ARTEMIS'12 (ECCV'12), AMDO'12, Looking at People'12 (CVPR12), Looking at People'11 (ICCV'11), Artemis'11 (ICCV'11), Artemis'10 (MM'10), THEMIS'08 (ICCV'09) and THEMIS'08 (BMVC'08).

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