Gender and Ethnicity Classification based on Palmprint and Palmar Hand Images from Uncontrolled Environment

Wojciech Michal Matkowski*, Adams Wai Kin Kong*
School of Computer Science and Engineering
Nanyang Technological University
Singapore

Abstract

Soft biometric attributes such as gender, ethnicity or age may provide useful information for biometrics and forensics applications. Researchers used, e.g., face, gait, iris, and hand, etc. to classify such attributes. Even though hand has been widely studied for biometric recognition, relatively less attention has been given to soft biometrics from hand. Previous studies of soft biometrics based on hand images focused on gender and well-controlled imaging environment. In this paper, the gender and ethnicity classification in uncontrolled environment are considered. Gender and ethnicity labels are collected and provided for subjects in a publicly available database, which contains hand images from the Internet. Five deep learning models are fine-tuned and evaluated in gender and ethnicity classification scenarios based on palmar 1) full hand, 2) segmented hand and 3) palmprint images. The experimental results indicate that for gender and ethnicity classification in uncontrolled environment, full and segmented hand images are more suitable than palmprint images.

1. Introduction

Attributes such as gender/sex, ethnicity/race, age, weight, body mass index also known as soft biometrics have been addressed by many researchers [1]. Contrary to traditional - hard biometrics, soft biometrics are less distinctive but still may provide additional and useful information about the individual [2]. The applications of soft biometrics are, e.g., improving the performance of biometric recognition system, forensics investigation, automatic image tagging and passive demographic data collection [1].

Soft biometrics can be extracted from different biometric traits, e.g., gender [3], ethnicity [4], weight, height, body mass index [5] from face; age and gender from ear [6]; gender from gait [7], iris [8] and hand [9], etc. Surveys of soft biometrics can be found in [1] and [2]. Using soft biometrics from hand has been mostly studied based on measurements of remains, i.e., hand bones [10], [11], to infer gender for forensic, medical or archaeological applications. In biometric recognition applications such as user access control or time and attendance, hand images from controlled environments have been widely studied using, e.g., hand geometry [12], fingers [13], finger-knuckles [14], dorsal skin texture [15], vein [16] and palmprint [17], which recently also gains attention in uncontrolled environments [18]. With few exceptions, estimating soft biometrics from hand has received relatively little attention in the biometrics community.

Previous studies [9, 16, 18, 19] used hand images taken in well-controlled environment and aimed at gender classification for commercial biometric applications. However, uncontrolled environment and some forensic applications are not well investigated. In digital and multimedia forensics, child sexual assault materials (CSAM) [21], rioter and terrorist images with no obvious traits such as face, are always taken in uncontrolled and uncooperative environment. Subject’s hands are visible in rioter and terrorist images during salute or waving [22], and in CSAM [23], e.g., when they touch the victim or offender. Thus, using hand image to extract soft biometrics such as gender or ethnicity, which are inherent to a subject, could give useful clues to forensic investigator and reduce a list of subjects to search.

In this study, gender and ethnicity labels are collected and provided for subjects from a publicly available database and selected deep learning methods are evaluated in gender and ethnicity classification scenarios based on three types of palmar hand images taken in uncontrolled and uncooperative environment.

The rest of this paper is organized as follows. Section 2 provides related studies of soft biometrics based on hand images. Section 3 presents collected gender and ethnicity attributes for hand images. Section 4 evaluates the existing five deep learning methods in gender and ethnicity classification scenarios. Section 5 gives conclusions.

*Corresponding authors: W.M. Matkowski, email: wojciech.matkowski@ntu.edu.sg, matk0001@e.ntu.edu.sg
A.W.K. Kong, email: adamskong@ntu.edu.sg

© 2020 IEEE. Accepted in the International Joint Conference on Biometrics (IJCB 2020), scheduled for Sep 28-Oct 1, 2020. Personal use of this material is permitted. Permission from IEEE must be obtained for all other uses, in any current or future media, including reprinting/republishing this material for advertising or promotional purposes, creating new collective works, for resale or redistribution to servers or lists, or reuse of any copyrighted component of this work in other works.
2. Related work

Up until now, available biometric studies of hand\(^1\) soft biometrics explored gender information and well-controlled imaging environment. Typically, hand-crafted as well as deep learning based approaches were proposed and evaluated in two-class classification scenarios.

Afifi [9] established a database from 190 subjects and studied recognition and gender classification using palmar and dorsal hand. Hand images were taken in well-controlled environment on a white background. For recognition and classification, the authors proposed to use two stream convolutional neural network (CNN) which takes RGB and local binary pattern (LBP) images. For the CNN, the author used pre-trained AlexNet model. Then, the author extracted features from the CNN and used SVM for gender classification achieving 94.2\% and 97.3\% accuracy for palmar and dorsal hand, respectively.

Xie et al. [15] established a database from 80 subjects and studied gender classification based on skin texture from hand dorsal images taken in well-controlled environment, achieving 98.65\% accuracy. To capture skin texture, the authors proposed an imaging device which takes images under relatively high resolution of 450 dpi.

Xie et al. [19] used a pre-trained modified VGG network for gender classification on publically available, well-controlled multispectral (250 subjects) and contactless (312 subjects) palmprint databases, reporting 75.17\% and 89.2\% average accuracy, respectively.

Motivated by anthropometry and psychology, Amayeh et al. [20] investigated gender classification from palmar hand shape using a database from 20 male and 20 female subjects in well-controlled environment. The authors used hand-crafted features from segmented hand silhouette, and evaluated 3 different classifiers, namely, Minimum Distance, k-Nearest Neighbors (k-NN) and Linear Discriminant Analysis (LDA). The highest reported accuracy 98\% was achieved by LDA. Note that the method from [20] cannot be directly applied to images considered in this study because it requires well-controlled environment and user cooperation to extract the desired features.

Matkowski et al. [22] established a large NTU-PI-v1 database of palmar hand images downloaded from the Internet, to study palmprint recognition in uncontrolled and uncooperative environment for forensic applications. However, soft biometric information such as gender and ethnicity is not available. Thus, in this paper, for each of 1093 subjects in NTU-PI-v1 database, which is the largest publically available palmprint image database in terms of subjects, ethnicity and gender labels are collected and provided.

3. Labelled hand attributes

In this paper, class labels of two attributes are provided: gender and ethnicity. Gender refers to biological sex, whereas ethnicity refers to person’s physical appearance related to biological factors also known as race in the literature [1].

The NTU-PI-v1 database is the only palmprint database collected from uncontrolled environments. Thus, it is selected for this study. It contains 7881 palmar hand images of 1093 subjects and corresponding segmented hand images and hand landmarks which can be used to extract palmprint region of interest (ROI) [22]. Hand image sizes range from 30 x 30 to 1415 x 1415 pixels. Fig. 1 shows image size distribution in NTU-PI-v1. This database was initially established to study biometric recognition and contained identity labels only. However, other, e.g., soft biometric labels were not provided. In this work, for each of 1093 subjects in this database, gender and ethnicity class labels are searched and collected from the Internet and will be available online for research purpose after this work is published.

For gender, there are two labels considered: either male or female. Table 1 shows the number of male and female samples in the database. Fig. 2 shows examples of male and female hands in the database. Following the most popular and recent forensic anthropology terminology, the subjects are also classified into three different classes namely Asian, White, and Black [24]. Thus, for ethnicity, three labels are collected: 1) Asian mainly containing Chinese, Japanese, Korean and South East Asians; 2) White mainly containing people from Europe, Middle East and the Americas; 3) Black mainly containing African Americans and Africans.

If a subject is a descendant of two different ethnicity persons, then he/she has two labels. E.g. if a subject’s one parent is Asian and the other parent is White, then the subject is labelled as Asian and White. Totally, there are 255 images of 33 subjects with more than one ethnicity label. Note that multi-labelling has been done for data collection purpose and this multi-label\(^2\) classification

---

\(^1\) Fingerprints with available features such as minutiae and ridges have also been applied to soft biometrics. Nevertheless, they are out of scope in this paper because they require high resolution image.

\(^2\) Multi-label classification refers to a classification problem where each sample can be classified into multiple classes. In this work, in experiments, each sample can be classified into only one class.
problem is not further investigated in this paper and left for future work. Table 2 shows the number of images and subjects falling into different ethnicity classes. Fig. 3 shows hand image examples of different ethnicity.

| Class  | No. images | No. subjects |
|--------|------------|--------------|
| Male   | 4810       | 655          |
| Female | 3071       | 438          |

Table 2. Distribution of ethnicity classes in NTU-PI-v1.

| Class | No. images | No. subjects |
|-------|------------|--------------|
| White | 3894       | 588          |
| Asian | 3529       | 444          |
| Black | 679        | 94           |

4. Experiments and results

In the experiments, gender and ethnicity classification scenarios are performed and the results are reported in Sections 4.3 and 4.4, respectively. Section 4.1 describes the experimental protocol and evaluation metrics. Section 4.2 provides five selected deep learning methods, implementation details and three types of images used in experiments.

4.1. Protocol and metrics

In the experiments, NTU-PI-v1 database is split into subject-disjoint training, validation and testing sets. 70%, 15% and 15% of different subjects are used for training, validation and testing, respectively. Each experiment is repeated five times using a different database split controlled by predefined random seeds, and average accuracy and correct classification rates for each class with standard deviations are reported. Accuracy, which is defined as a correct attribute classification rate is a common metric used to evaluate algorithm’s performance based on soft biometrics in classification scenarios [8], [9], [3], [4], [20], on well-balanced datasets.

4.2. Classification algorithms and implementation details

Five state-of-the-art, pre-trained deep neural networks from PyTorch models zoo, namely AlexNet [25], DenseNet [26], ResNet-50 [27], SqueezeNet [28] and VGG-16 [29] are selected for evaluation in each experiment. Note that AlexNet and modified VGG have also been previously used in gender classification from hands in [9] and [19]. Three different types of images from NTU-PI-v1 database are considered as input: full hand image, segmented hand image, and palmprint ROI (see Fig. 4). The input images are resized to 224 x 224 pixels and normalized following the network’s requirements. For augmentation, random horizontal flip, random rotation, translation, and scale are applied on-the-fly to compensate differences between hand poses in different images. In training, cross entropy loss is used and networks are fine-tuned using ADAM [30] optimizer with, learning rate 0.001 and 0.0001 for the last and all other layers, respectively. The batch size is 64 and number of epochs is 10, which always results in convergence. Networks achieving the highest accuracy on validation set are deployed for testing. The experiments are implemented in Python using PyTorch library and run on a single GPU card. Totally, there are 150 experiment runs: 5 repetitions × 5 networks × 3 types of images × 2 classification scenarios.
4.3. Gender classification

Gender classification is performed as a two-class classification because there are male and female classes available in the labelled NTU-PI-v1 database. The experimental results for full hand image, segmented hand image and palmprint ROI (see Fig. 4) are reported in Tables 3, 4 and 5, respectively. Examples of correctly classified and misclassified full hand images are presented in Fig. 5.

Generally, DenseNet, ResNet-50 and VGG-16, achieve comparable but higher than AlexNet and SqueezeNet accuracy in all three experiments. The highest reported gender classification accuracy 88.13% is achieved by fine-tuning DenseNet using full hand images. Correct Male classification rates (CCR-Male) tend to be slightly higher than correct Female classification rates (CCR-Female), which is likely caused by some imbalance in class distribution (see Table 1). On average, CCR-Male are 0.13, 3.50 and 8.67 percentage points (p.p.) higher than CCR-Female for full hand, segmented and palmprint ROI images, respectively. Interestingly, the average accuracies for full hand images are 0.47 - 2.63 p.p. higher than for segmented hand images. One possible explanation could be that full hand images contain background which may also carry some gender related information learnt by networks, e.g., clothes, accessories, hair, body, head, etc. (see Figs. 5 and 6). Using palmprint ROI gives the lowest gender classification accuracy, e.g. DenseNet on full hand images outperforms DenseNet on palmprint ROI by 8.18 p.p.

The experimental results highlight the importance of hand geometry in gender classification from hand, which is in accordance with the previous studies [10], [20]. Note that we do not explicitly use features from hand geometry but let networks to learn features. Therefore, the experimental results indicate how much gender related information, the selected networks are able to extract from 1) palmprint ROI containing, e.g., flexion creases, wrinkles, skin color and texture; 2) segmented hand image containing 1) and fingers and hand shape; 3) full hand image containing 1) and 2) and background with, e.g., clothes, accessories, etc. Fig. 6 shows examples of gender classification results from three corresponding experiments. The only difference between these three experiments was the type of input image. It is noted in our preliminary analysis and also pointed out in Fig. 6 that in some cases, one type of image is misclassified, whereas two other corresponding images are classified correctly. It could be caused by background noise but should be investigated more in future work. For example,
in Fig. 6a (second row) male hand image containing female face in background is misclassified as female. Also, misclassified female hand image in Fig. 6b (second row), contains shirt’s sleeve which is more likely to be visible in male hand images.

Comparing with previous works [9], [15], [19], [20] (see Section 2) of gender classification from hand, accuracy reported in this study is around 10 p.p. lower. However, the images used in this study come from uncontrolled and uncooperative environment and some of them are low quality and low resolution (see Fig. 1). Thus, lower accuracy can be expected [22], [31]. Note that in forensic applications, it is common that images are low quality and taken in uncontrolled environment.

Table 3. Gender classification accuracy and correct classification rates (CCR) of the deep neural networks using full hand images.

| Network  | Accuracy (%) | CCR-Male (%) | CCR-Female (%) |
|----------|--------------|--------------|----------------|
| AlexNet  | 82.14 ± 0.81 | 83.24 ± 3.19 | 80.27 ± 3.70   |
| DenseNet | 88.13 ± 1.01 | 87.75 ± 1.36 | 88.96 ± 1.58   |
| ResNet-50| 87.87 ± 1.45 | 89.40 ± 2.03 | 85.37 ± 2.16   |
| SqueezeNet| 83.48 ± 2.08 | 84.39 ± 2.22 | 82.39 ± 4.61   |
| VGG-16   | 86.14 ± 1.77 | 84.10 ± 3.19 | 91.22 ± 2.73   |

Table 4. Gender classification accuracy and correct classification rates (CCR) of the deep neural networks using segmented hand images.

| Network  | Accuracy (%) | CCR-Male (%) | CCR-Female (%) |
|----------|--------------|--------------|----------------|
| AlexNet  | 81.66 ± 1.09 | 85.52 ± 1.75 | 75.88 ± 2.59   |
| DenseNet | 86.52 ± 0.75 | 87.21 ± 1.69 | 85.48 ± 3.78   |
| ResNet-50| 85.23 ± 0.91 | 87.23 ± 2.16 | 82.57 ± 5.85   |
| SqueezeNet| 81.56 ± 2.04 | 82.70 ± 2.66 | 79.82 ± 4.17   |
| VGG-16   | 85.58 ± 1.09 | 85.44 ± 2.44 | 86.83 ± 4.61   |

Table 5. Gender classification accuracy and correct classification rates (CCR) of the deep neural networks using palmprint ROI.

| Network  | Accuracy (%) | CCR-Male (%) | CCR-Female (%) |
|----------|--------------|--------------|----------------|
| AlexNet  | 77.30 ± 1.05 | 79.29 ± 1.36 | 73.39 ± 1.80   |
| DenseNet | 79.95 ± 0.97 | 83.33 ± 2.69 | 74.94 ± 5.20   |
| ResNet-50| 79.04 ± 1.48 | 83.46 ± 2.08 | 72.42 ± 3.82   |
| SqueezeNet| 75.29 ± 1.35 | 78.19 ± 1.27 | 69.98 ± 2.17   |
| VGG-16   | 79.69 ± 0.89 | 83.49 ± 2.14 | 73.67 ± 1.87   |

4.4. Ethnicity classification

Ethnicity classification is performed as a three-class classification, where each subject is being classified into either Asian, White or Black class (see Section 3). A number of Black subjects in NTU-PI-v1 is relatively low (see Table 2). Thus, in training and validation sets, this class is oversampled. If a subject has multiple labels (see Section 3), then he/she is relabeled for the experimental purpose and merged with the shared majority class. The experimental results are summarized in Tables 6, 7 and 8 for full hand, segmented and palmprint ROI images (see Fig. 4), respectively. Fig. 7 shows examples of classified full hand images.

DenseNet achieves the highest ethnicity classification accuracy of 81.09% on the segmented hand images outperforming the second best ResNet-50 by 1.79 p.p. CCR-White is on average 3.86, 4.28 and 2.66 p.p. lower than CCR-Asian, on full hand, segmented and palmprint ROI, respectively. It could be related to the fact that the White class considered in this work contains populations
from various continents (see Section 3) with relatively high diversity. It should be noted that the reported average CRC-Black come from a relatively small sample size of testing set (around 70 images) comparing to CRC-Asian (around 500 images) and CRC-White (around 500 images). In addition, CRC-Black standard deviations are 9.90 – 18.81 p.p. Thus the CRC-Black results should be treated with less significance because they are highly affected by random split sampling of a relatively small number of subjects.

As with the experimental results from Section 4.3, using palmprint ROI, provides less discriminative information comparing with full and segmented hand images. The highest reported accuracy for full hand, segmented and palmprint ROI image are 78.97%, 81.09% and 73.14%, respectively. These results also indicate that hand shape is a contributing trait in ethnicity classification based on considered hand images. Moreover, using segmented hand image results in higher classification accuracy than full hand image, where background is visible. This is in contrast to gender classification results, where background can also provide some useful information. These experimental results suggest that differences in hand image backgrounds containing clothes, part of body or hair are higher between gender classes, rather than ethnicity classes.

5. Conclusions

In this preliminary work, gender and ethnicity classification based on palmar hand images taken in uncontrolled environment are investigated. Gender and ethnicity labels for all the subjects in NTU-PI-v1 database are provided. Five selected deep neural networks are fine-tuned and evaluated in gender and ethnicity classification scenarios on full hand, segmented, and palmprint ROI images. The experimental results indicate that full hand and segmented hand images provide more discriminative information than palmprint ROI image and thus higher accuracy in both gender and ethnicity classification experiments. The highest reported accuracy for gender and ethnicity classification are 88.13% and 81.09%, respectively. In future, joint gender and ethnicity classification as well as fusion of different hand image types could be considered. We also plan to use gender and ethnicity information to improve the hand and palmprint recognition performance.

Acknowledgment

This work is partially supported by the Ministry of Education, Singapore through Academic Research Fund Tier 1, RG21/19 (2019-T1-001-102). The authors would like to thank Soohyun Park from MSE, NTU for help with establishing ethnicity labels, including multiple discussions and searching the Internet.

References

[1] A. Dantcheva, P. Elia, and A. Ross, “What else does your biometric data reveal? A survey on soft biometrics,” IEEE TIFS, vol. 11, no. 3, pp. 441–467, 01-Mar-2016.
[2] M. S. Nixon, P. L. Correia, K. Nasrollahi, T. B. Moeslund, A. Hadid, and M. Tistarelli, “On soft biometrics,” Pattern Recognit. Lett., vol. 68, pp. 218–230, Dec. 2015.
[3] R. Ranjan, V. M. Patel, and R. Chellappa, “HyperFace: A Deep Multi-Task Learning Framework for Face Detection,
Landmark Localization, Pose Estimation, and Gender Recognition,” IEEE TPAMI, vol. 41, no. 1, pp. 121–135, Jan. 2019.

[4] N. Narang and T. Bourlai, “Gender and ethnicity classification using deep learning in heterogeneous face recognition,” in 2016 International Conference on Biometrics, ICB 2016, 2016.

[5] A. Dantcheva, F. Bremond, and P. Bilinski, “Show me your face and i will tell you your height, weight and body mass index,” in Proceedings - International Conference on Pattern Recognition, 2018, vol. 2018-August, pp. 3555–3560.

[6] D. Yaman, F. I. Eyiolek, N. Segzin, and H. K. Ekenel, “Age and gender classification from ear images,” in IWBF 2018 - Proceedings: 2018 6th International Workshop on Biometrics and Forensics, 2018, pp. 1–7.

[7] J. Lu, G. Wang, and P. Moulin, “Human identity and gender recognition from gait sequences with arbitrary walking directions,” IEEE TIFS, vol. 9, no. 1, pp. 51–61, Jan. 2014.

[8] J. E. Tapia, C. A. Perez, and K. W. Bowyer, “Gender Classification From the Same Iris Code Used for Recognition,” IEEE TIFS, vol. 11, no. 8, pp. 1760–1770, Aug. 2016.

[9] M. Afifi, “11K Hands: Gender recognition and biometric identification using a large dataset of hand images,” Multimed. Tools Appl., vol. 78, no. 15, pp. 20835–20854, Aug. 2019.

[10] T. Kanchan and K. Krishan, “Anthropometry of hand in sex determination of dismembered remains - A review of literature,” Journal of Forensic and Legal Medicine, vol. 18, no. 1. J Forensic Leg Med, pp. 14–17, Jan-2011.

[11] R. A. Lazenby, “Identification of Sex from Metacarpals: Effect of Side Asymmetry,” 1994.

[12] R. Sanchez-Reillo, C. Sanchez-Avila, and A. Gonzalez-Marcos, “Biometric identification through hand geometry measurements,” IEEE TPAMI, vol. 22, no. 10, pp. 1168–1171, 2000.

[13] S. Ribaric and I. Fratric, “A biometric identification system based on eigenpalm and eigenfinger features,” IEEE TPAMI, vol. 27, no. 11, pp. 1698–1709, Nov. 2005.

[14] A. Kumar and Z. Xu, “Personal Identification Using Minor Knuckle Patterns From Palm Dorsal Surface,” IEEE TIFS, vol. 11, no. 10, pp. 2338–2348, Oct. 2016.

[15] J. Xie, L. Zhang, J. You, D. Zhang, and X. Qu, “A Study of Hand Back Skin Texture Patterns for Personal Identification and Gender Classification,” Sensors, vol. 12, no. 12, pp. 8691–8709, Jun. 2012.

[16] R. Das, E. Piciu, E. Maiorana, and P. Campisi, “Convolutional Neural Network for Finger-vein-Based Biometric Identification,” IEEE TIFS, vol. 14, no. 2, pp. 360–373, Feb. 2019.

[17] D. Zhang, W. K. Kong, J. You, and M. Wong, “Online palmprint identification,” IEEE TPAMI, vol. 25, no. 9, pp. 1041–1050, Sep. 2003.

[18] A. S. Ungureanu, S. Salahuddin, and P. Corcoran, “Toward Unconstrained Palmprint Recognition on Consumer Devices: A Literature Review,” IEEE Access, vol. 8, pp. 86130–86148, 2020.

[19] Z. Xie, Z. Guo, and C. Qian, “Palmprint gender classification by convolutional neural network,” IET Comput. Vis., vol. 12, no. 4, pp. 476–483, Jun. 2018.

[20] G. Amayeh, G. Bebis, and M. Nicolescu, “Gender classification from hand shape,” in 2008 IEEE Computer Society Conference on Computer Vision and Pattern Recognition Workshops, CVPR Workshops, 2008.

[21] INTERPOL, “Towards a Global Indicator on Unidentified Victims in Child Sexual Exploitation Material,” 2018.

[22] W. M. Matkowski, T. Chai, and A. W. K. Kong, “Palmprint Recognition in Uncontrolled and Uncooperative Environment,” IEEE TIFS, vol. 15, pp. 1601–1615, 2020.

[23] N. A. Spaun, “Forensic Biometrics from Images and Video at the Federal Bureau of Investigation,” in BTAS, 2007, pp. 1–3.

[24] R. B. Pickering and D. Bachman, The Use of Forensic Anthropology. CRC Press, 2009.

[25] A. Krizhevsky, I. Sutskever, and G. E. Hinton, “ImageNet classification with deep convolutional neural networks,” in NIPS, 2012, pp. 1097–1105.

[26] G. Huang, Z. Liu, L. Van Der Maaten, and K. Q. Weinberger, “Densely connected convolutional networks,” in Proceedings - 30th IEEE Conference on Computer Vision and Pattern Recognition, CVPR 2017, 2017, vol. 2017-Janua, pp. 2261–2269.

[27] K. He, X. Zhang, S. Ren, and J. Sun, “Deep Residual Learning for Image Recognition,” in CVPR, 2016, pp. 770–778.

[28] F. N. Iandola, S. Han, M. W. Moskewicz, K. Ashraf, W. J. Dally, and K. Keutzer, “SqueezeNet: AlexNet-level accuracy with 50x fewer parameters and <0.5M model size,” 23-Feb-2016.

[29] K. Simonyan and A. Zisserman, “Very Deep Convolutional Networks for Large-Scale Image Recognition,” in ICLR, 2015.

[30] D. P. Kingma and J. Ba, “Adam: A Method for Stochastic Optimization,” in ICLR, 2014.

[31] A. K. Jain, K. Nandakumar, and A. Ross, “50 years of biometric research: Accomplishments, challenges, and opportunities,” PRL, vol. 79, pp. 80–105, 2016.