# Human Gender Classification: A Review

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**Abstract:** The gender recognition is essential and critical for many applications in the commercial domains such as applications of human-computer interaction and computer-aided physiological or psychological analysis, since it contains a wide range of information regarding the characteristics difference between male and female. Some have proposed various approaches for automatic gender classification using the features derived from human bodies and/or behaviors. First, this paper introduces the challenge and application of gender classification research. Then, the development and framework of gender classification are described. We compare these state-of-the-art approaches, including vision-based methods, biological information-based methods, and social network information-based methods, to provide a comprehensive review of gender classification research. Next we highlight the strength and discuss the limitation of each method. Finally, this review also discusses several promising applications for future work.

**Keywords:** Gender classification; vision-based feature; biometrics; bio-signals; social network information.

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## 1 Introduction

Automatic gender classification is receiving increasing attention, since gender carries rich and distinguished information concerning male and female social activities[1]. The aim of gender classification is to recognize the gender of a person based on the characteristics that differentiate between masculinity and femininity. In the area of artificial intelligenceIt, gender classification is considered to be one of the most important applications of pattern recognition method [2]. The progress of gender classification research has driven many potential applications. For instance, a computer system with gender recognition fucntions has a wide range of applications in fundamental and applied research areas including: human-computer interaction (HCI) [3], the security and surveillance industry [4], demographic research [5], commercial development [6], and mobile application and video games [7]. Furthermore, multi-mechanisms are proposed to enhance the performance of gender recognition in terms of both accuracy and efficiency [8].

To date, however, few related surveys exist regarding human gender recognition and classification. Mäkinen *et al*. [9] carried out a comparative study of the gender classification methods combined with automatic real-time face detection. Poppe *et al*. [10] provided a detailed overview of vision-based human action recognition, where they focused on using body movements to generalize variations of human activities. Delac *et al*. [11] reviewed biometric recognition methods by describing their advantages and disadvantages, where biometric recognition refers to an automatic recognition of individuals based on feature vectors derived from their physiological and behavioral characteristics. Gender classification based on facial/body images and gait videos have been summarized by Khan *et al*. [8] and Ng *et al*. [12].

To understand the current research challenges, progress, and opportunities of gender classification, in this paper we draw a comprehensive overview by systematically summarizing and comparing the existing gender classification methods which are based on the characteristics of appearance, behavior, biometrics, bio-signals, and social network-based information. These characteristics or features are highlighted in several aspects, including universality, distinctiveness, permanence, and collectability to perform gender classification [13]. In particular, these four requirements for the qualified features are listed below:

1. Universality: The features should be universal among each individual which can be used for distinguishing gender. If the feature is unable to be extracted from each individual, it is not appropriate for gender classification.

2. Distinctiveness: The features should be sufficiently discriminative between male and female, e.g., features such as appearance, biometrics, bio-signal, and social network-based information.

3. Permanence: The features should be stable and not change over a long period of time, e.g., regardless of age and environment.

4. Collectability: The features should be measured quantitatively, which has a great effect on the applications. The approach based on features with high collectability such as a vision-based application is suitable for real-time or on-line applications. In contrast, the approach based on features with lower collectability can only be utilized in complicated or off-line applications.

We compare and evaluate existing gender recognition approaches in terms of accuracy, trustworthiness, invasiveness, collectability, and scope of the application. Accuracy demonstrates the effectiveness of a gender classification system. Trustworthiness indicates robustness and reliability. Invasiveness and collectivity jointly imply the complexity of the system. The scope of application is based on the merit of each system, which is a case-by-case study. By going through these five evaluation standards, we highlight the strengths and discuss limitations for each method.

The remainder of this review paper is organized as follows. Section II introduces the applications of gender classification. Section III gives an overview of gender classification systems. In Section IV , V and VI , three different approaches of gender classification are described. Section VII compares these approaches. Finally, Section VIII concludes this study and presents opportunities for future work.

## 2 Applications

The development and progress in gender recognition technology has lead to many potential uses in a large application scope, because the gender classification techniques can significantly improve the computer's perceptional and interactional capabilities. For example, gender classification is able to improve the intelligence of a surveillance system, analyze the customers' demands for store management, and allow the robots to perceive gender, etc. To be concrete, applications of automatic gender classification can be categorized in the following fields.

### *2.1 Human-Computer Interaction*

In the field of HCI [14], robots or computers need to identify and verify human gender to improve the system performance based on personalized information. By successfully determining gender, the system can provide appropriate and customized services for users by adapting to them according to their gender [5].

### *2.2 Surveillance Systems*

Classifying gender in surveillance systems for public places (e.g., bank, school) can assist intelligent security and surveillance systems to track moving objects, detect abnormal behaviors, and facilitate the security investigation off criminals who intentionally try to hide their identity information. In addition, gender-focused surveillance can helop evaluate the threat level for a specific gender if the gender information can be automatically obtained in advance [13].

### *2.3 Commercial Development*

Gender classification is useful for guiding effective marketing and establishing smart shopping environment, in which production can be directed to specific users through websites, electronic marketing, and advertising [15], etc. For instance, in a supermarket or department store, knowing the number of male and female customers helps the store managers to make effective sales and managing decisions.

### *2.4 Demographic Research*

The application of a gender classification system helps demographic research in efficiently collecting demographic information [7]. Automatic identification of human gender enhances demographic statistics (e.g. gender, disability status, race definition) and population prediction [16]. The ability to automatically detect gender information acts as a supplementary method to demographic research conducted on the web or in public places [17].

### 2.5 Mobile Application and Video Games

Gender classification can provide supportive information to improve the user experience in mobile applications (apps) and video games. In mobile apps, some researchers use this method to facilitate the use of the mobile Internet by customizing apps according to gender. In video games, male and female often have different preferences, which would enable the use of gender information to provide their preferred game characters or contents. For example, to optimize the realism of a video game, character features, such as gait, can be analyzed using gender classification techniques. Then applying different gait patterns to virtual characters in the games according to gender will apparently enhance the sense of reality [18].

## 3 Overview of Gender Classification Methods

### 3.1 Challenges of Gender Classification

In practice, gender classification is a two-class problem in which the given information is assigned as male or female. Gender classification is a relatively easy task for humans but a challenging task for machines. Human beings are often able to make accurate and fast decisions on gender through visual inspection. For example, on the most basic characteristic, gender is a relatively invariant aspect of faces [19]. Humans can readily determine gender for most faces, and additional information from hairstyle, body shape, clothing, eyebrows, and posture will support the evidence gained from the visual image [20]. Acoustical differences between male and female voices have been discussed by various investigators [21]. Besides the differences between males and females in physical features, psychological and neural signals provide a dynamic cue for gender analysis. Previous psychological and neural studies [22][23] indicated that different gender exhibits diversity in changing facial expressions and head movement when they are stimulated. In addition, according to physiological measurements including electroencephalograph (EEG) and deoxyribose nucleic acid (DNA), as well as the daily social information such as handwriting, blog, email, etc, males and females also reveal different features or properties for the machine to classify.

Some researchers have explored these aforementioned cues and made significant progress for gender classification. Some of these features are in the form of images and can be analyzed by image processing[17]. Research on gender classification using facial images started at the beginning of the 1990s. In 1990, Golomb *et al*. [24] used a multi–layer neural network to classify gender based on human faces. They reported a gender classification error rate of 8.1% by using a Cottrell-style back-propagation image compression network. Since then, applications of gender classification were developed extensively in various domains, bringing the emergence of gender classification approaches, from which iris [16], hand shape [14] and eyebrows [25] were considered as features in the literature.. In recent years, clinical signal processing techniques have been proposed to serve in the field of gender recognition using EEG [26] and electrocardiograph (ECG) [27] signals.

Although some progress is reported, gender classification is still challenging work for the machine because of the variation in gender features, particularly, gender characteristics of the face may result in problems with automatic gender detection. Variation in gender information extraction occurs due to changes in illumination, pose, expression, age, and ethnicity [15]. Similarly, during the image capturing process the factors of image quality like dithering, noise, and low resolution also make image analysis a challenging task. On the other hand, the choice of features is one of the most critical factors [12]. The classification techniques are also affected by feature extraction and classification algorithms.

### *3.2 Classification Framework*

The gender classification framework generally consists of five procedures, which is demonstrated in Fig. 1 including sensing, preprocessing, feature extraction, classification, and evaluation.


**Figure 1**: The general classification framework.

*Sensing*: The first step of gender classification is to obtain the effective raw data using specific sensors, including camera (images, videos) [8], recorder (voice), physiological measurements (EEG, ECG), social network-based information (e.g., Facebook posts, Tweets, blogs). Based on the acquired features, various approaches are employed to perform gender classification.

*Preprocessing*: Preprocessing is a necessary procedure to improve the quality of raw data, which includes the normalization of the main signal detection, the extraction of the informative area, and the correction of imperfections such as filling holes, noise removal, face detection, etc. With the appropriate signal preprocessing procedure, the undesired information is eliminated from the raw information and has few effects on the quality of the feature extraction, leading to an improvement in the identification accuracy rate.

*Feature extraction*: Feature extraction captures the main characters of the preprocessed signal as the input parameter for the classification algorithm. The feature extraction module minimizes the size of data by extracting the features of the preprocessed information that are useful for classification. The desired features should be easily computed, robust, distinctive, and insensitive to various conditions. In the next phase, the classifier will process these extracted features and conduct the classification.

*Classification algorithm*: The classification algorithm is the core of gender identification. Generally, classification approaches can be divided into two categories: appearance-based approaches and non-appearance-based approaches. The appearance-based approach is using a static image or an animated video to conduct gender classification. The non-appearance-based approach classifies the gender by analyzing a person's physical, biometric, or social network-based information. Among these two approaches, several types of classifiers have been utilized for gender classification, such as support vector machine (SVM) [28], *k*-nearest neighbors (*k*NN) [29] and Gaussian mixture models (GMM) [30]. The choice of the classification algorithm is crucial depending on each acase in order to achieve a higher identification accuracy.

*Evaluation*: In this step some measures are used to assess the performance of the gender classification system. Basically, the system is tested in terms of accuracy, trustworthiness, invasiveness, etc. One of the most important standards is accuracy, which refers to the probability of correct recognition of a person as a male or a female. Publicly available databases can be used to investigate and verify gender classification algorithms, such as the Multiple Biometric Grand Challenge (MBGC) database [31] and the Face Recognition Grand Challenge (FRGC) database [32].

### *3.3 Gender Classification Taxonomy*

In the gender classification research community, several approaches have been proposed such as face, apparel, gait, iris, hand shape, and hair. Generally, in this paper we categorize these approaches into two categories: the appearance approach and the non-appearance approach, as shown in Fig. 2. The appearance-based approach recognizes gender based on the features derived from the external information of individuals. It includes static body feature (face, eyebrow, body-shape, hand shape, fingernail, etc.), dynamic body feature (gait, motion, gesture, etc.) and the apparel information feature (clothing, footwear, etc.). The non-appearance-based approach uses the biological feature and human daily social network information (email, blog, hand-writing, etc.) for gender classification. Biological features include biometrics information (fingerprint, iris, voice, emotion-speech, ear, etc.) and bio-signals features (ECG, EEG, DNA, etc.).

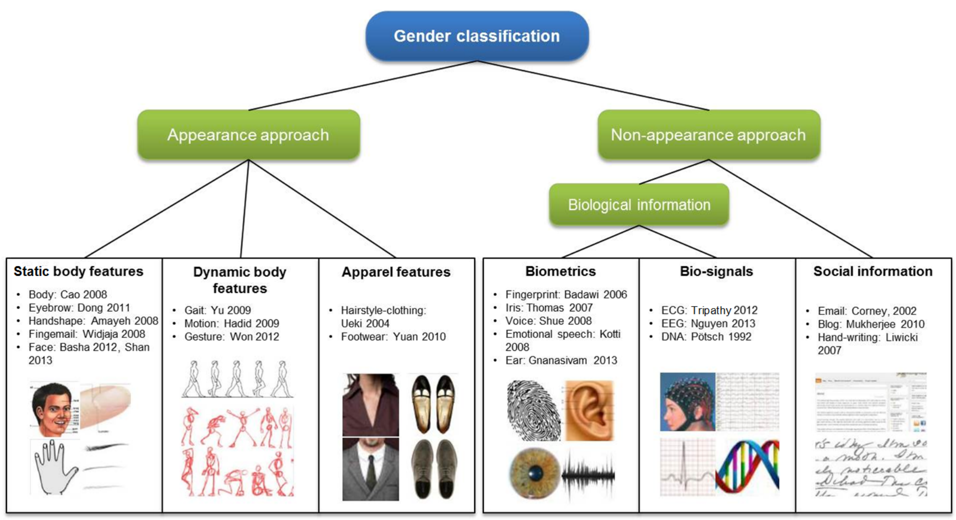


**Figure 2**: The human gender classification taxonomy.

**Appearance Approach**: The appearance approach is a vision-based approach, and has three categories of features that can be extracted. They are static body feature, dynamic body feature, and apparel feature. The static body features are the static traits of the human body, including body-shape [33], face [34, 35, 8, 36], eyebrows [25], hand shape [14], and fingernails [37]. Dynamic body feature refers to the movement and activity of a human body such as gait [7], motion [38], etc. Apparel feature is derived from what a person wears, including footwear [39], clothing [40], etc. The vision-based approach utilizes the image processing method to conduct gender identification. Images of human appearance exhibit many variations which may affect the accuracy of a computer vision system. Thus, gender classification based on vision-based approaches is relatively fragile because these features are easily affected by illumination changes, poses, age, and ethnicity, or different facades on the face (e.g., glasses, jewelry, and hats).

**Non-appearance Approach**: The non-appearance approach refers to the features extracted from the person's physical and biometric information. With the non-appearance approach, features are extracted from biological information and social network-based information. Biological information comes from biometrics, e.g., voice [41], iris [16], fingerprint [42], emotional speech [43], and bio-signals, e.g., EEG [44, 45], ECG [27] and DNA [46] information. The Bio-signal refers to human biometric information, which is used for gender classification. In clinical psychophysiology, the effects of age and gender on the EEG signal have been investigated and brain maturation is found to associate with the topographic differences [45]. Social network-based information means the information from the daily social activities of a person, which includes email [47], hand-writing [48], blog [49]. Thus with distinguished language and social styles among males and females, it is possible to conduct gender classification using these features.

## 4 Appearance-based Gender Classification

The vision-based approach utilizes the classification features extracted from exterior information of the human body. This approach was used for gender classification universally in the early stage of gender recognition research. Table 1 lists the examples that work on gender classification using appearance-based features.

### *4.1 Static Body Feature-based Gender Classification*

Facial imaging is the most common method for gender classification. It is non-intrusive and suitable for the real-time recognition application. Basha *et al*. [34] proposed a novel approach to recognize gender using face images where the continuous wavelet transform was employed to perform the feature selection from each image, and an SVM with linear kernel classified the data as male or female. Their method performs well in images containing variations in lighting and facial expression, pose angles, aging effects, etc. Moreover, This method consumes less time compared with other classification approaches. Shan *et al* [35] employed local binary patterns (LBP) to describe faces and they used the Adaboost method to select discriminative LBP features. They obtained the performance of 94.81% by applying SVM with the boosted LBP features. Li *et al*. [50] classified gender by utilizing only five facial features (nose, eyes, mouth, forehead, brows). One problem with their approach is that their feature extraction method is affected by complex backgrounds. Based on the different parts of facial feature extraction, the gender classification via face can be divided into local feature extraction and global feature extraction methods [8]. The local feature extraction method extracts features from certain facial points like the mouth, nose and eyes [50], whereas the global features extraction method extracts features from the whole face instead of extracting features from facial points [34][35].

Dong *et al*. [25] presented a new approach using eyebrows to classify gender. They used shape-based eyebrow features under non-ideal imaging conditions for biometric recognition and gender classification. They compared three different classification methods: minimum distance (MD) classifier, linear discriminant analysis (LDA) classifier and SVM classifier. The methods were tested on images from two publicly available facial image databases, i.e., the Multiple Biometric Grand Challenge (MBGC) [31, 51] database and the Face Recognition Grand Challenge (FRGC) [32, 52] database. This classification algorithm obtained a biometric recognition rate of 90% using the MBGC database and 75% using the FRGC database as well as the gender classification rates of 96% and 97% for each database, respectively.

Amayeh *et al*. [14] suggested that hand shape is a prominent feature for gender classification, and they segmented the hand silhouette into six different parts corresponding to palm and fingers. To represent the geometry of each part, they used region and boundary features based on Zernike moments and Fourier descriptors. In addition, they computed the distance of a given part from two different eigenspaces for classification, one is the male class and another is the female class. The identification rate of this approach was 98%. Cho *et al*. [53] used heat-earth mover's distance (EMD) to identify different people based on thermal handprint. The method is even feasible when users wear a glove.

Cao *et al*. [33] built a system of recognizing gender from full body images; their work was the first attempt to investigate gender recognition using static human body images. By integrating the part-based representation and ensemble learning algorithms, they proposed a part-based gender recognition (PBGR) method to classify gender using either a single front or a back view image with an accuracy of 75.0%. Their method is robust when small misalignment occurs. Kakadiaris *et al*. [54] used ratios of anthropometric measurements from still images as features to classify human gender. The classification accuracy using SVM+ achieves 98.18%. Linder *et al*. [55] used a novel gender recognition method based upon a depth-based tessellation learning approach, which is able to learn the best selection, location and scale of a set of simple point cloud features. This approach achieves 90% accuracy.

Fingernails can also be a feature to distinguish between males and females. HongáLim *et al*. [37] demonstrated a novel method for human gender classification by measuring the Raman spectrum of fingernail clippings. Because Raman spectroscopy reveals the characteristics of vibrational frequencies of the fingernails, the result can be used to describe the molecular structure differences of fingernails between males and females. In their work, principal component analysis (PCA) and the SVM algorithm were used for classification. The classification accuracy for male and female was about 90%.

The first part of Table 1 (Table 1-I) describes different gender classification techniques based on static body features. Recognition based on face and hand shape achieve higher accuracy due to the fact that face and hand shape features are more discriminative compared with to other features. On the other hand, the body shape feature has a higher similarity between males and females, leading to a lower recognition accuracy rate. Although static body features can be easily captured with a camera, they are easily affected by the quality of the image.

## *4.2 Dynamic Body Feature-based Gender Classification*

Gender classification based on static body features can perform identification. However, since people constantly change their appearance, styles, and locations, some proposed to utilize behavioral features for gender classification such as body movement and activity. Yu *et al*. [7] firstly demonstrate an experiment in which they asked participants to identify the gender of moving human silhouettes. Then their appearance-based gender classification was enhanced by the extracted human knowledge from the experiment. In the experiment, they chose the CASIA Gait Database. The result of their study indicated that gait features

**Table 1** Gender classification via appearance approach.

| **I: Gender Classification via Static Body Feature** | | | | | |
|---|---|---|---|---|---|
| **Static Body Features** | **Publications** | **Feature Extraction Algorithms** | **Classification Algorithms** | **Database Description** | **Accuracy** |
| Face | Basha *et al*., 2012 | Continuous wavelet Transform | SVM | ORL | 98% |
| | Caifeng Shan, 2013 | LBP | SVM | Labeled Faces in the Wild (LFW) | 94.81% |
| | Li *et al*., 2012 | LBP | SVM | FERET and BCMI data set | about 90% |
| Eyebrow | Dong *et al*., 2011 | Global shape features (GSF), Local area features (LAF) and Critical point features (CPF) | MD, LDA, and SVM | MBGC database and FRGC database | 96% and 97% for each database respectively |
| Hand shape | Amayeh, G. *et al*., 2008 | Zernike moments and Fourier descriptors | Score-level fusion and LDA | A small database containing 20 males and 20 females | 98% |
| Body-shape | Cao *et al*., 2008 | Adaboost and Random Forests (RF) | HOG feature, Part-Based Gender Recognition (PBGR) algorithm | MIT pedestrian database | 76.0% accuracy for frontal view images and 74.6% for back view images. |
| | Kakadiaris *et al*., 2016 | LUPI | SVM+ | CAESAR database | 98.2% |
| | Linder *et al*., 2016 | Geometric point cloud | Tessellation learning | RGB-D database | 90% |
| Fingernail | HongáLim *et al*., 2008 | Raman spectrum | PCA and SVM | A total of 80 samples of fingernail clippings were kindly donated by 40 people | About 90% |

| **II: Gender Classification via Dynamic Body Feature** | | | | | |
|---|---|---|---|---|---|
| **Dynamic Body Features** | **Publications** | **Feature Extraction Algorithms** | **Classification Algorithms** | **Database Description** | **Accuracy** |
| Gait | Yu *et al*., 2009 | Gait energy image (GEI) | SVM | CASIA Gait Database | 87% |
| Motion | Hadid *et al*., 2009 | EVLBP (extended volume local binary pattern) features (combining appearance and motion) | Five different algorithms including HMMs and ARMA models as benchmark methods for spatio-temporal representations and PCA, LDA and LBP for still image-based ones | MoBo, USCD/HONDA and CRIM | Best: 93.4% |
| | Williams *et al*., 2016 | Principle component analysis | AdaBoost | Twenty five men and twenty four women | 87.8% |
| Gesture | Won *et al*., 2012 | Calculated the angles between two different bones of the skeleton | Linear regression | 12 men and 12 women | 83% |

| **III: Gender Classification via Apparel Feature** | | | | | |
|---|---|---|---|---|---|
| **Apparel Features** | **Publications** | **Feature Extraction Algorithms** | **Classification Algorithms** | **Database Description** | **Accuracy** |
| Clothing | Ueki, K. *et al*., 2004 | PCA | GMM | 2,397 female images and 5,035 male images | 92.2% |
| Footwear | Yuan *et al*., 2010 | HOG | Non-linear SVM | Established the first footwear image | 85.49% |

could help improve the accuracy of gender classification. Besides, Abdenour *et al*. [38] proposed and compared various schemes for facial recognition. Their experimental results showed that the combination of motion and appearance were only useful for gender analysis for the familiar faces. Their analysis clearly assessed the promising performance of the LBP-based spatio-temporal representations for describing and analyzing faces based on three video databases (MoBo, USCD/HONDA and CRIM). The obtained recognition rates were 90.3%, 78.3%, and 88.7%, respectively, by using the VLBP-based spatio-temporal approach. Williams *et al*. [56] propose novel automated gender classification of subjects while engaged in running activity. The method with preprocessing steps using principle component analysis and AdaBoost classifier [57] achieves an accuracy of 87.8%.

Nonverbal behavior is a very important part of human interactions. Previously, the study [58] described a new method for determining gender identity using machine learning with gestures taken from Microsoft Kinect. Their method achieved 83% accuracy in predicting one's gender, even from very short exposures such as ten seconds exposure of the participants.

In the second part of Table 1 (Table 1-II), the gender recognition approaches using dynamic body features performs better because of adding features such as gait and gestures. The method to capture dynamic body feature is similar to that of static body feature by using a camera, except that it will need more continuous frames to acquire the dynamic body feature. Thus, this gender classification also requires a higher computational complexity because behavior features need image sequencing for recording movements.

### *4.3 Apparel Feature-based Gender Classification*

Males and females have distinctive preferences regarding dressing. Thus, according to an individual's dressing feature, Ueki *et al*. [40] proposed a method of gender classification that integrates the information from different parts of a single image. By integrating likely hairstyle and clothing and applying the PCAs and GMMs on thousands of sample images, experimental results demonstrated that their integration strategy significantly lowered the error rate by 25.1% in gender classification than the conventional approaches that use facial features only.

The study conducted by Yuan *et al*. [39] for the first time demonstrated the effectiveness of footwear appearance for gender recognition as a feature. According to preliminary experimental results, they concluded that the histogram of oriented gradient (HOG), which represented a footwear image plus nonlinear SVM classifier, has given satisfactory results with the average recognition rate of 85.49%.

Apparel features can serve as another source of features to classify gender, which is easier to obtain and discriminative even within low-quality images. The approaches based on apparel features are summarized in the third part, Table 1 (Table 1-III).

### *4.4 Multi-Factors-based Gender Classification*

The gender recognition classifier with single feature achieves a classification accuracy that is far from perfect. One possibility to improve gender classification accuracy is to combine several features together to perform multi-factor-based gender classification. The multi-factors means gender classification using several features together. Hadid *et al*. [38] combined motion and appearance for gender analysis, and they obtained recognition rates of 90.3%, 78.3% and 88.7%, respectively, which are tested over the three different databases.

Ueki *et al*. [40] presented a method of gender classification that integrated facial information, hairstyle, and clothing information. They were able to reduce false classifications made by the conventional approach that only uses facial features by 25.1%. Xia *et al*. [59] investigated the combination of shape and texture modalities for gender classification. They performed the experiment in two ways: one fuses the results from gray images and range images, and the other fuses the results from gray images and 3D meshes. They achieved a correctness of about 94%, which outperformed the results obtained with one modality and was comparable to state-of-the-art. Erno Mäkinen and Roope Raisamo [60] combined all the classifier outputs together using four types of combination methods: voting, class voting, arithmetic, and arithmetic class voting, and found that using more than one gender classifiers decreased the classification speed. However, when classification was preceded by face detection, the more important factor was the face detection speed.

### *4.5 Summary of Appearance-based Gender Classification*

Vision-based gender classification methods utilize different characteristics of the body, body movement, and clothing to identify a person as male or female. As a non-invasive approach, it does not require wearing any sensors. The static body and apparel features are the still information derived from the human body, which are easy to use and can achieve a high accuracy. However, these approaches might be limited by the application conditions and may not be suitable for applications such as surveillance system and video games. On the other hand, a dynamic body features-based method capture a person's activity information, which makes it applicable in dynamic environments, e.g., when a person is walking. However, processing sequence images of movements may lead to high computational complexity. For example, Hadid *et al*. [38] extracted over 4000 video shots with 15-300 frames in each. Static body and apparel feature extraction only need one frame of each person. Moreover, all the gender classification approaches using vision-based features are affected by the quality of the image. Hence, an image with deteriorated quality will decrease the accuracy for gender identification. This issue can be resolved by combining several features, namely the multi-factors-based method, to improve the classification accuracy.

## 5 Biological Information-based Gender Classification

Biological information does not change over a long period of time compared with the vision-based approach, therefore some have proposed the biological information-based approaches for gender classification as shown in Table 2.

### *5.1 Biometric Information-based Gender Classification*

Biometric data are considered as an alternative to be used in gender recognition because they are comparatively less affected by factors such as mood and clothing. A list of representative studies on gender classification using biometric information is presented in the first part of Table 2 (Table 2-I).

Because the complex patterns of the iris contain many distinctive features such as arching ligaments, furrows, ridges, crypts, rings, and corona, Thomas et. al. [16] predicted human gender based on iris image data by employing a decision tree classifier that could reach an accuracy of around 80%, with a biometric database built from 40 subjects.

**Table 2** Gender classification via biological information.

| **I: Biometric Information-based Gender Classification** | | | | | |
|---|---|---|---|---|---|
| **Biometrics** | **Publications** | **Feature Extraction Algorithms** | **Classification Algorithms** | **Database Description** | **Accuracy** |
| Iris | Thomas *et al.*, 2007 | Geometric features(machine learning) | C4.5 decision tree algorithm(machine learning) | Built a small database containing 40 people | 80% |
| Fingerprint | Badawi *et al.*, 2006 | RTVTR and the white lines count | fuzzy C means (FCM), LDA, and artificial neural network (ANN) | 10-fingerprints for 2200 persons of different ages and gender (1100 males and 1100 females) | 80.39%, 86.5%, and 88.5% using FCM, LDA, and ANN |
| Voice | Shue *et al.*, 2008 | Min-max normalization feature selection algorithm (MFCC) | SVM | CID database | About 90% |
| Emotional Speech | Kotti *et al.*, 2008 | MFCC | SVM | BDES and the Danish Emotional Speech (DES) | 99.07% and 99.00% with different database |
| Ear | Gnanasivam *et al.*, 2013 | Euclidean distance | Bayes classifier, KNN, and ANN | Internal database of about 342 samples of male and female ears | 90.42% |

| **II: Bio-signal Information-based Gender Classification** | | | | | |
|---|---|---|---|---|---|
| **Bio-signal Information** | **Publications** | **Feature Extraction Algorithms** | **Classification Algorithms** | **Database Description** | **Accuracy** |
| EEG | Nguyen *et al.*, 2013 | Popular EEG features and paralinguistic features (MFCC) | SVM | Australian EEG database | Near 97% |
| ECG | Ku. *et al.*, 2012 | Features of HRV | least square support vector machine (LS-SVM) and SVM | In-house developed ECG data acquisition system | 92% |
| DNA | Pötsch *et al.*, 1992 | Not applicable | Dot hybirdization | Patients | Near 100% |

Fingerprints have been used as vital parts for gender classification because of their unique properties. They are also important factors in forensic anthropology used to identify gender [61]. A previous study [62] analyzed different features from a fingerprint that are significantly different between males and females, where the highest gender classification rate was 88% using a neural network classifier and 86.5% using LDA classifier, respectively.

Gnanasivam *et al.* [18] used the biometric information from the ear for gender classification. The ear hole was considered as the primary reference point. Relative (Euclidean) distance has been measured between the ear identification points (ear features) and the ear hole. They used an extensive internal database of about 342 measurements of male and female ears. A Bayes classifier, a $k$NN classifier, and a neural network classifier have been used for the classification, respectively. The overall gender classification rate of 90.42% was achieved with the $k$NN classifier, which performed the best among the three classifiers.

Analyzing emotional speech [43] for identifying gender made the problem even more interesting. A branch and bound feature selection algorithm was applied to select a subset of 15 features among 1379 originally extracted features. SVM classifiers with various kernels were tested on two databases, namely the Berlin database of Emotional Speech and the Danish Emotional Speech database. The reported classification results outperformed those techniques obtained by that time. A perfect classification accuracy was obtained. Because males and females have different voice characteristics, Yen *et al.* [41] examined the role of acoustic measures related to the voice source in automatic gender classification, implemented using SVMs. Gender classification accuracy was about 90%.

However, gender classification via ear, fingerprint, and iris also are based on image processing techniques, from where researchers selected the biometrics as the features for gender recognition. The data processing speed made them appropriate for a large-scale identification system. On the other hand, voice and emotional speech are based on measurements of physical and behavioral characteristics, the feature extraction algorithm, which applies global information and requires a large amount of computational resources.. Meanwhile, voice and emotional speech are sensitive to background noise. These disadvantages of voice and emotional speech-based methods are not suitable for a large-scale classification system.

### *5.2 Bio-signals Information-based Gender Classification*

With the development of bio-signal information technology, the bio-signals that can be measured and monitored from humans has gained increasing interest among researchers. In this sense, the bio-signals such as EEG and DNA are feasible for gender classification. The advantages of bio-signals are their inherent uniqueness, universality and resistance to spoofing. A list of representative works on gender classification by bio-signals are summarized in the second part of Table 2 (Table 2-II).

Bio-signals can also mean biomedical signals originating from many sources such as the heart, brain, and blood. The analysis of these signals is important for gender identification. To study the EEG information for gender classification, Phuoc *et al*. [26] proposed a framework of automatic age and gender classification using EEG data from a person. The features were sent to a machine learning module, for example, SVM, to build age and gender models for that person. The experiments suggested that the paralinguistic features were very promising for this task.

Besides EEG data, other biomedical signals were also used for classification. Rajesh *et al*. [27] dealt with gender classification from ECG signals using least squared SVM (LS-SVM) and SVM techniques. Different features extracted from ECG signals using heart rate variability (HRV) analysis were applied to the LS-SVM and SVM classifier. The LS-SVM classifier with a radial basis function (RBF) kernel produced a classification rate of 92%, which is higher than the accuracy of other models. Up to now, there have been reports on various means of gender classification using DNA and chromosome techniques. It is well known that DNA conveys a considerable amount of personal information. Pötsch *et al*. [46] investigated the use of human dental pulp as a source of DNA for determining gender in the 1990s. The gender was correctly classified for all cases in the study.

Gender classification via bio-signal information is an invasive approach. These bio-signals were reliable methods for gender classification up to now. The preceding studies show the potential trustworthiness of these signlas for gender classification, since tangible gender differences exist within the bio-signals. However, the limitations of these approaches cannot be overcome in some real applications. For instance, the technique of acquiring a bio-signal requires extra professional devices and the individual to wear the sensors. Thus, it is not suitable for on-line and real-time recognition.

### *5.3 Summary of Biological Information-based Gender Classification*

Gender classification via biological information is relatively unaffected by aging, making it more suitable for long-term identification compared with other non-invasive techniques such

**Table 3** Gender classification via social information.

| Social Network Information-based Gender Classification | | | | | |
|---|---|---|---|---|---|
| **Social network information** | **Publications** | **Feature Extraction Algorithms** | **Classification Algorithms** | **Database Description** | **Accuracy** |
| Email | Corney *et al.*, 2002 | Manual extraction | SVM | The inbox of a member of a large (greater than 15,000 users) academic organization | About 70% |
| Blog | Mukherjee *et al.*, 2010 | A new ensemble feature selection (EFS) algorithm | SVM classification, SVM regression and naïve Bayes (NB) as learning algorithms | Real life Blog dataset(and blog search engines, e.g., blogger.com, technorati.com, etc. The data set consists of 3100 blogs) | 88.56% |
| Hand writing | Liwicki *et al.*, 2007 | eBeam (eBeam System by Luidia, Inc.) interface | SVM and GMM | IAM-OnDB, a large on line handwriting database acquired from a whiteboard (Liwicki and Bunke, 2005b) | 67.06% |

as vision-based recognition. A gender classification approach via biometric information has a lower anti-tamper and distinctive trait than the classification approach via bio-signals. In general, the gender classification via bio-signal information can obtain an accuracy of 90% or even higher, according to the aforementioned studies. This indicates that biological information provides relatively credible data for gender classification. One problem with an approach using bio-signals is that those signals can not be easily acquired in an unobtrusive way. In other words, subjects need to wear sensors to acquire the data. The invasiveness makes such signals difficult to acquire and not practical for real-time applications. Further investigations may solve these problems and lead to a better approach to bio-signal based gender classification.

## 6 Social network information-based Gender classification

The way that men and women use languages and converse are different, even sharing the same language. This could be a feature to identify gender. Traditionally, handwriting is used as social information for gender classification. The Internet has transformed the traditional social networks. Email, blogs, etc., are becoming important forms of communication. Several researchers have studied the problem of gender classification based on social information. Suitable corpora of social information are needed to be generated for the study. The attributes/features being selected from the corpora for classification include language structure, gender-preferential words, character based styles, etc. The procedure of extracting attributes from social data (e.g., email, blogs, and documents) is called text mining [63], which makes predictions or classifications for new data, explains existing data, and summarizes the contents of a large database to support decision making for gender classification. Table 3 lists some representative studies on gender classification using daily social network-based information.

The classification of gender based on handwriting has been a research topic for many decades. However, only a few study reports exist that investigate automatic detection of gender from handwriting. The writing samples, which are similar to body language, can serve as a behavioral representation to interpret human behavior related to thinking styles, personal traits, and social skills. For example, Liwicki *et al.* [48] proposed a system that can classify gender and handedness by online, Roman handwriting. In that study, both of the problems are binary-class problems, i.e., male/female and left-/right-handedness. Thus two classifiers were applied to the gender and the handedness classification problems. The first classifier used GMM to model the classes, while the second one was based on SVMs. The GMM classifier achieved a gender classification rate of 67.06%, which is better than that obtained with SVM.

With the emergence of email and blog in the computer era, these domians provide additional sources for gender classification. Corney *et al*. [47] conducted an investigation on authorship gender attribution mining from email text. The researchers used an extended set of content-free email document features, such as style markers, structural characteristics, and gender-preferential language features, together with an SVM learning algorithm to make the gender classification. Rjun *et al.* [49] introduced a new set of features, which are variable length part of speech (POS) sequence patterns that are extracted from the training data using a sequence pattern mining algorithm. In the same work, another new feature selection method based on an ensemble of several feature selection approaches was proposed. Experimental evaluation using a real-life blog dataset showed that these two feature selection methods could improve the classification accuracy significantly.

Gender classification via social network-based information captures the communication and interaction among human beings. However, the accuracy of it is lower than the other gender classification approaches. The number of features of this information usually is very large, and the dataset is massive because individuals receive a large number of emails that usually increase with elasped time. For example, in the literature [47], the corpora of email documents used in the experimental evaluation came from the inbox of a person who worked in a large academic organization (greater than 15,000 users), and the total number of attributes used in the experiment was 222. The resource for gender recognition needed extensive preprocessing work. The complexity and collectability of these approaches may limit their use in some areas from a practical perspective.

## 7 Comparison and Discussion

According to the previous investigation on the aforementioned gender classification methods, each has distinct advantages and disadvantages depending upon the requirements of the application. We compared those approaches from the application point of view. The comparison was carried out based on several characteristics, including accuracy, trustworthiness, invasiveness, collectability, and application scope. More details are explained and discussed in the following paragraphs.

### *7.1 Accuracy*

Accuracy implies the probability of the correct recognition results. Distinctive features and an effective classifier determine the classification accuracy. Features of a vision-based approach can be damaged by image processing, and the accuracy also can decline as a result of frequent changes in hair, weight, and clothing. The approach based on biological information delivers higher accuracy by extracting the particular feature from the biometric and bio-signal information of humans. Besides the distinct feature, the choice of classification algorithm also influences the classification accuracy.

### *7.2 Trustworthiness*

Trustworthiness indicates the reliability and robustness of an approach for gender classification. According to the previous research results, approaches based on appearance and social information with the features extracted from images or text may fail due to noise, low resolution, and tampering. However, a biological information-based approach uses physiological signals that make identification difficult. However, biological information usually does not change over time and has the highest rate of uniqueness. Therefore, it is a reliable way to identify the gender.

### *7.3 Invasiveness*

The means of acquiring data can be invasive or non-invasive. Gender classification via vision-based feature is a non-invasive approach. However, gender classification via a biological information requires specific devices invading the human body to record the internal information. In other words, biological information cannot be casually acquired in an unobtrusive way.

### *7.4 Collectability*

Collectability means the information can be acquired. Vision-based features are conveniently obtained from videos or images, thus the approaches utilizing them with a strong computation ability are appropriate for real-time or online applications. For biological information and social information, it is difficult to acquire since they require more invasive techniques to obtain information from the human body and activity.

### *7.5 Application Scope*

Methods of acquiring information correspond to various application scopes, and the choice of features depends on the specific applications. Gender classification by vision-based approaches which have the requirement of real-time and convenience of information acquirement is appropriate for surveillance, the security industry, and HCI applications, etc. Gender classification based on internal information, especially approaches via bio-signal features, is suitable for the security system, commercial development, and demographic research because of its high reliability. The applicability of a specific gender classification technique mainly depends on the requirements of the application field. There is no a single approach that outperforms all the others in various conditions. In other words, each gender classification approach is suitable in a particular field according to performance and requirements of data acquisition. Table 4 presents the performance comparison.

## 8 Conclusion and Future Research

In this paper, we reviewed the state-of-the-art gender classification approaches, which are divided into two groups according to these metric traits: the appearance approach (i.e., static body features, dynamic body features, and apparel features) and the non-appearance approach (i.e., biometrics, bio-signals, and social network information). Moreover, a comparison among them was presented. We found that biology information using the physiological signal is not easily tricked in the classification and it has a higher accuracy

**Table 4** Comparison of various approaches based on appearance feature, biometric feature, bio-signal and social information.

| Feature | Distinctiveness | Permanence | Trustworthiness | Invasiveness | Collectability | Accuracy | Application scope |
|---|---|---|---|---|---|---|---|
| Appearance (Vision-based) | Medium | Low | Low | Low | High | High$\sim$Medium (74.6%$\sim$98.2% ) | Security and surveillance industry, HCI application |
| Biometric | High | Medium | Medium | High | Medium | High (80%$\sim$99% ) | Security industry, HCI application, demographic research, commercial development, mobile application and video games |
| Bio-signal | High | High | High | High | Low | High (92%$\sim$100% ) | HCI application, commercial development, demographic research, security and surveillance industry |
| Social | Medium | Medium | Low | Medium | Low | Low (67%$\sim$88.6% ) | Security and surveillance industry, commercial development |

(92%$\sim$100%) than other gender classification methods since it is directly measured from the human body. However, it is invasive and has low collectability compared with the vision-based approach. As an alternative to bio-signals, biometric information also has a high accuracy (80%$\sim$99%) because it is comparatively less affected by other factors such as mood and clothing. Appearance-based methods achieve high to medium accuracy (74.6%$\sim$98.2%), which depends on the specific appearance feature and algorithm used for classification. Accuracy can be compromised with the deteriorated quality of collected images or videos. Social network information-based methods have the lowest accuracy (67%$\sim$88.6%) because social behaviors are apt to be assimilated by ambient environment and social activities. We also concluded that the applicability of a particular gender classification technique depends on the environmental requirements. A single approach cannot satisfy all the gender classification requirements in various conditions, and each gender classification approach is suitable in a particular field according to the characteristic of performance.

The existing approaches also have some limitations such as low accuracy, low efficiency, and restricted application domain. This review brings a new insight analysis on various gender classification methods in different contexts. To improve the performance of the gender classification system, the upcoming research effort should focus on the enhancement of accuracy and reliability. The reviews of these approaches suggest that more in-depth studies are required focusing on the following:

First, we should improve the preprocessing and classification algorithm to enhance accuracy and efficiency. The classification algorithm is key for gender recognition. Therefore, it is suggested to utilize more advanced classification approaches to strengthen the performance, such as multi-objective synchronous recognition or a larger-scale recognition system.

Second, we should seek and employ new features for gender classification. The features that are used for classification often depend on the particular application. Therefore, one should seek new features that satisfy the four requirements (universality, distinctiveness, permanence, collectability) for gender recognition.

Third, we could combine the three vision-based, biological information-based, and social network-based gender classification approaches to improve accuracy, i.e., multi-factor combination approaches for recognition. The combined approaches will outperform any method with one single technique.

## References

[1] J Richard Udry. The nature of gender. *Demography*, 31(4):561–573, 1994.

[2] Gautam Bommagani Omveer Singh. Pattern based gender classification. *International Journal of Advanced Research in Computer Science and Software Engineering*, 3(10):888–895, 2013.

[3] Laura Beckwith, Margaret Burnett, Susan Wiedenbeck, and Valentina Grigoreanu. Gender hci: Results to date regarding issues in problem-solving software. In *AVI 2006 Gender and Interaction: Real and Virtual Women in a Male World Workshop paper*, pages 1–4, 2006.

[4] Meltem Demirkus, Kshitiz Garg, and Sadiye Guler. Automated person categorization for video surveillance using soft biometrics. In *SPIE Defense, Security, and Sensing*, pages 76670P–76670P. International Society for Optics and Photonics, 2010.

[5] Jürgen HP Hoffmeyer-Zlotnik and Christof Wolf. *Advances in cross-national comparison: A European working book for demographic and socio-economic variables*. Springer Science & Business Media, 2003.

[6] Rachel Maldonado, Patriya Tansuhaj, and Darrel D Muehling. The impact of gender on ad processing: A social identity perspective, 2003.

[7] Shiqi Yu, Tieniu Tan, Kaiqi Huang, Kui Jia, and Xinyu Wu. A study on gait-based gender classification. *Image Processing, IEEE Transactions on*, 18(8):1905–1910, 2009.

[8] Sajid Ali Khan, Maqsood Ahmad, Muhammad Nazir, and Naveed Riaz. A comparative analysis of gender classification techniques. *Middle-East Journal of Scientific Research*, 20(1):1–13, 2014.

[9] Erno Mäkinen and Roope Raisamo. An experimental comparison of gender classification methods. *Pattern Recognition Letters*, 29(10):1544–1556, 2008.

[10] Ronald Poppe. A survey on vision-based human action recognition. *Image and vision computing*, 28(6):976–990, 2010.

[11] Kresimir Delac and Mislav Grgic. A survey of biometric recognition methods. In *Electronics in Marine, 2004. Proceedings Elmar 2004. 46th International Symposium*, pages 184–193. IEEE, 2004.

[12] Choon Boon Ng, Yong Haur Tay, and Bok Min Goi. Vision-based human gender recognition: a survey. *arXiv preprint arXiv:1204.1611*, 2012.

[13] Anil K Jain, Arun Ross, and Salil Prabhakar. An introduction to biometric recognition. *IEEE Transactions on circuits and systems for video technology*, 14(1):4–20, 2004.

[14] Gholamreza Amayeh, George Bebis, and Mircea Nicolescu. Gender classification from hand shape. In *Computer Vision and Pattern Recognition Workshops, 2008. CVPRW'08. IEEE Computer Society Conference on*, pages 1–7. IEEE, 2008.

[15] Muthumari Paluchamy, D Suganya, and S Ellammal. Human gait based gender classification using various transformation techniques. *IJRCCT*, 2(11):1315–1321, 2013.

[16] Vince Thomas, Nitesh V Chawla, Kevin W Bowyer, and Patrick J Flynn. Learning to predict gender from iris images. In *Biometrics: Theory, Applications, and Systems, 2007. BTAS 2007. First IEEE International Conference on*, pages 1–5. IEEE, 2007.

[17] Oksam Chae Taskeed Jabid, Md. Hasanul Kabir. Gender classification using local directional pattern (ldp). In *International Conference on Pattern Recognition*, pages 2162–2165, 2010.

[18] P Gnanasivam and S Muttan. Gender classification using ear biometrics. In *Proceedings of the Fourth International Conference on Signal and Image Processing 2012 (ICSIP 2012): Volume 2*, volume 2, page 137. Springer, 2013.

[19] Vicki Bruce and Andy Young. *In the eye of the beholder: the science of face perception.* Oxford University Press, 1998.

[20] Vicki Bruce, A Mike Burton, Elias Hanna, Pat Healey, Oli Mason, Anne Coombes, Rick Fright, and Alf Linney. Sex discrimination: how do we tell the difference between male and female faces? *Perception*, 1993.

[21] Elvira Mendoza, Nieves Valencia, Juana Muñoz, and Humberto Trujillo. Differences in voice quality between men and women: use of the long-term average spectrum (ltas). *Journal of Voice*, 10(1):59–66, 1996.

[22] Harold Hill and Alan Johnston. Categorizing sex and identity from the biological motion of faces. *Current Biology*, 11(11):880–885, 2001.

[23] Alice J O'Toole, Dana A Roark, and Hervé Abdi. Recognizing moving faces: A psychological and neural synthesis. *Trends in cognitive sciences*, 6(6):261–266, 2002.

[24] Beatrice A Golomb, David T Lawrence, and Terrence J Sejnowski. Sexnet: A neural network identifies sex from human faces. In *NIPS*, pages 572–579, 1990.

[25] Yujie Dong and Damon L Woodard. Eyebrow shape-based features for biometric recognition and gender classification: A feasibility study. In *Biometrics (IJCB), 2011 International Joint Conference on*, pages 1–8. IEEE, 2011.

[26] Phuoc Nguyen, Dat Tran, Xu Huang, and Wanli Ma. Age and gender classification using eeg paralinguistic features. In *Neural Engineering (NER), 2013 6th International IEEE/EMBS Conference on*, pages 1295–1298. IEEE, 2013.

[27] Rajesh Ku Tripathy, Ashutosh Acharya, and Sumit Kumar Choudhary. Gender classification from ECG signal analysis using least square support vector machine. volume 2, pages 145–149. Scientific & Academic Publishing, 2012.

[28] Johan AK Suykens and Joos Vandewalle. Least squares support vector machine classifiers. *Neural processing letters*, 9(3):293–300, 1999.

[29] Leif E Peterson. K-nearest neighbor. *Scholarpedia*, 4(2):1883, 2009.

[30] Sinjini Mitra and Marios Savvides. Gaussian mixture models based on the frequency spectra for human identification and illumination classification. In *Automatic Identification Advanced Technologies, 2005. Fourth IEEE Workshop on*, pages 245–250. IEEE, 2005.

[31] Multiple Biometric Grand Challenge (MBGC). `https://www.nist.gov/programs-projects/multiple-biometric-grand-challenge-mbgc`, August 2016. Accessed by October 30, 2016.

[32] Face Recognition Grand Challenge (FRGC). `https://www.nist.gov/programs-projects/face-recognition-grand-challenge-frgc`, August 2016. Accessed by October 30, 2016.

[33] Liangliang Cao, Mert Dikmen, Yun Fu, and Thomas S Huang. Gender recognition from body. In *Proceedings of the 16th ACM international conference on Multimedia*, pages 725–728. ACM, 2008.

[34] Amjath Fareeth Basha and Gul Shaira Banu Jahangeer. Face gender image classification using various wavelet transform and support vector machine with various kernels. *International Journal of Computer Science Issues*, 9(6):150–157, 2012.

[35] Caifeng Shan. Learning local binary patterns for gender classification on real-world face images. *Pattern Recognition Letters*, 33:431–437, 2013.

[36] Juan Bekios-Calfa, José M Buenaposada, and Luis Baumela. Robust gender recognition by exploiting facial attributes dependencies. *Pattern Recognition Letters*, 36:228–234, 2014.

[37] Effendi Widjaja, Geok Hong Lim, and An An. A novel method for human gender classification using raman spectroscopy of fingernail clippings. *Analyst*, 133(4):493–498, 2008.

[38] Abdenour Hadid and Matti Pietikäinen. Combining appearance and motion for face and gender recognition from videos. *Pattern Recognition*, 42(11):2818–2827, 2009.

[39] Yuan Yuan, Yanwei Pang, and Xuelong Li. Footwear for gender recognition. *IEEE transactions on circuits and systems for video technology*, 20(1):131–135, 2010.

[40] Kazuya Ueki, Hiromitsu Komatsu, Satoshi Imaizumi, Kenichi Kaneko, Nobuhiro Sekine, Jiro Katto, and Tetsunori Kobayashi. A method of gender classification by integrating facial, hairstyle, and clothing images. In *Pattern Recognition, Proceedings of the 17th International Conference on*, volume 4, pages 446–449. IEEE, 2004.

[41] Yen-Liang Shue and Markus Iseli. The role of voice source measures on automatic gender classification. In *International Conference on Acoustics, Speech and Signal Processing*, pages 4493–4496. IEEE, 2008.

[42] Ahmed Badawi, Mohamed Mahfouz, Rimon Tadross, and Richard Jantz. Fingerprint-based gender classification. In *IPCV*, pages 41–46. Citeseer, 2006.

[43] Margarita Kotti and Constantine Kotropoulos. Gender classification in two emotional speech databases. In *Pattern Recognition, 19th International Conference on*, pages 1–4. IEEE, 2008.

[44] Julie Carrier, Stephanie Land, Daniel J Buysse, David J Kupfer, and Timothy H Monk. The effects of age and gender on sleep eeg power spectral density in the middle years of life (ages 20–60 years old). *Psychophysiology*, 38(2):232–242, 2001.

[45] Adam R Clarke, Robert J Barry, Rory McCarthy, and Mark Selikowitz. Age and sex effects in the EEG: development of the normal child. *Clinical Neurophysiology*, 112(5):806–814, 2001.

[46] L Pötsch, U Meyer, S Rothschild, PM Schneider, and CH Rittner. Application of dna techniques for identification using human dental pulp as a source of dna. *International journal of legal medicine*, 105(3):139–143, 1992.

[47] Malcolm Corney, Olivier de Vel, Alison Anderson, and George Mohay. Gender-preferential text mining of e-mail discourse. In *Computer Security Applications Conference, 2002. Proceedings. 18th Annual*, pages 282–289. IEEE, 2002.

[48] Marcus Liwicki, Andreas Schlapbach, Peter Loretan, and Horst Bunke. Automatic detection of gender and handedness from on-line handwriting. In *Proc. 13th Conf. of the Graphonomics Society*, pages 179–183, 2007.

[49] Arjun Mukherjee and Bing Liu. Improving gender classification of blog authors. In *Proceedings of the 2010 conference on Empirical Methods in natural Language Processing*, pages 207–217. Association for Computational Linguistics, 2010.

[50] Bing Li, Xiao-Chen Lian, and Bao-Liang Lu. Gender classification by combining clothing, hair and facial component classifiers. *Neurocomputing*, 76(1):18–27, 2012.

[51] P Jonathon Phillips, Patrick J Flynn, J Ross Beveridge, W Todd Scruggs, Alice J Otoole, David Bolme, Kevin W Bowyer, Bruce A Draper, Geof H Givens, Yui Man Lui, et al. Overview of the multiple biometrics grand challenge. In *International Conference on Biometrics*, pages 705–714. 2009.

[52] P Jonathon Phillips, Patrick J Flynn, Todd Scruggs, Kevin W Bowyer, Jin Chang, Kevin Hoffman, Joe Marques, Jaesik Min, and William Worek. Overview of the face recognition grand challenge. In *Computer vision and pattern recognition, IEEE computer society conference on*, volume 1, pages 947–954. IEEE, 2005.

[53] Kun Woo Cho, Feng Lin, Chen Song, Xiaowei Xu, Fuxing Gu, and Wenyao Xu. Thermal handprint analysis for forensic identification using heat-earth mover's distance. In *International Conference on Identity, Security and Behavior Analysis (ISBA)*, pages 1–8. IEEE, 2016.

[54] Ioannis A Kakadiaris, Nikolaos Sarafianos, and Christophoros Nikou. Show me your body: Gender classification from still images. In *Image Processing (ICIP), International Conference on*, pages 3156–3160. IEEE, 2016.

[55] Timm Linder, Sven Wehner, and Kai O Arras. Real-time full-body human gender recognition in (rgb)-d data. In *International Conference on Robotics and Automation (ICRA)*, pages 3039–3045. IEEE, 2015.

[56] Christina M Williams, Jeffrey Flora, and Khan M Iftekharuddin. Gender classification of running using full-body kinematics. In *SPIE Defense+ Security*, pages 984107–984107. International Society for Optics and Photonics, 2016.

[57] Xuezhi Wen, Ling Shao, Yu Xue, and Wei Fang. A rapid learning algorithm for vehicle classification. *Information Sciences*, 295:395–406, 2015.

[58] Andrea Stevenson Won, Le Yu, Joris H Janssen, and Jeremy N Bailenson. Tracking gesture to detect gender. `http://vhil.stanford.edu/mm/2012/won-ispr-gesture-gender.pdf`, 2012.

[59] Baiqiang Xia, Boulbaba Ben Amor, Di Huang, Mohamed Daoudi, Yunhong Wang, and Hassen Drira. Enhancing gender classification by combining 3d and 2d face modalities. In *Signal Processing Conference (EUSIPCO), 2013 Proceedings of the 21st European*, pages 1–5. IEEE, 2013.

[60] Roope Raisamo Erno Mäkinen. An experimental comparison of gender classification methods. *Pattern Recognition Letters*, (29):1544–1556, 2008.

[61] Chengsheng Yuan, Xingming Sun, and Rui Lv. Fingerprint liveness detection based on multi-scale lpq and pca. *China Communications*, 13(7):60–65, 2016.

[62] P Gnanasivam and Dr S Muttan. Fingerprint gender classification using wavelet transform and singular value decomposition. *arXiv preprint arXiv:1205.6745*, 2012.

[63] N.Sankarram G.Murugaboopathy, S.Hariharasitaraman and T.K.S.Rathish Babu. Appropriate gender identification from the text. *International Journal of Emerging Research in Management and Technolog*, pages 58–61, 2013.