[1]Sanjay Pandey,
Shashank Dwivedi,
Shabnam Sharma

Electrocardiogram: A Burgeoning Biometric Modality for Automated Gender Recognition

Journal of Electrical Systems

***Abstract:* -** Recent studies has examined the viability of obtain- ing secondary identifiers from core biometric traits including the iris, face, and fingerprints. This type of supplemental data, referred to as soft biometrics, includes personal traits e.g., age, gender, ethnicity, height, weight etc. Soft biometric attributes can be utilised in a variety of scenarios, such as monitoring and indexing biometric databases, enhancing the performance of primary biometric systems, and providing qualitative descriptions of an individual's qualities. It is especially helpful for bridging the gap that exists between how people and machines describe biometric data. In this work, we present an introduction of soft biometrics and describe existing methodologies to extract one of the soft biometrics, namely gender. In addition, a taxonomy for recognising gender based on numerous soft biometric factors is offered, along with a listing of the advantages and disadvantages of using these qualities within the context of a gender recognition system. Additionally, the practicality of using ECG to determine gender is studied. In conclusion, we discuss potential applications, challenges, and future approaches for gender recognition using ECG.

Keywords: Soft Biometrics, Biometric Recognition, Gender Recognition, Electrocardiogram.

I. INTRODUCTION

A. Biometrics Emergence

Security breaches and identity theft issues are rising continuously as a result of the tremendous rise of online industries like commerce and education. In addition to access control, healthcare, border control, financial services, and transac- tion and digital rights management, computing and Internet technologies are widely utilised in a number of applications [1]. As a result, automatic and precise identity verification techniques are critical in today's digital society [2], [3]. Usually, people prove who they are by remembering something (like a password or PIN) or by showing something they have (e.g., ID cards). Due to the possibility of these items being lost or stolen, these methods are vulnerable to identity fraud [4]. Biometrics technology has developed as a more secure alternative for establishing identity. For human recognition, biometric technologies utilise either

[1]*Department of Computer Science and Engineering,*

Shri Jagdishprasad Jhabarmal Tibrewala University, Rajasthan, India.

Sanjay Pandey is research scholar in Department of Computer Science and Engineering, Shri Jagdish prasad Jhabarmal Tibrewala University, Rajasthan, India e-mail: (sanjaypandeyucer@gmail.com), Shashank Dwivedi Associate Professor (CSE) United Institute Of Technology, Naini Prayagraj (UP)

(shashank7united@gmail.com)

Dr. Shabnam Sharma is Professor in the Department of Computer Science and Engineering, Shri Jagdish prasad Jhabarmal Tibrewala University, Rajasthan, India e-mail: (shabnam09sharma@hotmail.com).

physiologic (such as the face, fingerprint, or iris) or behavioural (such as the gait, voice, or signature) traits. Thus, there is no need to remember or carry anything for the purpose of establishing one's identity. As a result, biometric technology has grown in prominence as a more secure method of human recognition. However, con- fidentiality and liveness concerns make the system vulnerable to spoofing [5].

To address these concerns electrocardiogram (ECG) has evolved as a more advanced biometrics than conventional biometrics. The ECG is produced by the heart's ingenious self-regulating mechanism. It is extremely secure, private, and impossible to duplicate. It is found in all live organisms and so allows for real-time vitality assessment [6]. Several ECG based biometrics system has been developed in the past with higher accuracy [7], [8], [9], [10], [11]. A list of biometric modalities being used for identity verification is shown in Fig. 1. The biometrics based on physiological, behavioural or bioelectrical traits are considered hard biometrics. Gender, ancestry, skin tone, scars, and height are all examples of soft biometrics that can help fill in the blanks when it comes to identifying a person but are not conclusive on their own [12], [13]. However, with the use of soft biometrics, the efficiency and reliability of hard biometrics can be greatly improved.

B. Soft Biometrics: Scope and Benefits

The identification system using single biometric modality usually suffers from high enrollment failure rates, limited coverage areas, and low recognition rates due to low-resolution data from the person or sensor. Thus, achieving high identifi- cation rates with a uni-biometric system is practically difficult [14]. Increasing recognition rates demands more sensor fea- tures, which increases complexity and processing time. The usage of multi-biometric systems can alleviate some of the issues associated with the use of unimodal biometric systems [15]. Building such a system can be prohibitively expensive because to the requirement for more high-quality sensors, a massive storage capacity, and high computing needs. Second, the verification process takes longer under the new system, which is inconveniencing users [16]. Soft biometrics, on the other hand, offer a low-cost alternative that makes use of the same sensor.

Soft biometrics can give auxiliary information (e.g., colour skin, gender, ethnic origin), clothing (e.g., clothing's colour), or accessories (e.g., jewellery, glasses, hat) [17]. It can be used to supplement hard biometric characteristics (e.g., face, iris, ECG). Soft biometrics can be used with hard biometrics to • improve authentication speed and accuracy of biometric systems.

• provide robustness to poor quality data due to sensor error, distance acquisition or non-cooperation of users. improve acceptability due to consent free acquisition. facial features. There are numerous architectures [21], [22], achieve low computation cost due to parallel processing [23], feature descriptors [24], [25], classifiers [26], [27], [28],

with hard biometrics. and benchmark datasets [29] accessible in the literature withbridge the semantic gap between the processing of machine and human brain. be unconcerned about user privacy.

• provide restricted search on large database. The rest of the paper organized as follows: Sec. II presents all the possible modalities that can be used for recognizing gender. The characteristics of ECG to be used for gender recognition and its brief literature review is presented in Sec. III. The application domains, challenges and future perspective of gender recognition system is described in Sec. IV. Finally the conclusions are drawn in Sec. V.

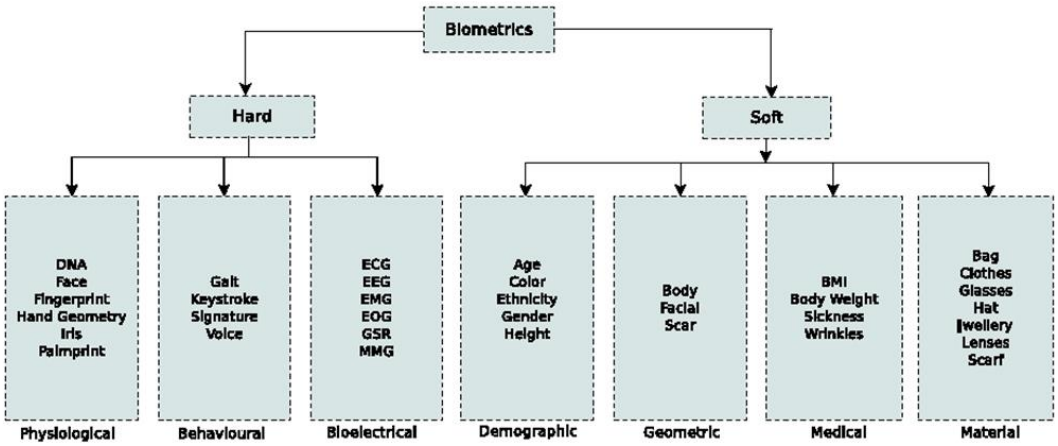


Fig. 1. Biometric Modalities.

II. GENDER RECOGNITION SYSTEM

In this paper, we focus on one of the soft biometrics i.e., 'gender'. In today's networked information societies, gender recognition is crucial; it is employed in a range of industries, including security surveillance, targeted advertising, and human-robot interactions. Gender recognition remains challenging, as it is intrinsically related to a range of biometric modalities, including fingerprints, face, iris, voice, body shape, stride, signature, DNA, clothing, hair, and jewellery [18]. According to forensic literature, the skull, particularly the chin and jaw, and the pelvis are gender identifiers [19]. These shape-based characteristics have been found in children and demonstrated to have a classification accuracy of 91% to 99%. It has been stated that no single skeletal trait conclusively demonstrates sexual dimorphism and that there is up to 85% cross-gender metric overlap, which can be linked to environ- mental factors and pathological circumstances such as diet and work stress [19]. Despite this, forensic experts assert that a visual examination of the entire skeleton can reach near-perfect accuracy in determining gender [20].

A. Gender Recognition using Face

To determine a person's gender using feature-based tech-

niques, the system extracts and analyses a set of distinguishing the optimal outcomes. Despite the results, face gender recog- nition remains a complex and unsolved issue, and researchers are striving to discover a solution [27], [30].

There are a variety of reasons why face gender identification should be viewed as an emergent research topic. To begin, face images presented a variety of challenges because to the variation in appearance, position, lighting, background, and noise. Nonetheless, numerous results have been published in the literature utilising simple constrained datasets, such as facial recognition technology (FERET) and UND [31], [32], [33], [34]. These datasets contain frontal face images shot under controlled illumination, facial expression, and backdrop conditions. As a result, they are inaccurate representations of real-world situations. Second, several proposed algorithms are designed to address a specific issue in face images and may therefore perform less well in real-world situations [34], [35], [36]. Third, due to the lack of standard procedure for gender recognition, authors employ a variety of experimental setups, including the number of model parameters rendering result comparisons inapplicable.

B. Gender Recognition using Fingerprint

Fingerprint-based gender recognition has garnered attention as it can reduce the search area by determining whether a fingerprint is male or female. Various indicators, such as the count of ridge and white lines, ridge and valley thickness, and their ratio, can be used to determine gender [37].

The majority of the works examine the spatial domain, with only a few investigating the frequency domain. Females showed a higher ridge density than males, according to previous research [38], [39]. The researchers discovered that males had higher mean ridge counts than females [40]. The significance of ridge distance [41], ridge period [42], and ridge frequency [43] measurements as spatial attributes is discussed in relation to fingerprint gender classification. Apart from a few publications, fingerprint gender identification is performed manually by measuring inked fingerprints. Numerous studies E. Gender Recognition using Body-Shape have been undertaken to categorise human faces according to their gender using the frequency domain and a variety of classifiers [21]-[28]. Only a few attempts have been made to categorise people's fingerprints according to their gender.

C. Gender Recognition using Iris The first method that employed near-infrared iris scans

to estimate gender was developed by Thomas et al. [44]. They classified gender using a blend of textural and geo-metric characteristics, including the horizontal, vertical, and Euclidean distances between the pupil and iris centres. Later, Lagree et al. examined additional texture elements that are not geometric in nature [45]. They took gender and race into account. Their experiment made an interesting observation: gender categorization using iris is quite challenging than race prediction, which is worse for women. In order to develop a gender prediction model, Bansal et al. integrated analytical and lexical data with wavelets and then used support vector machines [46]. Khalifa et al. proposed a deep convolutional neural network-based approach for gender recognition using iris [47]. In the suggested architecture, the iris is distinguished from a background image using the graph-cut segmentation technique. Three convolutional layers for feature extraction follow a fully connected layer for classification.

Recently, Khan et al. have suggested an SVM-based iris

classification for gender recognition [48]. Using Zernike, Leg- endre invariant moments, and a gradient-oriented histogram, the suggested technique exhibits a good responsiveness to prolonged changes. Invariant moments are utilised to extract features from iris images in this study. After extracting the attributes from these descriptors, the attributes are classified using keycode fusion. SVM is used to classify individuals based on their gender using a fused feature vector.

D. Gender Recognition using Hand

As far back as the forensics and archaeology investigations that identified gender from severely injured skeletons' pelvis, skull, and massive long bones that are usually strong pre- dictors of gender. Because hand images are often obtained in a controlled environment, with consistent alignment and luminance, they exhibit less variability than facial images that may be affected by many factors including variations in facial expression. This makes hand-based gender classification useful in the biometrics context.

The index to ring finger ratio and hand breadth may indicate a person's gender, but they vary throughout societies and are impacted by genetics, environment, and social situations. Falsetti [49] and Lazenby [50] achieved gender identification rates of up to 92% using dimensions of the metacarpals of the prosthetic arm. Krishan et al. identified gender using the size of the hand and feet [51]. According to the study, left foot breadth was the most accurate technique of detecting gender based on hand length and breadth, and foot length and breadth 86.9% of the time.

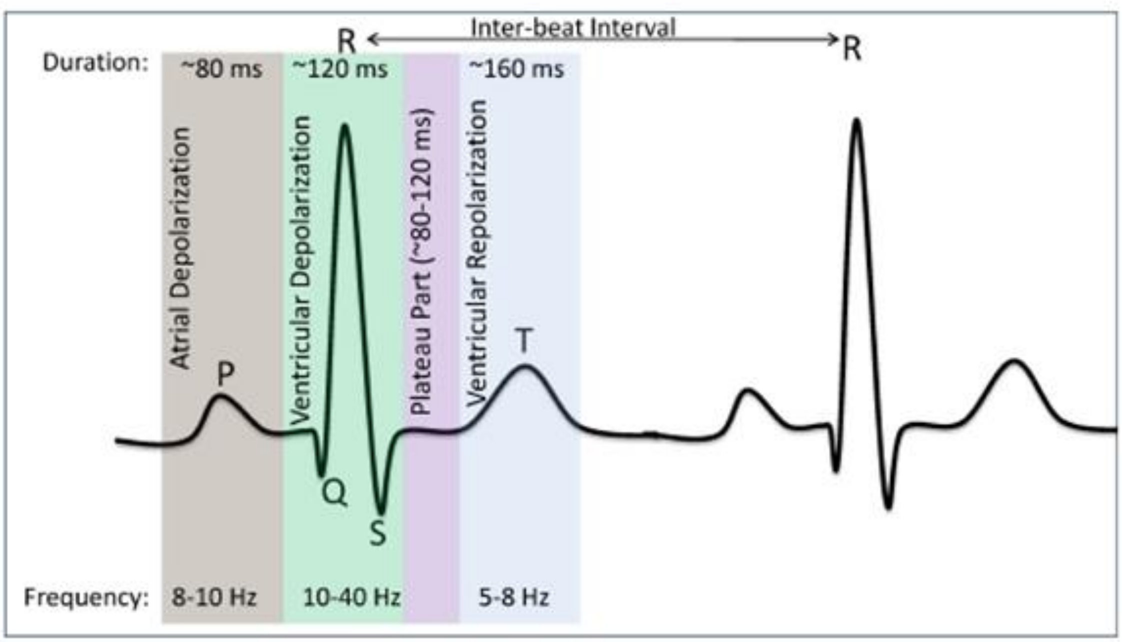
Certain biometric characteristics, such as gait, necessitate the acquisition of complete body scans. Gender classification on the basis of the human body has gained considerable interest due to the fact that the human body contains several indications for gender differentiation. In addition, Body shape and posture might disclose gender from afar. The swing of the body, the waist-hip ratio, and the shoulder-hip ratio are all examples of these cues [52]. For example, a woman's waist- to-hip ratio is different, and women tend to move their hips more than men, who have wider shoulders and swing them more. Furthermore, gender identification using body is affected by a number of relevant aspects, including background and clothing.

F. Gender Recognition using Voice Male and female voices are regarded to have considerable differences. Even with children and the elderly, vocal signals can provide accurate traces for audio-based gender detection [53]. Traces of gender that are derived from audio can either be of the voice source, or they can be of the vocal tract. (e.g., timbre of the voice) [54]. For approaches that rely on the user's voices, gender classification remains an issue. Despite the fact that the female frequency range of 170-275 Hz is unique from the male frequency range of 112-146 Hz [55], human voices can be distorted in a noisy environment with poor recording quality, making audio-based gender recognition a significant challenge [56]. Childers and Wu identified a person's gender by analysing ten vowels in clean speech data [57]. The technique was proven to be 100% accurate in predicting the gender of each individual speaker in a sample of 52 participants. Sorokin et al. found that the maximal glottal area, its maximum derivative, and harmonic amplitude ratios can result in male and female voice recognition accuracy of 94.7% and 95.9%, respectively [58].

TABLE I

NORMAL VALUES OF HEARTBEAT MEASUREMENTS FOR MALE AND FEMALE, RESPECTIVELY, INUPPER ROW AND LOWER ROWS [3].

Parameters	1-3 years	3-5 years	5-8 years	8-12 years	12-316 years	*M ean*□□ *SD*
Heartbeat (bpm)	119	98	88	78	73	91.2□□ 18.27
	128	101	89	80	76	94.8□□ 20.9
P width (ms)	80	87	92	98	100	91.4□□ 8.17
	83	84	89	94	98	89.6□□ 6.43
P R interval (ms)	118	121	129	134	139	128.2□□ 8.76
	113	123	124	129	135	124.8□□ 8.14
QRS width (ms)	71	75	80	85	91	80.4□□ 7.92
	68	71	77	82	87	77□□ 7.78
QT_c interval (ms)	412	412	411	411	407	410□□ 2.07
	417	415	409	410	414	413□□ 3.39
Amplitude *P* wave	0.15	0.13	0.12	0.12	0.13	0.13□□ 0.01
	0.16	0.13	0.12	0.14	0.15	0.14□□ 0.02
Amplitude *R* wave	0.77	0.63	0.62	0.59	0.58	0.64□□ 0.08
	0.68	0.65	0.49	0.54	0.48	0.57□□ 0.09
Amplitude *S* wave	0.27	0.21	0.22	0.22	0.19	0.22□□ 0.03
	0.35	0.2	0.22	0.16	0.13	0.21□□ 0.08



III. ECG-BASED AUTOMATED GENDER RECOGNITION

The electrical activity of the heart is measured using electrodes and is referred to as an ECG. ECG signals are widely employed in health context. The appropriateness of ECG for biometric application is also on the rise, as evidenced by the discriminatory strength of ECG features [7]. ECG- based human recognition has garnered considerable attention, particularly over the last decade. Among all biometrics, the ECG is practically impenetrable due to the fact that it is generated by an intrinsic organ, namely the heart. It includes an intrinsic function for detecting vitality [59]. Additionally, the ECG biometric approach offers a high degree of accuracy and reliability. Thus, the ECG signal possesses features such as detection of life, universality, difficulty of replication, and continuity, and reclaims the requirement of user presence. Due to these characteristics, ECG analysis has the potential to be implemented in smartphone applications in the Internet of Things generation. As a result, its applications are prevalent in fields where security is a primary concern, such as national ID cards, UIDAI, border and immigration control, banking and financial services, and airports, among others. Biometrics used in these fields can be enhanced by incorporating soft qualities such as age, gender, and ethnic origin. The purpose of this research is to investigate the possibility of gender identification using ECG.

Heartbeats are made up of waves such as P, Q, R, S, and T, as illustrated in Fig. 2. There are three sorts of heartbeat properties based on these waves: interval, amplitude, and angle [6]. Numerous researches have demonstrated that the heartbeats of various individuals exhibit distinct character- istics. Individuals' heartbeats vary due to variances in their heart's architecture and physiology. Typically, from infancy to puberty (16 years of age), an individual's anatomy undergoes progressive alteration. Certain characteristics of the heartbeat may change with age and sex. In Table I, we can observe how the characteristics of a healthy heartbeat change with gender and age. It demonstrates that as people age, their heart rate falls significantly, causing the P wave, the QRS complex, and the PR interval to last longer. While the P wave amplitude remains constant with age, the amplitudes of the R and S waves decline from childhood to adolescent. David has reported that the T wave changed gradually from childhood to adulthood [60]. These alterations are not constant and can vary significantly between individuals, making generalisation difficult. From these observations, it can be concluded that gender and age may affect heartbeat parameters.

The majority of the literature in the topic of ECG biometrics focuses on strategies for boosting segmentation, feature extraction, and recognition accuracy. Only a limited number of researchers have concentrated on deriving gender and age from ECG [61], [62], [63], [64]. Results from cutting-edge techniques have shown that the ECG characteristics distinguish between genders. The impact of ageing on ECG characteristics has been demonstrated by some studies in the literature.

Goshvarpour et al. have analysed gender and age disparities using Poincare section indices [61]. They focused on detecting and classifying dynamical ECG trajectories based on gender, and age-based categorization. They have created ECG's 2D phase space followed by generation of Poincare sections at diverse angles and recovered some geometric indices. The algorithm was tested on 79 healthy individuals. The gender

Fig. 2. ECG waves [7].

and age-based categorization techniques reached a maximum accuracy of 93.33% using SVM. When both age and gender were taken into consideration, gender were recognised with the accuracy of 94.66%. Cabra et al. provides a system for gender recognition and person authentication [63]. For both experiments, the same characteristics are utilised to evaluate the classification accu- racy of multiple machine learning systems perceiving ECG signals in different body positions. They get an accuracy score greater than 98% for ECG authentication and 94% for gender identification. Using Least Square Support Vector Machine (LS-SVM) and Support Vector Machine (SVM) techniques, Tripathy et al. offer a method for gender detection from an ECG signal [64]. The various features collected from the ECG signal using Heart Rate Variability (HRV) analysis are the input to the LS-SVM and SVM classifiers, and the output classifies whether the patient corresponding to the needed ECG is male or female.

IV. GENDER RECOGNITION: APPLICATIONS, CHALLENGES AND FUTURE PERSPECTIVE

Automated gender recognition has a variety of applications, ranging from security to image and video labelling and index- ing. For instance, detection algorithms can identify an individ- ual of interest depending on their gender [65], [66]. Various context in which gender recognition system can be utilized is shown in Fig. 3. Usually, the gender recognition system is utilized with hard biometrics attributes (multi-modal) to im- prove the authentication speed and accuracy [67]. For example, in human-computer interaction, data and personalized avatars can be generated automatically based on the user's gender. There are industrial systems that collect data on customers' demographics in order to personalise advertisements to them or to compile aggregate data on how people spend their money (e.g., based on age, gender, ethnicity).

Uni-modal system for recognizing gender may also be developed. For instance, electronic customer relationship man- agement (ECRM) can also leverage gender classification to manage customers successfully by providing them with per- sonalised products and services. Advertisements targeting spe- cific age groups or genders can be shown for products such as mobile phones, fashion, and food. In cosmetology, it is critical to determine how cosmetics and surgery can make people appear younger by determining their age based on their facial image. Additionally, soft biometrics traits such as gender can be used to prune databases. By eliminating out subjects, it may speed up the search in larger biometric datasets. Numerous variables, including age, gender, hair colour, and skin tone, have been proposed for effective face database filtering. Addi- tionally, [68] gave an examination of the filtering-gain versus filtering-reliability trade-off when employing soft biometric features to prune huge databases.

There are many difficulties in the developing field of gender recognition. Constraints on hardware resources and recogni- tion algorithms are one of the main difficulties. For instance, there can be limitations on gender recognition due to the image quality and the estimation algorithms used. As a result, although one set of hardware and an algorithm may be able to distinguish between genders with reasonable accuracy, another set may not, demanding cautious assessment of the potential resources. In conclusion, the system's resources must be taken into account while classifying a soft biometric system.

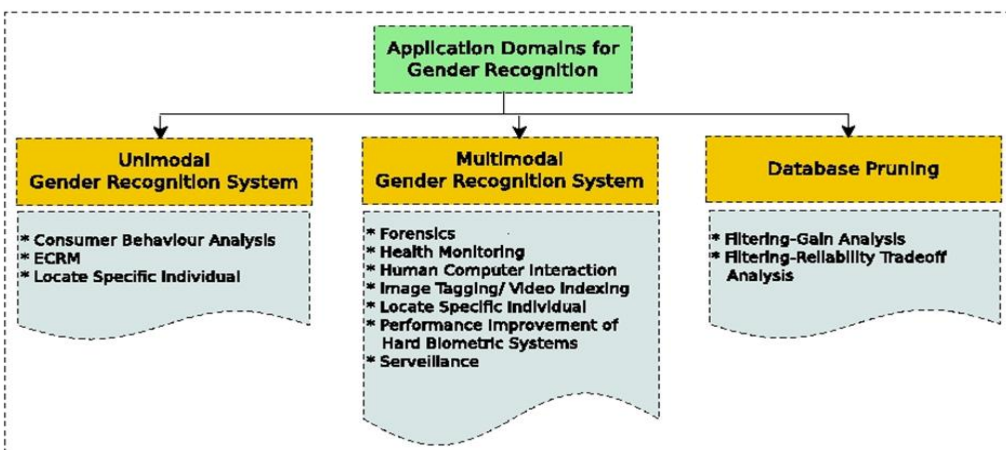


Fig. 3. Applications for gender recognition.

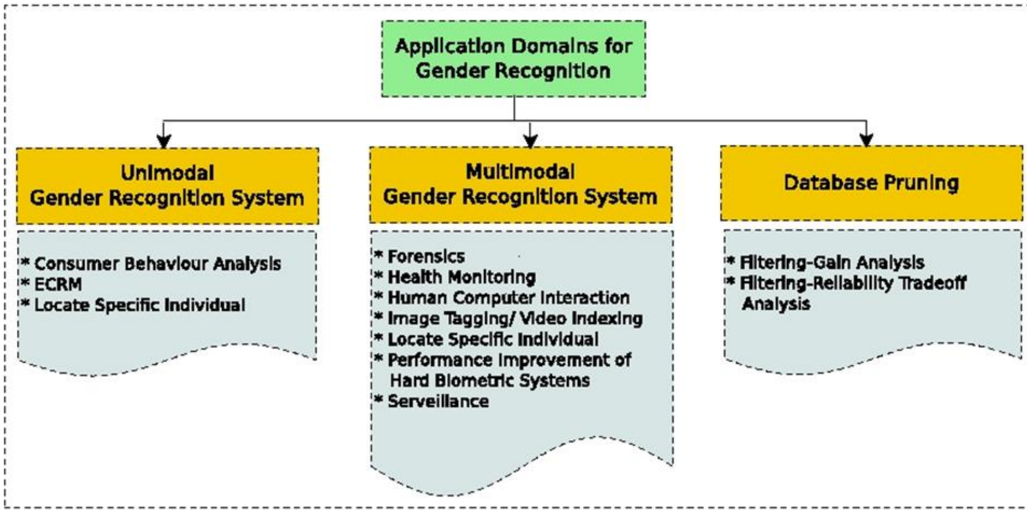


Fig. 3. Applications for gender recognition.

Similar to the previous point, another difficulty is accurately extracting the necessary features. For instance, the difficulty of precise feature extraction is frequently influenced by ambient conditions such as illumination. It is a major problem that frequently results in enormous hue discrepancies, especially in surveillance applications. In addition, soft biometrics typically permit a greater amount of acquisition flexibility. For example, attributes such as height, weight, skin tone, and numerous facial characteristics can be recognised out of a variety of angles. Therefore, the challenge is to optimise the number of categories that can be used for a particular soft biometric trait in order to strike a balance between the acquisition flexibility provided by those traits and the variations caused by sensing. Consequently, the need for automatic data quality evaluation may arises.

Use of soft biometric biometric characteristics in main biometric systems is an additional topic of interest. Imagine a biometric technology that can rapidly sort and filter a database and then uses a stronger but slower traditional search algorithm to find the best matches. Thus, component systems must be integrated into the overall system in a manner that meets their specific requirements for speed and dependability. It should also forecast how performance and computation complexity will increase when soft biometric features are used as filters on massive datasets. This type of analysis might be valuable for tasks such as the rapid identification of individuals in systems for surveillance. The research should consider the flaws that are already integrated into soft biometric classifi- cation, as these flaws will impact the overall effectiveness of identification.

Understanding and reducing the susceptibility of such features to obfuscation and spoofing is necessary to strike a balance between the potential of adopting soft biometrics in a variety of critical commercial and security applications. This is crucial because soft biometrics, by their very nature, are more easily spoofable than traditional biometric features. The use of cosmetic cosmetics for soft biometric spoofing would pose be found in [69], which looks at how makeup affects algorithms for estimating gender and age. In particular, the writers in this study explore age alteration, in which women try to make themselves look younger or older than they are, and gender spoofing, in which both sexes are obsessed with emulating the other's appearance.

Males and females have distinctive physiological, biochemical, biomedical, hormonal, and anatomical characteristics. Consequently, gender identification by ECG signals is feasible [61]. Srivastva et al., have statistically proved and demon- strated that individual ECG signals are distinguishable among whole world population [70]. Thus, making it a valid method for classifying individuals according to their gender. The fact that employing ECG for gender recognition is very secure and resistant to spoof attacks is the most significant benefit of doing so [8]. In addition, a number of studies have devised reliable methods for ECG analysis, which perform effectively despite being independent of signal quality and health condi- tions [7]. Therefore, the most significant difficulties that are associated with gender recognition systems can be circum- vented by employing ECG signals.

It is widely known that the concentrations of certain hor- mones can have an effect on ECG traces. Researchers have suggested that ECG may be able to identify a person's sexual orientation. Some of the factors that go into determining a person's gender are characteristics of the QT interval and the ST segment, among other factors [71], [72]. The significance of establishing that an ECG can correctly determine gender has repercussions for the direction of future research [73]. Changes in the ECG could be caused by hormonal fluctuations, since this is a possibility. In addition to this, the literature indicate the utilisation of ECG in large population-based research to reaffirm the data that was entered manually concerning sexual orientation. These results cast doubt on the usefulness of risk prediction models that incorporate both sexual activity and electrocardiograms. Based on previous research, it was hypothesised that include age and gender in the ECG did not result in an improvement in the ability to accurately predict a low ejection fraction. It's possible that this is because certain aspects of the ECG already take into consideration both of these parameters. In conclusion, additional research is required to fully comprehend the possible implications of the situation in which there is a discordance between the predicted and the actual gender. This final argument is probably the most interesting since it raises the question of why a particular algorithm would be incorrect when it is, on average, accurate.

V. CONCLUSION

The ability of soft biometric features to represent individuals

from a human perspective is the primary advantage of these attributes. Consequently, it helps bridge the gap between how a person is described by a machine and person. The performance of soft biometric systems requires careful investigations, as several factors, including sensing and feature extraction, can have a significant impact on the performance of these systems. It is possible to make intelligent use of a number of soft bio- metric attributes in large-scale biometric systems if one does in-depth study into the accuracy, reliability, and distribution of these qualities. However, it is vital to be mindful of the potential privacy risks associated with the use of soft biometric features. Because of their capacity to achieve a compromise between privacy and performance, soft biometric traits are projected to play a key role in the recognition techniques of the next generation.

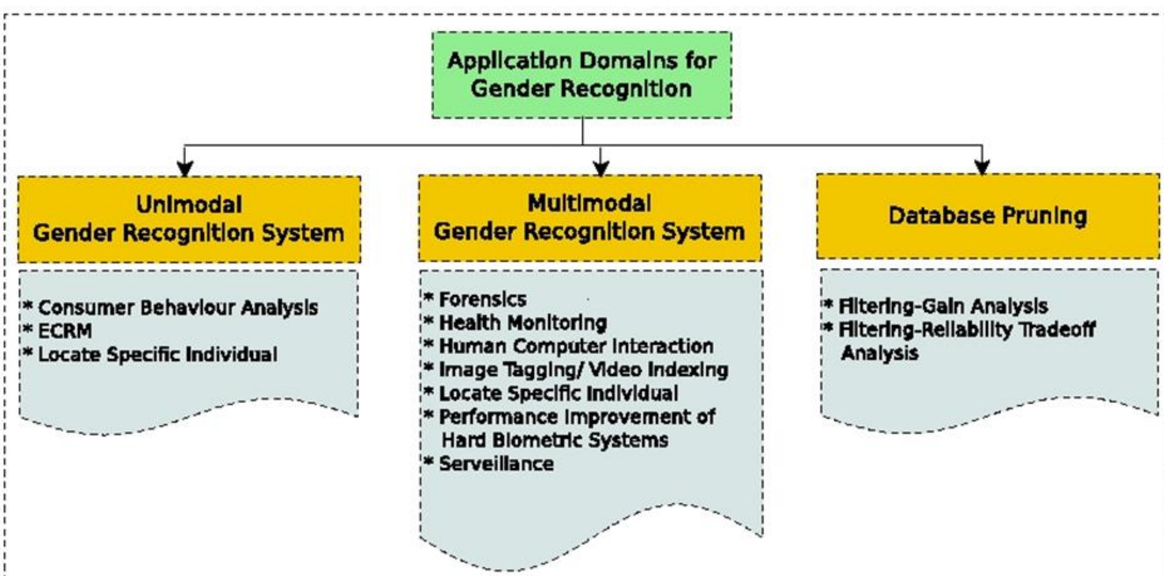


Fig. 3. Applications for gender recognition.

Research in soft biometrics seems to be picking up steam,

according to a survey of the existing biometrics literature. The vast variety of applications that stand to gain from the extraction of soft biometric features is largely responsible for this expansion. The terms 'security', 'surveillance', 'retrieval', and 'healthcare' are all examples of uses in this category. In this article, we took a look at a few of the techniques that have been developed over the years in order to extract one of the soft biometric characteristics, namely gender. In addition to this, we devised a taxonomy as a means of classifying the numerous soft biometric characteristics addressed in the biometrics literature. In addition, various uses, advantages, and disadvantages of the various approaches to gender recognition are also discussed. In conclusion, we spoke about some of the potential future research directions in the field of gender identification research.

REFERENCES

[1] S. Pouryayevali, "ECG Biometrics: New Algorithm and Multimodal Biometric System", Master of Applied Science Thesis, University of Toronto, 2015.

[2] Y. N. Singh and P. Gupta, "ECG to individual identification", in Proc. of 2nd IEEE International Conference on Biometrics: Theory, Applications and Systems (BTAS '08), pp. 1-8, October 2008.

[3] Y. N. Singh and P. Gupta, "Correlation based classification of heartbeats for individual identification", Soft Computing, Vol. 15, no. 3, pp. 449- 460, 2009.

[4] Y. N. Singh and S. K. Singh, "Identifying individuals using eigenbeat features of electrocardiogram", Journal of Engineering, Vol. 2013, pp. 1-8, 2013.

[5] Y. N. Singh, S. K. Singh, and P. Gupta, "Fusion of electrocardiogram with unobtrusive biometrics: an efficient individual authentication system", Pattern Recognition Letters, Vol. 33, no. 14, pp. 1932-1941, 2012.

[6] Y. N. Singh, "Human Recognition using Fisher's Discriminant Analysis of Heartbeat Interval Features and ECG Morphology", Neurocomputing, Elsevier, Vol. 167, pp. 322-335, 2015.

[7] R. Srivastava, A. Singh and Y. N. Singh, "PlexNet: A Fast and Robust ECG Biometric System for Human Recognition", Information Sciences, vol. 558, pp. 208-228, May 2021.

[8] R. Srivastva and Y. N. Singh, "ECG Analysis for Human Recognition using Nonfiducial Methods", IET Biometrics, 8 (5), pp. 295–305, 2019.

[9] Salloum, R. and Kuo, C.-C. J., "ECG-based biometrics using recurrent neural networks", 2017 IEEE International Conference on Acous- tics, Speech and Signal Processing (ICASSP), New Orleans, LA, pp. 2062–2066, 2017.

[10] R. D. Labati, E. Munoz, V. Piuri, R. Sassi and F. Scotti, "Deep ECG: Convolultional Neural Networks for ECG Biometric Recognition", Pattern Recognition Letters, vol. 126, pp. 78–85, 2019.

[11] Kim M., Ko H. and Pan S. B, "A study on user recognition using 2D ECG based on ensemble of deep convolutional neural networks", Journal of Ambient Intelligence and Humanized Computing, 11, pp. 1859–1867, 2020.

[12] Jain A., Verma C. K., "A framework based on hybrid biometrics for personal verification systems" International Journal of Applied. 2012;1(1):55-58.

[13] Kim M-G, Moon H-M, Chung Y., Pan S. B., "A survey and proposed framework on the soft biometrics technique for human identification in intelligent video surveillance system", BioMed Research International, 2012.

[14] Zewail R., Elsafi A., Saeb M., Hamdy N., "Soft and hard biometrics fusion for improved identity verification", In: The 2004 47th Midwest Symposium on Circuits and Systems, 2004. MWSCAS'04. Vol. 1. IEEE; 2004. pp. I-225.

[15] Khalifa AB, BenAmara NE, "Contribution to the fusion of biometric modalities by the choquet integral", International Journal of Image, Graphics and Signal Processing, 2012;4(10):1.

[16] Jain AK, Dass SC, Nandakumar K, "Can soft biometric traits assist user recognition?" In: Defense and Security. International Society for Optics and Photonics; 2004. pp. 561-572.

[17] Jain AK, Park U., "Facial marks: Soft biometric for face recognition", In: 2009 16th IEEE International Conference on Image Processing (ICIP), 2009, pp. 37-40.

[18] J. C. McLachlan and H. Storey, "Hot male: can sex in humans be modified by temperature?", Journal of theoretical biology, 222:71-72, 2003.

[19] S. R. Loth and M.Y. Iscan, "Sex determination, Encyclopedia of forensic Sciences", vol. 1, Academic Press, San Diego, 2000.
[20] W. M. Krogman and M. Y. Iscan, "The human skeleton in forensic medicine", Charles C. Thomas Springfield, 1986.
[21] Carletti V., Greco, A., Saggese A. and Vento M., "An effective real time gender recognition system for smart cameras", J. Ambient. Intell. Humaniz. Comput. 2019, 11, 2407-2419.
[22] Greco A., Saggese A. and Vento M., "Digital Signage by Real-Time Gender Recognition from Face Images", In Proceedings of the 2020 IEEE International Workshop on Metrology for Industry 4.0 & IoT, Rome, Italy, 3-5 June 2020; Vol. 2020, pp. 309-313.
[23] Khan K., Attique M., Syed I. and Gul A., "Automatic Gender Classification through Face Segmentation", Symmetry 2019, 11, 770.
[24] Ren H. and Li Z.-N, "Gender Recognition Using Complexity-Aware Local Features", In Proceedings of the 2014 22nd International Conference on Pattern Recognition, Stockholm, Sweden, 24-28 August 2014; Volume 2014, pp. 2389-2394.
[25] Zhang C., Ding H., Shang Y., Shao Z. and Fu X., "Gender Classification Based on Multiscale Facial Fusion Feature", Math. Probl. Eng. 2018, 2018, 1-6.
[26] Lin C.-J., Li Y.-C. and Lin H.-Y., "Using Convolutional Neural Networks Based on a Taguchi Method for Face Gender Recognition", Electronics 2020, 9, 1227.
[27] Greco A., Saggese A., Vento M. and Vigilante V., "A Convolutional Neural Network for Gender Recognition Optimizing the Accuracy/Speed Tradeoff", IEEE Access 2020, 8, 130771-130781.
[28] Rafique I. Hamid A., Naseer S., Asad M., Awais M. and Yasir T., "Age and Gender Prediction using Deep Convolutional Neural Networks. In Proceedings of the 2019 International Conference on Innovative Computing (ICIC), Seoul, Korea, 26-29 August 2019; Volume 2019, pp. 1-6.
[29] Eidinger E., Enbar R. and Hassner T., "Age and Gender Estimation of Unfiltered Faces" IEEE Trans. Inf. Forensics Secur. 2014, 9, 2170-2179.
[30] Azzopardi G., Greco A., Saggese A. and Vento M., "Fusion of DomainSpecific and Trainable Features for Gender Recognition From Face Images", IEEE Access 2018, 6, 24171-24183.
[31] Jabid T., Kabir H. and Chae O., "Gender Classification Using Local Directional Pattern (LDP)", In Proceedings of the 2010 20th Inter- national Conference on Pattern Recognition, Istanbul, Turkey, 23-26 August 2010; pp. 2162-2165.
[32] Tapia J.E. and Perez C.A., "Gender Classification Based on Fusion of Different Spatial Scale Features Selected by Mutual Information From Histogram of LBP, Intensity, and Shape", IEEE Trans. Inf. Forensics Secur. 2013, 8, 488-499.
[33] Makinen E. and Raisamo R., "An experimental comparison of gender classification methods", Pattern Recognit. Lett. 2008, 29, 1544-1556.
[34] Rai P. and Khanna P., "A gender classification system robust to occlusion using Gabor features based (2D)2PCA", J. Vis. Commun. Image Represent. 2014, 25, 1118-1129.
[35] Aslam A., Hussain B., Cetin A.E., Umar A.I. and Ansari R., "Gender classification based on isolated facial features and foggy faces using jointly trained deep convolutional neural network", J. Electron. Imaging 2018, 27, 053023.
[36] Yang M.-H. and Moghaddam B., "Support vector machines for visual gender classification", In Proceedings of the 15th International Conference on Pattern Recognition, ICPR-2000, Barcelona, Spain, 3- 7 September 2002.
[37] P Gnanasivam and S. Muttan, "Fingerprint Gender Classification using Wavelet Transform and Singular Value Decomposition", IJCSI International Journal of Computer Science Issues, Vol. 9, Issue 2, No 3, March 2012.
[38] M. Acree, "Is there a gender difference in fingerprint ridge density?", Forensic Science International, vol. 102, no.1, 1999, pp.35-44.
[39] M.D. Nithin, B. Manjunatha, D.S. Preethi, and B.M. Balaraj, "Gender differentiation by Finger ridge count among South Indian population", Journal of Forensic and Legal Medicine, vol. 18, no. 2, pp. 79-81, 2011.

[40] G. G. Reddy, "Finger dermatoglyphics of the Bagathas of Araku Valley (A.P.)", American Journal of Physical Anthropology, vol. 42, no. 2, 1975, pp. 225-228.
[41] Y.Yin, J. Tian, and X. Yang, "Ridge Distance Estimation in Fingerprint Images," EURSIP Journal on Applied Signal Processing, vol. 4, no. 4, 2004, pp. 495-502.
[42] D. C. Douglas Hung, "Enhancement and feature purification of fingerprint images", Pattern Recognition, vol. 26, no. 11, 1993, pp. 1661-1671.
[43] L. Hong, Y. Wan, and A. K. Jain, "Fingerprint image enhancement: algorithm and performance evaluation", IEEE Transactions on Pattern Analysis and Machine Intelligence, vol. 20, no. 8, 1998, pp. 777-789.
[44] V. Thomas, N. V. Chawla, K. W. Bowyer, and P. J. Flynn, "Learning to predict gender from iris images", In Proc. of IEEE International Conference on Biometrics: Theory, Applications and Systems, 2007.
[45] S. Lagree and K. W. Bowyer, "Predicting ethnicity and gender from iris texture", In Proc. of IEEE Symposium on Technologies for Homeland Security, 2011.
[46] A. Bansal, R. Agarwal, and R. K. Sharma, "Predicting gender using iris images", Research Journal of Recent Sciences, 3(4):20-26, April 2014.
[47] Khalifa, Nour Eldeen M et al. "Deep Iris: Deep Learning for Gender Classification Through Iris Patterns", Acta informatica medica : AIM : journal of the Society for Medical Informatics of Bosnia & Herzegovina : casopis Drustva za medicinsku informatiku BiH vol. 27,2 (2019): 96- 102.
[48] Khan AR, Doosti F, Karimi M, Harouni M, Tariq U, Fati SM, Ali Bahaj S., "Authentication through gender classification from iris images using support vector machine" Microsc Res Tech. 2021 Nov;84(11):2666- 2676.
[49] A. B. Falsetti, "Sex assessment from metacarpals of the human hand", Journal of Forensic Sciences, 40:774776, 1995.
[50] R. A. Lazenby, "Identification of sex from metacarpals: effect of side asymmetry", Journal of Forensic Sciences, 39:11881194, 1994.
[51] K. Krishan, T. Kanchan, and A. Sharma, "Sex determination from hand and foot dimensions in a North Indian population, Journal of Forensic Sciences, 56(2):453-459, 2011.
[52] G. Mather and L. Murdoch, "Gender discrimination in biological motion displays based on dynamic cues", In Biological Sciences B, pages 273- 279, 1994.
[53] M. Madry-Pronobis, "Automatic gender recognition based on audiovisual cues", Master Thesis, 2009.
[54] J. A. Bachorowski and M. J. Owren, "Acoustic correlates of talker sex and individual talker identity are present in a short vowel segment produced in running speech", Journal of Acoustic Society Americas, 106(2):1054-1063, 1999.
[55] K. Wu and D. G. Childers, "Gender recognition from speech. part I: Coarse analysis", Journal of the Acoustical Society of America, 90:1828-1840, 1991.
[56] M. Pronobis and M. Magimai.-Doss, "Analysis of F0 and cepstral features for robust automatic gender recognition", IDIAP Technical Report, 2009.
[57] D. G. Childers and K. Wu, "Gender recognition from speech. part II: Fine analysis", Journal of the Acoustical Society of America, 90:1841- 1856, 1991.
[58] V. N. Sorokin and I. S. Makarov, "Gender recognition from vocal source", Acoustical Physics, 54(4):571-578, 2008.
[59] R. Srivastva, Y.N. Singh, "Identifying Individuals using Fourier and Discriminant Analysis of Electrocardiogram", in Proc. of 4th International Conference on Mathematics and Computing (ICMC 2018), CCIS 834, pp. 286-295, 2018.
[60] David FD, "The normal ECG in childhood and adolescence", Heart, 91, pp. 1626-1630, 2005.
[61] Goshvarpour, A., Goshvarpour, A., "Gender and age classification using a new Poincare section-based feature set of ECG", Signal, Image and Video Processing, 13, 531-539, 2019.
[62] Fomin, A., Da Silva, C., Ahlstrand, M., Sahl´n, A., Lund, L., Stahlberg, eM.,Gabrielsen, A.,Manouras,A., "Gender differences in myocardial function and arterio-ventricular coupling in response to maximal exercise in adolescent floor-ball players. BMC Sports Sci. Med. Rehabil. 6, 24, 2014.

[63] J.L. Cabra, D.Mendez, L.C. Trujillo, "Wide Machine Learning Algorithms Evaluation Applied to ECG Authentication and Gender Recognition", Proceedings of the 2018 2nd International Conference on Biometric Engineering and Applications, pp. 58-64, May 2018.

[64] R. K. Tripathy, A. Acharya, S. K. Choudhary, "Gender Classification from ECG Signal Analysis using Least Square Support Vector Machine", American Journal of Signal Processing, 2(5), pp. 145-149, 2012.

[65] M. Halstead, S. Denman, S. Sridharan, and C. Fookes, "Locating people in video from semantic descriptions: A new database and approach", In Proc. of International Conference on Pattern Recognition, pages 4501- 4506, Aug 2014.

[66] J. Thornton, J. Baran-Gale, D. Butler, M. Chan, and H. Zwahlen, "Person attribute search for large-area video surveillance", In Proc. of IEEE Symposium on Technologies for Homeland Security, pages 55-61, 2011.

[67] A. K. Jain, S. C. Dass, and K. Nandakumar, "Soft biometric traits for personal recognition systems", In Proc. of International Conference on Biometric Authentication, 2004.

[68] A. Dantcheva, A. Singh, P. Elia, and J.-L. Dugelay," Search pruning in video surveillance systems: Efficiency-reliability tradeoff", In Proc. of International Conference on Computer Vision Workshops, 2011.

[69] C. Chen, A. Dantcheva, and A. Ross, "Impact of facial cosmetics on automatic gender and age estimation algorithms", In Proc. of International Conference on Computer Vision Theory and Applications, 2014.

[70] R. Srivastva, Y. N. Singh, A. Singh, "Statistical Independence of ECG for Biometric Authentication", Pattern Recognition, 127 (2022), 108640, July 2022.

[71] Salama G, Bett GC, "Sex differences in the mechanisms underlying long QT syndrome", American Journal of Physiology-Heart and Circulatory Physiology, 2014;307:H640-H648. doi: 10.1152/ajpheart.00864.2013

[72] Kurokawa J, Kodama M, Clancy CE, Furukawa T., "Sex hormonal regulation of cardiac ion channels in drug-induced QT syndromes", Pharmacology & Therapeutics, 2016;168:23-28. doi: 10.1016/j.pharmthera.2016.09.004

[73] Kvedar JC, Fogel AL., "mHealth advances clinical research, bit by bit", Nature Biotechnology, 2017;35:337-339. doi: 10.1038/nbt.3851.