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Towards a Mobile Biometrics Privacy Requirement Model

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Arbeitsgruppe Multimedia and Security

Technical report

Fakultät für Informatik
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Towards a Mobile Biometrics Privacy Requirement Model

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***Abstract*—The broad prevalence of biometric applications has the potential to record much more than what is merely necessary for intended functionality. Exactly what is contained in biometric readings is of significant privacy concern. There is a need to identify and assess the capabilities of present day biometric technologies, as basis and motive for requirements in appropriate privacy-protection methods. In this paper, an existing taxonomy is extended to classify additional tertiary information contained in biometric readings. Focusing on health and emotion, a review of information capture in biometric technologies is provided, alongside future considerations including modern machine learning approaches.**

I. INTRODUCTION

Users of mobile devices today engage with their various services across multiple devices at their own convenience. With adoption of biometric systems within mobile devices, there are gains to be made in applying biometric recognition to these services over more traditional means. However, in application of biometric technologies, there are many privacy issues surrounding these developments. There is importance in protection of the privacy of the data itself, as well as controls on metadata and profiling. As a stepping stone towards definition of a privacy requirement model, there is a need to first identify and assess the capabilities of present day biometric technologies, as basis and motive for requirements in appropriate privacy-protection methods.

The focus of this paper is an issue specific to biometrics: concerning the potential of biometric readings to record much more than merely what is necessary for intended functionality. Specifically, the privacy sensitive aspects of soft-biometrics: biometric characteristics without the necessary uniqueness and permanence for effective identification. While services may be enhanced by the additional information, the misuse potential is great and the disclosed information may be unwittingly provided. What exactly is contained in these readings is of significant privacy concern. Mobile devices are a specific area of vulnerability considering the prevalence and capabilities of sensors attached to modern devices.

In this paper, Section II classifies soft-biometrics, Section III concerns **Health and Diseases** as a category, with Section IV similarly considering **Emotional Expression**. Section V concerns future potential. Finally Section VI discusses applications of the identified features, in the context of privacy.

II. TAXONOMY OF SOFT-BIOMETRICS

Soft-biometrics have the capacity to contain sensitive non-identification data. Privacy of features naturally visible versus those humans cannot spot without aid. In the case of hiding data in the public eye, an argument for systems such as CCTV in public places is that it is no invasion of privacy when in public and in view of fellow people. However people do reserve their rights for reasons of purely privacy, religion, or other personal concern. Especially when biometric technologies can determine that which is actively kept private, or even that which a subject is not aware is visible.

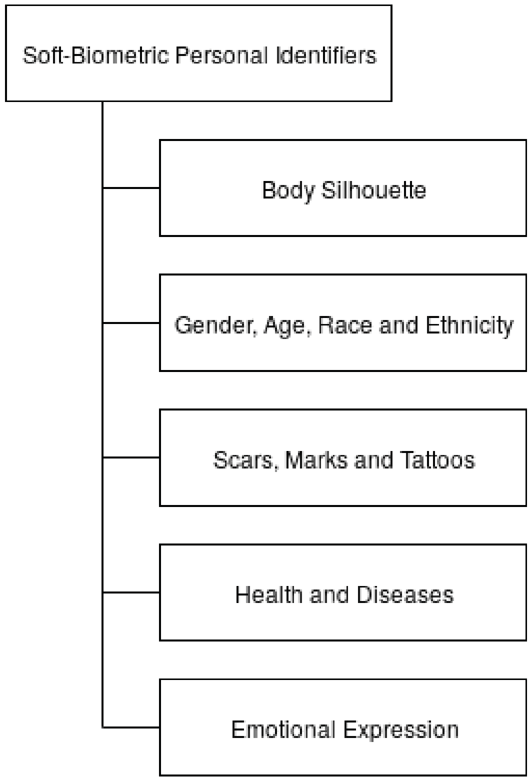

FIGURE 1: Extended taxonomy of soft-biometrics based on the work of Ribaric et al. [1].

Figure 1 presents an extended taxonomy of soft-biometrics based on [1]. The existing categories, e.g. Gender, Age, Race and Ethnicity, are thoroughly studied as soft-biometrics. **Health and Diseases** alongside **Emotional Expression** broaden the soft-biometrics review. This paper focus on review of the extension categories.

III. Health and Diseases

There has been widespread adoption of wearable devices, particularly in fitness technology as well as smart watches. This may also be small devices attached to clothing, or even clothing themselves. Their intimate nature gives them access to all sorts of physiological measures, and can easily be worn ubiquitously. Additionally these measures are accessible from an ordinary modern smartphone [3]. That introduces images and videos of the face and body, as well as captured speech, as further modalities.

The technology in capture devices of modern consumer mobile devices is always advancing, and catching up to medical grade of the years before it [2]. This opens up a lot more angles for self diagnosis and monitoring of one's personal emotions and health. This may be through passive use of wearables or typical smartphones [3].

The following **Health and Diseases** capabilities relevant to mobile biometrics are given in turn under groupings of modalities. The examples given are not exhaustive, but demonstrate vulnerabilities in each of the covered areas.

The eye contains multiple modalities of sensitive medical nature. These may be captured in high quality face images, closer in iris readings, or most intimately with retina scans. [4] uses sclera images to find signs of liver and pancreatic disorders (scleral jaundice). The sclera is part of the eye not commonly used for verification or identification (however there are methods, such as using its texture and vasculature patterns [5]). However it could very well be captured as part of frontal eye imagery, e.g. in the case of a iris reading. Furthermore, iris recognition itself is affected by medical conditions [6]. Retina as an intimate capture, displays patterns which disclose presence of diabetes, glaucoma or retinal degenerative disorders [7].

The face itself can disclose genetic conditions, which leave markers on bodies and faces detectable by humans in many cases, thus also by computer systems [8]. An image recognition system could pick up on the more subtle markers missed by humans, and classify abnormalities with great accuracy using the data of training sets.

The skin of the face is pigmented by diet (carotenoid) and visually perceptible by humans [9], not merely providing a perception of wellness. The skin itself may also betray diseases visible to cameras, and most certainly when in contact with physical sensors [10].

Body movement, particularly gait, naturally displays visible injuries in motion. Furthermore discoverable through biometrics are motor diseases of disorders such as Parkinson's disease, even at a very early stage [11]. Tremors in speech even go so far as to be identifiable symptoms of Parkinson's disease [12]. Subtleties in the mental condition of people too can be noticed in gait [13] and modalities involving movement.

IV. Emotional Expression

Human and computer interaction involving emotions is often referred to affective computing. Heralded as a method in which humans can communicate with machines more effectively.

Collection can require a significant physical presence and obtrusiveness like electroencephalogram (EEG), but equally emotions are also frequently recorded through various means unbeknownst to the people expressing them [14].

The obvious collector would be on cameras in videos or images capturing facial expressions [15]. Additionally gait has to an extent be shown to be an effective method of determining emotional states [16]. Wearables by design have easy access to biological readings that can determine stress through breathing or sweat, and smartphones themselves can record some such information even when carried in a bag [3]. There is further capability of new capture devices and technology like that within the iPhone X to capture emotion data intentionally [17].

Between emotional and health there is some overlap. Emotional expressions of pain and tiredness can be symptoms of physical state. Furthermore, emotions recorded long term could form evidence for mental illness. Nonetheless these are considered part of **Emotional Expression** on an individual basis under this classification.

TABLE 1: Soft biometric features relevant to Health and Emotion

Biometric Modality	**Health Features**	**Emotion Features**
Eye (Pupil, Iris, Sclera and Retina)	Blood vessel patterns [7] Scleral jaundice [4]	Pupil tracking [24] Pupil dilation [24]
Electrocardiogram	Heart rate variability [25]	Heart rate [26]
Electrodermal response	Disease diagnosis [27]	Stress [27]
Electroencephalogra m	Cognitive state [28]	Emotional state [29]
Fingerprint	Skin diseases [10]	-
Body Movement (Gait, Gesture, Handwriting, and Keystroke)	Cognitive state [13] Motor diseases [11]	Emotional state from movement [16]
Face	Skin pigment [9] Genetic conditions [8]	Visual expression of emotion [15]
Speech	Motor diseases [12]	Audible expression of emotion [15]

V. Future Potential

Following the success of aforementioned works in biometrics, identifying soft-biometrics in many cases beyond the ability of humans, there is further interest in finding even more abstract classifications. The extent of what is contained in our biometrics has not been fully explored, and boundaries continue to be pushed. Research in the area is supported by advances in machine learning, such as deep learning, which naturally obscures the decision making process in the produced models. These works may be controversial, such as attempts to identify criminality or terrorist suspects. Here we take the study of Wang and Kosinski [18], an effort to determine sexual orientation from face images, as an example.

Initially assessing the research, due to the use of Deep Neural Networks (DNN), precisely understanding what features caused successful classification is difficult to say. The neural networks are fed in data and make their own determinations on potentially unconventional combinations of features.

However, as part of the work, feature maps created from isolating parts of the images do show increased influence from the facial features over environment. This is a worthwhile attempt at understanding the process inside the “black box” of the trained classifier. The masculinity and femininity of features—notably the jawline, nose length, and forehead size—appeared to have the most significant influence.

In this case, there are questions over the datasets used to train the DNN. The DNN did produce results above that of humans, which already perform above random chance. However, the photos taken from a dating website. What the influence on (both human and machine) of these self-curated photos could be and the soft biometric factors are of importance. More research is necessary to thoroughly substantiate or refute the claims.

The results are claimed to support the pre-natal hormone theory, but are not enough. However it does pose the possibility of identifying human sexuality from images, but not conclusively, and not how. It is difficult to pick out the exact reasons and multiple factors used for decisions in a deep learning approach.

VI. Discussion

In the business of healthcare, there is growing popularity in patient administrative systems using biometrics for patient identification. The Biometrics Research Group Inc. [19] estimates the global biometrics healthcare market shall reach US $5 billion by 2020. It offers increased convenience and more options for access to personal patient data remotely using own mobile capture devices. However the argument for biometrics has to be made against the functional possession-based Smartcard system which involves less risk to privacy and is revocable.

Combining the health information alongside biometrics for patient management is an appealing prospect. In the connected world, there is potential to see more remote healthcare. For example Australia is encouraging telehealth [20]. Driven by its natural geography and population distribution, telehealth is particularly useful, but could provide improved convenience in any region. Biomedical data through biometric technologies aid in patients travelling, contact with known doctors and healthcare organisations independent of present location. The management and process of exchange of this data are naturally privacy issues.

Through mobile devices such connectedness of medical information could be continuous and seamless. Continuous monitoring of health and emotional well-being could advise about how to correct through diet or adjustment in behaviour, or refer to medical professional. Of course, the data in question is ultimately personal, and privacy-preservation is thus of high importance.

Cross-domain risks are high with such personal health or emotional information in question. Discrimination risks are compounded from what exists today. There are views on the potential for this technology and the ethical concerns surrounding it [21][22]. Organisations in a position of power over individuals (e.g. government, employers, insurers) with access to this information could be encouraged or misled into increased discrimination.

For machine learning approaches in particular, some modern machine learning (e.g. deep learning in [18]) techniques build models with a lack of clarity on the decision making process. It is difficult to pick out the exact reasons and multiple factors used for decisions in a deep learning approach. This could lead to discrimination of those a machine decides to be less worthy, based on some immoral rules buried deep in complex and incomprehensible decision making.

Even if the trained classifiers are only able to identify a few select individuals in a set with particularly high accuracy. If such a system were able to merely confidently single out a small subset of a community with high certainty, that remains a significant risk for those individuals.

The potential applications for computer system’s understanding of human emotional responses are manifold. Emotion detection, perhaps with the aid of eye tracking, would have great appeal to marketing for reviewing the success of advertising and tuning advert preferences [23]. With biometric readings, there is not only the potential to place targeted adverts from improved behavioural biometric data, but to be able to place that according to eye movements, or to target people when they are seen to be in a vulnerable emotional state. Some other affective displays can include indicators of stress and fatigue, which can have safety applications such as for detecting driver fatigue or monitoring mental health.

These examples provide a level of insight of what can or will be determined from biometric readings. There is a real need for understanding of what has been disclosed when using biometrics. Moreover, what exactly has been disclosed in captured readings, if there has not been appropriate privacy preserving measures, may only come to light in years to come. There is real incentive for continuous and pre-emptive development of privacy protection approaches alongside the development of emergent technologies.

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References

[1] Ribaric, Slobodan; Ariyaeeinia, Aladdin; Pavesic, Nikola, "De-identification for privacy protection in multimedia content: A survey". In: Signal Processing: Image Communication. 47: 131–151.

[2] Gan, S.KE. & Poon, JK. Sci Phone Appl Mob Devices (2016) 2: 6. https://doi.org/10.1186/s41070-016-0009-2.

[3] Hernandez, Javier & McDuff, Daniel & Picard, Rosalind. (2015). Biophone: Physiology monitoring from peripheral smartphone motions. 7180-7183. 10.1109/EMBC.2015.7320048.

[4] Mariakakis, Alex & A. Banks, Megan & Phillipi, Lauren & Yu, Lei & Taylor, James & N. Patel, Shwetak. (2017). BiliScreen: Smartphone-Based Scleral Jaundice Monitoring for Liver and Pancreatic Disorders. Proceedings of the ACM on Interactive, Mobile, Wearable and Ubiquitous Technologies. 1. 1-26. 10.1145/3090085.

[5] Simona Crihalmeanu, Arun Ross, Multispectral scleral patterns for ocular biometric recognition, In Pattern Recognition Letters, Volume 33, Issue 14, 2012, Pages 1860-1869, ISSN 0167-8655, https://doi.org/10.1016/j.patrec.2011.11.006.

[6] S. Rakshit and D. M. Monro, "Medical Conditions: Effect on Iris Recognition," 2007 IEEE 9th Workshop on Multimedia Signal Processing, Crete, 2007, pp. 357-360. doi: 10.1109/MMSP.2007.4412890.

[7] U.S. Department of Health and Human Services, Diabetic Retinopathy What You Should Know, Retrieved from https://nei.nih.gov/sites/default/files/health-pdfs/Diabetic_Retinopathy_What_You_Should_Know.pdf. Accessed 20.02.2018.

[8] Quentin Ferry , Julia Steinberg , Caleb Webber , David R FitzPatrick, Chris P Ponting, Andrew Zisserman, Christoffer Nellåker. Diagnostically relevant facial gestalt information from ordinary photos. eLife 2014;3:e02020 doi: 10.7554/eLife.02020.

[9] Stephen, Ian D. et al., Carotenoid and melanin pigment coloration affect perceived human health, Evolution and Human Behavior, Volume 32, Issue 3 , 216 – 227.

[10] Martin Drahansky, Michal Dolezel, Jaroslav Urbanek, Eva Brezinova, and Tai-hoon Kim, “Influence of Skin Diseases on Fingerprint Recognition,” Journal of Biomedicine and Biotechnology, vol. 2012, Article ID 626148, 14 pages, 2012. doi:10.1155/2012/626148.

[11] Anne Trafton. Typing Patterns Diagnose Early Onset Parkinson’s. Retrieved from https://news.mit.edu/2015/typing-patterns-diagnose-early-onset-parkinsons-0401. Accessed 20.02.2018.

[12] Parkinson’s Voice. Retrieved from http://www.parkinsonsvoice.org/science.php. Accessed 20.02.2018.

[13] Pam Belluck. Signs of cognitive decline and alzheimer’s seen in gait. Retrieved from http://www.nytimes.com/2012/07/17/health/research/signs-of-cognitive-decline-and-alzheimers-are-seen-in-gait.html?pagewanted=all. Accessed 20.02.2018.

[14] Eugenia Politou, Efthimios Alepis, Constantinos Patsakis, A survey on mobile affective computing, In Computer Science Review, Volume 25, 2017, Pages 79-100, ISSN 1574-0137, https://doi.org/10.1016/j.cosrev.2017.07.002.

[15] Meng, Hongying & Bianchi-Berthouze, Nadia. (2013). Affective State Level Recognition in Naturalistic Facial and Vocal Expressions. IEEE transactions on cybernetics. 44. . 10.1109/TCYB.2013.2253768.

[16] M. Karg, K. Kuhnlenz and M. Buss, "Recognition of Affect Based on Gait Patterns," in IEEE Transactions on Systems, Man, and Cybernetics, Part B (Cybernetics), vol. 40, no. 4, pp. 1050-1061, Aug. 2010. doi: 10.1109/TSMCB.2010.2044040.

[17] Natasha Lomas, A closer look at the capabilities of iPhone X face mapping, retrieved from https://techcrunch.com/2017/11/04/a-closer-look-at-the-capabilities-and-risks-of-iphone-x-face-mapping/. Accessed 28.11.2017.

[18] Wang, Y., & Kosinski, M. (in press). Deep neural networks are more accurate than humans at detecting sexual orientation from facial images. Journal of Personality and Social Psychology.

[19] Rawlson O’Neil King. Biometrics and Healthcare. Biometrics Research Group Inc. Retrieved from https://www.scribd.com/doc/255979360/Biometrics-in-Healthcare. Accessed 28.11.2017.

[20] Victoria A Wade, Jaklin A Eliott, , Janet E Hiller, A qualitative study of ethical, medico-legal and clinical governance matters in Australian telehealth services, Journal of Telemedicine and Telecare, Vol 18, Issue 2, pp. 109 – 114, First Published January 20, 2012, https://doi.org/10.1258/jtt.2011.110808.

[21] Stephen Hoffman. "Biometrics, Retinal Scanning, and the Right to Privacy in the 21st Century" Syracuse Sci. & Tech. L. Rep. (2010). Available at: http://works.bepress.com/stephen_hoffman/1/.

[22] Rachel J. Minter. American Bar Association. The Informization of the Body: What Biometric Technology could reveal to employers about current and potential medical conditions. Retrieved from https://www.americanbar.org/content/dam/aba/administrative/labor_law/meetings/2011/eeo/014.authcheckdam.pdf. Accessed 28.11.2017.

[23] Daniel McDuff, Rana El Kaliouby, Thibaud Senechal, David Demirdjian, Rosalind Picard, Automatic measurement of ad preferences from facial responses gathered over the Internet, In Image and Vision Computing, Volume 32, Issue 10, 2014, Pages 630-640, ISSN 0262-8856, https://doi.org/10.1016/j.imavis.2014.01.004.

[24] lanatà, Antonio & Armato, Antonio & Valenza, Gaetano & Scilingo, Enzo. (2011). Eye tracking and pupil size variation as response to affective stimuli: A preliminary study. 2011 5th International Conference on Pervasive Computing Technologies for Healthcare (PervasiveHealth). 78-84. 10.4108/icst.pervasivehealth.2011.246056.

[25] Agrafioti, Foteini & Minhthang Bui, Francis & Hatzinakos, Dimitrios. (2011). Medical biometrics in mobile health monitoring. Security and Communication Networks. 4. 525-539. 10.1002/sec.227.

[26] H. Schut, Marleen & Tuinenbreijer, Kees & van den Broek, Egon L. & Westerink, Joyce. (2010). Biometrics for Emotion Detection (BED): Exploring the Combination of Speech and ECG.. 59-66.

[27] Jason Heikenfeld. Sweat Sensors Will Change How Wearables Track Your Health. Retrieved from https://spectrum.ieee.org/biomedical/diagnostics/sweat-sensors-will-change-how-wearables-track-your-health. Accessed 28.11.2017.

[28] Chu, Leo & Qiu, Robert & Liu, Haichun & Ling, Zenan & Shi, Xin. (2017). Individual Recognition in Schizophrenia using Deep Learning Methods with Random Forest and Voting Classifiers: Insights from Resting State EEG Streams.

[29] Abeer Al-Nafjan, Manar Hosny, Areej Al-Wabil and Yousef Al-Ohali, “Classification of Human Emotions from Electroencephalogram (EEG) Signal using Deep Neural Network” International Journal of Advanced Computer Science and Applications(IJACSA), 8(9), 2017. http://dx.doi.org/10.14569/IJACSA.2017.080955.

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