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Handbook of Multibiometrics

by

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Handbook of Multibiometrics
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The pronounced need for reliably determining or verifying the identity of a person has spurred active research in the field of biometric authentication. Biometric authentication, or simply biometrics, is the science of establishing an identity based on the physical or behavioral attributes of an individual, including fingerprint, face, voice, gait, iris, signature, hand geometry and ear. It is becoming increasingly apparent that a single biometric trait (used in a unibiometric system) is not sufficient to meet a number of system requirements - including matching performance - imposed by several large-scale authentication applications. Multibiometric systems seek to alleviate some of the drawbacks encountered by unibiometric systems by consolidating the evidence presented by multiple biometric sources. These systems can significantly improve the recognition performance of a biometric system besides improving population coverage, deterring spoof attacks, and reducing the failure-to-enroll rate. Although the storage requirements, processing time and the computational demands of a multibiometric system can be significantly higher (than a unibiometric system), the above mentioned advantages present a compelling case for deploying multibiometric systems in large-scale authentication systems (e.g., border crossing) and systems requiring very high accuracies (e.g., access to a secure military base).

The field of multibiometrics has made rapid advances over the past few years. These developments have been fueled in part by recent government mandates stipulating the use of biometrics for delivering crucial societal functions. The US-VISIT program (United States Visitor and Immigration Status Indicator Technology) is a border security system that validates the travel documents of foreign visitors to the United States. Currently, fingerprint images of left- and right-index fingers of a person are being used to associate a visa with an individual entering the United States; in the future, all ten fingers may be used thereby necessitating the development of efficient data capture as well as fusion algorithms. The International Civil Aviation Organization (ICAO) has unanimously
recommended that its member States use Machine Readable Travel Documents (MRTDs) that incorporate at least the face biometric (some combination of face, fingerprint and iris can also be used) for purposes of establishing the identity of a passport holder. Thus, research in multibiometrics has the potential to impact several large-scale civilian and commercial applications.

From an academic perspective, research in multibiometrics has several different facets: identifying the sources of multiple biometric information; determining the type of information to be fused; designing optimal fusion methodologies; evaluating and comparing different fusion methodologies; and building robust multimodal interfaces that facilitate the efficient acquisition of multibiometric data. One of the goals of this book is to lend structure to the amorphous body of research work that has been conducted in the field of multibiometrics. To this end, we have attempted to assemble a framework that can be effectively used to understand the issues and progress being made in multibiometrics while identifying the challenges and potential research directions in this field.

The book is organized as follows. Chapter 2 introduces the notion of information fusion in the context of biometrics and enumerates the advantages imparted by multibiometric systems. The various sources of biometric information that can be integrated in a multibiometric framework, such as multiple sensors, multiple algorithms and multiple samples, are then discussed with examples from the literature. This chapter also examines different types of acquisition and processing schemes that are relevant to multibiometric systems. Finally, the types of information (also known as the levels of fusion) that can be accommodated in a fusion architecture are briefly visited. In Chapter 3, the sensor-level, feature-level, rank-level and decision-level fusion schemes are explored in detail along with examples highlighting the pros and cons of each fusion level. Integration strategies for each of these fusion levels are presented, both from the multibiometric as well as the multiple classifier system literature. The chapter concludes by categorizing some of the representative publications in multibiometrics on the basis of the sources of biometric information used and the level of fusion adopted. Chapter 4 is entirely dedicated to score-level fusion, since fusion at this level has been elaborately studied in the literature. The integration strategies pertinent to this level are presented under three distinct categories: (i) density-based score fusion, (ii) transformation-based score fusion, and (iii) classifier-based score fusion. This chapter discusses examples embodying each of these categories; a mathematical framework is adopted in order to assist the reader in understanding the differences between the three categories. The chapter concludes by indicating how the performance of a score fusion system can be further enhanced by utilizing user-specific parameters. In Chapter 5, the possibility of incorporating ancillary information, such as the quality of the biometric data and the soft biometrics of individuals, in a biometric fusion framework is discussed. Soft biometric traits include char-
acteristics such as gender, height, weight, eye color, etc. that provide added information about an individual, but lack the distinctiveness and permanence to sufficiently differentiate between multiple individuals. The chapter presents an information fusion framework to include soft biometric traits in the authentication process. The final contribution of this book is an Appendix that lists some of the databases that have been used for evaluating the performance of various multibiometric algorithms.

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This book has been written for researchers, engineers, students and biometric system integrators who are keen on exploring the fundamentals of multibiometrics. It can be used as a reference guide for a graduate course in biometrics. Some of the concepts presented in this book are applicable to the general domain of information fusion and, hence, students of this field will also benefit from the book. We hope that the concepts and ideas presented in the following pages will stimulate the reader’s curiosity and help develop an appreciation for this rapidly evolving field, called Multibiometrics.

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