Human Ear Recognition

Arun Ross
West Virginia University

Ayman Abaza
West Virginia High Tech Consortium Foundation

Ear recognition technology is a potentially valuable tool in the biometric arsenal.

In a world where social interaction is increasingly digital in nature (Facebook, Google+, Skype) and financial transactions are routinely conducted over the Internet (online banking), reliably establishing an individual's identity is of paramount importance. Several law enforcement and military applications also need a dependable method to identify people—for example, to determine if an encountered individual is a potential threat or criminal suspect.

The limitations of traditional modes of authentication based on ID cards and passwords have led to the development of sophisticated biometric systems that establish human identity using an individual's physical or behavioral attributes, such as fingerprints, face, iris, hand geometry, voice, or gait. Biometric systems are now being incorporated in various applications ranging from personal laptop access to international border control. The US-VISIT program, for example, employs fingerprint recognition to determine if a traveler to the US is on a government watch list. Similarly, the United Arab Emirates uses the Iris Expellee Tracking System to identify and apprehend deported individuals who attempt to reenter the country using false travel documents.

In spite of tremendous biometric advances, identifying noncooperative individuals in public spaces and other unconstrained environments remains a challenging problem. Only partial or corrupted biometric information might be available—for example, a surveillance video might capture only a portion of an individual's face.

To improve human recognition, biometric researchers are exploring the use of ancillary characteristics such as scars, marks, tattoos, height, and body shape in conjunction with primary features like the face. The ear is one such promising "soft" biometric.

The external ear flap, known as the pinna, has several morphological components as Figure 1a shows. While its structure is relatively simple, it varies significantly across individuals. Figure 1b shows examples of these variations, which, along with the ear's size, color, and texture can serve as a distinguishing characteristic. Changes in facial expression and age do not significantly impact the ear's appearance, although the effect of gravity and ear accessories can perturb the length of the ear lobe.

EARLY RESEARCH

The ear's potential for use in human identification was recognized as early as the 1880s by Alphonse Bertillon, a French police officer who pioneered the use of physical measurements to identify criminals. Bertillon combined qualitative and quantitative descriptions of various body parts, including the ear, in what he called anthropometry (*Identification anthropométrique: instructions signalétiques,* 1885).

In 1906, R. Imhofer, a doctor in Prague, studied a set of 500 ears and noted that he could clearly distinguish between them based on only four features ("Die Bedeutung der Ohrmuschel für die Feststellung der Identität," *Archiv für die Kriminologie*, vol. 26, pp. 150-163).

More than 50 years later, a team of researchers visually assessed 206 sets of ear photographs of newborn babies and concluded that the morphological constancy of the ear could be used to establish a newborn's identity (C. Fields et al., "The Ear of the Newborn as an Identification Constant," *Obstetrics and Gynecology,* July 1960, pp. 98-102).

Between 1948 and 1962, Alfred Iannarelli collected ear photographs of thousands of individuals and extracted 12 different geometric measurements of the ear based on the crus of helix (*The Iannarelli System of Ear Identification,* Foundation Press, 1964), as Figure 2 shows. Iannarelli claimed that this set of measurements

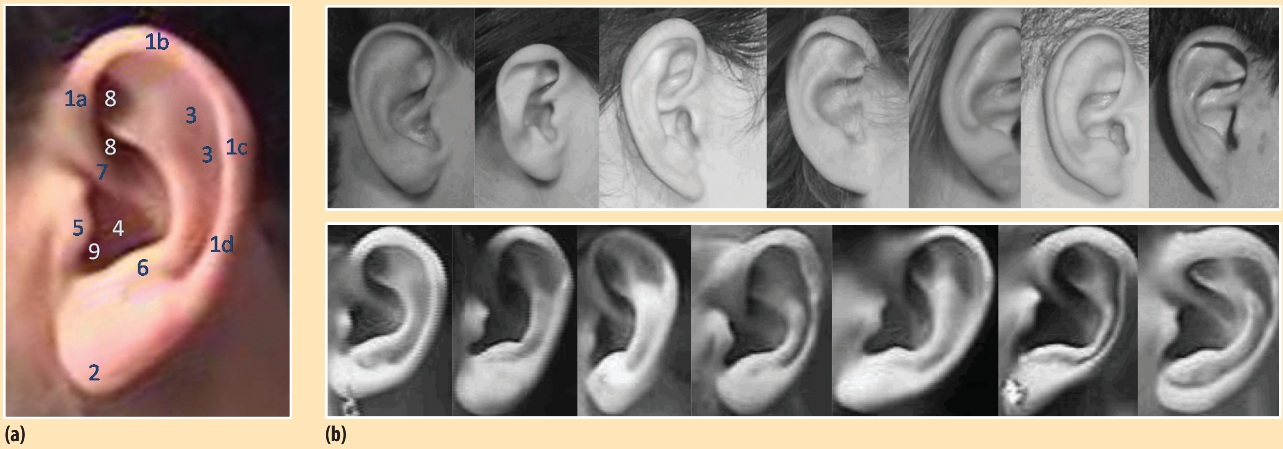

Figure 1. External anatomy of the ear. (a) The external flap, referred to as the pinna, has several morphological components: (1) helix rim, (2) lobule, (3) antihelix, (4) concha, (5) tragus, (6) antitragus, (7) crus of helix, (8) triangular fossa, and (9) incisure intertragica. (b) The pinna's structure varies across individuals. Examples of right (top row) and left (bottom row) ear images.

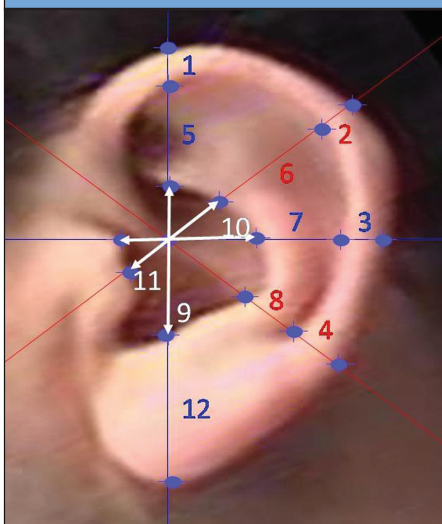

Figure 2. The Iannarelli identification system entails the extraction of 12 geometric measurements of the ear based on the crus of helix.

was reasonably unique across individuals.

EAR BIOMETRICS

An ear biometric system can be viewed as a typical pattern recognition system that reduces an input image to a set of features and then compares this against the feature sets of other images to determine its identity. Ear recognition can be accomplished using either a 2D digital image of the ear or a 3D point cloud that captures the ear's surface.

Ear recognition involves four steps.

Ear detection. The first step is to localize the ear's position in an image. The system typically uses a rectangular boundary to indicate the ear's spatial extent in the side profile of a face image. Ear detection is critical because errors at this stage can undermine the system's utility.

Feature extraction. While the system can directly use the segmented ear during the matching stage, most systems extract a salient set of features to represent the ear. Feature extraction reduces the segmented ear to a mathematical model—for example, a feature vector—that summarizes the discriminatory information present in the ear image.

Matching. The system compares the features extracted from the input ear image to those stored in the database to establish the ear's identity. In its simplest form, matching generates scores indicating the similarity to other ear images.

Decision. The system uses the match scores to render a final decision. In verification mode, a "yes" indicates a genuine match and a "no" an impostor. In identification mode, the output is a list of potential matching identities ranked by match score.

AUTOMATED EAR RECOGNITION

Mark Burge and Wilhelm Burger reported the first attempt to automate the ear recognition process in 1997 ("Ear Biometrics for Computer Vision," *Proc. 21st Workshop Austrian Assoc. for Pattern Recognition*, 1997, pp. 275-282). They used a mathematical graph model to represent and match the curves and edges in a 2D ear image.

Two years later, Belén Moreno, Ángel Sanchez, and José Vélez described a fully automated ear recognition system based on various features such as ear shape and wrinkles ("On the Use of Outer Ear Images for Personal Identification in Security Applications," *Proc. 33rd Ann. Int'l Carnahan Conf. Security Technology*, IEEE, 1999, pp. 469-476).

Since then, researchers have proposed numerous feature extraction and matching schemes, based on computer vision and image processing algorithms, for ear recognition. These range from simple appearance-based methods such as principal component analysis and independent component analysis to more sophisticated techniques based on scale-invariant feature transforms, local binary patterns, wavelet transforms, and force fields. (D.J. Hurley, M.S. Nixon, and J.N. Carter, "Force Field Feature Extraction

Figure 3. Occlusion due to accessories and hair can lower or inhibit ear recognition system performance.

for Ear Biometrics,” *Computer Vision and Image Understanding*, June 2005, pp. 491-512).

In 2005, Hui Chen and Bir Bhanu presented a 3D ear recognition system that exploited the depth and structure of the ear’s morphological components (“Contour Matching for 3D Ear Recognition,” *Proc. 7th IEEE Workshop Applications of Computer Vision* [WACV 05], IEEE, pp. 123-128).

IMPROVING MATCHING ACCURACY

As Figure 3 shows, occlusion due to hair and accessories can lower or inhibit ear recognition system performance. Changes in external lighting and variations in facial pose with respect to the camera can also have a negative impact.

In addition, the recognition accuracy of ear recognition algorithms has predominantly been evaluated using ear images acquired under ideal conditions, such as an indoor environment with highly controlled lighting. This has generated criticism that the matching accuracy of these algorithms, as reported in the literature, could be overly optimistic.

Nevertheless, ear recognition technology is a potentially valuable tool in the biometric arsenal. For example, forensic examiners reviewing surveillance videotapes in the Netherlands used the ear biometric to identify suspects in gas station robberies who had covered their faces, but not their ears, (A.J. Hoogstrate, H.V.D. Heuvel, and E. Huyben, “Ear Identification Based on Surveillance Camera Images,” *Science & Justice*, July 2001, pp. 167-172).

To improve matching accuracy, researchers are exploring the possibility of combining images of the ear and the face. Even if the ear cannot be used to verify human identity in a given situation, it could *exclude* an identity from being considered as a potential match if it is sufficiently different from the input probe image.

EARPRINTS

The use of 2D or 3D ear images for human recognition differs from the use of *earprints*: marks left by secretions from the outer ear when someone presses up against a wall, door, or window. Earprints have been introduced as physical evidence in several criminal cases in the US and other countries, although some convictions that relied on earprints have been overturned. Earprints haven’t been widely accepted in court due to a lack of scientific consensus as to their individuality.

Currently, there are no commercially available ear recognition systems. However, the future holds tremendous potential for incorporating ear images with face images in a multibiometric configuration, even as researchers continue to refine the technology. For example, assigning an ear image to one of several predefined categories could allow for rapid retrieval of candidate identities from a large database. In addition, the use of ear thermograms could help mitigate the problem of occlusion due to hair and accessories. As the technology matures, both forensic and biometric domains will benefit from this biometric.

Arun Ross *is an associate professor in the Lane Department of Computer Science and Electrical Engineering at West Virginia University. Contact him at arun.ross@mail.wvu.edu.*

Ayman Abaza *is a senior scientist in the Advanced Technology Group at the West Virginia High Technology Foundation. Contact him at aabaza@wvhtf.org.*

Editor: Karl Ricanek Jr., director of the Face Aging Group at the University of North Carolina Wilmington; ricanekk@uncw.edu