CHAPTER 15

SPECIAL ABILITIES AND VULNERABILITIES IN FORENSIC EXPERTISE

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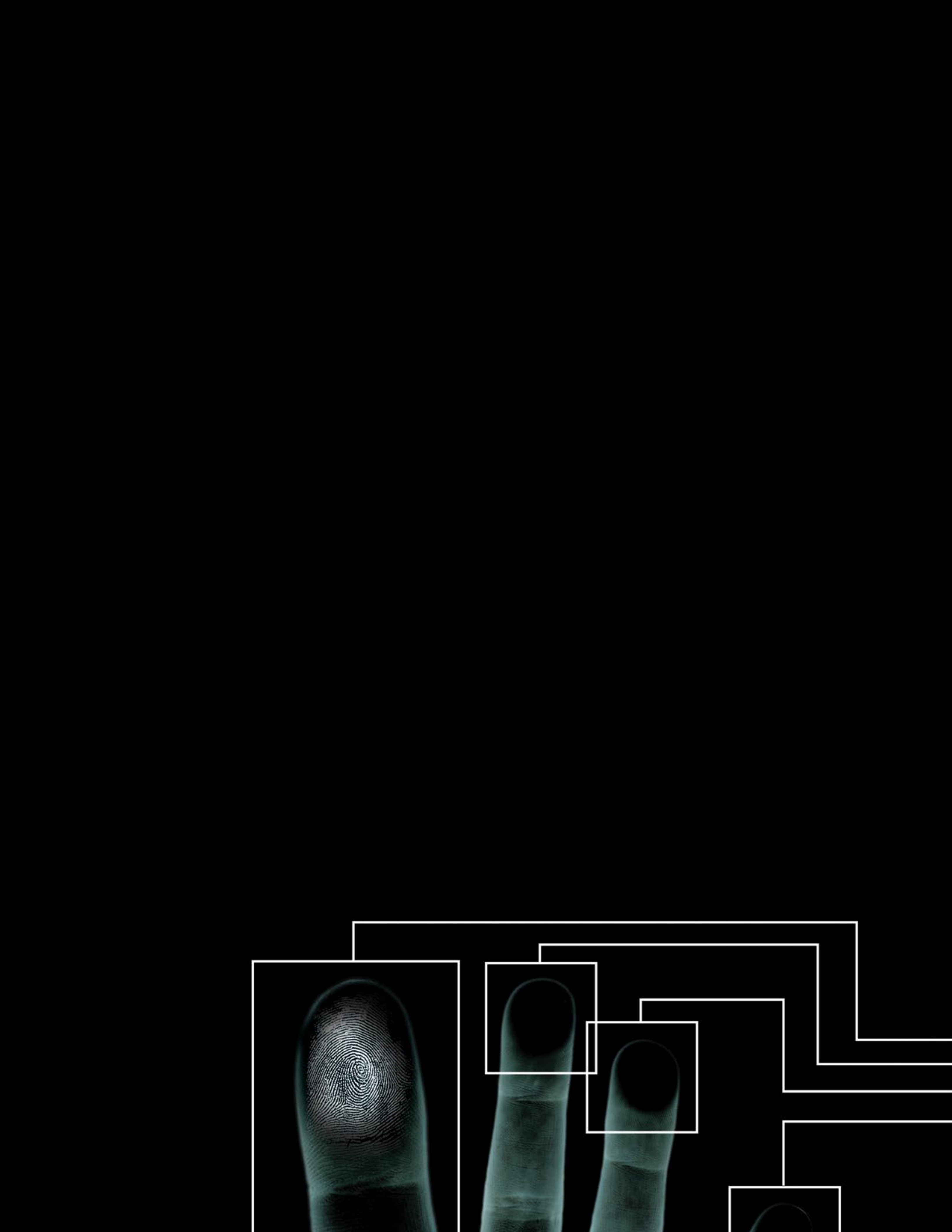

CHAPTER 15

SPECIAL ABILITIES AND VULNERABILITIES IN FORENSIC EXPERTISE

THOMAS A. BUSEY AND ITIEL E. DROR*

15.1 The Relevance of the Human Mind

Latent print examinations are complex perceptual and cognitive tasks. Examiners rely on their visual systems to find similarities in pairs of prints. They then must compare the degree of perceived similarity against that found in previous examinations, and ultimately must decide whether the commonalities found between prints (as well as regions of unexplainable disagreement) merit the conclusion that the prints either did or did not come from the same source (or are inconclusive). This process involves perception, similarity judgments, memory, and decision-making. These abilities vary among people and can be improved with training and experience. They are also subject to potential biases and external influences. This chapter will illustrate, based on knowledge from the visual and cognitive sciences, how an understanding of the human mind is relevant and critical to the fingerprint domain. Such an understanding clearly shows the unique cognitive processes and special abilities of experts, along with their vulnerabilities. This chapter begins with a quick overview of foundational findings in cognitive science and then discusses how these research areas have been extended to latent print examiners. Where possible, links are drawn between basic science findings and the relevant domains of training, selection, and procedures of latent print examinations.

In expert domains, as well as in everyday life, humans process information. Information is perceived, encoded, represented, transformed, stored, retrieved, compared to other information, and evaluated, to name just a few processes. However, the human mind is not a camera and we do not passively process information. It is naïve to think that humans construct and experience reality passively and perceive the environment as "it really is". *Perception is*

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far from perfection (Dror, 2005a; see also Humphreys, Riddoch, and Price, 1997; Snyder, Tanke, and Bersheid, 1977). People engage in a variety of active processes that organize and impose structure on information as it comes in from the external world. Information is then further interpreted and processed in ways that highly depend on the human mind and cognition, and less on the environment and the actual content of the information itself. As we dynamically process information, we affect what we see, how we interpret and evaluate it, and our decision-making processes. Thus, to understand expert performance, especially in a highly specialized domain such as human identification, one needs to examine the roles of the human mind and cognition (Dror, in press; Dror and Fraser-Mackenzie, 2008).

Human cognition has been neglected by the fingerprint community, both by the forensic experts themselves as well as by those who design and develop related technology. This chapter is a step toward addressing this oversight; fingerprint identification will be presented within its appropriate context—that of human cognition. The reader will first be introduced to principles that underlie much of cognition and perception, which serve to illustrate human information processing. These principles are illustrated with examples of psychological phenomena that have been chosen for their direct relevance to the latent print examination process. The chapter then turns to a discussion of the development of expertise and how the tools of cognitive neuroscience can be used to describe differences between experts and novices. Finally, important vulnerabilities in the development of expertise are discussed. Throughout this chapter, the authors will argue that it is incumbent upon practicing examiners to treat their professional practice as a scientific endeavor in which they continue to question all aspects of their examinations, gather data on the effectiveness and accuracy of their decisions, and refine training and best practices procedures to avoid cognitive contamination and optimize their decision-making.

15.2 Cognitive Psychology

The human mind is a complex machine. It is incredible in its range and scope, and it is dynamic, flexible, and adaptive. Although complex and intriguing, the essence of the human mind is nevertheless an information-processing machine. As information comes in through our sensory systems, it is processed. This processing may include transformations, comparisons and consolidation with information already stored in the system, evaluations, making decisions, and so forth.

Humans are fortunate to have such a strong computing mechanism as our brain at our disposal because the comparison of two different fingerprints requires a number of cognitive and perceptual capacities that hardware-based computers have yet to equal. Factors such as attention, motivation, perceptual processing, and decision-making all must be brought to bear on the task. In the section below, we briefly cover some of the basic findings in cognitive psychology in order to lay the groundwork for the application of these findings to latent print examinations. It should be noted that a rather large gulf still exists between these basic findings and specific questions related to the forensic sciences. As a result, these topics may seem somewhat abstract but, where possible, links to specific training prescriptions and suggestions for changes in procedures will be made where the science can make a strong case for them.

15.2.1 Studying Human Information Processing

Science without data is not science. Although theorizing and arguments have a role, scientists rely primarily on a dispassionate and agenda-free evaluation of data collected in experiments that are designed to find the truth. Data underlie theory rather than vice versa. Data can come directly from behavioral experiments, in which subjects perform tasks similar to latent print examinations, or data can be gathered indirectly by the use of eyetracking, electrophysiological recordings, computer modeling, or brain imaging.

These data require models for interpretation, which can take the form of verbal descriptions, mathematical formulas, or computer programs, and the field of cognitive psychology has been developed to apply models to such psychological data. An example perhaps familiar to many readers is that of AFIS, which can serve as a model of the fingerprint matching process. This model does not capture the full performance of human experts. Selecting one model out of a set of candidate models or explanations is accomplished on the basis of the level of consistency with the data gathered in experiments. It does not matter whether the data come from behavioral or cognitive neuroscience experiments because the ultimate goal is to use converging methods to place constraints on what the most viable model might be.

In recent years, cognitive psychology has evolved into cognitive neuroscience. In cognitive neuroscience, the study of human information processing has been further advanced by relating it to the human brain (Kosslyn and Koenig, 1992). Examination and studies of the human brain are used to constrain and guide information-processing theories. Although the mind is as distinct from the brain as software is from hardware, the brain provides many important insights into the nature and characteristics of the mind. In cognitive neuroscience, the underlying hardware mechanisms are regarded as being relevant for understanding the higher level mental processes, but that is as far as the interest goes. Thus, in cognitive neuroscience, the neuroscience is a tool for cognitive study rather than a goal itself. The development of cognitive neuroscience came about from novel ways of conceptualizing the brain as an information-processing system. This was achieved, in part, through advanced technologies that allowed new ways to view and study the brain and its operations (CT and MRI, and in particular the functional images PET and fMRI). Such technologies have already been applied to the study of fingerprint expert performance (Busey and Vanderkolk, 2005), as discussed below.

15.2.2 Principles and Key Issues in Understanding Human Cognition

Three issues are especially critical for understanding human cognition: (1) the brain is a limited resource with limited processing capacity. (2) it processes information in an active and dynamic fashion, and (3) performance is dependent on, and limited by, mental representations and *how* information is stored (as much as what information is actually stored). These issues will be explained and illustrated.

The brain is a finite machine and thus its capacity to process information is limited. Information processing has evolved to working within (and overcoming) the confines of this resource. For example, because humans have limited resources, we cannot process all incoming information and thus focus our attention on a subset of the input we perceive and disregard the rest (Sperling, 1960). Our limited resources have, in fact, given rise to much of human intelligence. For instance, because we can only attend to a subset of the information, we need to prioritize which information is the most important to be processed. Thus, we developed sophisticated mechanisms (i.e., intelligence) so as to overcome the limitations in our information-processing capacity and best utilize available resources.

Other ways we deal with our limited resources include data compression. In addition to selective attention, we have developed ways to reduce cognitive load by compressing information to more computationally efficient bits of information (Dror, Schmitz-Williams, and Smith, 2005).

The way information is organized and represented has profound effects on how we process it, what we can do with it, and what information is available. For example, how we represent numbers is not a technical and trivial matter; whether we use “3” or “III” has far-reaching implications on the mathematical operations we can (or cannot) perform. Indeed, Marr (1982, p 21) claims, “This is a key reason why the Roman culture failed to develop mathematics in the way the earlier Arabic cultures had.”

The representation of information is also determined by the way people internally encode it. For example, people will find it easy to name the months of the year by their chronological order but impossible to name them by alphabetical order (try it!). In many cases, the same information can be represented in a variety of ways and the specific way that it is represented will later determine how the information can be used and manipulated. The way the mind will mentally manipulate images is highly dependent on how the images are initially represented and encoded (e.g., holistic vs. piecemeal) (Smith and Dror, 2001), and this depends on a variety of factors, including the available cognitive resources (Dror, Schmitz-Williams, and Smith, 2005). These issues are especially acute in experts and affect expert performance in a variety of domains, such as military, medical, policing, financial, and forensics (Dror, in press).

Mental and cognitive representations are essential to the latent print comparison process because individual bits or features of one print must be held in memory long enough to compare against a second image. This process would be impossible without mental representations, and one element of expertise may be an improvement in the ability to hold more information in memory for longer periods of time (Busey and Vanderkolk, 2005).

Before illustrating how these principles and key issues manifest themselves in perceptual, cognitive, and psychological phenomena, it is important to make a distinction between bottom-up and top-down processes (e.g., Humphreys et al., 1997). The bottom-up processes are data driven. The incoming information from the external environment guides the processing mechanisms and the content of information. These types of processes are passive and are dependent on the input itself. Top-down processes are those that depend on the processor (humans in this case) and less on what is processed. In these processes, the state of mind and the information already contained in the system drives the processes. The top-down processes do not depend on the input itself as much as on what is already in the mind of the person processing the information. Every cognitive process, such as learning, thinking, identifying, comparing, matching, decision-making, problem-solving, and all other processes contain at least some elements of top-down processing.

It is not a matter of choice or even conscious processing; the information already contained in the brain, one's state of mind, and many other factors are deeply intertwined in how information is perceived, interpreted, and processed. The dynamic nature of cognition and how the mind works is a clear characteristic of intelligent systems. In fact, as individuals get more experienced and become real experts, the top-down processes play a greater role in how they process information (Dror, in press).

At the psychological level, as attention is turned to the nature and architecture of the human mind, one can observe how the mind has a major role in determining if and how humans understand and interpret information. An intuitive illustration would be when you (or your partner) are pregnant and you start to notice many pregnant women. This is not because there are more pregnant women, but rather your own mental circumstances affect whether and what you see. It is beyond the scope of this paper to give a detailed account of how the mind works and its implications. However, there are many such influences, for example, self-fulfilling prophecies, that illustrate how the mind and psychological elements (such as what we want and wish for) affect what we actually see and are able to do. If we are thirsty, we are more likely to perceive images as containing characteristics of water; our state of thirst modulates our perception (Changizi and Hall, 2001). Our emotional state and mood are further examples of effects of the mind on how we interpret information (Byrne and Eysenck, 1993; Halberstadt et al., 1995; Niedenthal et al., 2000).

Other elements relate to decision-making. As people weigh alternative choices, they consider the evidence for choosing each one. Sequentially moving toward different decision options, one accumulates evidence toward a decision threshold (Dror, Busemeyer, and Basola, 1999). These decision thresholds and evaluating information in support of decision choices are dependent on psychological elements. Furthermore, one needs to distinguish when information is sought in order to make a decision, and when information is sought out selectively to support an already chosen (or preferred) choice alternative. When information is collected, examined, and interpreted to generate and consider different alternative choices, then information and data are driving the decision-making process; this is a bottom-up progression. However, before information is even collected and processed, people usually already have a preference. This top-down component is often unconscious. Even during the decision-making process itself, even if the decision-maker comes initially with no preconceived decisions or notions, as decisions are considered and made, information is gathered and processed for the purposes of examining, confirming, and validating these decisions. These processes are highly dependent on psychological elements and processes rather than purely on the relevant information. Thus, our mind and mental states play active roles in whether and how we acquire, process, and interpret information as well as in our decision-making (Dror, 2008).

15.2.3 Visual Expertise and Latent Print Examinations

The preceding section illustrates how seemingly simple tasks such as recognition and comparison can be influenced by many different factors. This section discusses results from vision experiments that attempt to explain how practice and experience can improve performance on visual tasks. The discussion is limited somewhat by the fact that relatively little data have been collected on latent print examiners, but fortunately the vision community has adopted a stimulus called a *sine-wave grating* that, with its patterns of light and dark bars, is actually fairly similar to a small patch of a latent print. The following sections summarize the data from different experiments that illustrate how practice can improve performance and offer specific models that explain these improvements. One caveat must be made up-front: the perceptual learning experiments discussed very often have a scale of training on the order of days and weeks, rather than the years that experts often acquire. Thus, smaller differences would be expected between the trained and the untrained subjects in these experiments than when latent print examiners are tested.

15.2.3.1 Overview and studies of perceptual learning. Perceptual learning is the process by which the sensory system selectively modifies its behavior to important environmental input. The challenge faced by the brain is that, although it needs to change its connectivity and strengthen its neural synapses in order to learn new information, it must also protect itself from unwanted modification that would degrade existing knowledge (Fusi et al., 2005; Kepecs et al., 2002). At the same time, the visual system must select which is the relevant information to be learned. (Using technology and science-based training, the visual system can learn this more efficiently and effectively. See Dror, Stevenage, and Ashworth, 2008.) Humans are consciously aware of only a small part of the visual world, and the bulk of visual processing and visual learning takes place without conscious awareness (Turk-Browne et al., 2005). Somehow, the processes and functionality that make up the visual system, with contributions from higher level conscious processes, must extract the regularities from a set of images or scenes and alter their connectivity to highlight these regularities. The key to this process is the detection of *structure* in a set of images or objects. Without the ability to detect regular structure that brings objects together, the visual system would be forced to adjust its processing anew in response to the latest image received.

Fingerprints, including latent prints, contain regular features that provide structure to guide the learning process. This structure includes the regularity of ridge widths and the existence of eight broad classes of fingerprints as well as smaller features such as minutiae and individual ridge units. The human visual system is well-designed to exploit this regularity. What follows is a discussion of the changes that can occur in the visual system, how these changes are affected by attention and feedback, and how environmental conditions such as the presence of "noise" in latent prints alters the learning process.

Once visual input enters the visual processing stream, it must be interpreted. For the identification sciences, including latent print comparison, the examiner must consider two prints or images and determine whether they come from the same source. This is essentially a similarity computation, since the two versions will never be exact copies. A great deal of work in cognitive science has focused on how humans determine similarity between two objects, and how expertise affects this computation (Dror, in press). This literature can be applied to understanding how latent print examiners consider similarity in the context of a latent print identification, that is, the nature of the features that are used in latent print examinations, how they are processed, and how experience changes how these features are perceived by experts. In order to determine whether two source images such as two fingerprints match, an examiner must first perceive features from one source image and compare them with a second image. Determining the nature of these visual features and the relation between them—and how these features are compared across different instances of an object to enable identification or categorization—is a central goal of the vision sciences. For stimuli such as faces, we suspect that the features are likely to be elements such as the eyes, nose, and mouth. Yet, even with faces, there is much debate in the literature about the exact feature set of faces: these could include eyes and mouths, or even parts of these, or possibly their relation to each other (Zhang and Cottrell, 2004). Less is known about fingerprints, although the features likely include the shape and flow of the ridges, macro-features of core and delta, minutiae and ridge path, ridge edges, and pore shapes and positions. The next section addresses the nature of the development of expertise and looks at studies that help delineate what constitutes a feature from a human perceptual and cognitive perspective.

15.2.3.2 Creation of new feature detectors. One of the reasons that the feature set is so hard to pin down is that the human visual system is extremely flexible, in that it can adapt its responses to novel stimuli and learn new features. When applied to multiple dimensions, this process is called *unitization.* The neural basis of this kind of perceptual learning was extensively studied by Leventhal and Hirsch (1977), who reared kittens in deprived visual environments and recorded their responses to different patterns. Kittens reared in environments that contained only vertical lines had cells in the visual system that produced only weak responses to horizontal lines. Thus the visual system develops much of its sensitivity to features through experience. These changes in neural processing due to experience can also support new abilities. Unitization creates perceptual units that combine object components that frequently co-occur, such that components that were once perceived separately become psychologically fused together (Schyns and Rodet, 1997). Both Goldstone (2000) and Shiffrin (Shiffrin and Lightfoot, 1997) have addressed the role of unitization in the development of expertise, as discussed below.

Many of the processes of individualizing a print involve comparison of individual features. Unitization may improve the way that candidate features (such as minutiae or ridge features) are extracted from "noisy" stimuli. Latent fingerprints are often corrupted by visual noise when the development medium sticks to the recording surface due to substrates other than the oil left by skin. Experts likely learn to overcome this noise; as one expert put it, their job is to "see through the noise". (This also seems to be an important ability of military fighter pilots; see Dror, Kosslyn, and Waag, 1993, Experiment 5, illustrated in Figure 15–1).

Several possible mechanisms might enable such learning, such as internal noise reduction and improved strategies on the part of observers, and a later section discusses how techniques developed to study visual processing allow tests of these mechanisms. There are specific demonstrations of unitization in the literature. Goldstone (2000) gave participants extended practice in learning to place a complex collection of doodles into Catagory 1, and all of the "near misses" to this pattern belonged in Category 2, as shown in Figure 15–2.

This task encourages unitization. All of the pieces of the Category 1 pattern must be attended to in order to accurately categorize it because each piece is also present in several Category 2 patterns. After 20 hours of practice with these stimuli, participants eventually were able to categorize the Category 1 doodle very accurately and more quickly than would be predicted if they were explicitly combining separate pieces of information from the doodle together. Consistent with other work on perceptual unitization (Gauthier et al., 1998; Shiffrin and Lightfoot, 1997), the theory here is that one way of creating new perceptual building blocks is to create something like a photographic mental image for highly familiar, complex configurations. Following this analogy, just as a camera store does not

FIGURE 15–1

"Seeing through noise" in Dror et al., (1993), Experiment 5, examining the abilities of novices and expert fighter pilots to determine if the 'X' probe is on or off the shaded area with and without visual noise.

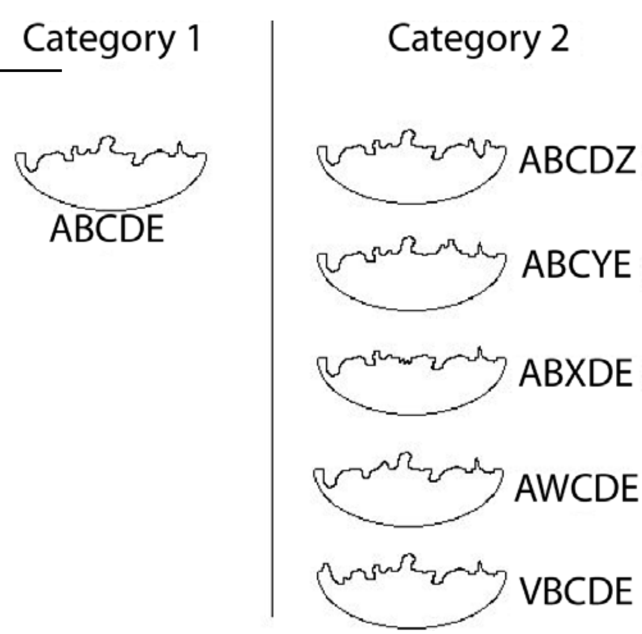


FIGURE 15–2

Doodles in two categories. The letters indicate which segment in the Category 2 items is different from the doodle in Category 1.

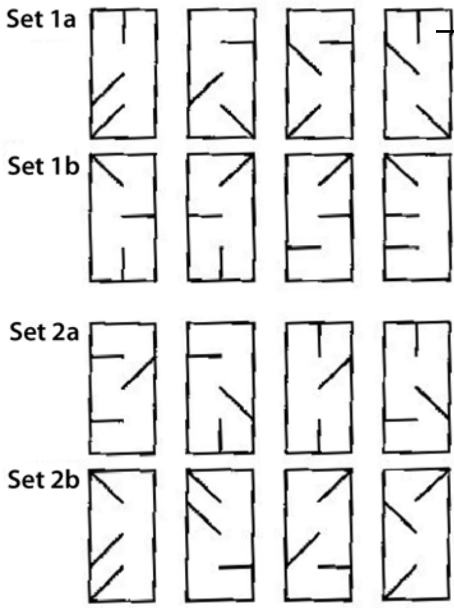


FIGURE 15–3

Stimuli used by Shiffrin and Lightfoot (1997). Over time, observers began to treat the individual line segments as unitary features.

charge more money for developing photographs of crowds than pictures of a single person, once a complex mental image has been formed, it does not require any more effort to process the unit than the components from which it was built. A more complete definition of such a "gestalt" can be found in O'Toole et al. (2001). Blaha and Townsend (2006) have shown that changes in capacity can occur when unitization has taken place. However, the mental representation of the information is critical, and this is highly dependent on the way the objects are presented during learning (e.g., their orientation) and their relative similarity (see Ashworth and Dror, 2000).

Czerwinski et al. (1992) have proposed a process of perceptual unitization in which conjunctions of stimulus features are "chunked" together so that they are perceived as a single unit (see also Newell and Rosenbloom, 1981). Figure 15–3 illustrates this type of stimuli.

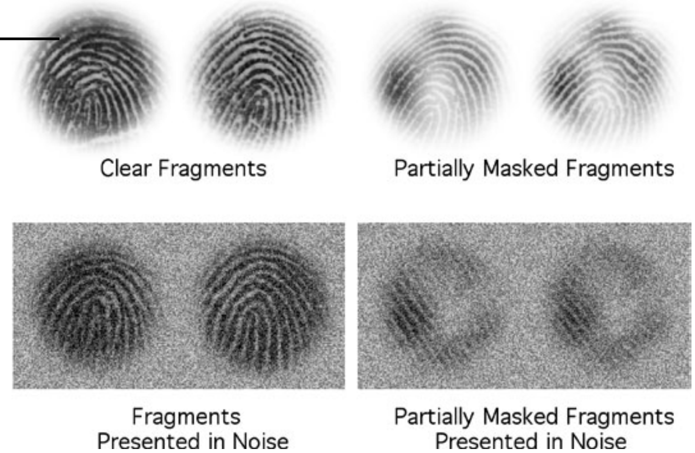
Shiffrin and Lightfoot (1997) argued that separated line segments can become unitized following prolonged practice with the materials. Their evidence came from subjects' performance in a feature search task where observers had to scan a visual display of eight items looking for a particular target item. The target item could be either quite similar to the other items (called distracters) or relatively dissimilar. When participants learned a difficult search task in which three line segments were needed to distinguish the target from distracters, impressive and prolonged decreases in reaction time were observed over 20 hour-long sessions. These prolonged decreases were not observed for a simple search task requiring attention to only one component. In addition, when participants were switched from a difficult task to a simple feature search task, there was initially little improvement in performance, suggesting that participants were still processing the stimuli at the level of the unitized chunk that they formed during the conjunctive training component. The authors concluded that training with difficult stimuli that requires attention to several features at once leads to unitization of the set of diagnostic line segments, resulting in fewer required comparisons. Similar conclusions were drawn by Ahissar and Hochstein (1997) in their work on the "Eureka effect", in which learned stimuli appear to be recognized effortlessly and in an all-or-none fashion.

Although this work has yet to be extended to latent prints, unitization in the context of fingerprints may come about through the analysis of constraints that occur in the development of the friction ridges. For example, ridges have a very even spacing, and features such as ridge endings are associated with nearby ridges shifting inward to preserve this spacing. Fingerprint experts have found that they can use these features in their identifications.

What would it mean for fingerprint experts to develop newly differentiated features? This would change the field's *perceptual vocabulary.* A perceptual vocabulary is the set of functional features that are used for describing objects. A functional feature is defined as any object property that can

FIGURE 15–4

Stimuli used by Busey and Vanderkolk (2005) to address configural processing in latent print examiners.



be selectively attended to and is relevant to the task. This implies that the visual system treats it as a unique part of an object. For example, feature X can be used to describe an object if there is evidence that X can be considered in isolation from other aspects of the object. Tying the uniqueness of a feature to selective attention conforms to many empirical techniques for investigating features. Garner (1976) considers two features or dimensions to be separable if categorizations on the basis of one of the features are not slowed by irrelevant variation on the other. Treisman (e.g., Treisman and Gelade, 1980) argues that features are registered separately on different feature maps, giving rise to efficient and parallel searches for individual features and the automatic splitting apart of different features that occupy the same object. Within fingerprints, there are several highly correlated features that are candidates for unitization. As noted, the width between the ridges is very regular, which may provide constraints on how information in degraded areas is interpreted if clear detail is present in adjacent areas. Likewise, y-branching, cores, and deltas are all stereotypical features in prints that are composed of smaller features that have the potential to be joined into a new feature in an hierarchical manner through unitization.

One implication of these studies for training of latent print examiners is that we find fairly consistent and long-lasting effects of perceptual learning after relatively brief training (weeks to months). These studies have not identified how long these changes persist, however.

15.2.3.3 Configural processing of images. Work by Busey and Vanderkolk (2005) looked at configural processing as one technique by which fingerprint examiners could improve the quality of information coming from fingerprint impressions, especially when the prints are corrupted by visual noise. Configural processing is related to unitization in that it allows for the combination of individual features into a larger representation that codes relational information and possibly treats the entire image as a unitary image rather than a collection of features. Because relatively few studies have addressed the expertise exhibited by latent print examiners, these experiments are described in detail below. Busey and Vanderkolk (2005) tested 11 experts and 11 novices with 144 experimental trials. In each trial they presented a fingerprint briefly for one second and then, after a short delay, they presented two prints: one that was a rotated version of the same print, and one that was chosen by human experts to be a very similar print but from a different source. Figure 15–4 shows examples of the test stimuli, and Figure 15–5 shows the technique by which partially masked fingerprints are created.

The researchers modified the two test prints to be either whole or partial prints embedded in visual noise and asked the subjects to identify which print they had seen before. They used the accuracy in the partial print condition along with a mathematical model known as *probability summation* to make a prediction for performance in the whole image condition. They found that experts exceeded this prediction, which is consistent with configural processing.

They followed this finding with an electroencephalogram (EEG) experiment that found similar evidence for configural processing in fingerprint experts (but not novices). Upright faces produce a different brain response than inverted faces when the two EEG waveforms are compared; this has been attributed to configural processing that occurs only for upright faces. In their experiment, they found that experts showed differences for faces as well as fingerprints when both stimuli were inverted. Novices showed

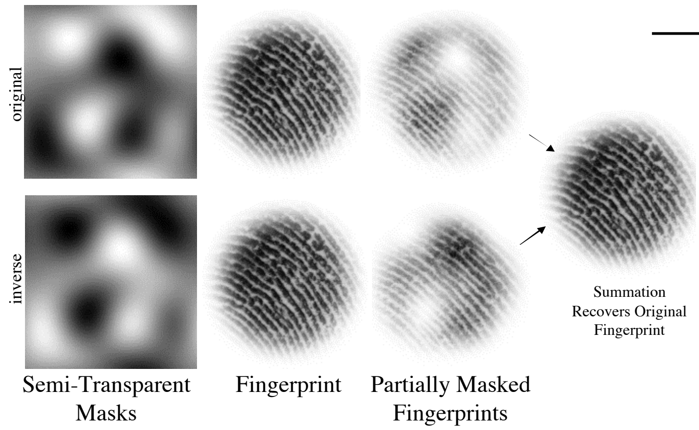


FIGURE 15–5

Method of creating partial masks to test configural processing.

differences only for faces. Thus, the signature of configural processing evidence in the EEG waveform for faces generalizes to fingerprints in latent print examiners. Due to the complex nature of EEG data and analyses, the reader is referred to the primary article (Busey and Vanderkolk, 2005) for more information. These two experiments demonstrate that experts use configural processing to improve their perception of individual features by using evidence from nearby features.

15.2.3.4 Statistical learning of visual input without attention or awareness. What brain processes might support the creation of new features through unitization and holistic representations through configural processing? The basis for this learning is rooted in the notion of *co-occurrences,* which are statistical descriptions of the fact that, in images and objects, two features tend to occur simultaneously. For example, it is the rare face that has only one eye, and this fact does not escape the visual system, which will begin to build up a representation such that when one eye is present, it more readily codes the presence of the other eye. Eventually, cells may emerge in the visual processing stream that code only the conjunction of the two eyes. Evidence with novel stimuli for this process at the single neuron level comes from Baker et al. (2002).

Recent work by Turk-Browne et al. (2005) suggests that this statistical learning (i.e., learning that two features or parts are related to each other in that they tend to co-occur) can occur automatically. Attention is required to select the relevant population of stimuli or features, but learning takes place automatically after that.

This work is an extension of prior studies by Fiser and Aslin (2001), who tested a proposal originally put forth by Barlow (1990), which posited that the visual system initiates learning by detecting "suspicious coincidences" of feature or elements. They presented observers with sets of well-defined simple shapes and varied the likelihood that one feature would appear with another. They gave the observers no instructions about what to do, and no feedback that might identify the nature of the relations among the objects. Despite this, observers spontaneously learned a variety of relations, including which features were presented most often, where they tended to occur on the display, the positions of pairs (regardless of position), and finally which shapes occurred together (regardless of position). These results are important because models of object recognition (presumably including fingerprints) require that the visual system learn these types of relations among features. Similar arguments have been made by Anderson and Schooler (1991), who argued that the structure of human memory may have been influenced by the structure present in the environment.

The fact that learning is relatively automatic and unconscious suggests that the mere act of looking at fingerprints will allow the visual system to extract the statistical regularities that are contained in prints. AFIS operators, for instance, might not perform the actual identifications in large labs but are good candidates for latent print work because of their incidental exposure to fingerprints.

15.2.3.5 How noise and feedback affect learning. Experts who work with visually noisy images (e.g., radiologists, fighter pilots, satellite image analysts, radar operators, and latent print examiners) must learn which aspects of their images are meaningful and which are visual noise. The issue is one of learning to separate the image information from the noise of the images. Dosher and Lu (2005) addressed the question of whether it is better to train using noisy images or clear images. Perhaps surprisingly, participants who trained with clear images were able to generalize this knowledge to noisy images, whereas participants who trained with noisy images were only expert with noisy images and acted like novices with clear images. They attributed this to the existence of two independent processes: external noise filtering and improved amplification or enhancement of weak stimuli. Both of these processes will lead to better performance, but external noise filtering only works when there is noise to filter. Thus, training with clear items allows both processes to develop.

When experts learn in noisy images, they can perform what is called "signal enhancement", which is the process by which the neural detectors in the visual system match their profiles to fit the to-be-perceived features. This could include the process of learning what to look for in an image, which has been demonstrated in the "Eureka phenomenon" (Ahissar and Hochstein, 1997) and more recently has received support from Gold et al. (1999) and Lu and Dosher (2004).

A very faint fingerprint image is limited not by visual noise but by the examiner's ability to discern the structure in the print. One implication of this is that novices (including latent print trainees) should receive much of their training using relatively clear prints shown at different levels of brightness so they can learn both the features they need to attend to and how to improve the amplification of very faint images. This perceptual learning should then generalize to noisy images, which can be introduced later in training.

The notion that expertise relies on conscious and intentional processes as well as unconscious and incidental processes has been addressed by Maddox and Ing (2005). They suggest that the role of the conscious system is to develop and test hypotheses related to a particular task. In their studies, the task was to categorize an object into one of several categories. The unconscious system performs primarily as an information integration process similar to the statistical learning described earlier. When a task involves a simple rule (i.e., red objects belong in one category and blue objects in another), the hypothesis testing system is primarily involved. Not only does feedback improve performance in this task, but delaying the feedback for 5 seconds has no deleterious effects. However, for tasks that involve combinations of dimensions (i.e., Category 1 is small red objects and large green objects, and Category 2 is large red objects and small green objects), delaying the feedback by 5 seconds hurts performance. This suggests that immediate feedback can aid the learning process, at least when the features or dimensions that are necessary for a task are easy to express verbally. However, feedback need not be required, and reliable perceptual learning can be obtained in the absence of feedback (Fahle and Edelman, 1993; Wenger and Rasche, 2006). For fingerprint examinations, when examiners rely on print information that is not easy to verbalize (such as the amount of curvature along a ridge path), they should refine their learning by training on stimulus sets for which the ground truth is known and can be immediately verified.

15.2.3.6 Computing similarity between features. Any comparison between a latent print and a candidate known print will involve some computation of similarity because the latent print is never an exact copy of the inked print. This comparison may be performed on the basis of individual features or the general direction of the first-level general ridge flow, or class characteristics (often used to quickly eliminate a known print from consideration). In some sense, the entire latent-to-inked print comparison can be viewed as a similarity computation with a decision stage at the back end. Within the domain of facial recognition, Steyvers and Busey (2001) have looked at models of the similarity computation process and how similarity ratings can be used to construct dimensional representations that provide input to process-based memory models (Busey, 1998; Busey and Tunnicliff, 1999). This work has built upon prior work from the perceptual learning and categorization literature, done in part by Goldstone (1996, 1999, 2000). This prior experience highlights two areas that are readily generalized to fingerprints. These relate to how experts create psychological dimensions of stimuli (described in detail below) and how they integrate and differentiate these dimensions, depending on the nature of the task.

A *feature* is a unitary stimulus element, and a *dimension* is a set of ordered values. Dimensions for shape could include length, width, curvature, or size. To a novice observer, the many dimensions that make up a complex stimulus may be fused together, whereas an expert may separate out these dimensions through a process called *differentiation.* In the present context, latent prints correspond to one set of dimensions, and the noise that accompanies the prints corresponds to a second set. Experts may learn to separate the two sets of dimensions through dimensional differentiation, although this has not been extended empirically. Goldstone and Steyvers (2001) looked at how training affects dimension differentiation and found that, although experts learn to differentiate dimensions from each other (akin to perceiving the height of an object without being affected by its width), they can sometimes have difficulty switching their attention to previously ignored dimensions. In the process of learning to differentiate dimensions and, in the process, learning to ignore the irrelevant dimensions, experts perform poorly if meaningful variation is introduced into the previously irrelevant dimensions. Thus, fingerprint experts may have difficulty when asked to make judgments that depend in part on differences that exist in the noise dimensions, which presumably they have learned to ignore.

Burns and Shepp (1988) measured the similarity relations between color chips. They found that although novice observers tended to treat the dimensions of hue, saturation, and brightness as integral, experts were more likely to differentiate these dimensions. Goldstone (1996) extended this work to show that people who learn a categorization become sensitized to the relevant dimensions. The categorization work described above suggests that experts learn to separate out the relevant dimensions, which helps them more accurately gauge the similarity of two objects.

This dimensional approach has proven useful in the domain of face recognition, which reveals not only the nature of the dimensions of faces but also provides a psychological space that can be used to make predictions for memory experiments. A *psychological space* is an abstract representation that places more similar faces close together (Valentine, 1991). Busey (1998) gathered a large set of similarity ratings between all possible pairs of 104 faces. These ratings were analyzed using a multidimensional scaling (MDS) analysis package, which attempts to reduce the dimensionality of the data to relevant psychological dimensions that describe how humans compute similarity. The resulting psychological space not only proved interpretable but was then used to make predictions for memory experiments (Busey and Tunnicliff, 1999). Later work by Steyvers and Busey (2001) demonstrated the matches and mismatches between a physical representation computed from images and psychological spaces computed from similarity ratings. In part, the differences come from the fact that some features are more diagnostic than others; experts may use this diagnosticity to adjust their psychological space of fingerprints accordingly. The different processes used by experts result in enhanced performance but also, paradoxically, have degradation as a result of cognitive tradeoffs (Dror, 2009a).

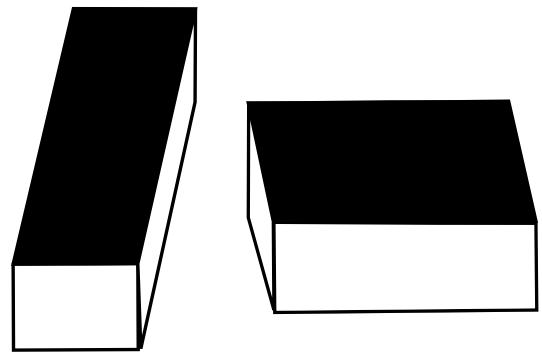
This work suggests that one element of training involves the discovery of relevant psychological dimensions that differentiate fingerprints. These dimensions are not yet known but could be something like general ridge flow, overall fingerprint type, density of minutiae in particular regions, and even idiosyncratic features such as particular constellations of ridges.

15.2.3.7 Similarity vs. categorical decision-making. The previous section describes how the psychological work on similarity computation applies to latent print examinations. There may appear to be a gulf between similarity judgments, which one may think of as a continuous measure, and the type of decision arrived at by latent print examiners. The language may be different in various jurisdictions, but typically examiners testify that two prints either came from the same source or did not come from the same source. They may or may not attach some kind of confidence rating to this conclusion. This might suggest that the similarity literature may have little to do with latent print examinations. However, the authors of this chapter would argue that the decision arrived at by the examiner is, in fact, an implicit similarity judgment. No two prints are ever identical; therefore, the task always requires some element of comparison and similarity computation. Examiners then translate this to a categorical judgment, presumably using some rule such as: "These two prints are more similar to each other than any other close non-match that I have observed" or "The two prints are sufficiently similar that I can conclude that they come from the same source" (see Dror, 2009a, for a discussion of sufficient similarity).

One may want to draw a distinction between the actual underlying cognitive processes involved in fingerprinting, the terminology and language used to express a conclusion, and how this is explained in court. Here, the focus is on the cognitive processes, which result from comparing the similarity of two images. The way fingerprint examiners explain their conclusions, and the way they express their decisions, may vary from one place to another and may change over time; however, the cognitive processes that are the focus of this chapter remain the same.

FIGURE 15–6

Both blackened areas are identical in shape.



15.2.3.8 Interim summary. This chapter thus far has summarized the findings from the perceptual learning literature as explored by cognitive scientists. What emerges from this summary is a view that the human visual system is remarkably good at extracting the structure that exists in a class of stimuli. This learning process occurs with very little conscious direction beyond the initial selection of relevant features. All that is required is a constant set of example stimuli that provide the kinds of statistical regularities among features or parts that are extracted by the visual processing mechanisms, as well as some selection of what are the relevant features required for the task. This is not to imply that this is an easy process; in fact, the field should argue for more hours of training to provide the large number of examples that are required to identify weak statistical relations. Such complex learning can be enhanced by developing scientific-based training and utilizing technology (see Dror, Stevenage, and Ashworth, 2008).

Experts often ask the question, how much matching information is enough? The perceptual learning literature does not provide a direct answer, but the tools from cognitive science illustrate how different factors trade off. In the next section, a computation modeling approach is used to address the relation between quantity and quality. Image quality could be measured in several ways but, in general, it represents the degree of visible print information relative to the amount of noise caused by dust or other artifacts created when the print was lifted. Image quantity represents the surface area of usable print information, which could be measured in units of ridge widths or square centimeters. Although image quantity and quality can be seen as going together, in principle it is possible to separate the two factors.

15.2.4 Weaknesses and Vulnerabilities in Perceptual, Cognitive, and Psychological Phenomena

Although the active and dynamic nature of cognition is the basis of intelligence and expertise, it also introduces a multitude of elements that make humans vulnerable to distorting information and thus making errors (Dror, in press). As many of these processes are unconscious (e.g., Greenwald, 1992), they are especially problematic and dangerous. This section elaborates and illustrates how human information processing can distort information in a variety of ways. The next section shows how these phenomena relate to fingerprint identification.

Our perceptual information processing can also distort our perception of images. Although the two black shapes above, in Figure 15–6, are identical, they are perceived as being totally different (Shepard, 1981). The active and dynamic nature of the perceptual system not only has the potential to distort the incoming data, as already illustrated, but it can also add information and make us perceive things that are not actually there. For example, in Figure 15–7, one perceives imaginary subjective contours making a white square on top of the black square (Kanizsa, 1976). Furthermore, this imaginary white square incorrectly seems to be of a different shade than its surroundings (compare the shade in points A and B, which are in fact identical).

These examples demonstrate that even the lower level sensory mechanisms are not passive or isolated from a variety of factors that can affect and distort what is perceived. Thus, much of what is perceived, even at the lower level mechanisms, is dependent on the perceiver rather than reflecting an "objective reality". The attention

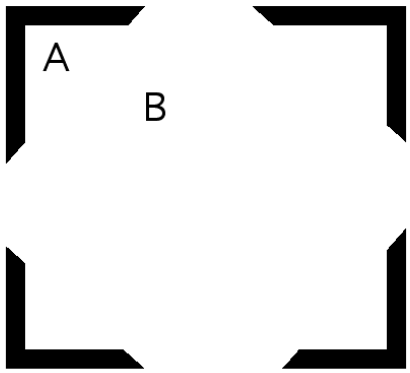


FIGURE 15–7

Example of subjective contours and illusionary differences in shading (point A and B).

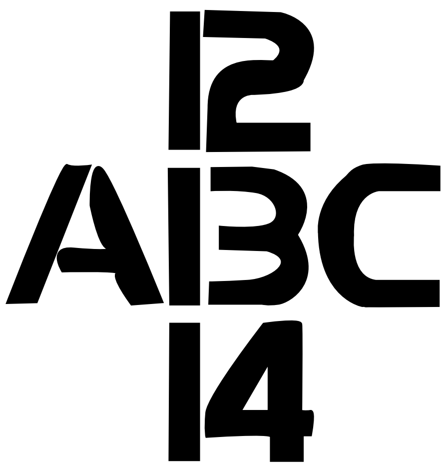


FIGURE 15–8

The same central image can get different interpretation based on visual or mental context.

mechanisms at the perceptual level, as well as at higher levels of information processing (discussed earlier in section 2.2), select only a subset of the information available for further processing. In this way, people actually do not process much of what they see. De facto, they disregard and miss possibly critical information in an image.

Because of these as well as other cognitive mechanisms, the same visual image can, in fact, get different interpretations depending on the context in which it is presented. The middle pattern in Figure 15–8 can either be interpreted as the letter "B" or as the number "13"; either can be induced by providing different contextual information ("13" with the vertical contextual information or "B" with the horizontal contextual information).

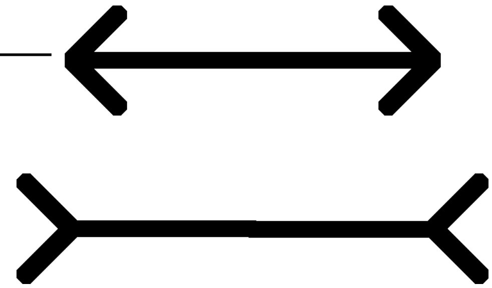
Because our minds and psychological state play a central role in how people process information, here too they are subject to vulnerabilities. In fact, the mind can "play many tricks" and cause a wide range of phenomena. The common saying that "love is blind" is a reflection of this effect.

Most people have experienced that when they expect and hope to see something, then they see it even when it is not there (and, similarly, when they are afraid of something, they see it even where it is not). In these situations, the context is not provided by the environment but rather by one's "state of mind" or mental context.

At a more scientific level, this can be demonstrated by showing that interpretation of the central image in Figure 8 as either a "13" or a "B" can be affected by one's state of mind. Rather than manipulating the external context of "A, B, C" vs. "12, 13, 14", the psychological state of mind, in terms of motivation, can be manipulated. If the central image is presented in a context that motivates people to see a number, then they will see it as "13", in contrast to seeing the same image as "B" when they are motivated to see it as a letter (Balcetis and Dunning, 2006). For example, one can be highly affected by states of wishful thinking, cognitive dissonance, escalation of commitment, or confirmation bias. In these cases, the collection and interpretation of

FIGURE 15–9

Both horizontal lines are of equal length



information are driven to justify and verify a decision that has already taken place or to confirm a pre-existing preference or bias.

Again, even if the decision-maker comes initially with no preconceived decisions or biases, as decisions are considered and made, information is gathered and processed for the purposes of confirming and validating these decisions. As already illustrated, these processes are highly dependent on psychological elements and processes rather than purely on the relevant information. Thus, one's mind and mental states can distort and interfere with whether and how information is collected, processed, and interpreted (e.g., Baumeister and Newman, 1994; Kunda, 1990). These effects happen most often without any awareness (e.g., Greenwald, 1992).

15.3 Cognitive and Psychological Elements in Fingerprint Identification

It is clear that fingerprint identification cannot be performed in isolation from human cognition. A whole range of perceptual, cognitive, and psychological elements play an integral role in all the stages of the identification process: from finding and collecting prints, perceiving them, and their analysis, comparison, and evaluation, to reaching judgments, making decisions, and verification. In the sections below, psychological and cognitive phenomena are tied together and related to the world of fingerprint identification, and research that directly examines the fingerprint domain is then presented. Finally, some practical implications and applications of these elements are discussed. Finding ways to move forward and enhance fingerprint identification can only be achieved once we are willing to accept that these influences exist.

15.3.1 Relevance of Cognitive Phenomena to Fingerprint Identification

It is obvious that fingerprint experts, like experts in other domains and nonexperts in everyday life, are susceptible to perceptual, cognitive, and psychological phenomena. However, not all psychological and cognitive phenomena are directly related to fingerprint identification. It is important to consider which ones are relevant, and how. For example, if fingerprint identification requires comparing the length of ridges, then the Müller-Lyer illusion (1889) may be very relevant. In Figure 15–9, the top horizontal line is perceived as shorter than the bottom horizontal line, although the two lines are in fact identical in length (Restle and Decker, 1977).

This is a demonstration of some potential psychological and cognitive phenomena that may be directly related to fingerprint identification. This and other phenomena have been researched within the general scope of psychological investigations. Other scientific investigations have been conducted to directly address fingerprint identification.

15.3.2 Cognitive Research on Fingerprint Expertise and Identification

A number of research studies have examined the possible influence of context on decisions about whether fingerprints match or not (see, for example, Langenburg et al., 2009; Schiffer and Champod, 2007; Dror, Péron, Hind, and Charlton, 2005; Dror and Charlton, 2006; Dror, Charlton, and Péron, 2006). In one study (Dror, Péron, Hind, and Charlton, 2005), pairs of fingerprints were presented to nonexperts. Some pairs of prints were clearly a match, some were clearly not a match, and others were ambiguous. Then, prior to the participants examining the fingerprints, contextual information about the crime at issue (including photos from the crime scene) was presented. Half of the time, the context was neutral. Participants had to judge whether there was sufficient information to make

FIGURE 15–10

An image used in the Dror et al. (2005) study.

a sound judgment and, if so, whether the prints matched. However, the other half of the prints were presented within a highly emotional condition, with photos that were scientifically proven to provoke emotional reactions (Lang et al., 1995), such as the photograph in Figure 15–10.

The results of the study showed that emotional context and mood affected how fingerprints were matched. However, the effect of emotional context was dependent on the difficulty of making the match. The emotional manipulation only affected matching decisions when the pairs of fingerprints were ambiguous and there was not enough data to make a clear and simple identification or exclusion decision. (For details, see Dror, Péron, Hind, and Charlton, 2005.)

The 2005 study was conducted on nonexperts. However, emotional experiences do seem to play a role in the work of fingerprint examiners (Charlton et al., in press). Even studies with real experts do not capture the reality in the workplace because the research is laboratory based. In fact, even in the normal working environment, experts behave differently if they know they are being observed, taking part in research, or being tested. As an analogy, if one wants to test and examine how people drive, then examining their driving during an official driving test, or even when they know they are being watched (or within the range of a speed camera), will hardly reflect how they actually drive every day in practice on the road (see Dror and Rosenthal, 2008; Dror, 2009b).

To collect ecologically valid and robust data, Dror and Charlton (2006) and Dror, Charlton, and Péron (2006) employed covert data collected from fingerprint experts during their routine work. A within-subject experimental design was used in which the same experts made judgements on identical pairs of fingerprints, but in different contexts. This is a very robust and powerful experimental paradigm, as participants act as their own controls. This not only provides more meaningful and interpretable data, but each data point carries more statistical power. Furthermore, this allows the researcher to isolate, focus on, and examine the contextual influences themselves rather than revealing possible individual differences between experts. Accordingly, pairs of fingerprints were collected (from archives) that the same experts being examined had examined and judged approximately 5 years earlier as a clear and definite match or exclusion. These previous identifications/exclusions were taken from real criminal investigations.

In these studies, the very same pairs of fingerprints were re-presented to the same experts, only now they were presented within an extraneous context that might bias them to evaluate the prints differently. A control condition included pairs of prints that were presented without manipulating the context. In these two studies, a total of 53 pairs of prints were presented to 11 experienced latent fingerprint experts (none of whom participated in both studies).

In a combined meta-analysis of these two experiments (Dror and Rosenthal, 2008), the reliability and biasability of the fingerprint experts was analyzed and determined. Eight out of the 11 experts made some inconsistent decisions that conflicted with their previous decisions on the same pair of fingerprints. These conflicting decisions mainly occurred in the more difficult prints and with prints that were originally judged as identifications. However, some inconsistent decisions also occurred with relatively easy prints and with prints that were originally judged as exclusions. Furthermore, some inconsistent decisions were observed in the control condition, in which the prints were presented without any contextual manipulation. (For full details and discussion of these results, see the studies; full citations are listed in the References.)

A number of new studies have followed up on this work (e.g., Langenburg et al., 2009; Hall and Player, 2008; Schiffer and Champod, 2007). Although there is some divergence on the interpretations of the different studies (see Dror, 2009b), all consistently and clearly show that biasing effects exist, although they do not necessarily change decision outcomes and their effects vary depending on circumstances. As stated in Langenburg et al. (2009), "There is strong evidence that some fingerprint specialists *can* be biased by contextual information. The decision made by a specialist is not necessarily based solely on the ridge detail when comparing images. More importantly, the bias effect was most often observed during complex comparison trials" (page 577; italics in the original). These studies illustrate some of the potential interferences of psychological and cognitive elements in fingerprint identification. These issues can be further exacerbated by technology (see Dror and Mnookin, 2010) and working procedures, as specified in section 15.3.3.

The changes in the low-level perceptual mechanisms, identified using brain recordings as described in section 15.2.3.3, illustrate that training affects the nature of the information processing mechanisms. As the quality of the information acquired by the visual system improves, the structure of the decision process also changes. For example, as an examiner begins to acquire more experience with harder images, he or she may feel more comfortable "calling" more difficult prints. This entails a change in the implicit decision criteria such that less evidence, if it is of higher quality, might be sufficient to make a determination. Models of decision-making, such as signal detection theory, actually support such a shift in the decision criteria to balance the tradeoffs between correct identifications, correct exclusions, misses, and erroneous identifications. The preceding section, however, does reinforce the conclusion that as an examiner shifts his or her decision criteria with changes in experience, care must be taken to avoid shifting them too much. Central to any shift in criteria must be a set of procedures to obtain accurate feedback from know fingerprints, either in the form of formal proficiency testing or informal practice working with a community of examiners.

15.3.3 Applications and Implications of Cognitive Research and Phenomena to Fingerprint Analysis and Comparisons

It is clear by now that cognition plays a critical role in fingerprint identification. Nevertheless, there has been relatively little attention to the cognitive and psychological perspectives, and only a small number of studies that are specifically directed at the fingerprint domain have been conducted to explore this or related issues (e.g., Busey and Vanderkolk, 2005; Schiffer and Champod, 2007; Wertheim et al., 2006; Haber and Haber, 2004; Dror, Schmitz-Williams, and Smith, 2005; Dror and Charlton, 2006; Dror, Charlton, and Péron, 2006; Dror, Stevenage, and Ashworth, 2008; Langenburg et al., 2009). The need for systematic research into the cognitive and psychological issues cannot be overstated.

15.3.3.1 Selection and Screening. Although many experts were biasable and unreliable in their judgments (Dror and Rosenthal, 2008), some experts seem to have been relatively immune to many cognitive and psychological influences. Why were those experts not as susceptible as the others? What was it about those experts that made them so consistent, reliable, and unbiasable? More systematic research needs to be done before it can be determined if it had to do with their personalities, cognitive style, training, working culture, or other factors. However, what is clear is that, whatever it is, it is something good that should be sought in every fingerprint expert.

But what are those things that make up a fingerprint expert? What are the cognitive skills and aptitudes that are needed for conducting fingerprint identification? As a first step to further professionalize and enhance fingerprint identification, the field must screen and select the correct people to become experts in this domain. In order to do this, the field first needs to understand the skills and cognitive styles that underpin the ability to conduct fingerprint identification. However, in contrast to other domains of expertise (e.g., Air Force pilots; see Dror, Kosslyn, and

Waag, 1993), there has been no research to this effect in the fingerprint domain; thus, there is a lack of standardized and scientifically based testing of screening applicants.

Only with systematic research into the skills and aptitudes needed for fingerprint identification can the field construct a cognitive profile of fingerprint experts. Then those abilities that are relatively hard-wired and do not change with training will be used for initial selection and screening (e.g., Dror, 2004). There is a need to establish a standardized test for recruitment screening of fingerprint examiners that is based on research and understanding. Proper screening and selection is critical for finding the best candidates for this profession. Investment in initially selecting the right people for the profession is not only very cost-effective but will also avoid problems in the long run.

15.3.3.2 Training. Training—whether it is the initial training involved in becoming an expert, or continuing professional development over the years via workshops and other training opportunities—is a critical aspect in fingerprint expertise. Training in all its forms needs to address the psychological and cognitive influences that may affect the workings of fingerprint experts. Such training can help minimize the elements that can lead to misjudgments and to error. However, such training is practically nonexistent.

This essential training would involve theoretical discussion and hands-on exercises on how to avoid error due to psychological and cognitive factors. To elucidate such training programs would require a whole book in its own right, but generally such training would need to intertwine knowledge of cognition, expert performance, and fingerprint identification. Along with training, continuous blind testing of expert performance is an important aspect that is not currently implemented in most places. Testing experts in nonblind conditions, when they know they are being tested, only examines their theoretical ability to match fingerprints. Just as driving tests do not reflect how people actually drive on the road, non-blind testing of experts does not reflect their practical performance in casework.

Choosing the right people to become fingerprint experts, training them properly, and continuously testing their performance will address many of the issues raised in this chapter, but only at a personal and individual level. Tackling the complexity of cognitive and psychological influences requires addressing these issues both at the individual expert level and at the organizational administrative level (Dror, 2009a).

15.3.3.3 Procedures. Correct working procedures are essential for minimizing psychological and cognitive interferences in making fingerprint matching decisions. Such procedures have to be pragmatic and adapted to the specific realities in which they are implemented. The procedures must consider the cognitive and psychological influences from the initial evaluation of the latent print to the final verification.

In the initial evaluation, for example, there is the issue of whether this should be done in isolation from seeing any potential tenprints (Dror, 2009a). Examining and evaluating the latent print by itself allows judgments to be independent; when such examinations are done with the accompanying tenprint, there are a number of potential problematic issues. The tenprint provides a context and a motivation that can change the way the latent print is examined and evaluated: It can affect the selective allocation of attention, change thresholds and standards for assessing information, cause the perception of characteristics that are not there and/or the dismissal of characteristics that are there, and many other unconscious cognitive and psychological phenomena that have been elaborated upon throughout this chapter.

However, the examination of a latent print against a suspect tenprint may also allow examiners to notice certain bits of information by directing their attention to those areas that do require special attention and further processing (Dror, 2009a). Thus, there is no simple solution and the problems are complex. A possible solution may entail an initial examination and analysis of the latent print in isolation but also allow for retroactive changes after comparison to the tenprints. There is a danger here, too, as this can bring about acceptance of low-quality latent prints that do not contain sufficient information as well as all the other cognitive and psychological issues discussed already. A way to move forward may be an initial examination of a latent print in isolation, and an analysis of it that comprises distinguishing characteristics that are strong and cannot be changed, with weaker characteristics considered when later examining the tenprints (see details at Dror, 2009a). This is only an illustration of the procedural changes that might address cognitive and psychological influences.

These types of issues continue throughout the entire procedure of fingerprint identification (and exclusion), all the way to the final verification procedures. Many existing verifications are perhaps no more than a rubber stamp. The very fact that identifications will be verified (sometimes by more than one verifier) introduces a whole range of issues, from diffusion of responsibility (Darley and Latané, 1968) to conformity, attention, self-fulfilling prophecies, and wishful thinking. Quality assurance would require that look-alike exclusions would be put together along with the real casework verifications, to keep the verifiers alert and to guarantee quality assurance. These issues and development of science-based procedures require further research.

15.3.3.4 Technology. The introduction and development of technologies has had a profound impact on fingerprint identification. These technologies offer great capabilities and opportunities and, with efforts in biometric identification, the field can expect new technologies to continue and emerge in the future. Many times, the overestimation and promise of technology, and the underestimation of the human mind and human experts, lead to a false expectation that machines and technology will take over human performance (Dascal and Dror, 2005). As powerful as these technologies are and will be in the foreseeable future, they will not replace latent print examiners. The important thing is to take advantage of these new technologies and harness them to enhance fingerprint identification. To achieve this, technologies need to be integrated properly with the human experts. This means designing and integrating the technology to work with experts and to complement their work (Dror, 2005b, 2006; Dror and Mnookin, 2010).

Although these technologies will not replace human experts, they will have a great impact on fingerprint identification (Davis and Hufnagel, 2007). In terms of some of the cognitive and psychological issues discussed in this chapter, some issues will be eliminated with the technological developments but other problems will not be affected. In fact, some issues will be exacerbated and new problems may even be created (Dror and Mnookin, 2010). For example, the Automated Fingerprint Identification System (AFIS) gives rise to giant databases that contain larger and larger numbers of fingerprints. With such large databases, the relative similarity of fingerprints found by pure coincidence will increase. With increased similarity and look-alike prints, the difficulty in matching will increase. With greater difficulty in the bottom-up matching of prints, greater opportunity and vulnerability is created for the top-down contextual and motivational components to distort and interfere with the matching process (see Dror et al., 2005; Dror and Mnookin, 2010).

Technological developments in the fingerprint domain are not limited to AFIS. For example, technology offers "image enhancements" (such as color and 3-D transformations). Such enhancements can offer clarity and improved accuracy, but at the same time they present great opportunities to strengthen and enable cognitive and psychological distortions. As before, there are no simple solutions, and the issues and problems are complex. Technology is an important ally to fingerprint experts but must be designed, developed, used, and integrated in a way that enhances fingerprint identification (Dror, 2005b; Dror and Mnookin, 2010).

15.4 Summary and Conclusions

The dynamic and active nature of human information processing enables us to become experts but also makes us distort incoming data and make erroneous decisions. These vulnerabilities are not limited to fingerprint experts and apply equally to other domains. However, the importance of fingerprint evidence being reliable and unbiasable requires that these potential weaknesses be addressed. To achieve this, systematic research must be conducted to examine the cognitive and psychological elements involved in fingerprint identification.

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