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Two Items of Evidence, No Putative Source: An Inference Problem in Forensic Intelligence

ABSTRACT: Intelligence analysts commonly associate cases on the basis of similarities found in compared characteristics of scientific evidence. The present paper studies some of the inferential difficulties associated with such operations. An analysis is proposed that breaks down the reasoning process into *inference to common source*, and *inference to case linkage*. The former requires an approach to the difficulty associated with evaluating the similarities of items of evidence from different cases with no putative source being available. The latter requires consideration to be given to the relevance of evidence. Throughout the paper, probability theory is used to describe the nature of the proposed inferences. Graphical models are also introduced with the aim of providing further insight into the dependence and independence relationships assumed to hold among the various propositions considered. Notions from decision theory are used to discuss ways in which intelligence analysts may assist investigators in deciding whether or not cases should be considered as linked.

KEYWORDS: forensic science, Bayes' theorem, scientific evidence, forensic intelligence, decision theory, graphical models

Forensic scientists are frequently concerned with situations in which more than one item of evidence is found. Two or more traces may be recovered, for example, at different locations where, at temporally distinct instances, crimes have been committed. At some stage of investigation, it may well be that a potential source is not available for comparison. However, analyses may be performed on crime samples with the aim of evaluating possible linkages between the cases. Here, the main proposition of interest is not whether a suspect is the source of the recovered materials, but whether the recovered materials have a common source, which is, however, *unknown*. This aspect represents the major difference with respect to a classic one-stain scenario where a potential source is available for comparison purposes.

Two-stain scenarios with no potential source available play an important role in forensic intelligence, a domain that seeks to produce accurate, timely, and useful information through the logical processing of forensic case data (1). Examples include scientific evidence such as DNA collected on distinct rape victims, offender characteristics recorded by surveillance cameras, shoe and tool marks encountered in burglary cases, samples of illicit drugs from different seizures, and so on. One may also imagine scenarios involving fiber evidence recovered from distinct locations (as in the Wayne Williams case (2,3) for example), or, tapes used in the context of speaker recognition.

Current forensic literature on evaluative procedures is almost exclusively concerned with situations where some item of evidence, associated with a particular (criminal) event, is compared with some sample from a known source (4). Various statistical, notably probabilistic methods, are available for addressing propositions at different hierarchical levels (5), e.g., the suspect being or not being the source of a crime stain (source level), or, the suspect being or not being the offender (crime level). Such evaluations play an important role in court proceedings. However, forensic literature has pointed out that, in crime analysis and criminal investigations, data may be used in quite a different way and that the use of probabilistic evaluations in such contexts still needs to be defined in order to provide real-time intelligence (6).

This then is the kind of topic that the present paper is concerned with in regard to the fields of evidence evaluation, forensic intelligence and forensic science in general. The primary aim is to study some of the issues that affect the assessment of scientific evidence in situations where no potential source is available for comparison. The discussion will focus on observations relating to selected features or characteristics of items of scientific evidence that originate from different cases. Such information will be used in order to construct arguments to the proposition according to which the two items have a common source. An attempt will be made to evaluate the degree to which probability theory is amenable to describing the nature and the strength of a potential link between two items of evidence, and, by extension, between two cases. This procedure will essentially be based on the assessment of a likelihood ratio.

The topic will be studied at several levels of detail using probabilistic approaches with various degrees of technicality. In "Discrete Attributes of the Evidence," a two-stain scenario with no potential source will be studied for discrete attributes of the evidence using a fairly general expression of a likelihood ratio formula. In "Use of Bayesian Networks," the discussion will be extended to graphical models, i.e., Bayesian networks, in order to deal with the increasing complexity of the probabilistic calculus that is implied by, for example, the consideration of additional discrete features of the evidence. "Continuous Measurements of the Evidence" deals with continuous measurements of the evidence, such as the height of persons recorded by surveillance cameras. A hypothetical example is approached using simulation techniques in order to cope with the absence of a potential source, i.e., reference samples from that source. This will also serve as an illustration of an alternative to the Bayesian network approach followed in earlier sections. An extension from reasoning about source level propositions, as was done through Sections "Discrete

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Attributes of the Evidence" to "Continuous Measurements of the Evidence," to crime level propositions is discussed in "Beyond Inference of Identity." Based on results obtained in "Beyond Inference of Identity" and borrowing notions from decision theory, "Linking Cases: A Problem of Decision Making" discusses on how investigators can be assisted in rationally approaching the question of whether or not cases should be considered as linked.

Discrete Attributes of the Evidence

Imagine two separate offences. Dead bodies have been found at two distinct locations. In both cases, evidence has been collected from the dead naked bodies. Let E_1 and E_2 denote items of evidence collected in the first and second case, respectively. The sets of evidence could consist of, for example, textile fibers, hairs, semen, or saliva.

An attempt will be made here to approach the scenario at a very general and broken-down level. It will notably be assumed that the compared characteristics are discrete. In the case of textile fibers, this could be a particular combination of fiber type and fiber color, e.g., red wool.

The two items of evidence are analyzed and both are found to be of, for example, type A, some sort of discrete physical attribute. For the current level of discussion, A is not specified in further detail. Addressing the case at the source level, propositions of interest can be defined as follows:

- H_1: the items of evidence E_1 and E_2 come from the same source;
- H_2: E_1 and E_2 come from different sources.

These propositions do not specifically relate to a prosecution's or defense's standpoint, so simple numerical subscripts are used for denoting the possible outcomes of H. Notice that issues such as the relevance of the evidential material are not considered here.

A likelihood ratio V may be developed in order to evaluate how well the available evidence allows discrimination between H_1 and H_2. Formally, one may write

$$V = \frac{\Pr(E_1 = A,\, E_2 = A|H_1)}{\Pr(E_1 = A,\, E_2 = A|H_2)}$$

Consider the numerator first. What is the probability of both items of evidence E_1 and E_2 being of type A, given that they come from the same source? Under H_1, there is a single source, and thus, the probability of E_1 and E_2 both being of type A critically depends on the probability of the single (common) source being of type A. In fact, the common source of the two items of evidence could either be of type A or $\bar{A}$, abbreviated by $H_{1,1}$ and $H_{1,2}$, respectively. With E denoting the conjunction of $E_1 = A$ and $E_2 = A$, the numerator is

$$\Pr(E|H_1) = \underbrace{\Pr(E|H_{1,1})}_{1}\underbrace{\Pr(H_{1,1})}_{\gamma_A} + \underbrace{\Pr(E|H_{1,2})}_{0}\underbrace{\Pr(H_{1,2})}_{\gamma_{\bar{A}}}$$

where γ_A denotes the probability by which a source of a relevant population would be found to be of type A.

Then, consider the denominator. If H_2 is true, then there may be different possibilities for there being two *different* sources: both sources are of type A ($H_{2,1}$), both sources are of type $\bar{A}$ ($H_{2,2}$), or one source is of type A and the other is of type $\bar{A}$ ($H_{2,3}$). The denominator can be rewritten as

$$\Pr(E|H_2) = \sum_{i=1}^{3} \Pr(E|H_{2,i})\Pr(H_{2,i})$$

E can only be true when the distinct sources of E_1 and E_2 are both of type A. Consequently, only the first product of this equation remains nonzero

$$\Pr(E|H_2) = \underbrace{\Pr(E|H_{2,1})}_{1}\underbrace{\Pr(H_{2,1})}_{\gamma_A^2} + \underbrace{\Pr(E|H_{2,2})}_{0}\underbrace{\Pr(H_{2,2})}_{\gamma_{\bar{A}}^2} + \underbrace{\Pr(E|H_{2,3})}_{0}\underbrace{\Pr(H_{2,3})}_{2\gamma_A\gamma_{\bar{A}}}$$

The likelihood ratio then becomes

$$V = \frac{\Pr(E_1 = A,\, E_2 = A|H_1)}{\Pr(E_1 = A,\, E_2 = A|H_2)} = \frac{\gamma_A}{\gamma_A^2} = \frac{1}{\gamma_A} \tag{1}$$

In the numerator and denominator, γ_A is a suitable statistic drawn from the same population. Notice that the validity of this assumption need reviewing whenever other kinds of evidence are considered.

Use of Bayesian Networks

In a Bayesian network, probability is associated with graph theory. Bayesian networks are a mathematically and statistically rigorous technique for representing and evaluating dependencies and influences among variables considered relevant for a particular inferential problem. Several authors have pointed out the utility of Bayesian networks for handling uncertainties associated with the evaluation of evidence in forensic science (7–11).

Bayesian networks represent variables by nodes. Directed edges are used to express assumed relationships among the nodes. Both nodes and edges are combined in order to form a directed acyclic graph (DAG). Probability is incorporated into a DAG by means of node probability tables: for a variable B with parents $A_1, \ldots, A_n$, there is a conditional node probability table $\Pr(B|A_1, \ldots, A_n)$, whereas a table containing unconditional probabilities $\Pr(A)$ is assigned to a variable A that has no parents. If the conditional relationships implied by the structure of a BN hold for a set of variables $A_1, \ldots, A_n$, then the joint probability distribution $\Pr(A_1, \ldots, A_n)$ is given by the product of all specified conditional probabilities:

$$\Pr(A_1, \ldots, A_n) = \prod_i \Pr(A_i|par(A_i)) \tag{2}$$

where $par(A_i)$ represents the set of parental variables of A_i. Equation (2) is called the *chain rule for Bayesian networks* (12) and formally defines what a Bayesian network means: a representation of the joint probability distribution for all the variables.

Bayesian networks greatly facilitate probabilistic calculus whenever multiple variables with a complex dependency structure need to be considered. For this purpose, various algorithms have been developed and implemented in academically or commercially available computer systems.

Bayesian networks are used below with the aim of studying in further detail scenarios for which a general probabilistic approach has been suggested in "Discrete Attributes of the Evidence." The construction of the proposed Bayesian networks is explained in a stepwise manner.

Start by considering the first item of evidence (collected in the first case). Let E_1 denote the outcomes of the observations made on this piece of evidence. The variable E_1 assumes the binary states A or $\bar{A}$, whereas the latter possibility covers all potential outcomes other than A. Information on the observed attributes of

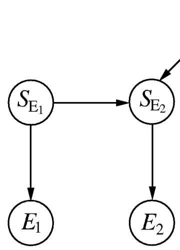

FIG. 1—*A Bayesian network for a scenario in which two stains are found on two different scenes.*

the first item of evidence is used to draw an inference about the characteristics of the source it comes from. Let S_{E_1} denote the characteristics of the source of the first item of evidence. This variable is also binary and has the following states:

- S_{E_1} : the source of the first item of evidence is of type A;
- $\bar{S}_{E_1}$: the source of the first item of evidence is $\bar{A}$.

Logically, the observed characteristics of the evidence are directly dependent on the attributes of the source, so, graphically speaking, a direct edge may be drawn from S_{E_1} to E_1.

The item of evidence recovered in the second case may be evaluated analogously. A variable E_2 is used to describe the observations made on the second item of evidence. A variable S_{E_2} describes the characteristics of the source. These two variables are related so that the following network fragment is obtained: $S_{E_2} \rightarrow E_2$.

Next, a variable H is defined, representing the proposition according to which E_1 and E_2 come from the same source (H_1), or come from different sources (H_2). H needs to be combined with the network fragments $S_{E_1} \rightarrow E_1$ and $S_{E_2} \rightarrow E_2$ in some meaningful way. One possibility would be to condition S_{E_2} on both H and S_{E_1}. This allows one to assess the following probabilities (Table 1):

- If the two items of evidence come from the same source and the source of the first item of evidence is of type A, then certainly the source of the second item of evidence is of type A: $\Pr(S_{E_2} = A|H_1, S_{E_1} = A) = 1$.
- If the two items of evidence come from the same source and the source of the first item of evidence is of type $\bar{A}$, then certainly the source of the second item of evidence is also of type $\bar{A}$: $\Pr(S_{E_2} = \bar{A}|H_1, S_{E_1} = \bar{A}) = 1$.
- If the two pieces of evidence come from different sources, then the probability of the source of the first piece of evidence being of type A is just given by the frequency of that characteristic in a relevant population, denoted γ_A. Notice that given H_2, S_{E_2} is assumed to be independent from S_{E_1} : $\Pr(S_{E_2} = A|H_2, S_{E_1} = A) = \Pr(S_{E_2} = A|H_2, S_{E_1} = \bar{A}) = \gamma_A$.

The conditional probabilities associated with the evidence nodes E_1 and E_2 reflect the degree to which the characteristics observed by the scientist are indicative of the characteristics of the sources from which the items of evidence originate. Generally,

TABLE 1—*Conditional probabilities applicable to the node S_{E_2}.*

	H:	H_1		H_2	
	S_{E_1}:	A	$\bar{A}$	A	$\bar{A}$
S_{E_2}:	A	1	0	γ_A	γ_A
	$\bar{A}$	0	1	$1-\gamma_A$	$1-\gamma_A$

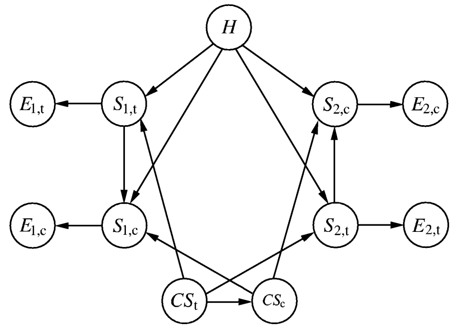

FIG. 2—*An alternative network structure for a scenario in which two stains are found on two different scenes.*

scientists tend to prefer methods for which $\Pr(E_1 = A|S_{E_1} = A) \rightarrow 1$ and $\Pr(E_1 = A|S_{E_1} = \bar{A}) \rightarrow 0$.

Notice that the proposed Bayesian network is somewhat more detailed than the formula (Eq. [1]). The major difference is that a distinction has been made between the observations made on the items of evidence (nodes E_1 and E_2) and the characteristics of their sources (nodes S_{E_1} and S_{E_2}). The latter are in fact unobserved variables not explicitly represented when deriving the formula of the likelihood ratio (Eq. [1]). Moreover, two distinct variables are used to represent the items of evidence. However, the likelihood ratio that may be derived from the Bayesian network depicted in Fig. 1 can be shown to be in agreement with Eq. (1).

An alternative network structure is shown in Fig. 2. A summary of the node definitions is given in Table 2. In this model, the observed characteristics—fiber type and color—of each item of evidence have been represented using distinct nodes. The characteristics of a potential common source of the two items of evidence are modeled by the nodes CS_t and CS_c, where the subscripts t and c refer to fiber type and color, respectively. The term "potential common source" is used here in order to express the idea that uncertainties about the variables CS_t and CS_c will be allowed to affect the truthstate of the nodes $S_{i,\{t,c\}}$ only if the two items of evidence do in fact come from a common source, i.e., H_1 being true. Note that the nodes referring to fiber color are conditioned on the fiber type: this should allow one to adjust the frequency of fiber color for a given fiber type.

The probability tables associated with the observation nodes $E_{i,\{t,c\}}$ can account for the relative performance of the examiner. For example, when it is thought that the examiner will always recognize a fiber's type as wool when in fact it is wool and never

TABLE 2—*Definition of the nodes present in the network shown in Fig. 2.*

Node	Definition	States	
H	The items of evidence come from the same source	H_1:	Yes
		H_2:	No
$E_{i,t}$	Observed fiber type of the item of evidence i	$E_{i,t}$:	Wool
		$\bar{E}_{i,t}$:	Other
$E_{i,c}$	Observed fiber color of the item of evidence i	$E_{i,c}$:	Red
		$\bar{E}_{i,c}$:	Other
$S_{i,t}$	Fiber type of the source of the item of evidence i	$S_{i,t}$:	Wool
		$\bar{S}_{i,t}$:	Other
$S_{i,c}$	Fiber color of the source of the item of evidence i	$S_{i,c}$:	Red
		$\bar{S}_{i,c}$:	Other
CS_t	Fiber type of a potential common source	CS_t:	Wool
		$\overline{CS}_t$:	Other
CS_c	Fiber color of a potential common source	CS_c:	Red
		$\overline{CS}_c$:	Other

Note that $i = 1$ and $i = 2$ denote the first and the second item of evidence, respectively.

TABLE 3—*Probability table of the nodes $S_{i,\,t}$.*

	H	H_1		H_2	
	CS_t	Wool	Other	Wool	Other
$S_{i,\,t}$	Wool	1	0	γ_w	γ_w
	Other	0	1	$1-\gamma_w$	$1-\gamma_w$

declare a fiber's type being wool when in fact it is not, then the following assessments are appropriate: $\Pr(E_{i,\,t}|S_{i,\,t}) = 1$ and $\Pr(E_{i,\,t}|\overline{S}_{i,\,t}) = 0$, for $i = 1, 2$. As far as the observation of the fiber's color is concerned, the argument applies analogously to the nodes $E_{i,c}$.

The probability tables associated with the source nodes $S_{i,\,\{t,c\}}$ contain either logical probabilities or frequencies. Consider, for example, the probabilities assigned to $S_{i,t}$ given H: if the two items of evidence come from a common source (H_1 being true), and that common source consists of wool ($\Pr(CS_t = wool) = 1$), then logically, $\Pr(S_{i,\,t} = wool|H_1, CS_t = wool) = 1$, with $i = 1, 2$ standing for the items of evidence 1 and 2, respectively. Analogously one has $\Pr(S_{i,\,t} = other|H_1,\ CS_t = other) = 1$. However, if the two items of evidence do not have a common source (H_2 being true), then the truthstate of CS_t is not relevant when assessing the nodes $S_{i,\,t}$. In the latter case the probability of the source of an item of evidence being wool is just given by the frequency γ_w of wool in a relevant population. Table 3 provides a summary of the probabilities assigned to the nodes $S_{i,\,t}$.

The probability tables of the nodes $S_{i,\,c}$ are completed in a similar way. When H_1 is true, i.e., the two items of evidence come from a common source, then the probability of $S_{i,\,c}$ being red, for example, depends on the probability of the common source being red: thus $\Pr(S_{i,\,c} = red|H_1,\ CS_c = red) = 1$ and $\Pr(S_{i,\,c} = red|H_1, CS_c = other) = 0$. Note that when H_1 is true, the truth or otherwise of the $S_{i,\,t}$ do not affect the $S_{i,\,c}$. The contrary holds when the two items of evidence do not come from a common source, i.e., H_2 being true. Then, the probability of the source of an item of evidence being red, for example, depends solely on the fiber's type. The variable γ_r denotes the frequency of red among woolen sources of fibers. The variable γ'_r denotes the frequency of red among sources of fibers other than wool. Note that the directed edge between the nodes $S_{i,\,t}$ and $S_{i,\,c}$ is justified as long as the parameters γ_r and γ'_r assume different values.

In a Bayesian network, set up according to the aforementioned specifications and hypothetical values $\gamma_w = 0.4$ and $\gamma_r = \gamma'_r = 0.1$, an initial (prior) probability of 0.5 for the proposition H_1 evolves to *c*. 0.9615; this corresponds to a likelihood ratio of $1/\gamma_w\gamma_r = 1/0.4 \times 0.1 = 25$ (Tables 3 and 4).

Notice that discussion so far has focused on *discrete* attributes of evidence whereas it may not be rare to have evidence characterized by *continuous* measurements (e.g., RI measurements on fragments of glass). The previously discussed Bayesian network shown in Fig. 1 could be modified to handle continuous variables. Such models would allow scientists to approach the problem in a way that agrees with literature (4) on situations involving one measurement and assumed Normal distributions for within- and between-source data.

Below we would like to invite the reader to consider an alternative approach—based on simulation techniques—to deal with continuous variables in situations where a potential source is unavailable. The proposed approach can help to generate a collection of cases assumed to occur in situations with a particular framework of circumstances (notably parameters thought to affect observations). The case under investigation is then considered with respect to a collection of cases of interest.

Continuous Measurements of the Evidence

Imagine two cameras, each of which records a temporally, and possibly geographically, distinct event. Let us assume that an individual (e.g., a male) is discernible in both recordings. From an investigative point of view, it may be of interest to know whether or not the two recordings display the same person.

Evaluation of evidence in such cases poses particular difficulties. For example, surveillance cameras often produce low-quality black-and-white images. Individuals would act so that characteristics of their faces are poorly visible, etc. Clothing may not be a reliable parameter either: the same individual may wear different clothing on temporally distinct occasions.

A parameter that might, however, be of interest is a person's height. The latter has a long tradition in forensic science, as it is, for example, one of the principal anthropometric measurements initially described by Bertillon's signaletic instructions (13). Even today, height measurements are still widely used, notably for criminal identification purposes.

In the scenario considered here, imagine that scientists were to consider the height of the individual recorded by each camera. It will be assumed that, based on a particular image produced by either camera, some method is available that allows scientists to obtain a presumed distribution of the height of the individual recorded by the respective camera. Two propositions of interest are defined as follows:

- H_1: The images obtained from the two cameras represent the same individual;
- H_2: The images obtained from the two cameras represent two different individuals.

Note that the present scenario assumes that there is no suspect from which height measurements could be taken.

Consider a generic individual that appears in a recording made by a camera. The height of this individual is a realization of a Normal random variable x, $x \sim N(\mu,\tau^2)$. The parameters of such a distribution are, however, unknown, but, through careful analysis of a recording, scientists may gather information that should allow them to infer something about the true values. The estimates thus obtained will be affected by a certain error whose amplitude is crucially dependent on the complexity of the scenario under consideration. Stated otherwise, the complexity of the scenario

TABLE 4—*Probability table of the nodes $S_{i,c}$.*

	H	H_1				H_2			
	$S_{i,\,t}$	Wool		Other		Wool		Other	
	CS_c	Red	Other	Red	Other	Red	Other	Red	Other
$S_{i,\,c}$	Red	1	0	1	0	γ_r	γ_r	γ'_r	γ'_r
	Other	0	1	0	1	$1-\gamma_r$	$1-\gamma_r$	$1-\gamma'_r$	$1-\gamma'_r$

and the consequent difficulties met by the experts tend to alter the perception of the real height of the person recorded. Generally, the more complicated a scenario, the higher the expected errors.

Thus, a difference in the estimated heights may not necessarily mean that individuals recorded by two cameras are different persons. The purpose of the discussion presented below is to investigate the effect that a scenario's complexity may have on height estimations. Also, simulations will be performed with the aim of providing scientists with a tool that may assist them in comparing height measurements pertaining to different cases, and drawing inferences regarding propositions of common source.

Assume that, given a particular scenario and circumstantial parameters (e.g., the position of the individual), the scientist is able to provide an estimate of the distribution of the error that affects an evaluation of height. As mentioned above, height evaluations may be more or less complicated, depending on the scenario. One should also be reminded that analytical procedures may vary from one expert to another, and so lead to different conclusions. Typically, positive and negative values for errors could be equally likely. It thus appears reasonable to assume a symmetric prior around 0 with standard deviation reflecting the range of plausible values that errors may take.

Consider this in terms of an example. Imagine video recordings made by two cameras during bank robberies committed in two different towns. Each recording depicts an individual. The time lapse between these two offences is such that it is conceivable that the same person could be involved. The case circumstances are as follows:

- *Case 1*: the image captured from the recording is rather sharp, depicting the shape of a person in an upright position (without headwear). Generally, the characteristics of the case are such as to induce low errors of evaluation. For the purpose of illustration let the error be represented by a distribution of type Normal with mean 0 and a variance fixed at 0.5, graphically represented in Fig. 3(*a*).
- *Case 2*: here, only a low quality image is available and the individual depicted stays partially behind a counter. In addition, the person is wearing a baseball cap. Greater errors may thus be expected. Assume a Normal distribution with 0 mean and variance 1 (see Fig. 3*b*).

Let e_j denote the error affecting an individual's unknown height any time the expert evaluates it. This error is the realization of a Normal random variable, $e_j \sim N(\bar{e}_j, \tau_e^2)$. Consider a distribution modeling the amplitude of the error affecting the estimated height distribution. In particular, the mean $\bar{e}_j$ is assumed to be Normally distributed, $\bar{e}_j \sim N(\theta_e, \sigma_e^2)$, while the variance is fixed. Summarizing, we have a hierarchical model:

First level

$$x_i \sim N(\mu_i, \tau^2)$$
$$e_j \sim N(\bar{e}_j, \tau_e^2)$$

Second level

$$\mu_i \sim N(\theta, \sigma^2)$$
$$\bar{e}_j \sim N(\theta_e, \sigma_e^2)$$

It is supposed here that the magnitude of error is independent of the height of a person. Denote with t_{ij} the height of a person, $i = 1, 2, \ldots$, evaluated on the basis of an image captured from a recording made by the jth camera. This can be considered as a random variable sum of the unknown height of the subject x_i and the error e_j:

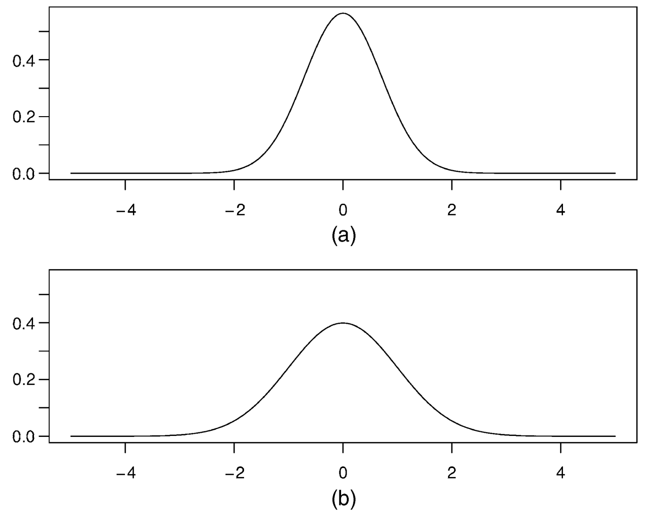

FIG. 3—*(a) Case 1: probability density of the error of type N(0, 0.5); (b) case 2: probability density of the error of type N(0, 1).*

$$t_{ij} = x_i + e_j \quad i = 1, 2, \ldots; \quad j = 1, 2 \tag{3}$$

where $x_i \sim N(\mu_i, \tau^2)$, $e_j \sim N(\bar{e}_j, \tau_e^2)$. The estimated height t_{ij} is then normally distributed with mean $\mu_i + \bar{e}_j$, and variance $\tau^2 + \tau_e^2$.

The difference d between the evaluated heights of two generic individuals, is still a normal random variable whose parameters follow from Eq. (3): $d \sim N(\mu_d, \tau_d^2)$.

So, given an observed difference, say d_{obs}, the aim is to compute a likelihood ratio, V, i.e., the ratio of the density of the difference between the estimated heights given that the images depict the same individual, and the density of the same value given that the images actually represent two different individuals:

$$V = \frac{f(d_{obs}|\mu_d, \tau_d^2, H_1)}{f(d_{obs}|\mu_d, \tau_d^2, H_2)} \tag{4}$$

In order to estimate the numerator and the denominator of V, a population of $n = 100{,}000$ individuals is generated. The height of each individual is normally distributed, $x_i \sim N(\mu_i, \tau^2)$, $i = 1, \ldots, n$. The mean is also normally distributed, $\mu_i \sim N(\theta = 175\,\text{cm}, \sigma^2 = 100\,\text{cm})$. The variance τ^2 is assumed constant and dependent on the overall precision of the analytic procedure, i.e., the higher the precision, the lower the variance and vice versa. Let τ^2 be 0.2 cm.

Next, the distribution for each individual's height is altered by the expected magnitude of the error that a given scenario is thought to induce. The error relating to the ith individual, captured by the jth camera, is modeled by a Normal distribution with mean $\bar{e}_j$ and variance τ_e^2. The parameter $\bar{e}_j$ is sampled from the distributions characterizing the aforementioned case scenarios 1 and 2 (see also Fig. 3).

For evaluating the numerator of the likelihood ratio V (Eq. [4]), n couples of identical individuals are considered, i.e., the differences between each individual's height under the two scenarios of interest, in order to estimate the distribution of d_{obs} under H_1. The

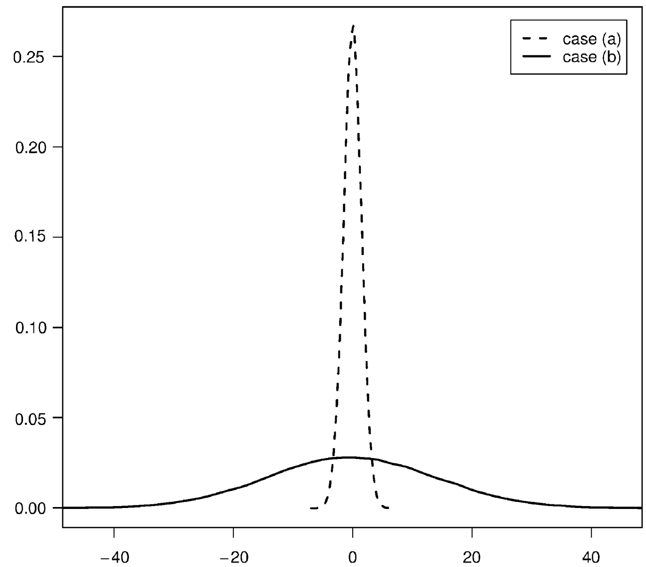

FIG. 4—*Probability densities of the estimated height differences for couples of identical individuals (a), and couples of random individuals (b).*

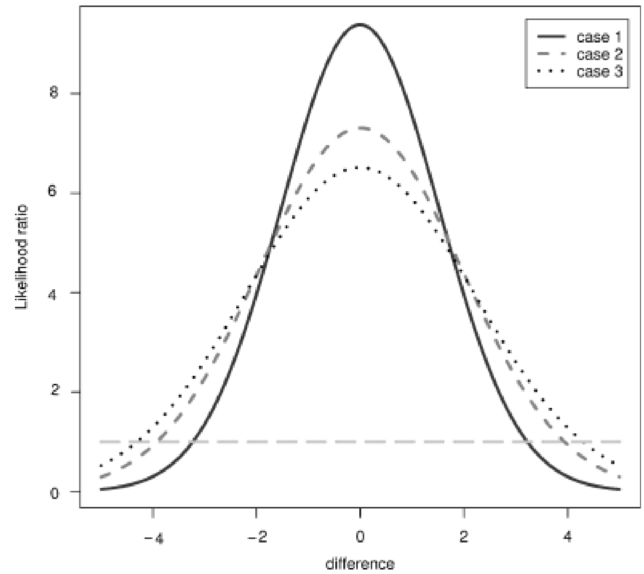

FIG. 5—*Likelihood ratio for three different scenarios. Case 1: $\bar{e}_1 \sim N(0, 0.5)$, $\bar{e}_2 \sim N(0, 1)$; Case 2: $\bar{e}_1 \sim N(0, 1)$, $\bar{e}_2 \sim N(0, 2)$; Case 3: $\bar{e}_1 \sim N(0, 2)$, $\bar{e}_2 \sim N(0, 4)$. The dashed horizontal line serves as a reference to locate likelihood ratios of 1.*

evaluation of the denominator is a consideration of n couples of randomly chosen distinct individuals, i.e., the difference on the one hand, between the height of an individual under scenario 1, and, on the other hand, the height of another individual under scenario 2. The latter allows for an estimation of the distribution of d_{obs} under H_2.

The approach can be summarized by the following three steps:

1. generate a population of n individuals;
2. alter the height distribution of every individual according to the errors that each scenario is thought to induce; and
3. compile sets of intra- and interindividual differences between height distributions given the two scenarios of interest and evaluate the likelihood of identity and nonidentity given a questioned difference.

Figure 4 displays the density of the intra- and interindividual differences between height distributions given the two alternative scenarios described above.

For the purpose of illustration, imagine the following two situations:

1. Suppose that the estimated mean of the height of the person recorded by camera 1 is $E(t_{i1}) = 172$, $i = 1, \ldots, n$, the estimated mean of height of the person recorded by camera 2 is $E(t_{i2}) = 178$, $i = 1, \ldots, n$, while the (error) variance is fixed at 0.4 for both cases. The likelihood ratio can be obtained as follows:

$$V = \frac{f(6|\mu_d, \tau_d^2, H_1)}{f(6|\mu_d, \tau_d^2, H_2)} = \frac{0.000101}{0.026030} = 0.0039 \qquad (5)$$

   V is a ratio between the densities of the questioned height, derived from the databases relating to the propositions H_1 and H_2, respectively. The likelihood ratio, *c*. 258, is moderately strong evidence to support the proposition according to which the images display two different individuals.
2. Suppose again that the estimated mean of the height of the person recorded by camera 1 is $E(t_{i1}) = 172$, while the estimated mean of height of the person recorded by camera 2 is $E(t_{i2}) = 173.5$. The estimated variance is still 0.4 for both cases. The likelihood ratio can be obtained as follows:

$$V = \frac{f(1.5|\mu_d, \tau_d^2, H_1)}{f(1.5|\mu_d, \tau_d^2, H_2)} = \frac{0.16038}{0.02807} = 5.71 \qquad (6)$$

   This result provides limited support for the proposition according to which the images obtained from cameras 1 and 2 display the same individual.

Error is one of the parameters that affect the values of the likelihood ratio. As mentioned earlier, the magnitude of error is closely dependent on the complexity of the scenario. Generally, the more complex a scenario, the higher the expected error, and the lower the likelihood ratio. Consider this through an analysis of three different cases where the level of complexity is such as to induce the following degrees of error:

- *Case 1* : $\bar{e}_1 \sim N(0, 0.5)$; $\bar{e}_2 \sim N(0, 1)$.
- *Case 2* : $\bar{e}_1 \sim N(0, 1)$; $\bar{e}_2 \sim N(0, 2)$.
- *Case 3* : $\bar{e}_1 \sim N(0, 2)$; $\bar{e}_2 \sim N(0, 4)$.

Figure 5 represents the values of the likelihood ratio as a function of the difference between the estimated heights. It may be seen that, when the height difference is small, for example, likelihood ratios tend to become lower when the potential of error increases. The dashed horizontal line aids to distinguish between likelihood ratios that are greater than or less than 1, respectively.

The likelihood ratio is also influenced by the precision of the measuring instrument, or more generally speaking, the method or procedure. Recall that his parameter has been modeled by τ^2, τ_e^2. In the examples discussed so far the value has been fixed at 0.2. Thus, starting from a common scenario, such as $\bar{e}_j \sim N(0, 0.5)$, one may also compute the likelihood ratio given different levels of instrument or overall method precision. A graphical representation of this is shown in Fig. 6.

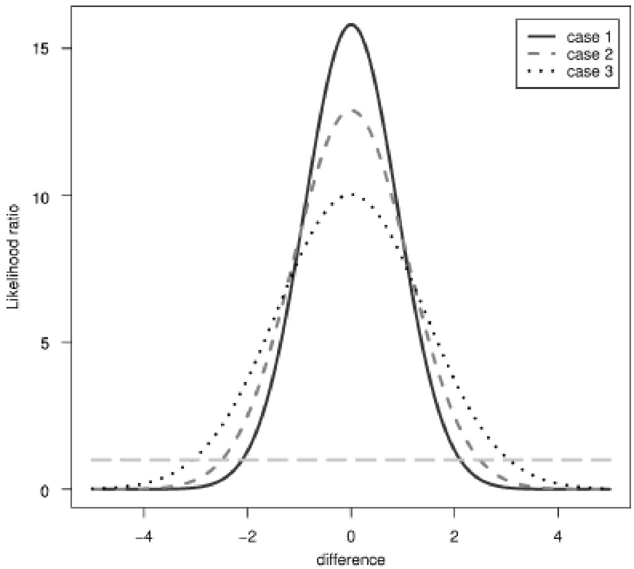

FIG. 6—*Likelihood ratios for a scenario with* $\bar{e}_j \sim N(0, 0.5)$ *but different levels of precision. Case 1:* $\tau^2 = \tau_e^2 = 0.1$*; Case 2:* $\tau^2 = \tau_e^2 = 0.3$*; Case 3:* $\tau^2 = \tau_e^2 = 0.5$*. The dashed horizontal line serves as a reference to locate likelihood ratios of 1.*

Beyond Inference of Identity

So far, the discussion has focused on items of evidence pertaining to distinct cases. The aim was to draw an inference regarding the proposition according to which the items of evidence considered share a common source. In practice, and in order to be pragmatic, information on a "common source" proposition is often interpreted as information that tends to "link" the cases of interest. However, one of the assumptions required for such inferences is that the items of evidence are relevant for the offences of interest. The notion of relevance, as it is taken here, is an attribute of evidence that expresses a true connection with the offender (14).

It is generally accepted that evidential relevancy is probabilistic in nature, as it "(. . .) may range from very likely to practically nil (. . .)" (14). In the analysis presented hereafter, Bayesian networks will be used to clarify the distinction between propositions of common source and propositions of linkage between cases, and the way in which reasoning from the former to the latter is affected by uncertainties in relation to evidential relevance.

For the purpose of illustration, consider the following scenario. Recordings are available from two distinct locations. In either recording, an individual is recorded as it leaves a building. It may be that these recordings are of interest because some sort of offense (a theft, posting of an anonymous letter, placing of a bomb, etc.) has been committed inside these buildings. Notice the following characteristics:

- Unlike the bank robbery scenarios discussed earlier in "Continuous Measurements of the Evidence," the recordings considered here do not actually capture offences. In fact, there may be many individuals leaving the building after the offense is thought to have been committed. This may be the case, for example, with a shopping mall, which is typically visited by a large number of individuals. Thus, one may be uncertain about whether the individual depicted in the recording is in fact the offender. It is assumed here that investigators are willing to provide a subjective judgment about the truth or otherwise of that proposition. To inform their judgment, they may consider whether or not the individual of interest was walking faster than other individuals, was seeming to behave such as to hide something under his coat, or was trying to hide his face while passing near the surveillance camera, etc.
- No suspect is available for comparison purposes.

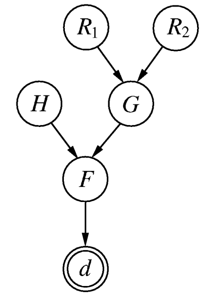

FIG. 7—*Bayesian network for inferring links between distinct cases.*

Let F be a binary variable that stands for propositions of common source:

- F_1: the images obtained from the two cameras represent the same individual.
- F_2: the images obtained from the two cameras depict two different individuals.

Imagine that the forensic scientist considers an evaluative framework as described in "Continuous Measurements of the Evidence." The estimated heights of the individuals are used as evidence for discriminating among the states of F. Let the evidence be defined as the height difference, written d for short with d_{obs} denoting a particular outcome. $F \rightarrow d$ is an appropriate Bayesian network fragment for describing the inductive process involved when reasoning from d to F. For the node d, means (μ_d) and variances (τ_d^2) need to be specified given, respectively, F_1 and F_2. Note that d is a continuous variable; this is highlighted in Fig. 7 through the use of a double-lined circle.

Evaluating the numerator and denominator of the likelihood ratio will lead the scientist to two expressions whose actual values are probability densities. These will be abbreviated here by, respectively, α and β:

- $\alpha : f(d_{obs}|\mu_d, \tau_d^2, F_1)$.
- $\beta : f(d_{obs}|\mu_d, \tau_d^2, F_2)$.

For the purpose of the current discussion, the actual values assumed by α and β are not of primary importance. It will suffice to note here that they can be assessed according to the procedure described in "Continuous Measurements of the Evidence."

When information is available about the truth or otherwise of F, the two recordings displaying the same individual, an inference may be drawn to the proposition according to whether the two offences have or have not been committed by the same individual. Let the latter proposition be denoted by H (with states H_1 and H_2). The degree to which knowledge about F provides evidence for H depends on whether either recording actually depicts the offender of the respective case. A new variable G is thus defined:

- G_1: Either recording depicts the offender of the respective case.
- G_2: Only one recording depicts the offender of the respective case.

TABLE 5—*Conditional probabilities applicable to the node F.*

	H	H_1			H_2		
	G	G_1	G_2	G_3	G_1	G_2	G_3
F	F_1	1	0	p	0	m	p
	F_2	0	1	$1-p$	1	$1-m$	$1-p$

- G_3: Neither recording depicts the offender of the respective case.

In analogy to (9), the nodes F, G, and H can be combined logically in a converging connection so that $H \rightarrow F \leftarrow G$ is obtained. The conditional node probabilities for the node F are a consideration of the following:

- If the two offences have been committed by the same individual (H_1), and the recordings of either camera depict the offender of the respective case (G_1), then certainly the two recordings depict the same individual: $\Pr(F_1|H_1, G_1) = 1$.
- If the two offences have been committed by the same individual (H_1), but only one recording depicts the offender of the respective case (G_2), then the persons depicted in the recordings must be different individuals: $\Pr(F_2|H_1, G_2) = 1$.
- If both offences have been committed by the same individual (H_1), but the recordings available for either case do not show the offender (G_3), then $\Pr(F_1|H_1, G_3)$ denotes the probability by which an innocent individual has, by chance, been recorded at two distinct events. Let $\Pr(F_1|H_1, G_3)$ be denoted by p.
- If the two offences have been committed by two different individuals (H_2), and either recording depicts the offender of the respective case (G_1), then certainly the two recordings depict different individuals: $\Pr(F_2|H_2, G_1) = 1$.
- $\Pr(F_1|H_2, G_2)$ is the probability that, given that the two offences have not been committed by the same individual (H_2), and only the recording of one case actually depicts the offender, the recording pertaining to the other case would display the same individual. This is an event in which the same individual has been recorded twice, but only once for noninnocent reasons. Let the occurrence of such an event be denoted m.
- Finally, when neither recording depicts the offender of the respective case (G_3), and, there are two different offenders, then, for F_1 being true, an individual must have been recorded twice for innocent reasons. This event may again be denoted p. In fact, the probability of recording the same individual twice for innocent reasons may be assumed to be independent of whether the two offences have or have not been committed by the same individual.

Table 5 provides a summary of the conditional probabilities assigned to the node F. Node G, a parent of F, relates to the "relevance" of the individual recorded by either camera, i.e., whether or not it is the offender of the respective case. However, while each state of G pertains to the joint occurrence of two events, scientists may find it easier to provide separate assessments of relevance in each case. This can be realized by specifying G as a logical combination of two binary nodes R_i ($i = 1, 2$).

- $R_{i,1}$: The recording pertaining to case i depicts the offender of the respective case.
- $R_{i,2}$: The recording pertaining to case i does not depict the offender of the respective case.

Generally, let r_i denote the probability that the recording of the ith case depicts the offender of the case.

For the purpose of the current example, two nodes R_1 and R_2 are chosen as parents for G. The corresponding conditional probabilities are listed in Table 6. The quantitative specification of the Bayesian network shown in Fig. 7 thus is complete.

Let us assume now, for the ease of exposition, that the parameters p and m are 0. The likelihood ratio then that is implied by the Bayesian network can be shown to be of the following form:

$$V = \frac{f(d_{\text{obs}}|H_1)}{f(d_{\text{obs}}|H_2)} = \frac{\alpha r_1 r_2 + \beta(1 - r_1 r_2)}{\beta} \tag{7}$$

The numerator of Eq. (7) is obtained by solving

$$\sum_{F,G,R,R1,R2} f(d_{\text{obs}}|F)\Pr(F|G, H_1)\Pr(G|R_1, R_2)\Pr(R_1)\Pr(R_2)$$

The denominator is obtained in an analogous way. A more formal outline of such calculus can be found, for example, in Garbolino and Taroni (9).

Equation (7) is a simplified version of a likelihood ratio earlier developed and proposed in (15) (for discrete items of evidence). Notice that when $r_1 \rightarrow 1$ and $r_2 \rightarrow 1$, the value of $V \rightarrow \alpha/\beta$. Thus, when both recordings depict the offender of the respective case, then the degree of support for the proposition of identity (i.e., the two recordings depicting the same individual) equals the degree of support for the proposition of case linkage (i.e., the cases being committed by the same individual).

Note also that in cases involving a discrete description of the evidence, α and β will refer to conditional probabilities (e.g., Pr ($E|F_1$) and Pr ($E|F_2$)) instead of probability densities.

Linking Cases: A Problem of Decision Making

Real-world circumstances in forensic science are such that lines of reasoning leading to definite conclusions of "common source," or, by extension, "case linkage," are generally not warranted. As noted throughout the previous Sections, limited variability of evidence characteristics in target populations, or measurement imprecision, are some of the factors that tend to make such inferences risky. Scientists may thus face uncomfortable situations when being asked to provide an opinion on whether or not, based

TABLE 6—*Conditional probabilities applicable to the node G.*

	R_1	$R_{1,1}$		$R_{1,2}$	
	R_2	$R_{2,1}$	$R_{2,2}$	$R_{2,1}$	$R_{2,2}$
G	G_1	1	0	0	0
	G_2	0	1	1	0
	G_3	0	0	0	1

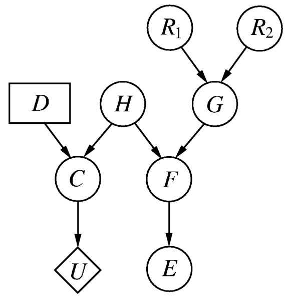

FIG. 8—*Decision network for addressing case linkage.*

on the scientific evidence considered, there is a "link" between two cases. The authors here feel that such questions emerge in part from a common misconception according to which scientific evidence by itself is thought to be sufficient for conclusively addressing propositions of common source or linkage. In general, due to lack of relevant background knowledge and the fact that this responsibility belongs to the recipient of expert information, scientists are not supposed to address such propositions.

It is in this context that it appears useful to draw the reader's attention to a distinction between, on the one hand, scientific evidence, which forms a basis for reasoning and the construction of arguments regarding propositions of interest (that may be probabilistic in nature, as suggested in this paper), and, on the other hand, the fact or state of actually believing in the truth or otherwise of such propositions, given the evidence. The former can be seen as a problem in inductive inference whereas the latter is a problem in decision making.

Earlier in this text, graphical models were used to clarify the inductive nature of the process of reasoning to propositions of interest, based on scientific evidence. The weight of the evidence was expressed in terms of a likelihood ratio. It provides rational actors with clear guidance as to how to revise their beliefs about a proposition, given newly acquired knowledge.

The question, however, whether there is a link between two cases, i.e., a proposition of case linkage being true, is a matter of subjective judgement. As certainty is practically unattainable, one may, at best, consider whether or not one's actual posterior odds, given all the available evidence, are such as to make it acceptable to believe in the truth or otherwise of the proposition of interest.

This aspect will be studied and illustrated below more formally using notions from decision theory. Decision theory combines utility theory and probability theory with the aim of describing what a particular agent should do. Expressed in very general terms, utility theory describes the preferences, desired outcomes, etc. of an agent, whereas probability theory provides an approach for evaluating what one should believe based on available evidence. Further details on forensic applications of decision analysis can be found, for example, in Taroni et al. (16).

As an example, let us consider a hypothetical scenario that can be described in terms of a Bayesian network similar to the one depicted in Fig. 7. H is the proposition according to which the two single-offender cases have been committed by the same individual. Scientists are in possession of information about a discrete proposition E, short for some item of scientific evidence. E could refer, for instance, to the combination $E = (E_1, E_2)$, where E_1 and E_2 represent the component evidence available from, respectively, cases 1 and 2. For the purpose of the current discussion, the continuous node d in Fig. 7 is thus replaced by a discrete node E (with states E and $\bar{E}$).

H is a proposition that may, for example, be of primary interest for an investigating magistrate. In his proceedings, it is common, and often necessary, to make a decision on whether or not the cases should be understood as being committed by the same individual. Such a decision might be required to lead further investigations in one direction or another. So far, the Bayesian network shown in Fig. 7 accounts for both the information provided by the scientist and the proposition of interest for investigators, but it does not yet wholly account for the decision problem that investigators are concerned with. Strictly speaking, the Bayesian network in Fig. 7 tells us what one should be thinking about H upon learning that E is true, but it does not explicitly account for the specific issues that affect the decision process of the investigator. An interesting question thus could be, whether the Bayesian network could be extended so as to aggregate within the same model the evaluative process of the scientist and the decision problem of the recipient of the expert information.

For this purpose, a decision network as shown in Fig. 8 is proposed. Decision networks, also called influence diagrams, contain, in addition to random variables, nodes for decisions and utilities. Decision and utility nodes are represented by, respectively, rectangles and diamonds. The different states of a decision node represent options for decisions or choices, whereas the utility provides a means for specifying the value of outcomes. Further details on how to work with these technicalities can be found, for example, in Taroni et al. (16) and references therein. Detailed presentations of decision networks are given in Jensen (12) or Cowell et al. (17). The practical implementation of decision networks is much the same as for Bayesian networks: conventional Bayesian network software allows decision and utility nodes to be readily incorporated.

While Bayesian networks are a tool for evaluating a current state of available knowledge, decision networks extend to a general framework for making rational decisions by incorporating an actor's possible actions, the state these actions will result in, and the desirability (i.e., utility) of these states. In other words, decision networks propose optimal decisions in the light of the available evidence and specified user preferences.

Note that in Fig. 8, a distinction has been made between the proposition H itself and an investigator's decision about this event: the proposition H is represented as a random variable, whereas the investigator's decision is represented by the node D. The rectangular shape of this node indicates that it is a decision node. The states "choose H" and "not-choose H," abbreviated D_1 and D_2, respectively, are proposed for the node D. A decision made at node D may be either correct (C_1) or incorrect (C_2), the latter being events modeled by a random variable C. Note that this node also has an entering arc from H. The probability table for C completes itself logically (see Table 7).

TABLE 7—*Numerical specification of the chance node C (left) and the utility node D (right).*

	H:	H_1		H_2				
	D:	D_1	D_2	D_1	D_2	C:	Correct	Incorrect
C:	Correct	1	0	0	1	Utility	10	0
	Incorrect	0	1	1	0			

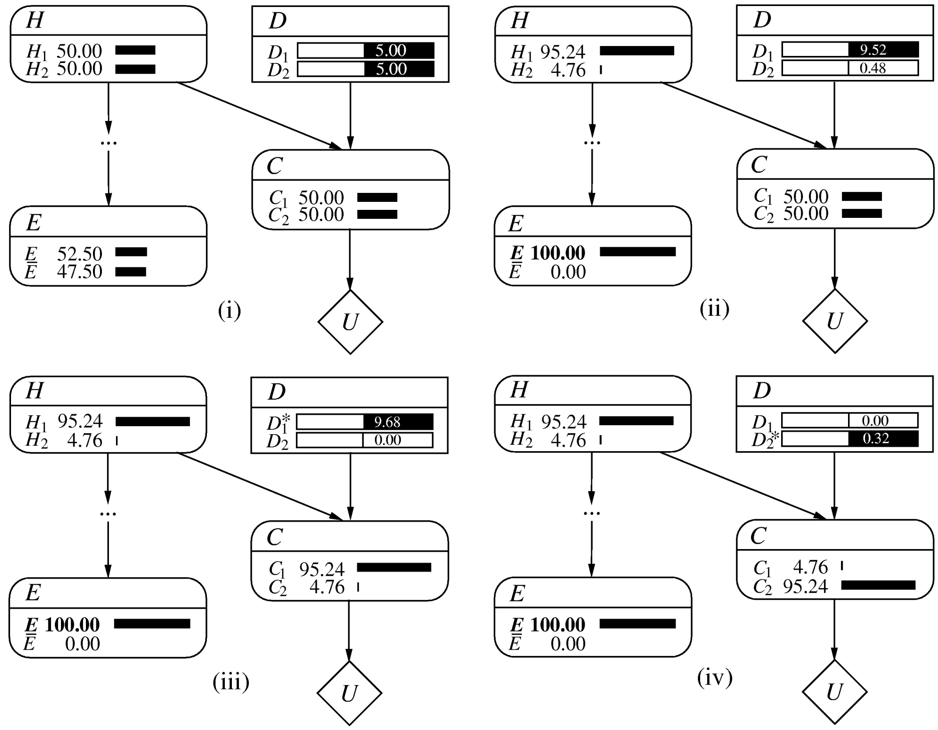

FIG. 9—*Different states of the decision network: (i) initial state, (ii) E is instantiated, (iii) E is instantiated and decision D_1 has been made, (iv) E is instantiated and decision D_2 has been made.*

In order to enable the system to recommend a certain decision, a utility needs to be defined. A utility scores the relative value of each outcome if correct. This utility is represented with the diamond-shaped node *U*, which has an entering arc from *C*. It seems natural to argue that a correct decision is preferable to an incorrect one. For the purpose of illustration, assign a utility of 10 for *C* being correct, and a utility of 0 for *C* being incorrect (Table 7). Notice, however, that the model is simplified in the sense that no difference is made in the utilities associated with incorrect decisions, i.e., falsely believing unrelated cases to be related, and related cases to be unrelated. Here, these situations are considered equally undesirable. Discussions on instances in legal contexts involving more detailed considerations can be found in, for example, (18) or (19).

With respect to Table 5, let $p = m = 0$. The respective outcomes of *E* given *F*, abbreviated by α and β, are set to 1 and 0.05, for instance. Evidence is assumed relevant in either case; thus $\Pr(G = G_1)$ is set to 1. An abbreviated representation of the decision network's initial state is shown in Fig. 9*i*.

Consider now what happens when node *E* is instantiated. This situation is shown in Fig. 9*ii*: the updated probabilities for *H* now are 0.9524 and 0.0476, respectively. This corresponds to a likelihood ratio of 1/0.05 = 20. One can also see that the values displayed in the decision node *D* have changed as well. Before receiving evidence *E*, deciding D_1 has the same utility as choosing D_2 (see Fig. 9*i*). Once *E* is known, *H* is considerably more probable to be true. Accordingly, it becomes more advantageous to opt for D_1 for which the node *D* now displays a value of 9.52 (Fig. 9*ii*). This value is termed *expected utility*, abbreviated *E*(*U*|*action*), where "action" refers to a particular option for a decision. Here, the expected utility of D_1 is calculated as follows: $E(U|D_1) = \Pr(C_1|E, D_1)u(C_1)+\Pr(C_2|E,D_1)u(C_2)$.

Note that the value of the node *C* does not change unless a decision has been made at the node *D*. Leave *E* instantiated and observe the changes in *C* while different states for *D* are chosen. This is shown in Fig. 9*iii* and *iv*. As may be seen, in these situations, the correctness of the decision is directly dependent on the truthstate of the variable *H*. All of these seem quite reasonable properties. They might even appear obvious. However, the actual numerical values are not of primary interest here. The aim is to show that, based on a specification of desirability of the various consequences of a decision, it is possible to evaluate which decision is advantageous in the light of specific evidence. In summary, the reader can realize that:

- A clear distinction can be made between what one should *think* about event *H*, based on evidence, and what one should *decide* about event *H*.
- A decision cannot be recommended unless values for outcomes are specified.
- The probability of event *H* is not affected by making a decision about that event. Stated otherwise, a decision *D* cannot affect a random variable occurring before *D*. This is also why there should be no directed link from *D* to *H*.

Although it would not be appropriate for a forensic scientist to propose a model including decision nodes that preferably concern investigators, it appears to be worth mentioning that graphical models provided by forensic scientists can be integrated in decision networks covering issues that are in the competence of other actors of the legal system. Ideally, a decision network for evaluating both the force of evidence and an investigative decision problem would be the result of the joint collaboration between forensic scientists and investigators.

Discussion

The present paper has focused on issues that may affect the evaluation of evidence in situations involving the comparison of crime material from different cases with no potential source being available. The assessment of such comparisons is a consideration of, for example, the nature of the data (discrete, continuous), the propositions of interest (proposition of common source, proposition of case linkage), or the level of detail at which the evaluation is made.

Generally, inferences of common source or case linkage involve risky arguments, requiring sound rules of reasoning. Throughout the text, probability theory has thus been used as a means to deal with uncertainty. In areas of forensic expertise, such as evaluation of evidence at trial, probability now represents a rather well-established framework. While reasoning under uncertainty is also an essential part of forensic intelligence, probability theory does not seem, however, to be systematically incorporated in such contexts.

In Ribaux et al. (20), a general model was proposed whose building blocks consist of so-called "primitive forms of inferences." These are routinely or occasionally performed when evaluating forensic case data. According to one of these forms of inference, observed similarities or close analogies between crime stains may be used to, for example, "infer that the traces are from common sources" (20). The concept of "primitive inference" can be helpful to scientists essentially when there is a need to process large amounts of case data. In a working procedure that goes from the general to the particular, scientists can be enabled to select "promising candidates." However, the argumentative foundations of such inferences are not stated explicitly. Analysts should thus take particular care, and the authors in (20) insist well on this point, that the application of primitive inferences is circumstantially evaluated within the respective criminal justice system.

Besides associating items of evidence on the basis of similarities in compared characteristics, scientists may also be called on to assist in the evaluation of the *nature* and the *strength* of inferred links. It is this particular aspect on which the present paper has primarily focused. The aim was to study in further detail the ways by which scientists may aid the construction of arguments regarding propositions of common source or case linkage. Within that process, several intermediate propositions are usually encountered together with distinct sources of uncertainty. Probability theory is an appropriate tool to guarantee coherence of one's inferences under such circumstances. However, even when considering only a few variables, formal probabilistic calculus may soon become intractable. Assistance in dealing with such difficulties is provided by formalisms such as Bayesian networks. Their application to the problems under study has been considered here in further detail.

It was found that, under certain assumptions, propositions of interest are supported by a likelihood ratio of $1/\gamma$, where γ is, roughly speaking, an expression of the rarity of the compared characteristic. This is a result already well known in forensic literature, notably in the context of comparisons of a single item of evidence with a known source (15). Thus, the proposed analysis may appear rather unspectacular. However, the reader should recall the conceptual differences that exist between one- and two-stain scenarios and that in the latter, the "$1/\gamma$-result" holds only under special circumstances. Consider the following.

In a classic one-stain scenario, reference material from a putative source is usually available in abundance and forensic scientists can perform extensive testing on it. Scientists will thus have little uncertainty about its characteristics. Observable traits on the crime stain, however, may—for various reasons such as degradation, low quantity, etc.—provide an incomplete or distorted representation of the characteristics of the source it comes from. These observations are then assessed in the light of what is known about the putative source (under H_1).

The "two-stain no putative source" scenario is different in that respect. Here, scientists are not in the privileged position to arrive at a detailed description of the potential common source. Instead, they must infer the characteristics of that source based on what they can observe on the item of evidence available in each of the two cases. The difficulty is that in either of these cases, the respective crime stain is likely to lack the qualities of reference material typically accessible in a one-stain scenario. This is why, for example, the Bayesian networks shown in Figs. 1 and 2 allow for a distinction between the observations made on a crime stain and the characteristics of the source that it comes from. This can allow scientists to account for uncertainties that they may have when drawing inferences about properties of a source based on observations made on a possibly non representative and/or degraded sample. In such situations, it may be that scientists prefer retaining values—considering Fig. 1 for instance—such that $\Pr(E_i|S_{E_i})<1$ and $\Pr(E_i|\bar{S}_{E_i})>0$ $(i=1,2)$, instances where the expression of the value of the evidence would deviate from $1/\gamma$.

Conclusions

A probabilistic approach paired with notions from graph theory has the potential of clarifying the assumptions underlying inferential procedures that intelligence analysts may be concerned with. The nature of the conclusions and the way by which they have been reached are compatible with current practices of probabilistic evaluation of evidence in forensic science.

Production of intelligence requires analysts not only to be of assistance in reasoning about what to believe about specific propositions of interest based on evidence, but also to be consultants when particular decisions need to be made. In such contexts, graphical probability models can be extended and used to incorporate notions from decision theory. These provide a logical extension to purely evidential reasoning and enable analysts to perform rigorous analyses of the risk associated with particular decisions.

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