Border Security Credibility Assessments via Heterogeneous Sensor Fusion

Douglas C. Derrick, Aaron C. Elkins, Judee K. Burgoon, Jay F. Nunamaker Jr., and Daniel Dajun Zeng, *University of Arizona*

A heterogeneous network of sensors that measure physiological and behavioral indicators of arousal, cognitive effort, and stress can facilitate deception detection, while limiting subjective judgments and improper profiling.

Assessing an individual's credibility is an increasingly urgent problem in light of escalating international security threats. Discriminating between deceit and truth is a constant security challenge in a variety of situations, including border crossings, job interviews, flight passenger screenings, and police interviews. Compounding this problem, a large body of research shows that humans are not proficient at detecting deception without special training or technological aid. A meta-analysis summary of more than 200 experiments shows that people can distinguish truths from lies, on average, 54 percent of the time.[1,2] This level of accuracy is statistically greater than chance but is extremely poor in practical applications. Furthermore, individual differences such as age, professional experience, education, cognitive ability, and social skills make little difference,[2] and little variance exists overall in a person's ability to detect deception.[3] Similarly, criticisms of existing tools such as the polygraph have motivated the search for alternative technologies to detect deception and hostile intent, especially ones that can be implemented unobtrusively and noninvasively in the field. These security demands, coupled with human limitations, have created a need for intelligent monitoring systems that provide accurate and objective credibility assessments.

As a case in point, more than 300 million people legally pass through the US-Mexico border every year, and border officers must simultaneously address security, immigration, and trade issues. Mexico and Canada are the largest trading partners of the US. However, intermingled with this huge volume of legal commerce, illegal border crossings are a persistent problem. Clearly, one of the most challenging and important aspects of border security is distinguishing truth from deceit in interpersonal communications, while limiting interference with vital, legal commerce.

To more completely understand this pressing need, we conducted a field study with agents from US Customs and Border

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Protection, Immigration and Customs Enforcement, and the Federal Bureau of Investigation. Our goal was to bring representatives from these agencies together where they could anonymously discuss the issues they face in their daily work. Agents indicated they would like to see technology fielded that will aid in the detection of hostile intent, criminal backgrounds, and deception when interviewing people at ports of entry and when apprehending suspects in the field.

In our ongoing research, we are developing a heterogeneous sensor network to help meet these border security challenges and help humans detect deception quickly and accurately. The US Department of Homeland Security (DHS) and the Defense Academy for Credibility Assessment (DACA) fund these efforts in order to bring objectivity and accuracy to screening decisions. This article discusses the underlying psychophysiological processes of deception and how they correlate to the heterogeneous sensors in our network. The raw data from these individual sensors might be contradictory or inconclusive and the varied types of data—including video, infrared pupillometry, thermal imaging, heart rate, blinks, and vocalic analysis—compound the problem of data fusion and interpretation. Therefore, we also show an example of how to fuse and evaluate the disparate data to provide a clear and distinctive classification. Finally, we describe a laboratory experiment and report the preliminary findings using a noncontact cardiorespiratory sensor fused with human judgment to predict deception.

Cues to Detecting Deception and Sensors

Most current deception-detection methods, both behavioral-observation and technological assessments, presume that emotions, arousal, and cognitive effort prompt physiological, psychological, or behavioral responses that provide a basis for reliable lie detection. Research has shown that those who are deceiving often experience a different state of arousal and stress than truth tellers. This state might manifest itself in several physiological responses, including pupil dilation; change in heart rate and blood pressure; increase in body temperature, especially around the face and eyes; and changes in blink patterns. Deception might also be associated with various behavioral responses called *leakage*—unintentional signs that "leak" out of the body.[4]

Screening technologies should take advantage of all these possible measures to obtain the most robust and reliable assessment of an individual's state of arousal and stress. Our leading-edge sensor network captures and evaluates these pyschophysiological and behavioral cues for deception. The goal is a seamless, unified, and automated system of deception detection from multiple sensors.

To test our sensor network, we performed noncontact monitoring of individuals as they were questioned about their involvement in a mock crime. In this first phase, each sensor collected their measurements individually, and then we combined the data after the experiment. We collected and stored the data on a storage area network (SAN).

Figure 1 shows how we arrayed the sensors for the mock crime experiment. We deployed a corresponding sensor to monitor each of the potentially relevant physiological and behavioral indicators.

Pupilometric Indicators

Pupilometry is the study of changes in pupil size and movement. Pupil dilation can result from sympathetic nervous system stimulation or suppression of the parasympathetic nervous system. These peripheral nervous system responses are theorized to reflect arousal or stress, which result in pupil dilations. Research has shown that the cognitive processes and arousal involved in deception impact pupillary response. Specifically, we can see larger pupil dilations in "guilty" participants of Concealed Information Tests (CITs).[5] Daphne P. Dionisio, and her colleagues also reported that deceptive responses to a recall task reliably produced larger pupil responses than truthful answers.[6]

To capture these types of responses, we integrated a Fujifilm FinePix IS-1 sensor into our network with infrared capabilities concentrated on the participant's eyes using external infrared light sources to magnify and detect pupil changes from a distance.

Thermal Indicators

Thermal-imaging technology measures changes in regional facial blood flow, particularly around the eyes. Changes in the orbital area might reflect changes in blood flow related to the fight-or-flight response mediated by the sympathetic nervous system. Ioannis Pavlidis and his colleagues created a thermal signature of deception that is detectable via infrared technology.[7] Using this technique, they were able to correctly classify 83 percent of the participants as innocent or guilty. They used the average pereorbital temperature to establish a baseline for an individual. A deceptive or nondeceptive classification is made based on the temperature signal patterns identified during the interaction.

Figure 2 shows thermal-imaging output and our control console using a FLIR thermal imaging camera. It is set on a QuickSet International

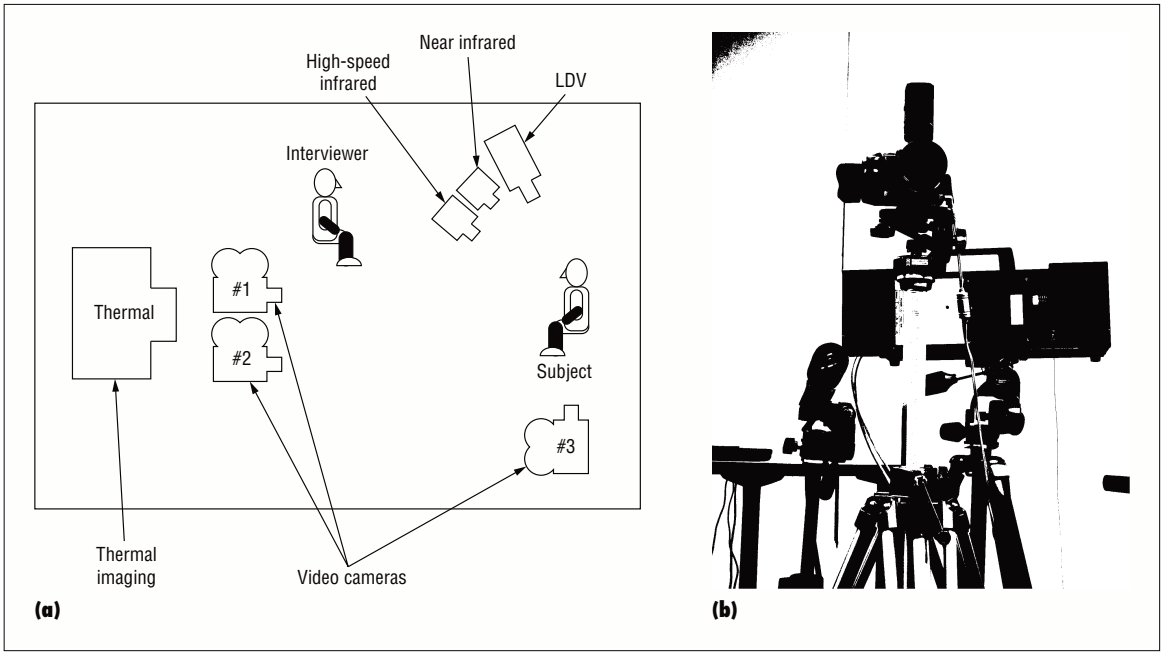

Figure 1. Capturing pyschophysiological and behavioral cues for deception. (a) Our sensor network consists of numerous sensors, such as (b) ultra-fast-infrared and near-infrared cameras, and the Laser Doppler Vibrometer (LDV).

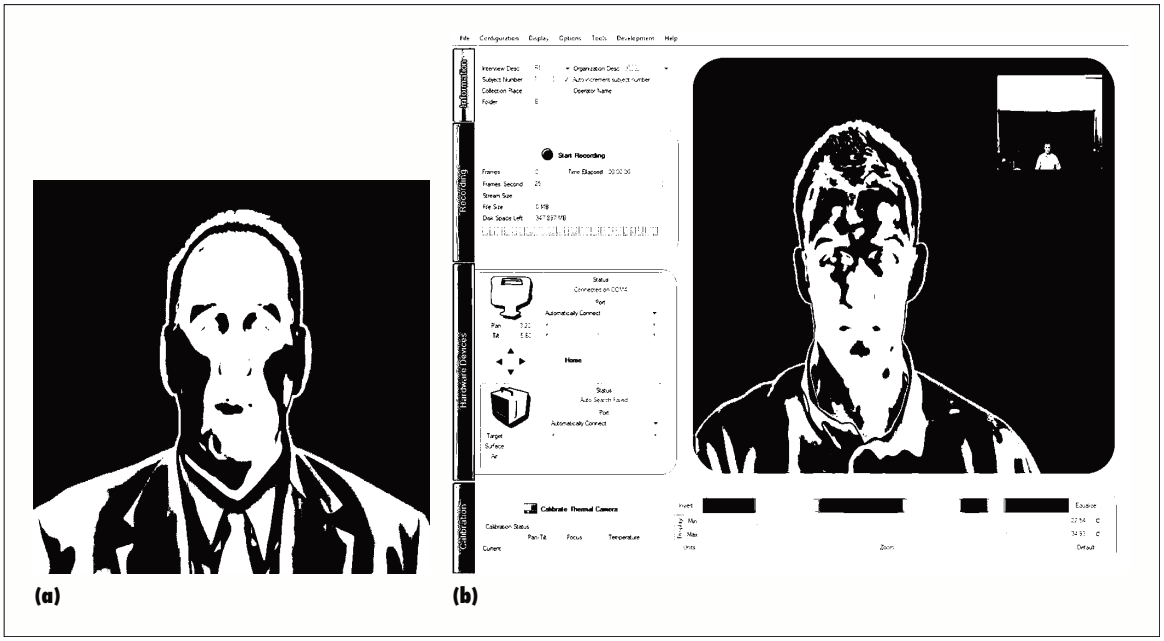

Figure 2. Thermal imaging. (a) This sample shows a participant's face with heat emanating around the cheeks and eyes (b) The console illustrates the visible light video (top right) and heat coming from the eyes and forehead.

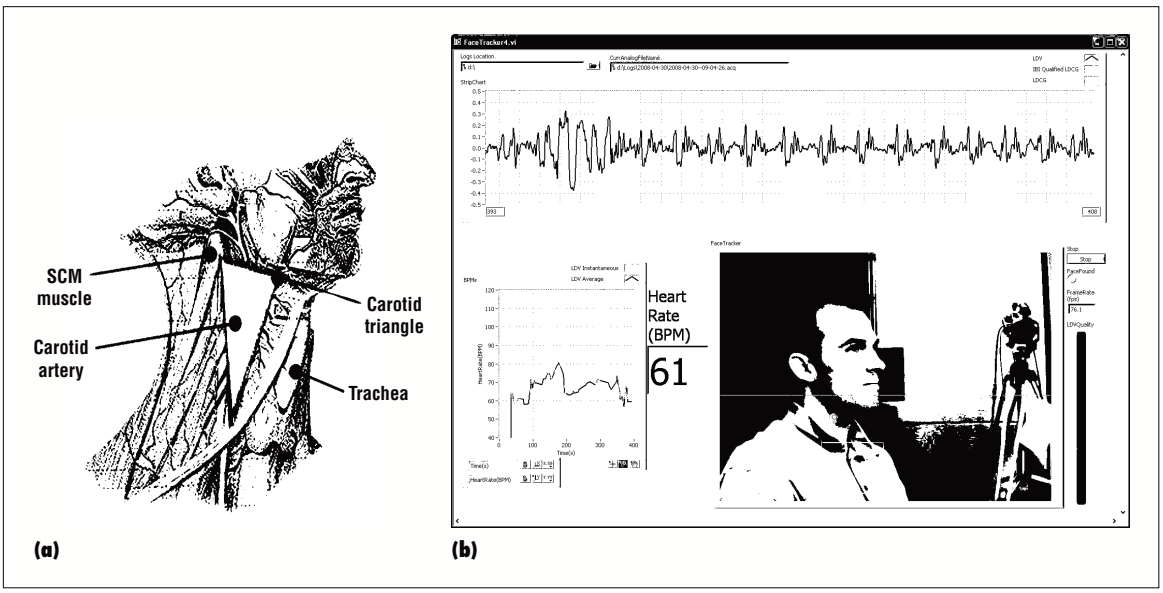

Figure 3. Collecting cardiorespiratory reponses. (a) The Laser Doppler Vibrometer (LDV) sensor targets the participant's neck. (b) The console shows changes in the participant's heart rate.

pan-tilt device and paired with an infrared black body and black body controller.

Cardiorespiratory Indicators

Research has shown that pulse rate, blood pressure, and respiration rate are also reliable indicators of deception. Cardiorespiratory measures are sensitive to emotional stress, which is predicted to vary between truth tellers and liars. This is believed to result from an increase in cognitive effort and behavioral control needed to appear convincing. Differences in cardiovascular measures such as increased pulse rate have been identified during deceptive communication.[8] Cardiovascular measures are particularly appealing because they remain involuntary, even though humans can regulate their breathing. Despite this fact, recent studies have shown that individuals tend to inhibit breathing when faced with stress commonly found during deceptive situations.[9] Continuing advances in technology promise to provide more potential cardiovascular indicators of deception including systolic time intervals and contractility.[10]

To noninvasively capture cardiorespiratory measurements, we used the Laser Doppler Vibrometer (LDV) sensor. The LDV system uses laser imaging and Doppler sound waves to measure the carotid artery's pulsations in a visible portion of the neck. The LDV technology is based on the theoretical concept that internal physiology has mechanical components that can be detected in the form of skin surface vibrations. The system utilizes a class-two (medically safe) laser and Doppler effect to sense and measure vibrations in the carotid artery by targeting the carotid triangle. The multiple cardiorespiratory measures obtained are used to differentiate among stress and emotional states. Automatic face-detection software keeps the laser on the participants' neck and is able to follow gentle movements.

Figure 3 shows the LDV console and sample output including a real-time heart rate. The cardiorespiratory sensor is the PolyTech LDV controlled by a prototype face tracking and monitoring system.

Blinks and Startle Response Indicators

Eye blink frequency and intensity can be accurate indicators of stress. Furthermore, the blink component of the startle pattern is related to a person's emotional state and attention. Kyosuke Fukuda reports that blink rates during a CIT are higher when participants falsely denied recognition of the familiar stimuli.[11] Additionally, blinks punctuate moments of taking in and processing information.

To capture such responses, we use an ultra-fast-infrared camera that can capture at 250 frames per second. This sensor is a Photron FastCam PC1 RS controlled by Photron FastCam Viewer software (see Figure 4).

Vocalic Indicators

Liars and truth tellers exhibit different acoustic vocal behavior.[12,13] Vocalic cues fall into three general categories: time (speech length and latency), frequency (pitch), and intensity

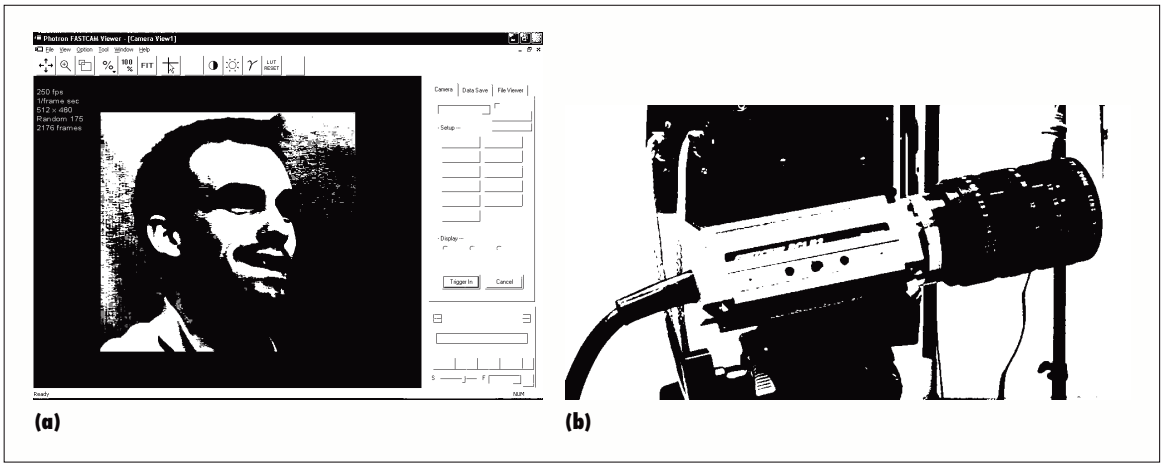

Figure 4. High-speed infrared console and camera for capturing blinks. Both blink frequency and a blink startle patterns relate to emotional state and stress. The camera allows for super-slow-motion processing of blinks.

(amplitude).[14] Previous research has demonstrated that when compared to truth tellers, deceivers speak less fluently, in shorter durations, and at slower tempos, and they exhibit greater response latencies.[12] Researchers have postulated that deceivers are more reticent to provide extra details, particularly during extemporaneous speech,[12] and require more cognitive effort to fabricate their responses. An increase in pitch or frequency has also been associated with arousal during deceptive responses,[12,13] which presumably results from the anxiety of being caught and facing negative consequences.

Using high-quality audio recording equipment and both commercial and custom vocal signal-processing software, we have been able to discriminated between truthful and deceptive speech.[15]

Kinesic and Proxemic Indicators

Empirical evidence suggests that deceivers move their hands and heads differently than truth tellers. Two meta-analyses found that deceivers perform significantly fewer illustrating gestures (those that normally accompany speech) compared to truth tellers.[13] Thomas Meservy and his colleagues developed a set of features that can be extracted from 2D image (frame) sequences that correspond to elements of these kinesic and proxemic indicators.[16] Past research has used these features to identify body movements that are related to deception.

Our sensor network contains three studio-quality video cameras focused on the face, body, and side profile. We synchronize the video streams and automatically extract the kinesic and proxemic features.

Initial Study

We collected experimental data using a protocol that required some participants to commit a mock crime and pass a credibility assessment about their involvement. We solicited participants for this study through local newspaper and Internet advertisements. Participants could earn $15 per hour for their participation, plus a $50 bonus if they were able to successfully convince the professional interviewer of their innocence. Participants were randomly assigned to conditions, with 40 percent assigned to the guilt/deception condition and 60 percent assigned to the innocence/truth condition. Of the 164 participants who reported for the experiment, 82 percent (N = 134) completed the tasks and interviews, and 18 percent were disqualified for confessing or not completing the tasks.

Procedure

Upon arrival, participants completed an informed-consent form, were randomly assigned to either the guilty or innocent condition, and received recorded instructions. The procedures were intended to heighten anxiety and simulate the circumstances surrounding actual criminal conduct. We took great care to limit and eliminate laboratory artifacts by restricting interaction with laboratory technicians, creating motivation for successful deception by offering substantial monetary bonuses to participants that were judged as credible, and by having the "crime" committed realistically. Those in the experimental group were asked to take part in a mock theft by taking a ring from a receptionist's desk and then attempting to conceal their actions during a subsequent credibility assessment. We instructed participants in the control (innocent) condition to report to the same locations. They were asked to cooperate with the credibility assessment process and be completely truthful.

All participants next reported to a nearby building, where they visited a reception office and asked for a fictitious Mr. Carlson. While the receptionist was ostensibly searching for Mr. Carlson, the "thieves" stole a diamond ring contained in a blue cashbox hidden under a tissue box within a desk drawer. The details of the crime were known only to the guilty. The "innocent" participants simply waited in the room until the receptionist returned and sent them to be interviewed.

Professional interviewers questioned all participants using a standardized interview protocol that consisted of a series of 24 short-answer and open-ended questions, CIT, and 10 questions during which the startle-blink manipulation was administered. The professional interviewer made a guilty or innocent judgment, which determined if participants received their monetary bonus. During the interview, sensors measured the participant's pupil dilation, preorbital temperature, cardiorespiratory activity, blink activity, kinesics (movements), and vocalics. Participants then completed a post-interview survey and were debriefed.

During this interaction, the noninvasive sensors detected and tracked physiology and behavior. Internal validity was a primary concern in this experiment, and the main intent was to show that the guilt manipulation resulted in measurable physiological or behavioral changes that when accurately captured can be fused to distinguish truth tellers from deceivers (see Figure 5).

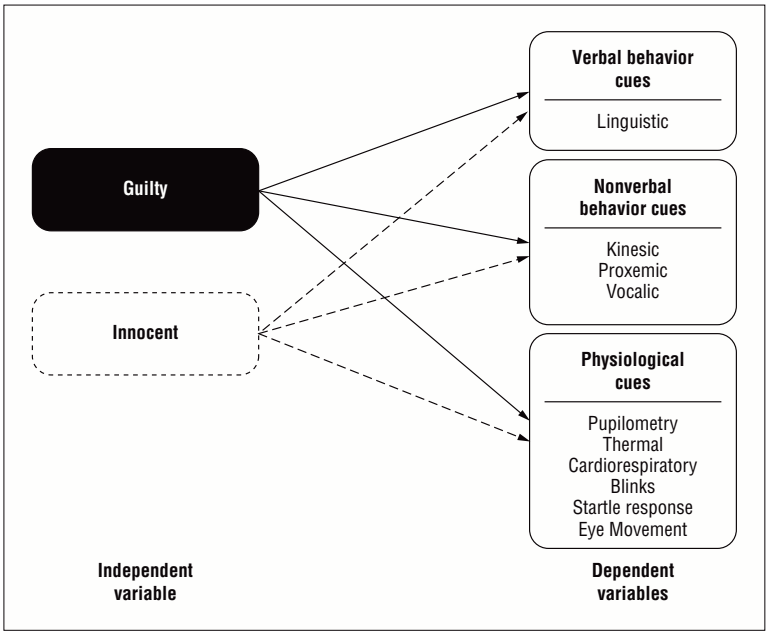

Figure 5. The two experimental treatments are shown on the left as the independent variables, and we expect the dependent measures on the right to manifest themselves during the guilty interactions.

Analysis

Our research is motivated to improve current state-based methods to achieve more accurate and robust deception detection in the context of sensor information fusion. From a modeling perspective, our approach considers a network of data streams as a whole instead of treating each data stream separately. The basic idea is that these data streams are closely correlated. We hypothesize that through explicitly considering such (probabilistic) correlations and estimating their strength by learning from historical data, we can achieve more accurate, holistic, and robust deception detection. We began our analysis by evaluating the data from the LDV.

Our initial analysis focused on three questions that formed the CIT, and we specifically examined the cardiovascular measure of interbeat interval (IBI). Several studies have shown that the IBI increases following all items in a CIT and the deceleration in heart rate is greater following responses to key items (such as items familiar only to the guilty).[17,18]

Interestingly, researchers have found that a comparable deceleration is highly diagnostic in laboratory studies using the Comparison Question Test (CQT).[19,20]

During our interviews, the professional interviewers asked the participants the following CIT items:

- If you are the person who stole the ring, you are familiar with details of the cash box it was stored in. Repeat after me these cash box colors: (a) green, (b) beige, (c) white, (d) blue, (e) black, (f) red.
- If you are the person who stole the ring, you moved an object in the desk drawer to locate the cash box containing the ring. Repeat after me these objects: (a) notepad, (b) telephone book, (c) woman's sweater, (d) laptop bag, (e) tissue box, (f) brown purse.
- If you are the person who stole the ring, you know what type of ring it was. Repeat after me these types of rings: (a) emerald ring, (b) turquoise ring, (c) amethyst ring, (d) diamond ring, (e) ruby ring, (f) gold ring.

Table 1. Concealed Information Test (CIT) Laser Doppler Vibrometer (LDV) classification results.

CIT set*	Accuracy (%)	True-positive rate (%)	False-positive rate (%)	True-negative rate (%)	False-negative rate (%)
Colors	56.1	43.3	33.3	66.7	56.7
Objects	63.6	66.7	38.9	61.1	33.3
Rings	66.7	76.7	41.7	58.3	23.3
Colors and objects	59.1	36.7	22.2	77.8	63.3
Objects and rings	68.2	60.0	25.0	75.0	40.0
Colors and rings	66.7	36.7	8.3	91.7	63.3
Colors, objects, and rings	65.2	33.3	8.3	91.7	66.7

*N = 66, with 30 guilty and 36 innocent.

We were interested in the behavioral and physiological responses to the blue, tissue box, and diamond ring items.

We needed to reduce the initial LDV data set because the targeting and tracking system was unable to target the carotid triangle because the interviewee moved too much, occluding the carotid triangle. The data were then processed to identify acceptable cardiovascular pulses and compute the IBI for each CIT items. IBI deceleration magnitude is the maximum IBI between two consecutive heartbeats in a six second period after a CIT item was repeated by the participant. We shortened the six-second-analysis periods if these intervals got too close to the beginning of the next CIT item. The decelerations following each of the neutral items' responses were averaged together, excluding the first and last neutral items in each set. Lastly, we calculated a single score for the expected deceleration for each participant by averaging the IBI decelerations for the remaining neutral CIT items.

Results

Of the 87 records initially deemed suitable for analysis, we rejected an additional 21 because of abnormal heartbeats and insufficient continuous heart-rate data. Using the neutral IBI CIT item deceleration averages and the decelerations based on the key items, we classified the remaining 66 participants as either guilty (where deceleration was greater after key items) or innocent for each CIT set and combination. Table 1 shows the results of this classification.

The true-positive rate (TPR) is the percentage correctly classified as guilty and the true-negative rate (TNR) is the percentage classified as innocent. The false-positive rate (FPR) is the percentage incorrectly classified and the false-negative rate (FNR) is the percentage incorrectly classified as innocent. For our purposes, the most accurate CIT set was the ring.

Our context is a high-stakes environment, so the FPR must be weighed against the FNR. If the FNR is high, it means that potential criminals are undetected in the screening process. If the FPR is high, it means that innocent people are being subjected to additional screening and we are slowing down the flow of legitimate border crossers. Based on this objective, the ring foil performed the best, catching 77 percent of the criminals, but at the cost of 42 percent innocent people being accused. This trade-off might be appropriate in a high-risk situation.

We see the real power of the sensor network when the LDV sensor data is fused with the human judgments. The interviewers were trained polygraph interviewers from the Department of Defense. Table 2 shows they performed at 71.2% accuracy in these 66 cases. However, they had a FNR of 30.0 percent, meaning that almost one-third of all the criminals went undetected. If we fuse the LDV data based on the following formula, $\text{HumanJudgment} \cup \text{LDVColor} \cap \text{LDVObject} \cap \text{LDVRing} = \text{Classification}$, the overall accuracy improves to 78.8 percent. More importantly, the FNR is decreased to 10 percent and the TPR increases to 90 percent, while only increasing the FPR by 2.8 percent. Clearly, fusing human judgments with LDV sensor classifications improves results.

We are in the process of empirically evaluating the technologies we describe here. In the near future, these technologies might be integrated into a system to objectively, automatically, and noninvasively assess credibility during rapid screening and border interactions.

There has been ever-increasing advancement in sensor technology allowing less invasive and noncontact measurement of behavior, physiology, and the environment. Although individual sensors provide valuable measurements, collectively they often introduce contradictory information, incompatible temporal scale and formats, noise, and redundancies. This situation has occurred because each sensor is designed to operate and perform best independently and not in

Table 2. Fusion of human judgment with Laser Doppler Vibrometer (LDV) data.

FOIL set*	Accuracy (%)	True-positive rate (%)	False-positive rate (%)	True-negative rate (%)	False-negative rate (%)
Human judgment	71.2	70.0	27.8	72.2	30.0
Human and LDV color	57.6	20.0	11.1	88.9	80.0
Human or LDV color	69.7	93.3	50.0	50.0	6.7
Human and LDV object	66.7	43.3	13.9	86.1	56.7
Human or LDV object	68.2	93.3	52.8	47.2	6.7
Human and LDV ring	71.2	53.3	13.9	86.1	46.7
Human or LDV ring	66.7	93.3	55.6	44.4	6.7
Human or LDV object and ring	74.2	93.3	41.7	58.3	6.7
Human or color and object and ring	78.8	90.0	30.6	69.4	10.0

*N = 66, with 30 guilty and 36 innocent.

the context of a sensor network. Currently, information quality is only as good as the lowest performing sensor in a heterogeneous and unfused sensor network. However, the potential exists for all the sensors to provide, collectively, more accurate and reliable information than any individual sensor.

Future research will need to address the challenge of fusing heterogeneous sensors, not only in the laboratory but in the field, where sensor data streams require fusion to occur in real time to aid decision making and alert agents and screeners to possible threats against homeland security. This will require investigation on techniques for analyzing and fusing real-time disparate sensors streams and determining how best to combine the sensor information to reduce false alarms during the decision process. A false alarm has measureable consequences on the border. In the context of border screeners, false positives waste resources and lead to increased traffic congestion, while a false negative equates to allowing terrorists or criminals to enter the United States.

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THE AUTHORS

Douglas C. Derrick is a PhD student at the University of Arizona. His research interests include human-computer interaction, agent-based computing, and persuasive technology. Derrick has a MS in computer science from Texas A&M University and an MBA from San Jose State University. Contact him at dderrick@cmi.arizona.edu.

Aaron C. Elkins is a PhD student at the University of Arizona. His research interests include credibility assessment, physiological and behavioral measurement, human-computer interaction, cognitive dissonance, and the role of identity and culture in IS and organizations. Contact him at aelkins@cmi.arizona.edu.

Judee K. Burgoon is a professor of communications, a professor of family studies and human development, the director of human communication research for the Center for the Management of Information, and the site director of the Center for Identification Technology Research at the University of Arizona. Her research interests are in deception, trust, interpersonal interaction, and new technologies. Burgoon has a PhD in communication and educational psychology from West Virginia University. Contact her at jburgoon@cmi.arizona.edu.

Jay F. Nunamaker Jr. is the Regents and Soldwedel Professor of MIS, computer science, and communication as well as the director of the Center for the Management of Information at the University of Arizona, Tucson. Nunamaker has a PhD in systems engineering and operations research from the Case Institute of Technology. Contact him at jnunamaker@cmi.arizona.edu.

Daniel Dajun Zeng is an associate professor and Honeywell Fellow in the Department of Management Information Systems at the University of Arizona, Tucson. He is also a research professor at the Institute of Automation at the Chinese Academy of Sciences. Zeng has a PhD in industrial administration from Carnegie Mellon University. Contact him at zeng@email.arizona.edu.

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