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# Robotics Applications In Criminal Investigations – A Novel Proposal Of Robots Potential For Assisting In Crime Suspects Interrogations and Human Questioning

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# Robotics Applications in Criminal Investigations—A Novel Proposal of Robots Potential for Assisting in Crime Suspects Interrogations and Human Questioning

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**Abstract:** Criminal acts deprive humanity of peace and safety. Therefore, all societies, including both governments and ordinary people tries to fight and minimize crimes. And it goes without saying that societies have developed post-crime mitigation for justice insurance and criminals trials. Moreover, one of the essential post-crime procedures is suspect interrogations and witness questioning. Nevertheless, interrogations take a lot of time and effort, and it requires high qualification from the interrogators. Thus, we propose a robust solution to implement robotics in the field of interrogations and questioning where our design could be implemented in police departments, schools, airports, and anywhere that requires human interaction and questioning for security or criminal investigation.

**Keywords:** robotics; investigations; HRI

## 1. Introduction

Criminal acts deprive humanity of peace and safety. Therefore, there are several ways to stand against such acts, like societies' norms, religions, and man-made laws. Furthermore, criminologists study crime and deviant behaviors to improve artificial counteract for crimes, where it could be beneficial to implement these studies to fight crime. Moreover, there are preventive crime regulations and corrective actions after the occurrence of such acts. Usually, corrective actions aim is to ensure prosecution of the criminal and justice. Typically, the process of investigations to find the criminal and the story behind a crime have three stages: Identifying and securing the crime scene where the evidence will be collected, and forensic photographs will be taken, then, Analyzing stage where lab specialists will analyze the collected evidence, witnesses questioning, and suspects interrogating, and the final stage is drawing conclusions and apprehending the primary suspects for prosecution and trial. In our study, we study the possibility of robotics applications implementation in the chain of the crime investigation, specifically through the interrogation of suspects and the productivity of such implementation.

Moreover, a robotic application in crime investigation has already been implemented by UK police [8]. However, one of the current challenges for robotics is human interaction, and this type of implantation requires a high level of human-robot interaction. There are many active and passive interrogation techniques and techniques within the law and ethics of interrogation, while others are against them. Moreover, these interactions will require natural language recognition and machine vision for passive interrogation interactions. In addition, they will require speaking and physical contact for active interrogation interactions.

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## 2. Literature Review

We have surveyed related work to multiple topics concerning our issue, and each topic will be implemented in our proposed system. The surveyed topics are as follows: interrogation techniques implementation, witness/interrogator reliability quantifying, lying detection, bluffing recognition, emotion recognition, and intent recognition from physical contact.

### *2.1. Interrogation Techniques*

Interrogation is an extraordinarily interactive and complex procedure. Such complexity stems from the complexity of humans and the variety in personalities, psychological states, norms, ideologies, among other factors. However, interrogators have several techniques for various situations and mentalities. Kassin et al. [1] surveyed 631 police investigators, took several statistical facts, and analyzed the interrogation techniques conducted as shown in Table 1. Further analyses concluded the correlation between various attributes during interrogation, as shown in Table 2.

**Table 1.** Self-reported frequency of usage of 16 techniques on a 1 (never) to 5 (always) scale.

| Interrogation techniques | *M (SD)* | *Med* | *% "Never"* | *% "Always"* |
|---|---|---|---|---|
| 1. Isolating suspect from family and friends | 4.49 (.86) | 5.00 | 2% | 66% |
| 2. Conducting the interrogation in a small, private room | 4.23 (.82) | 4.00 | 1% | 42% |
| 3. Identifying contradictions in the suspect's story | 4.23 (.78) | 4.00 | 1% | 41% |
| 4. Establishing a rapport and gaining the suspect's trust | 4.08 (.83) | 4.00 | 1% | 32% |
| 5. Confronting the suspect with evidence of his guilt | 3.90 (.77) | 4.00 | 1% | 22% |
| 6. Appealing to the suspect's self-interests | 3.46 (.94) | 4.00 | 3% | 11% |
| 7. Offering the suspect sympathy, moral justifications and excuses | 3.38 (1.05) | 3.00 | 6% | 13% |
| 8. Interrupting the suspect's denials and objections | 3.22 (1.09) | 3.00 | 7% | 13% |
| 9. Implying or pretending to have independent evidence of guilt | 3.11 (1.01) | 3.00 | 8% | 7% |
| 10. Minimizing the moral seriousness of the offense | 3.02 (1.10) | 3.00 | 11% | 8% |
| 11. Appealing to the suspect's religion or conscience | 2.70 (1.17) | 3.00 | 20% | 5% |
| 12. Showing the suspect photographs of the crime scene or victim | 2.27 (1.08) | 2.00 | 30% | 3% |
| 13. Expressing impatience, frustration or anger at the suspect | 2.04 (.88) | 2.00 | 30% | 1% |
| 14. Threatening the suspect with consequences for not cooperating | 1.86 (1.05) | 1.00 | 50% | 2% |
| 15. Having the suspect take a polygraph and telling him he failed it | 1.90 (1.12) | 1.00 | 51% | 3% |
| 16. Physically intimidating the suspect | 1.43 (.80) | 1.00 | 73% | 1% |

**Table 2.** Cross-loadings of interrogation items in rotated factor solution.

| | Factor 1: isolation, rapport, and minimization | Factor 2: confrontation | Factor 3: threatening the suspect | Factor 4: presentation of evidence |
|---|---|---|---|---|
| Sympathy | **.72** | .19 | .05 | .26 |
| Self-interest | **.68** | .06 | .10 | .11 |
| Religion | **.68** | −.15 | .15 | .24 |
| Rapport | **.67** | .13 | −.20 | .10 |
| Isolation | **.56** | .29 | −.05 | −.35 |
| Minimization | **.55** | .21 | .03 | .34 |
| Contradictions | .11 | **.78** | −.02 | .08 |
| Confrontation | .11 | **.77** | −.04 | −.03 |
| Interrupt Denial | .03 | **.58** | .12 | .36 |
| Threatening | .14 | −.06 | **.78** | −.12 |
| Physical | −.02 | .01 | **.73** | .11 |
| Impatience | −.04 | .09 | **.70** | .20 |
| Fail Polygraph | .20 | .06 | .09 | **.62** |
| Photographs | .27 | .08 | .05 | **.60** |

Furthermore, a particular interrogation technique was studied by Mann et al. [3]. They have examined the effect of a second interrogator's presence and interaction. Moreover, they have concluded that a second interrogator has a positive effect on interrogating and deception detection. Thus, making a robot as a second interviewer could have a positive effect if applied correctly.

### *2.2. Witness/Interrogator Reliability Quantifying*

Moreover, the witness's trustworthiness can influence the result of any investigation. For example, Surendran and Wagner show that a robot can decide while interacting with a person can detect and understand the level of trust based on surface cues [19]. An example is shown in Figure 1.

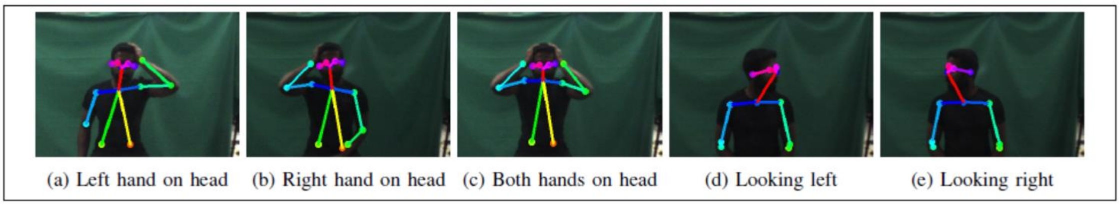


**Figure 1.** Example for surface cues.

Another motivation is to have a robot in the interrogation process to standardize the performance level for any interrogation. One paper studied three factors that lead to decreased quality of the interrogation based on a study conducted on 49 investigators. The first factor is time pressure on some cases where the information is needed in a short time and how this factor could produce poor judgment and restriction on decision making. The second factor is the heavy workload on the investigators, which could decrease their efforts during any investigation. The third one is the work environment and how this can influence the quality of work of individual investigators [20].

### *2.3. Lying Detection*

One paper introduced a humanoid robot solution to be used in lie detection by utilizing machine learning. Also, it showed that a robot could detect deception by the cognitive load needed when someone was lying compared with someone telling the truth as lying required a coherent story and plausible. This cognitive load can be linked with eye blinking and pupil dilatation, classified as

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oculomotor patterns. The machine learning result will be based on the higher cognitive cost as deception will result in a higher score [5].

Another paper used the same technique with two investigators: human to human and human to robot. The experiment was done for young people to witness a crime from a video where the victim is someone from their family. The outcome of this experiment showed that human data is better than robot data during an investigation by humans and robots. However, the level of accuracy from robot data is promising for improvement [4].


**Figure 2.** Result.

*2.4. Bluffing Recognition*

Some mind games require a high level of emotional intelligence and cognition to differentiate between the different states of mind, psychological background, and stress level to interpret the actions taken by other parties. These types of skills are valuable for detectives during questioning witnesses and suspects. Furthermore, understanding such behaviors will advance the human-robot interaction field and technology. For example, Kim and Suzuki [14] analyzed multiple human-human and human-robot poker games in a controlled environment, as shown in Figure 3. Moreover, they have made a truth table based on players' decisions, as shown in Figure 4. Also, as shown in Figure 5, they analyzed associated behaviors to make the robot know if the human is bluffing and how strong his card set is based on his behaviors, as shown in Table 3.

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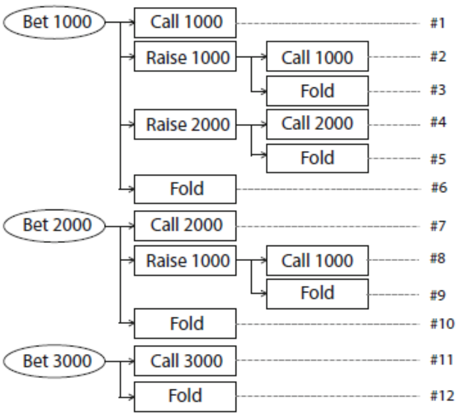
(a) Humanoid playmate (b) Human-robot poker game (left) and human-human poker game (right)

**Figure 3.** Experimental setup.

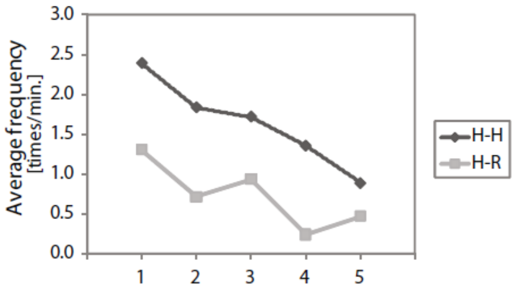



(a) Betting decision tree

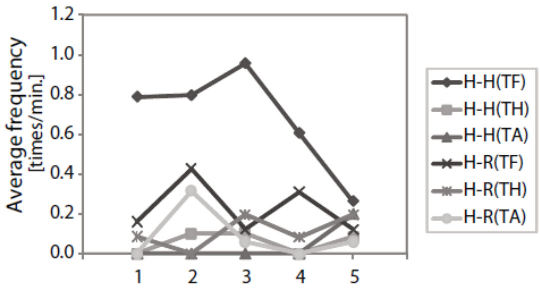
| Outcome | Strong hand | | Weak hand | |
|---|---|---|---|---|
| No. | Subject | Opponent | Subject | Opponent |
| 1 | Bluff | Bluff | Truth | Truth |
| 2 | Truth | Bluff | Bluff | Bluff |
| 3 | Bluff | Bluff | Truth | Bluff |
| 4 | Truth | Truth | Bluff | Bluff |
| 5 | Bluff | Truth | Truth | Bluff |
| 6 | Bluff | Bluff | Truth | Truth |
| 7 | Bluff | Bluff | Bluff | Bluff |
| 8 | Truth | Truth | Bluff | Bluff |
| 9 | Bluff | Truth | Truth | Bluff |
| 10 | Bluff | Bluff | Bluff | Truth |
| 11 | Truth | Truth | Bluff | Bluff |
| 12 | Truth | Bluff | Bluff | Truth |

(b) Result table for bluff and truth

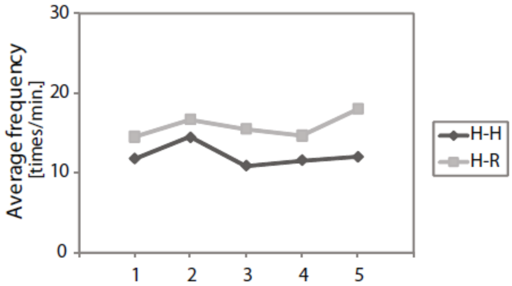
**Figure 4.** Judgement of bluff based on betting decision tree.



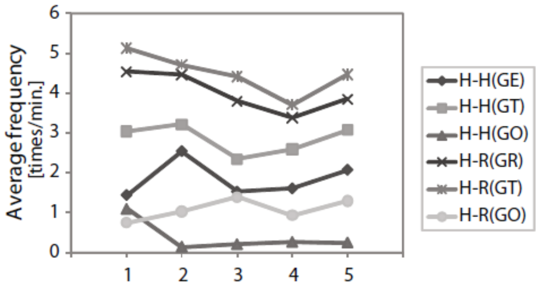

(a) Smile




(b) Hand movement




(c) Eye blink




(d) Eye gaze

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**Figure 5.** The frequency variation of nonverbal behaviors over the game rounds.

**Table 3.** Regression coefficients obtained by multiple regression analysis with stepwise selection.

| Independent variables | Partial regression coefficient | Standardized partial regression coefficient |
|---|---|---|
| Bluff ($\alpha_B$) | -0.018 | $-1.046^{***}$ |
| Touching Face ($\alpha_{TF}$) | 0.101 | $0.269^{*}$ |
| Touching Head ($\alpha_{TH}$) | 1.141 | $0.368^{*}$ |
| Touching Arm ($\alpha_{TA}$) | -1.070 | $-0.466^{**}$ |
| Gazing at Robot ($\alpha_{GR}$) | -0.102 | -0.626 |
| Gazing at Table ($\alpha_{GT}$) | 0.094 | 0.502 |
| Gazing at Other ($\alpha_{GO}$) | 0.102 | $0.269^{*}$ |
| Intercept | 0.983 | |

In addition, they have another paper [13] where they explore how humans interpret robot behaviors. Furthermore, the robot exhibits intentionality where it does nonverbal actions, and some of the actions are bluffs, as shown in Table 4. Also, the setup is shown in Figure 6. Thus, the experiment showed how robot verbal and nonverbal communication conveys a specific intention to humans. This outcome can be handy in the applications of active interrogations.

**Table 4.** THE VIDEO LIST OF ROBOT AND HUMAN BEHAVIORS.

| Number | Human/Robot | Nonverbal behavior | Role of nonverbal behavior | Verbal message |
|---|---|---|---|---|
| 1 | Robot | Head nod | Substitutes | Perfect |
| 2 | Robot | Head shake | Substitutes | Too Bad |
| 3 | Robot | - | (says) | Perfect |
| 4 | Robot | - | (says) | Too Bad |
| 5 | Robot | Head nod | Contradicts | Too Bad |
| 6 | Robot | Head nod | Complements | Perfect |
| 7 | Robot | Head shake | Complements | Too Bad |
| 8 | Robot | Head shake | Contradicts | Perfect |
| 9 | Human | Head nod | Contradicts | Too Bad |
| 10 | Human | Head nod | Complements | Perfect |
| 11 | Human | Head shake | Complements | Too Bad |
| 12 | Human | Head shake | Contradicts | Perfect |

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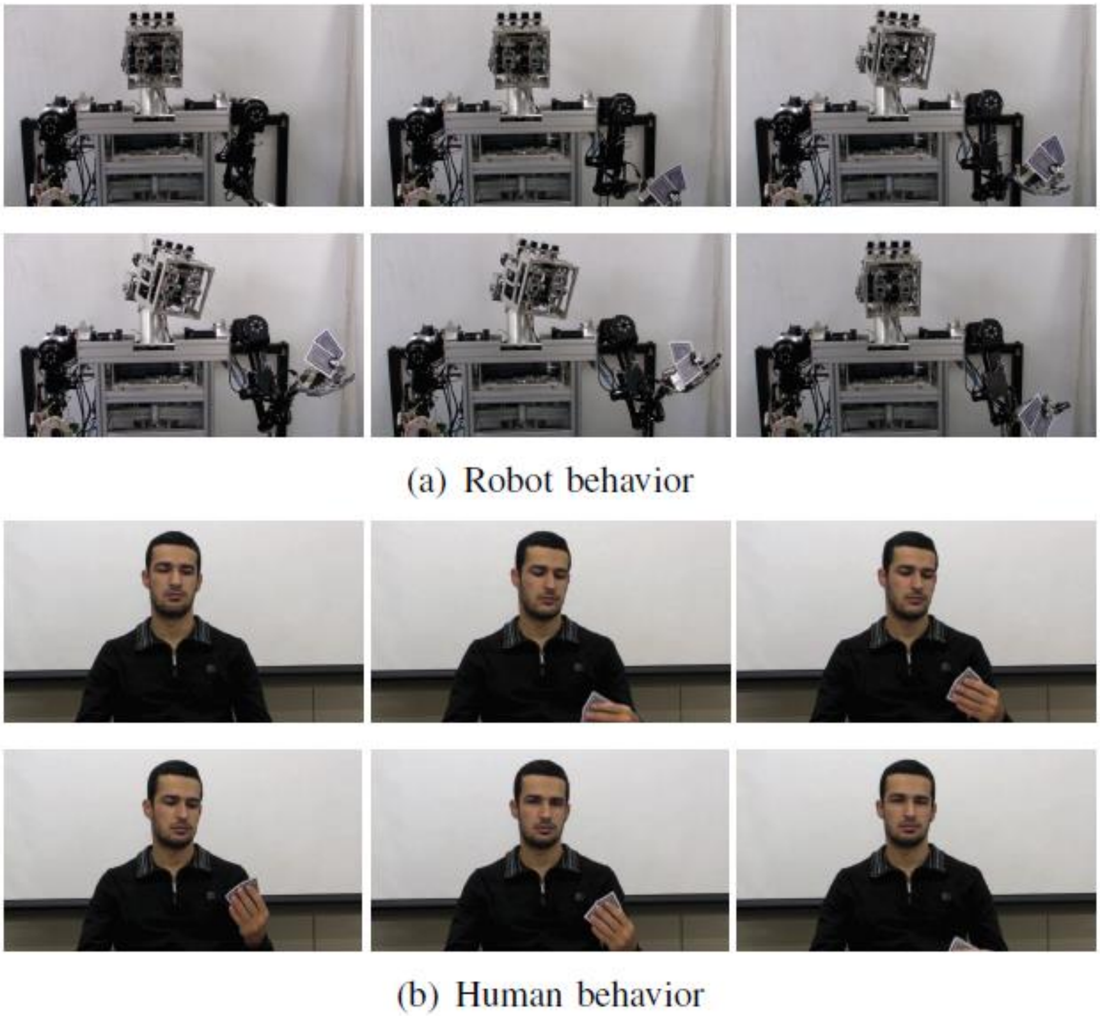


**Figure 6.** Snapshots of robot and human behaviors in the test videos.

*2.5. Emotion Recognition*

On the other hand, emotion plays an essential role during any social conversation between humans. Therefore, providing the ability of emotion recognition to any robot is essential in the HRI field. LUAN and et al. used a convolutional neural network (CNN) and a long short-term memory (LSTM) in motion detection. The model used several data sets of people images with different emotions: happy, angry, surprise, fear, disgust, and sad. The process used transfer learning further to improve the recognition success rate of the model. The result of the experiment increased the success from 58.62 % to 90.51 %; applying this model in any robot can improve HRI for any robot application [17].

Related research identified a relation between Action Units and facial expression. For example, affection and happiness came with a cheek riser and lip corner puller. They suggested using supervised neural networks based on Facial Action Coding System (FACS). It can identify basic emotions from 17 Action Units taken from a robot in real-time processing with a 78.6% accuracy rate [18]. The emotional expression will be added value for the interrogation process as this expression drives to a conclusion of a lie or truth for each question during this process.

In addition to machine vision techniques for emotion detection, recognizing human emotions from his vocals is a natural human skill. Furthermore, it is essential for a robust system for interrogation to integrate all possible media of information exchange (Multi-modal HRI communication). For example, S. Ramakrishnan [15] has analyzed and tested various SER (speech emotion recognition) databases and found promising results. Acoustic Characteristics of Emotions are shown in Table 5.

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**Table 5.** Acoustic Characteristics of Emotions.

| EMOTIONS / CHARACTERISTICS | JOY | ANGER | SADNESS | FEAR | DISGUST |
|---|---|---|---|---|---|
| Pitch mean | High | very high | very low | very high | very low |
| Pitch range | High | high | Low | High | high-male low-female |
| Pitch variance | High | very high | Low | very high | Low |
| Pitch contour | incline | decline | Decline | Incline | Decline |
| Intensity mean | High | very high-male high-female | Low | medium/ high | Low |
| Intensity range | High | high | Low | High | Low |
| Speaking Rate | High | low-male high-female | high-male low-female | High | very low-male low-female |
| Transmission Durability | Low | low | High | Low | High |
| Voice Quality | modal/ tense | Sometimes breathy; Moderately blaring timbre | Resonant timbre | Falsetto | Resonant timbre |

### 2.6. *Intent Recognition from Physical Contact*

In addition to the vision and vocal communication in HRI applications, De Carli et al. [16] have experimented with physical contact communication through a cooperative HRI environment, as shown in Figure 10. Basically, through measuring forces vectors applied, the robot will know the intent of the human as to where to move or orient.

### 2.7. *Staged Setup*

Another example given by Iacob and Tapus [9] has evaluated several staged interrogations in a human-robot environment, as shown in Figure 7. Moreover, the software setup is shown in Figure 8. Furthermore, they use noninvasive techniques, such as thermal and RGB-D imaging, to detect a person is deceitful or honest, based on an evaluation of their physiological state. Finally, the experiment was repeated with female participants, male participants, and Participants with high neuroticism. In conclusion, the final results were promising, as shown in Figure 9.

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**Figure 7.** This figure illustrates how the user and the robot interact through a shared load. The user manipulates one end of a long, slender load connected to the robot's end-effector by a 6-axis force/torque sensor. The robot used is a CRS A460 6-DOF.

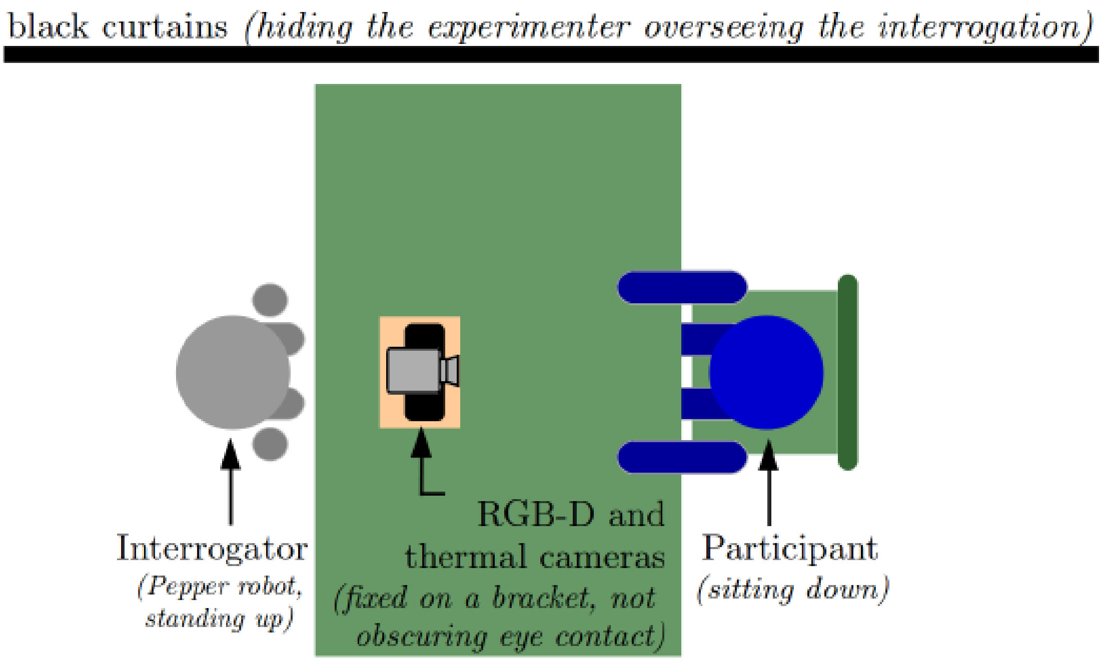

**Figure 8.** Interrogation experimental setup.

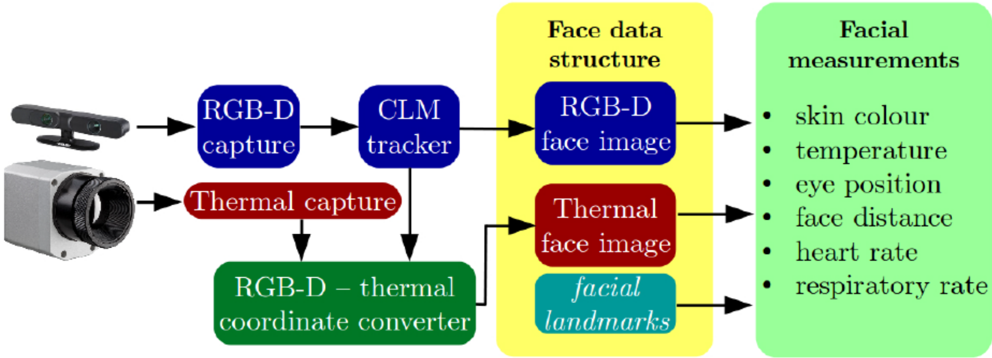


**Figure 9.** Software architecture.

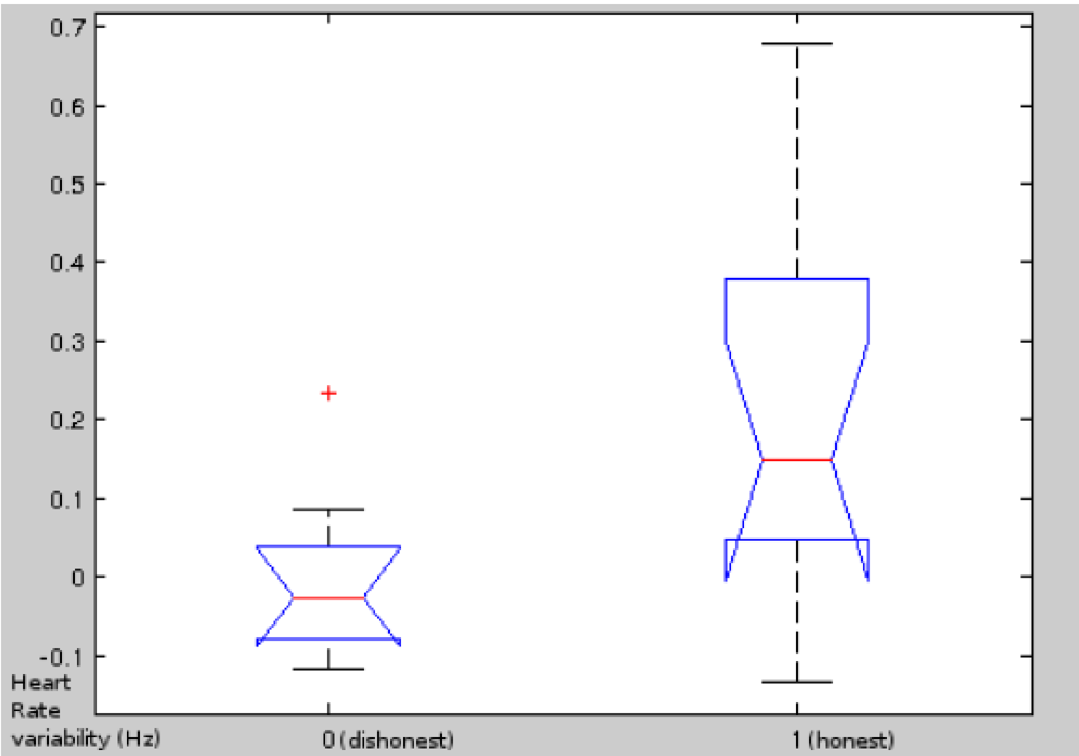


**Figure 10.** Female participants: heart rate variability.

## 3. Problem Statement

The criminal investigation process is susceptible to error. It is believed that an interrogation process best follows investigations to find out the criminal. The interrogation process varies in its techniques and procedures, which many investigators share with their peers. This variation causes two significant problems:

(1) time consumption and

(2) the quality of information extracted from the suspect can vary significantly due to different techniques and procedures.

The police departments worldwide are always looking for better ways to find out the truth from criminals. However, the manual investigation is time-consuming. Moreover, it might not be efficient enough because some criminals might have been arrested multiple times, or others might have eluded police officers many times already.

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Criminal interrogation is a crucial stage that led to identifying the criminal for any case. The interrogation quality in most cases will depend on the experience of the interrogator. A solution is needed to improve their chances of arrest the criminal or find out the truth. The main objective of this proposal is to enhance the effectiveness of criminal investigation by offering a standardized process. Moreover, this solution can be utilized in many organizations such as airports, universities, health, or even private sectors. This solution follows a specific standard that makes the process more efficient and effective.

## 4. System Design

A robotic system is a multi-modal system composed of mechanical, electrical, control, and software systems. Therefore, in our proposed solution, we will discuss the environmental setup of the system for optimum performance and the robotic system design. Furthermore, with highly interactive robots, HRI studies and human psychology rises in the robotics field. Hence, we will discuss the implementation of human studies in our suggested design.

### *4.1. Environment Setup*

In the beginning, each person has unique personality traits and behavior. Thus, making our mission challenging and complex. However, we suggest a pre-processing stage for interrogation where the robot will ask questions based on many psychologists and human studies scientists. Furthermore, the result of the questionnaire will lead to identifying the personality of the suspect. Thus, making the rest of the mission clearer for implementation after analyzing the answers and deciding which questioning method is optimum based on the human personality.

Before getting into the robot design, we will discuss the design of the environment and the limitation of the implementation. At first, we suggest implementing the questioning in two interrogators' scenarios since it has proved its efficiency [3]. Moreover, a specific interrogation technique will be implemented based on the analyzed human traits, as shown in Table 1.

### *4.2. Robot Design*

For the robot design, we consider constructing a High-level interaction robot with multi-modal communication for information exchange. Therefore, we will discuss the desired hardware properties, as well as the software properties.

#### 4.2.1. Hardware Properties

We consider constructing a humanoid robot focusing on functionality more than the appearance of the robot hardware. Therefore, we will discuss the frame, sensors, and actuators needed for robot construction.

Frame Design

The robot scope of implementation is indoor in a specific area. Therefore, we designed it to be a wheeled robot for simplicity in comparison with a legged one. In addition, it needs a rigid, reliable, and average size of a human. Moreover, we need a frame that is optimum for sensors and actuators implementation.

Sensors

To build a robot capable of emotion detection, heartbeat detection, body language recognition, voice recognition, speech processing, speaking, motion, and physical interaction, we need a set of sensors to fulfill these requirements. For example, we need depth cameras for 3D modeling of the suspect to recognize his body language—also, a set of RGB-D cameras and Thermal cameras for emotion detection. In addition, we need millimeter-wave radar sensors or IR sensors for heartbeat detection.

We need IMU, proximity sensors, ultrasonic sensors, encoders, and thermal sensors for motion and physical interaction.

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Actuators

Since our suggested design is a wheeled humanoid robot, we need a set of actuators for motion and physical interaction. First of all, we need microphones for robot speech enabling. As for the motion, we suggest a four-wheel differential drive system with a set of industrial motors on the base and manipulator joints for multiple-axis motion and maneuverability.

4.2.2. Software Properties

After we have discussed the brawl, the brain of the robot is what is left to design. Thus, we will discuss computer vision, and voice recognition algorithms for the robot.

Computer Vision

We suggest using the OpenCV library with Tensorflow and deep learning techniques to recognize body language, emotions, and gestures and improve the model using a neural network for optimum performance.

Voice Recognition

As in the S. Ramakrishnan [15] study, we plan to implement various SER (speech emotion recognition) databases to recognize Acoustic Characteristics of Emotions.

## 5. Performance Evaluation

### *5.1. Performance Measures*

After implementation, we plan to set performance measures for the robot and build upon them to keep improving our system.

5.1.1. Interaction Time

We are quantifying this based on the longevity of the interaction time between the human and the robot. Where if the interaction time is limited by any chance, this reduces the performance.

5.1.2. Cognitive Workload

We are quantifying this based on the capability of the system to handle variables and the continuous environment. Where if a certain scenario limits the robot's performance, this reduces the performance.

5.1.3. Responsiveness

We are quantifying this based on the speed of the system to analyze, quantify, and decide. Where if the robot is slow at any stage, this will reduce the performance.

### *5.2. Experimental/Simulation Design*

After building the prototype, we need experimental data to analyze and improve upon. Therefore, we suggest the following scenario for the experiments:

- Experimental staged questioning in Malls.
- Experimental staged questioning in Schools.
- Experimental staged questioning in Hospitals.
- Experimental staged questioning between two of our robots.
- Experimental staged questioning in Police stations.

And then, the data will be analyzed, and the benchmark will be set by human studies experts for error and metrics calculations.

## 6. Conclusion

The criminal investigation is a fun and unforgiving job. It requires a lot of determination, patience, and skills. Without the use of any special equipment or gadgets, criminal interrogation is done manually. Criminal investigators are often required to interrogate more than one suspect at once. The closer the investigator gets to the truth, the better the results will be. However, it is has been observed that most investigators are not good in their cases, and as a result, they fail in their intention to find out the criminal. Their inability to extract the truth from a suspect is not due to a lack of general experience but rather due to the process which they went through in their interrogation. The solution we propose will contribute to improving criminal investigation.

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