Identify a person face based on unconstrained face images is an increasingly prevalent task for law enforcement and intelligence agencies. In general, these applications seek to determine the identity of a face based on one or more probe (enquiry) face images or face videos. New challenges are encountered. These challenges are due to variations in ambient illumination, image resolution, face pose and expressions. In forensic investigations where the goal is to identify a person of interest, often based on low quality face images and videos, we need to utilize whatever source of information is available about the person. In this paper, we study about face identification of persons of interest in unconstrained imaging scenarios with uncooperative subjects. Given a face media collection of a person of interest (i.e., face images and video clips, 3D face models built from image or videos, face sketch).

1. INTRODUCTION
Face detection is a fundamental task for applications such as face tracking, red-eye removal, face recognition and face appearance recognition. To build flexible systems which can be executed on mobile products, like handheld PCs and mobile phones, efficient and robust face detection algorithms are required. Most of existing face detection algorithms consider face detection as binary classification problem. Even though it looks a simple classification problem, it is very complex to build a good face classifier. Identifying a person based on unconstrained face images is an increasingly prevalent task for law enforcement and intelligence operations. In general, these applications seek to
determine the identity of a subject based on one or more probe images or videos, where a top ranked list retrieved from the gallery may suffice for analysts to identify the subject. In many cases, such a forensic identification is performed when multiple face images and/or a face track (i.e., a sequence of cropped face images which can be assumed to be of the same person (men, women, children) from a video of a person of interest are available. For example, in investigative scenarios, multiple face images of an unknown subject often arise from an initial clustering of visual evidence, such as a network of surveillance cameras, the contents of a seized hard drive, or from open source intelligence (e.g., social networks). In turn, these probe images are searched against large-scale face repositories, such as mug shot or identity card databases.

2. REVIEW OF LITERATURE

Use of Commercial off the shelf (COTS) [1] faces recognition systems with respect to the aforementioned challenges in large-scale unconstrained face recognition scenarios. For a probe image, the COTS matcher assigns a face confidence value in the range of (0, 1), which is used as the quality value. For each video frame, the same face confidence value measure is used. The average face confidence value across all frames is used as the quality value for a video track. First, the efficacy of forensic identification is explored by combining two public domain unconstrained face databases. The release of the public-domain database Label Faces in the Wild5 (LFW) in 2007 spurred interest and progress in unconstrained face recognition. The LFW database is a collection of 13,233 face images, downloaded from the Internet, of 5,759 different individuals such as celebrities, publication [4]. These images were selected since they meet the criterion that faces can be successfully detected by the Viola-Jones face detector [8].

LFW database contains significant variations in facial pose, illumination, and expression, and many of the face images are occluded [3]. The LFW protocol consists of face verification based on ten-fold cross-validation, each fold containing 300 “same face” and 300 “not-same face” image pairs. The YouTube Faces6 (YTF) database, released in 2011, is the video-equivalent to LFW for unconstrained face matching in videos. The YTF database contains 3,425 videos of 1,595 individuals. The individuals in the YTF database are a subset of those in the LFW database. Faces in the YTF database were also detected with the Viola-Jones face detector at 24 fps, and face tracks were included in the database if there were at least 48 consecutive frames of that individual’s face. Similar to the LFW protocol, the YTF face verification protocol consists of ten-fold cross-validation, each fold containing 250 “same face” and 250 “not-same face” track pairs.

Local Binary Pattern (LBP) features have perform much well in various applications, including texture classification and segmentation, image retrieval and surface inspection, face features. The original LBP operator labels the pixels of an image by thresholding the 3-by-3 neighborhood of each pixel with the center pixel value and considering the result as a binary number (0, 1). Unconstrained face recognition methods can be grouped into two main categories: (a) Single face media based methods and face
media collection based methods. Single media based methods focus on the scenario where both the query and target instances contain only one type of face media, such as a still images, video tracks, or 3D image(s) or model(s). However, the query and target instances can be different media types, such as single image vs. single video. These methods can be effective for unconstrained illumination and expression variations but can only handle limited pose variations.

3. RESEARCH METHODOLOGY

We take gender and race attributes of each subject in the LFW and YTF face databases as one type of media. Since this demographic information is not available for the subjects in the LFW and YTF face databases. We pass the new image Face for analysis. In our paper, we use of LBP features and Genetic algorithm for finding features and recognition face from database with respect to the aforementioned challenges in large-scale unconstrained face recognition scenarios. First, the efficacy of forensic identification is explored by combining two public domain unconstrained face databases, Labeled Faces in the Wild (LFW) [4] and YouTube Faces (YTF), to create sets of multiple probe images and videos to be matched against a gallery consisting of a single image for each subject.

To replicate forensic identification scenarios, we further populate our gallery with one million operational mug shot images from the Pinellas County Sheriff’s Office database. Using this data, we are able to examine how to boost the like-hood of face identification through different fusion schemes, incorporation of 3D face models and hand drawn sketches, and methods for selecting the highest quality video frames. Researchers interested in improving forensic identification accuracy can use this competitive baseline to provide more objectivity towards such goals.

![Flow Graph of Face Recognition](image-url)

**Figure 1: Flow Graph of Face Recognition**
4. RESEARCH ANALYSIS AND DISCUSSION

GA is based on natural selection discovered by Charles Darwin. They employ natural selection of fittest individuals as optimization problem solver. Optimization is performed through natural exchange of genetic material between parents. Off-springs are formed from parent genes. Fitness of off-springs is evaluated. The fittest individuals are allowed to breed only. In a Genetic Algorithm, a population of candidate solutions (called individuals, creatures, or phenotypes) to an optimization problem is evolved toward better solutions. Each candidate solution has a set of properties (its chromosomes or genotype) which can be mutated and altered; traditionally, solutions are represented in binary as strings of 0s and 1s, but other encodings are also possible.

A typical GA requires:

i.) A genetic representation of the solution domain,

ii.) A fitness function to evaluate the solution domain.

A standard representation of each candidate solution is as an array of bits. Arrays of other types and structures can be used in essentially the same way. The main property that makes these genetic representations convenient is that their parts are easily aligned due to their fixed size, which facilitates simple crossover operations. Variable length representations may also be used, but crossover implementation is more complex in this case. Tree-like representations are explored in genetic programming and graph-form representations are explored in evolutionary programming; a mix of both linear chromosomes and trees is explored in gene expression programming.

GA (Genetic Algorithm) are as follows:

[1] [Start]:-Generate random population of \( n \) chromosomes.

[2] [Fitness \( f(x) \)]:- Evaluate the fitness \( f(x) \) of each chromosome \( x \) in the population

Figure 2: Schematic Diagram of Face Recognition
[3] [New population] :- Create a new population by following steps until the new population is arrive.
   a. [Selection] :- Select two parent chromosomes from a population according to their fitness (the better fitness, the bigger chance to be selected)
b. [Crossover]:- With a crossover probability cross over the parents to form a new offspring. If no crossover was performed, offspring is an exact copy of parents.
c. [Accept]:- Place new offspring in a new population

[4] [Replace]:- Use new generated population for a further run of algorithm
[5] [Test]:- If the end condition is satisfied, stop, and return the best solution in current population
[6] [Loop]:- Go to step Two

5. CONCLUSION
In this paper, we studied face identification of persons of interest in unconstrained imaging scenarios with uncooperative face using Genetic algorithm with LBP features. Given a face media collection of a person of interest (i.e., face images and video clips, 3D face model built from images, face sketch), rather than a ranked list for each face media sample. Evaluations are provided in the scenarios of closed set identification, open set identification, closed set identification with a large gallery, and verification.

6. REFERENCES