

Face Sketch to Photo Matching Using LFDA and Pre-Processing

Pushpa Gopal Ambhore¹, Lokesh Bijole²

¹Research Scholar, ²Assistant professor, Computer Engineering Department, Padm. Dr. V. B. Kolte College of Engineering, Malkapur, Maharashtra, India

Abstract: *The evolution of biometric technology has provided criminal investigators additional tools to determine the criminal's identity. Besides DNA and circumstantial evidence, if a dormant fingerprint is found at an investigative sight or a surveillance camera captures an image of a suspect's face, then these cues may be used to determine the identity of culprit's, using automated biometric identification. However, most of the times crimes occur when no such information is available, but in its place an eye-witness of the crime is on hand. In such situation a forensic artist is often used to work with the witness or the victim in order to draw a sketch that describes the facial appearance of the culprit according to the verbal description; such sketch drawn depending on the description given by an eye witness is called forensic sketch. Using feature based approach how to match a forensic sketch to a gallery of mugshot images described here. To match forensic sketches against mugshot images a robust framework called local feature-based discriminant analysis (LFDA) is used. Forensic sketches can be of poor quality, so to improve the quality of images and the identification performance a pre-processing technique is used. In this paper experiments are performed using 45 forensic sketches for matching against a gallery of 150 photo images. Sketch and photo images are used for extracting feature where we use LFDA framework which uses feature descriptor such as scale invariant feature transform (SIFT) and multiscale local binary pattern (MLBP) method. The experimental results demonstrate that the proposed algorithm with pre-processing approach gives enhanced identification accuracy.*

Keywords: Mugshot, forensic sketch, Local feature-based discriminant analysis, Feature-based approach, Texture descriptors, Feature descriptors

1. Introduction

Improvements in biometric technology have provided criminal investigators additional tools to help determine the identity of criminals. Besides incidental evidence, if a dormant fingerprint is found at the scene of crime or a surveillance camera captures an image of the face of a suspect, then these clues are used in determining the suspect using biometric identification techniques. However, many times a crime occur when such type of above information is not present. There is a lack of technology to efficiently capture the biometric data like finger prints within a short period after the scene of crime is a routine problem in remote areas. Despite these repercussions, many a times, an eyewitness account of the crime is available who had seen the criminal. The Police department arranges a forensic artist to work with the eyewitness so that he can portray sketch that depicts the facial appearance of the criminal. Sketches drawn by using such process is called as Forensic sketches. When the sketch is ready, it is sent to the law enforcement officers and media outlets with the hope of catching the suspect. Here, two different situations may occur for the culprit:

1. The person may have already been condemned once or
2. The person has not been condemned even once or this is the first time, he may be committing crime.

In general, sketches are classified into two categories: viewed sketches and forensic sketches.

- 1.1 Viewed Sketches: The sketches which are drawn by an artist, directly looking at the subject or the photograph of the subject.

- 1.2 Forensic Sketches: The sketches which are drawn by specially trained artists based on the description of subject by an eye witness.

Following are the key difficulties in matching forensic sketches:

- (1) Matching across image modalities.
- (2) Performing face recognition despite possibly inaccurate depictions of the face.

2. Related Work

Compared to traditional face recognition techniques the correctness of sketch recognition is very low. Research in this area of sketch matching started merely a decade ago. There is a large texture difference between a sketch and a photo. Even though all the methods that are applicable to viewed sketches, are also pertinent to forensic sketches, the unavailability of a public database for forensic sketches led to a lack of standard test procedure on the latter one. Because of that most of the premature work consists of analysis on just viewed sketches. Tang and Wang [1] [2] performed Most of the work in matching viewed sketches only. They first approached the problem using an eigen transformation method [1] to either project a sketch image into a photo subspace, or to project a photo image into a sketch subspace. An enhancement to this method was recommended by Wang and Tang [2], where the relationship between sketch and photo image patches was modeled with a Markov random field. Here, the synthetic sketches generated were matched to a gallery of photographs using a variety of standard face recognition algorithms. In the paper [3] the authors conferred a method for representing face which is based on the features which uses geometric relationship among the facial features like

mouth, nose and eyes. Feature based face representation is done by independently matching templates of three facial regions i.e. eyes, mouth and nose. In paper [4] which presents a novel and efficient facial image representation based on local binary pattern (LBP) texture features. To identify forensic sketches much efficient algorithm is presented here in [5]. Both sketches and photos are considered for extracting feature descriptors using Scale Invariant Feature Transform (SIFT). A feature-based method for matching sketches was presented by Klare and Jain [6], which serves as the motivation for the sketch matching method presented in this project. In this feature-based sketch matching approach uniformly samples both sketch and photo images using SIFT feature descriptors at different scales. From this A.K.Jain in [7] proposed a system which used SIFT and multiscale local binary pattern (MLBP) as feature descriptors with a new framework called as LFDA i.e. local feature based discriminant analysis. The paper [8] surveys about forensic face recognition approaches and the challenges they face in improving the matching and retrieval results as well as processing the low quality images.

3. Pre-Processing Algorithm

The digital images may be noisy and of sub-optimal quality because of printing and scanning. Forensic sketch-digital image pairs of lower visual quality may lead to condensed matching performance as compared to good quality sketch-digital image pairs. Forensic sketches may also contain distortions and noise introduced as a result of the excessive use of charcoal pencil, paper quality, and scanning (device noise/errors). In this paper, pre-processing technique [9] is used that enhances the quality of forensic sketch-digital image pair.

1. Let f be the color face image to be enhanced. Let f^r and f^y be the red and luma channels respectively. These two channels are processed using the multi-scale retinex (MSR) algorithm. MSR is applied on both red and luma channels to obtain f^{rm} and f^{ym} .
2. Image denoising is applied to get $f^{rm'}$ and $f^{ym'}$ respectively.
3. Noise removal may lead to burring of edges. Hence Weiner filter is applied to obtain f^1 and f^2 .
4. After computing globally enhanced red and luma channels, DWT fusion algorithm is applied on f^1 and f^2 to compute a feature rich and enhanced face image, F . Single level DWT is applied on f^1 and f^2 to obtain the detail and approximation bands of these images. Let f^{jLL} , f^{jLH} , f^{jHL} , f^{jHH} be the four bands and $j = 1, 2$. To preserve features of both the channels, coefficients from the approximation band of f^1 and f^2 are averaged. $f^{eLL} = \text{mean}(f^{1LL}, f^{2LL})$ Where f^{eLL} is the approximation band of enhanced image. All three detailed sub bands are divided into windows of size 3×3 and the sum of absolute pixels in each window is calculated. For the i^{th} window in HL subband of the two images, the window with maximum absolute value is selected to be used for enhanced subband f^{eHL} . Similarly, enhanced subbands f^{eLH} and f^{eHH} are obtained. Finally, inverse DWT is applied on the four subbands to generate a high quality face image.

$F = \text{IDWT}(f^{eLL}, f^{eLH}, f^{eHL}, f^{eHH})$ This DWT fusion algorithm is applied on both forensic sketches and digital face images.

4. Process of Sketch to Photo Matching

The proposed feature-based method used for sketch to photo matching is shown in following block diagram:

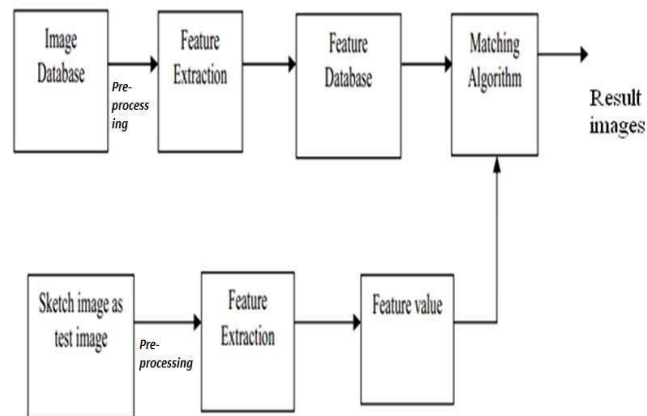


Figure 1: Sketch matching system

We have a set of sketches (Probe images) and a set of mugshot photo images. Following are the steps involved in sketch to photo matching:

1. Apply feature extraction techniques on each input sketch image and the corresponding photo and store results in the database.
 2. Accumulate this feature extraction results for every image into a feature database.
 3. For every probe or query image, the corresponding match is that with the minimum distance calculated with the nearest or normed neighbor matching method.
 4. The final top retrieved images from the database are then displayed. From the figure 1, we can say that the image database represents the gallery of images of the culprits. These images are called as the mugshot images. A photograph taken after one is arrested is called as mug shot. Sketch image is the probe or query sketch which is the input given to the matching system that is to be identified against the available mugshot images.
- Feature extraction: Feature extraction correspond to any feature-based sketch matching technique. For instance there are different types of feature descriptors which can be used that are SIFT, MLBP, SURF (Speeded up Robust Features) and intensity.
 - Feature database: All the results or values obtained from the feature extraction method are stored in Feature database. These are later used for matching purpose with the probe or query sketch.
 - Matching algorithm: To find a proper match between the query or probe sketch images with the mugshot images a matching algorithm is used. "Nearest or normed distance neighbor matching" method is used to match sketch to photo. The minimum distance between the calculated

values of the mugshot images and the probe sketch is found out by using this method.

- The images need to be pre-processed first as given below and then matching can be performed on them.

5. Feature Based Sketch Matching

In feature-based technique [7], feature descriptors describe an image or image region using a feature vector that captures the distinct characteristics of the image. Here we find out feature based representation of both sketch and photograph. For both, we compute a SIFT feature descriptor. Because most image descriptors are not sufficiently verbose to fully describe a face image, the descriptors are computed over a set of uniformly distributed sub-regions of the face. The feature vectors at sampled regions are then concatenated together to describe the entire face. The feature sampling points are chosen by setting two parameters: a region (or patch) size s and a displacement size δ . The region size s defines the size of the square window over which the image feature is computed. The displacement size δ states the number of pixels the patch is displaced for each sample; thus, $(s - \delta)$ is the amount of overlapping pixels in two adjacent patches. For an $H \times W$ image, the amount of horizontal (N) and vertical (M) sampling locations is given by $N = (W - s) / \delta + 1$ and $M = (H - s) / \delta + 1$. At each of the $M \times N$ patches, we compute the d -dimensional image feature vector ϕ . These image feature vectors are concatenated into one single $(M * N * d)$ -dimensional image vector Φ . Minimum distance sketch matching can be performed directly using this feature-based representation of subjects I and j by computing the normed vector distance $\|F(I_i) - F(I_j)\|$.

A. Local Feature-Based Discriminant Analysis:

In the LFDA framework [7], each image feature vector is first divided into “slices” of smaller dimensionality, where slices correspond to the concatenation of feature descriptor vectors from each column of image patches. Next, discriminant analysis is performed separately on each slice by performing the following three steps: 1) PCA, 2) within class whitening, and 3) between class discriminant analyses. Lastly, to remove redundant information among the feature slices to extract the final feature vector. To remove redundant information among the feature slices to extract the final feature vector, PCA is applied to the new feature vector. Figure. 2 shows the training and matching phases of LFDA framework.

B. Feature descriptors:

Two feature descriptor are used in LFDA framework [7], they are scale invariant feature transform (SIFT) and multiscale local binary pattern (MLBP).

- Scale Invariant Feature Transform (SIFT):

The algorithm for SIFT is as follows:

Step 1: Scale-Space Extrema Detection: The scale space is defined by the function:

$L(x, y, \sigma) = G(x, y, \sigma) * I(x, y)$ Where $*$ is the convolution operator, $G(x, y, \sigma)$ is a variable scale Gaussian and $I(x, y)$ is the input image. Difference of Gaussians technique is used for locating scale space extrema, $D(x, y, \sigma)$ by computing the difference between two images, one with scale k times the other. $D(x, y, \sigma) = L(x, y, k\sigma) - L(x, y, \sigma)$

Step 2: Keypoint Localization Elimination of more points by finding those that have low contrast or are poorly localized on an edge. This is achieved by calculating the Laplacian.

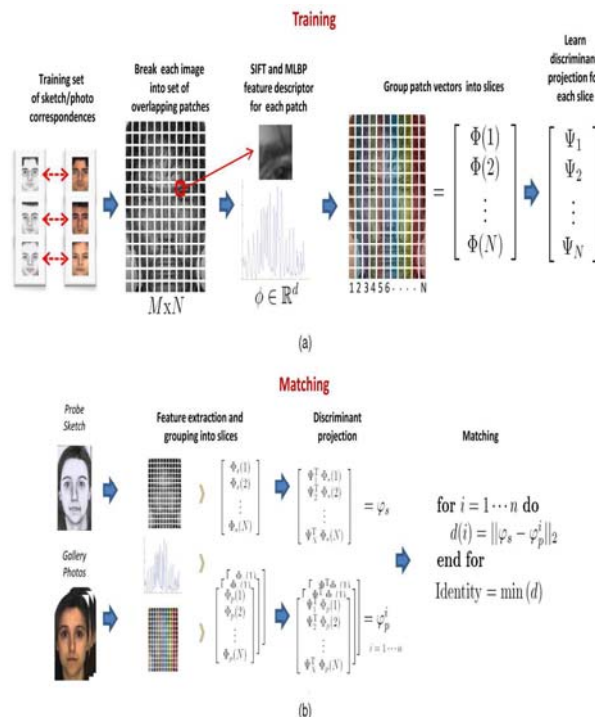


Figure 2: An overview of the (a) training and (b) recognition using the LFDA framework

Step 3: Orientation Assignment

To assign an orientation we use a histogram and a small region around it. Using the histogram, the most prominent gradient orientation(s) are identified. If there is only one peak, it is assigned to the keypoint. If there are multiple peaks above the 80% mark, they are all converted into a new keypoint (with their respective orientations). Next, we generate a highly distinctive “fingerprint” or “feature vector”, having 128 different numbers for each keypoint.

Step 4: Keypoint Descriptor:

Keypoint descriptor typically uses a set of 16 histograms, aligned in a 4x4 grid, each with 8 orientation bins, one for each of the main compass directions and one for each of the mid-points of these directions. This result in a feature vector containing 128 elements. These resulting vectors are known as SIFT keys and are used in a nearest-neighbors approach for sketch to photo matching. The nearest neighbors are defined as the keypoints with minimum Euclidean distance from the given descriptor vector. The probability that a match is correct can be determined by taking the ratio of distance from the closest neighbor to the distance of the second closest.

• Multiscale Local Binary Pattern (MLBP):

The original local binary patterns (LBP) operator takes a local neighborhood around each pixel, thresholds the pixels of the neighborhood at the value of the central pixel and uses the resulting binary-valued image patch as a local image descriptor. It was originally defined for 3×3 neighborhoods, giving 8 bit codes based on the 8 pixels around the central one. The operator labels the pixels of an image by thresholding a 3×3 neighborhood of each pixel with the centre value and considering the results as a binary number, and the 256-bin histogram of the LBP labels computed over a region is used as a texture descriptor. The limitation of the basic LBP operator is that its small 3×3 neighborhood cannot capture the dominant features with large scale structures. As a result, to deal with the texture at different scales, the operator was later extended to use neighborhoods of different sizes called as MLBP. It describes the face at multiple scales by combining the LBP descriptors computed with radii $r \in \{1, 3, 5, 7\}$.

6. Experimental Results

Here experiments are performed using the grouping of viewed sketches and forensic sketches to increase the size of dataset. The database consists of 28 viewed sketch-photo pairs from CUHK database [2] and 70 viewed sketch-photo pairs from IIIT- D database [9]. Forensic pairs are collected as 25 pairs from Forensic composite sketch database [10], which contains sketch photo pairs from L. Gibson [11] and 27 pairs are taken from IIIT-D forensic database. In the beginning training was performed on all the sketches with its corresponding photographs. And the probe set consisting of 45 forensic sketches were used to match against a gallery of 150 gallery images. Matching forensic sketches to large mug shot galleries is special in several respects from traditional face identification techniques. Hence, when matching forensic sketches we are generally concerned with the accuracy at rank-50 i.e. whether or not the true subject is present within the top-50 images that were near (Euclidean distance between descriptors) or top-50 retrieved images. Hence with 45 probe set of forensic sketches, the results obtained are shown in the following Table 1.

Table 1: Rank-10 and Rank-50 accuracies obtained for matching 45 forensic sketches to 150 gallery images

Methods	Rank-10 Accuracy (%)	Rank-50 Accuracy (%)
LFDA	31.11%	68.88%
LFDA with Pre-Processing	26.66%	62.22%

Examples of the forensic sketches correctly identified at Rank-1 with both methods are as shown in Fig. 3(a). These two sketches were good quality sketches resembling perfectly with the suspects photo. In Fig 3(b) one more good quality sketch is shown which LFDA failed to recognize at rank-1 top position, but with preprocessing it is identified at top position.

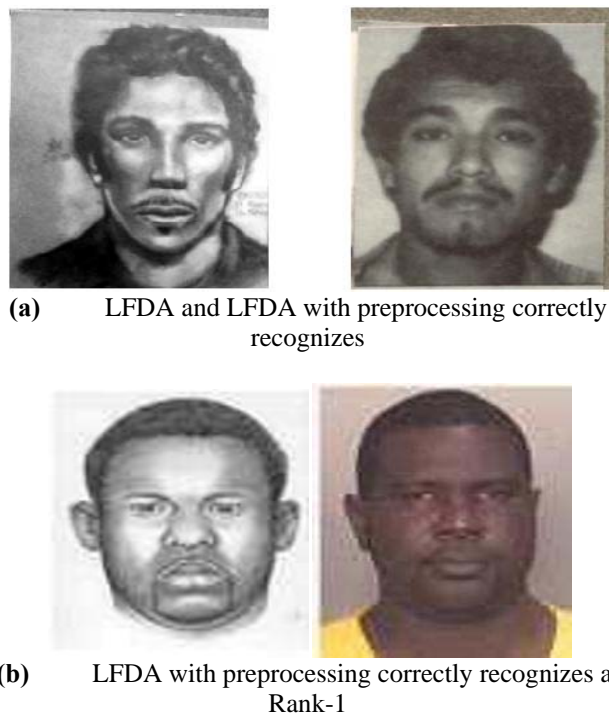


Figure 3: Examples of Recognition at Rank-1 position

Comparison of all the other methods with the proposed method at Rank-50 accuracy is shown as follows in Table 2.

Table 2: Comparison of Rank-50 Accuracy

Methods	Rank-50 Accuracy (%)
LFDA with Pre-Processing	68.88%
LFDA	62.22%
SIFT	55.55%
LBP	53.33%

The CMC curves in Fig.4 (a) and (b) show that the preprocessing technique used along with the LFDA method i.e. proposed approach enhances the quality of images and also helps to improve the rank-50 accuracy of the system.

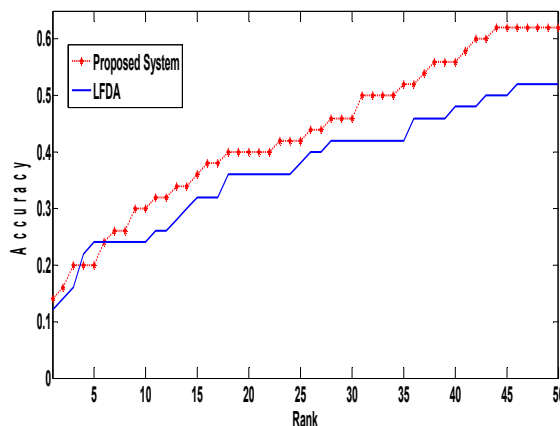


Figure 4 (a): Rank curve of LFDA with preprocessing

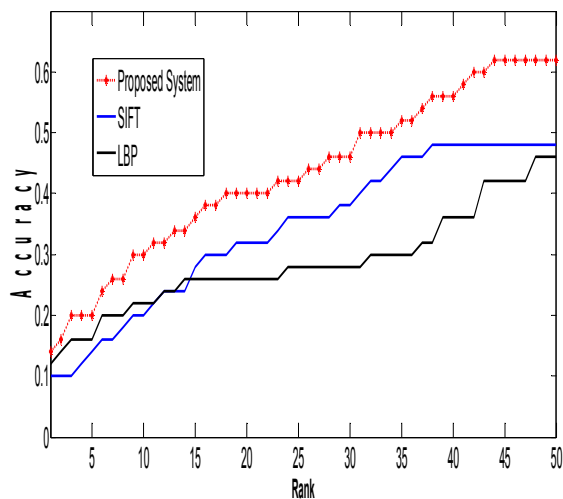


Figure 4 (b): Rank curve with comparison

7. Conclusion

Experiments are performed intended for matching forensic sketches to mugshot photos using a robust feature based method LFDA with additional pre-processing method. This pre-processing algorithm facilitates to improve the forensic images by removing the irregularities and noise. Matching forensic sketches is a very difficult problem in heterogeneous face recognition for two main reasons. (1) Forensic sketches are often an incomplete portrayal of the subject's face. (2) We must match across image modalities since the gallery images are photographs and the probe images are sketches. Forensic sketches are drawn by interrogating a witness to gain a description of the suspect. Research on sketch to photo matching to this point has primarily focused on matching viewed sketches despite the fact that real-world scenarios only involve forensic sketches. Forensic sketches cause additional challenges due to the inability of a witness to exactly remember the appearance of a suspect and her subjective account of the description, which often results in inaccurate and incomplete forensic sketches. All-inclusive analysis, including comparison with different methods is performed using the viewed, semi-forensic, and forensic sketch databases. Using a collection of 45 forensic sketches, we performed matching against a gallery of 150 images. The results with preprocessing with LFDA method shows the rank 50 accuracy at 68.88%, while the same with only LFDA framework gives accuracy at 62.22%. It helps to improve the accuracy. Thus, the results show that the proposed approach with the help of pre-processing performs significantly better than other methods. There is incessant research going on for matching forensic sketches. In prospect a larger collection of forensic sketches needs to be collected to further understand the complexity of the problem.

References

- [1] X. Tang and X. Wang, "Face sketch recognition," IEEE Trans. Circuits and Systems for Video Technology, vol. 14, no. 1, pp. 50–57, 2004.
- [2] X. Wang and X. Tang, "Face photo-sketch synthesis

and recognition," IEEE Trans Pattern Analysis & Machine Intelligence, vol. 31, no. 11, pp.1955–1967, Nov. 2009.

- [3] Amit R. Sharma and Prakash. R. Devale "An Application to Human Face Photo- Sketch Synthesis and Recognition," International Journal of Advances in Engineering & Technology May 2012.
- [4] Timo Ahonen, Abdenour Hadid and Matti Pietikainen, "Face Description with Local Binary Patterns: Application to Face Recognition," IEEE Transactions on Pattern Analysis and Machine Intelligence, Vol. 28, No. 12, December 2006.
- [5] Mohd. Ahmed and F. Bobere, "Criminal Photograph Retrieval based on Forensic Face Sketch using Scale Invariant Feature Transform," International Conference on Technology and Business Management, Mar 2012.
- [6] B. Klare and A. Jain, "Sketch to photo matching: A feature-based approach," in Proc.SPIE Conference on Biometric Technology for Human IdentificationVII, 2010.
- [7] Anil K. Jain, Z. Li and Brendan Klare, "Matching Forensic Sketches and Mug Shot Photos," IEEE Transactions on Pattern Analysis and Machine Intelligence, pages 639–646, March 2011.
- [8] Anil K. Jain, B. Klare, and Unsang Park, "Face Matching and Retrieval in Forensics Applications," Multimedia in Forensics, Security, and Intelligence, Published by the IEEE Computer Society, 2012.
- [9] H. S. Bhatt, S. Bharadwaj, R. Singh, Mayank Vatsa, "Memetic Approach for Matching Sketches with Digital Face Images", Submitted to IEEE transactions on IFS.
- [10] Scott Klum, Hu Han, Anil K. Jain, "Sketch Based Face Recognition: Forensic vs. Composite Sketches", International Conference on Biometrics, June 4-7, 2013.
- [11] Website <http://www.loisgibson.com/sketches.asp>
- [12] H. Bhatt, S. Bharadwaj, R. Singh, and M. Vatsa, "On matching sketches with digital face images", in Proceedings of International Conference on Biometrics: Theory Applications and Systems, 2010.
- [13] Pushpa Gopal Ambhore, Prof. Lokesh Bijole, "Forensic Sketch to Photo Matching using SIFT method", International Journal of Multidisciplinary Research (IJMR) ISSN: 2277-9302, Volume-II issue-8, pp. 46-49, November 2013.
- [14] Pushpa Gopal Ambhore, Prof. Lokesh Bijole, "Face Sketch to Photo Matching using LFDA", International Journal of Science and Research (IJSR) ISSN: 2319-7064 (Online): Volume 3 Issue 4, April 2014.

Author Profile

Pushpa Gopal Ambhore received B.E (Computer Engg.) from Mumbai University in May-2005 and currently doing M.E in Computer Eng. from Amravati University.

Lokesh Bijole received B.E from M.I.T.S. Gwalior (M.P.) and ME (Spl. in Information Security) from D.A.V.V. Indore (M.P.). At present working as Assistant Professor in Department of Computer Science & Engineering Dr. V. B Kolte College of Engg. Amravati University