Future Generation Computer Systems ▮ (▮▮▮▮) ▮▮▮–▮▮▮

Contents lists available at ScienceDirect

Future Generation Computer Systems

journal homepage: www.elsevier.com/locate/fgcs

Raspberry Pi assisted face recognition framework for enhanced law-enforcement services in smart cities

Muhammad Sajjad [a], Mansoor Nasir [a], Khan Muhammad [b], Siraj Khan [a], Zahoor Jan [a], Arun Kumar Sangaiah [c], Mohamed Elhoseny [d,e], Sung Wook Baik [b,*]

[a] *Digital Image Processing Laboratory, Department of Computer Science, Islamia College Peshawar, Pakistan*
[b] *Intelligent Media Laboratory, Digital Contents Research Institute, Sejong University, Seoul, Republic of Korea*
[c] *School of Computing Science and Engineering, VIT University, Vellore, India*
[d] *CoVIS Lab, Department of Computer Science and Engineering, University of North Texas, Denton, TX, USA*
[e] *Faculty of Computers and Information, Mansoura University, Egypt*

HIGHLIGHTS

- Framework for suspect identification to passively enable security in smart cities.
- Computationally inexpensive Viola Jones algorithm for face detection on Raspberry Pi.
- ORB features extraction from only face regions for recognition and classification.
- Energy-aware offloading of features to cloud for real-time suspect identification.

ARTICLE INFO

Article history:
Received 9 May 2017
Received in revised form 10 October 2017
Accepted 7 November 2017
Available online xxxx

Keywords:
IoT and smart cities
Face recognition
Video processing
Image prioritization
Machine learning
Multimedia

ABSTRACT

Similar to a fingerprint search system, face recognition technology can assist law enforcement agencies in identifying suspects or finding missing persons. Face recognition technology lets the police detect a suspect's face and compare it with image databases of known criminals and provides investigators with a match list of the most similar faces. Face recognition is a highly efficient and accurate tool in investigation processes. However, in some sensitive scenarios covert methods are required for the detection of suspects or missing persons without risking the lives of police. With the availability of the nano devices such as Raspberry Pi, law enforcement agencies such as police can be equipped with a concealed and secure face recognition system. In this paper, a Raspberry Pi and cloud assisted face recognition framework is proposed. A small-sized portable wireless camera is mounted on a police officer's uniform to capture a video stream, which is passed to Raspberry Pi for face detection and recognition. The proposed method uses Bag of Words for extraction of oriented FAST and rotated BRIEF points from the detected face, followed by support vector machine for identification of suspects. Raspberry Pi has limited resources such as storage space, memory, and processing power, and therefore the proposed classifier is stored and trained on the cloud. The proposed method is implemented on Raspberry Pi 3 model B in Python 2.7 and is tested on various standard datasets. Experimental results validate the efficiency of the proposed method in accurate detection of faces compared to state-of-the-art face detection and recognition methods, and verify its effectiveness for enhancing law-enforcement services in smart cities.

1. Introduction

In recent years, with the explosive growth of smart devices, a change in user preferences has been observed [1]. Advancement in recent technologies like 3G/4G networks help users while connecting to the grid from remote locations and enjoy a richer user experience with a wide spread use of social networking features [2]. Such services can be exploited to make the work of security agencies more manageable and reliable. Law enforcement agencies usually encounter problems when it comes to public surveillance and suspect detection, as it is not an easy task especially in third world countries where budgets are limited and solutions for thwarting crimes can be very expensive and harder to implement. Therefore, cheap and simple solutions for suspect detection is becoming

* Corresponding author.
E-mail addresses: muhammad.sajjad@icp.edu.pk (M. Sajjad), khanmuhammad@sju.ac.kr (K. Muhammad), sbaik@sejong.ac.kr (S.W. Baik).

https://doi.org/10.1016/j.future.2017.11.013
0167-739X/

increasingly challenging to ensure public security and to deliver security services regardless of time and place. The proposed system is a step towards modern public security solutions remotely in a cost-effective way in smart and emerging cities.

Face recognition is becoming a multi-disciplinary research area and it has vast applications in the field of security, i.e., identification and verification of a person in image/video frames. Identifying humans from faces is what humans do implicitly and we are quite good at it. However, when it comes to computers, it is not an easy task for image processing applications as there are several parameters that need to be calculated precisely before recognition [3]. Over the past several years, the face recognition technology has engaged an overwhelming number of researchers and it is slowly replacing other biometrics security systems [4–6]. This is mainly due to its capability to record at a distance without interacting with the subject itself, making it convenient for a wide range of applications. Face recognition systems range from criminal detection in national databases to social media websites, and is also used for the identification of suspects on international borders [7].

The human face is regarded as a good metric for identification along with other biometric techniques such as fingerprints and irises. In most cases, the face provides sufficient information to identify any suspect to a reliable extent [8]. Although other biometric techniques such as fingerprint scanning are generally more accurate than face recognition, face recognition methods are advantageous due to the fact that they do not require the cooperation of the suspect. A number of techniques exist in the literature that can be used for face recognition. For instance, Yang et al., [9] presented an appearance-based face representation and recognition system using two dimensional PCA. This technique makes use of a 2D matrix as opposed to a 1D vector for vector covariance. This method claims to be less resource intensive and suitable for smaller image size. This method does not address the problems of illumination, variation, or pose directly, and therefore its performance and robustness is somewhat unpredictable. However, in real-world situations, images are prone to damage like scratches, blurring, or distortions. Kshirsagar et al., [10] used the Eigen faces technique which makes use of linear discriminant analysis [11]. LBP based descriptors are usually effective in representing spatial structure information and it has been successfully applied to face recognition with good results. The simplicity in computation as well as low-dimensional space requirement makes it ideal for small problem size; however, the redundancy in features and increasing feature length leads to compromised accuracy.

Besides the above, the Hidden Markov Model [12] has also been used for features extraction and face recognition but due to the high computational demand and lack in performance, it cannot be reliably used in real-time situations. Recently, researchers used artificial neural networks [13] and convolutional neural networks (CNNs) [14] which provide better results in both face detection and recognition. Additionally, some machine learning techniques such as classification can be used to classify faces to their respective classes. Linear SVM [15] is a classifier most commonly used for binary classification which can also be used for multi-class classification [16] with some variations.

The aforementioned methods are computationally expensive, making them less suitable for real-time detection and recognition of faces during public surveillance. Therefore, the proposed framework uses Bag of Words with the ORB (Oriented FAST and Rotated BRIEF) [17] feature extraction method for feature extraction which is cost-effective, thus making it more feasible for our system. Further, our framework uses a cloud-based ensemble support vector machine (ESVM) to recognize the suspects. This type of recognition uses pretty number of feature vectors to train the model and identify suspects later on with good accuracy. The main original contributions of this work are listed as follows:

1. A novel Raspberry Pi based cloud assisted framework is proposed for suspect detection and recognition. Suspects are identified in video streams which passively facilitate law enforcement agencies to provide better safety in smart cities.
2. The Viola Jones face detector is incorporated in the proposed framework, providing efficient face detection results compared to state-of-the-art schemes. Furthermore, the Viola Jones face detection algorithm is computationally inexpensive, making it suitable for the Raspberry Pi based framework.
3. The proposed system considers ORB points as extracted from the detected face region for face recognition. The ORB technique uses a fast binary descriptor based on BRIEF, and is rotationally invariant. Further, it is effective and computationally feasible for embedded and smart devices such as smart phones, tablets, and Raspberry Pi, where resources are limited.
4. Our framework uses an SVM model which is trained on the cloud to recognize faces and categorize them into their respective classes. Instead of sending entire face image, only extracted features are transmitted to the cloud server, saving transmission energy and bandwidth. This makes our system more affordable and implementable for security in smart cities.
5. Securing the features of a query image is not necessary because the image cannot be recreated from the limited set of features. However, for an added layer of security we calculate the hash of each vector using the SHA-128 algorithm. This creates a 128-bit hash for a given vector that is then transferred to the cloud implicitly, along with the feature vector to provide integrity and confidentiality. Similar security mechanisms are proposed in our previous works [17–19] where we proposed methods of encrypting medical images using stenographic techniques on cloud in resource constrained devices.

The rest of the paper is organized as follows: Section 2 reviews related works, followed by Raspberry based applications for smart cities. The proposed work is explained in Section 3. Experimental results and discussion are given in Section 4. The conclusion and future research directions are given in Section 5.

2. Literature review

This section reviews state-of-the-art schemes for face detection and recognition in public security applications for law-enforcement agencies. In recent years, various public security applications for public safety such as remote traffic monitoring and tele-security services have been developed, utilizing smart phones and tablets. The gradual advancement of techniques for face identification have been presented to explore their role in suspect detection because suspect identification plays a vital role in thwarting crimes by detecting criminals to reduce crimes and provide safety for the public.

There are many algorithms that can automatically detect a face in an image/video frame, e.g., a cascading object detector, but the Viola Jones algorithm is one of the most popular for face detection [20,21]. Faces are easily cropped from an image/video frame using the face detection algorithms. Facebook uses a deep-face system in which a 3D face model is employed to apply a piecewise affine transformation [22]. A nine-layer deep neural network is used to derive a face. Their system is trained with the largest labeled dataset of four million faces belonging to four thousand individuals and a simple classifier reaches an accuracy of 97.35% [23]. A new feature extraction method is used for face recognition that uses Hough transform peaks [24]. These peaks are used for feature extraction and binary particle swarm optimization (BPSO) is used for selecting optimal features from the feature vector. The testing image is then classified using the Euclidean classifier. The Euclidean distance of a new Eigen face between the stored Eigen faces, and the lowest Euclidean distance between the new Eigen face and the stored Eigen face is considered the matched face [25]. Learned Local Gabor Patterns (LLGP) is a technique used for face representation and recognition. This technique is based on Gabor features, which makes use of intensity mapped masking to reduce the intensity of the background of a face image. The edges are improved using a Laplacian of Gaussian filter, while BPSO is used for optimal features selection and the Euclidean classifier is used for classification [26]. A 2D Laplacian face method is used for feature extraction, which is more accurate than one dimensional Laplacian faces, and KNN is used for classification purposes [27].

A novel feature extraction method for face images has many advantages over other traditional feature extraction methods, and these features are particularly suitable for face recognition when used with the KNN classifier for classification. A face recognition system that uses Scale Invariant Feature Transform (SIFT) [28] algorithm for the extraction of features from faces. These features are robust and fast but are weaker, and the algorithm requires more time to process than SURF [29]. In the proposed work, the ORB technique is used for feature extraction, which uses a fast binary descriptor based on BRIEF and is rotationally invariant. ORB is suitable in the proposed framework because it is extremely cost effective and computationally feasible for embedded and smart devices such as smart phones, tablets, and Raspberry Pi, where resources are limited. Experimental results demonstrate that the ORB feature extraction method is more efficient on a Raspberry Pi based framework for suspect recognition in comparison with state-of-the-art SIFT and SURF. In the following section, we investigate some real world applications designed by enthusiasts and researchers to facilitate daily life challenges. The versatility and diversity of the Raspberry Pi system makes it easy for developers to create useful, dynamic, and intelligent solutions for real world problems.

2.1. Raspberry Pi based applications

In the last few years, a significant amount of research work has been done using Raspberry Pi and other Nano (smart) devices. Chowdhury et al., [30] developed a home automation solution that facilitates the everyday activities of the home owner by automating doors, the home electric grid, and other appliances. All these operations can be controlled via the Internet using web services. Xu et al., [31] presented a test bed for wireless sensor nodes using RPi, making use of several logistic regression techniques to make routing more intelligent. Shah et al., [32] introduced a new application of Raspberry Pi using the Internet-of-Things (IoT). These applications of Raspberry Pi, combined with computational resources provided by the cloud, have opened new opportunities for richer applications and user experiences.

Agrawal et al., [33] presented a low-cost irrigation and water management solution that is energy efficient and serves as a proof of concept. The initial setup makes use of some scalar sensors like ultrasonic sensors and solenoids to water some 50 pots in a garden, but the design can potentially be used to irrigate large fields as well. Januzaj et al., [34] developed a security access control application based on face recognition. Due to its versatility, the Raspberry Pi device is popular among researchers. With its programmable pins, low cost, and easy to use software, some interesting projects have been proposed recently. In the medical field, Sethia et al., [35] proposed a method of transferring patient information more securely to repositories. The author used an ABE based encryption technique that encrypts data using a custom designed java applet that ran on Raspberry Pi. Raspberry Pi has been immensely popular in the IoT too. For instance, Imteaj et al., [36] used the device to design an automatic fire alarm system for warehouses and custom designed it for a garment factory. Furthermore, the system also sends an SMS along with evidence of the damaged area in the form of a picture. The fire brigade is also informed autonomously and special care has been taken to ensure fewer false alarms. Due to the small size of the device, it can be placed in a very confined space. For example, Chungki et al., [37] used the Raspberry Pi to act as an automatic charging mechanism for drones and quad copters. Similarly the same device is used by [38] to balance power loads among power meters. The authors introduced a new technique based on computer-network load balancing. They claim to have successfully implemented the technique and had profound results.

2.2. Support vector machine

Support Vector Machine is one of the most famous classifiers used in many classification problems. The reason for being used so widely is its simplicity and ease in implementing details. The reason that we chose SVM as classifier is that its performance on small devices with limited resources is implacable. SVM has been used by many researchers in the past and proved its significance over the other classifiers available [39]. There are other variants of SVM such as Fuzzy SVM and LS-SVM but the performance to accuracy ratio of the original SVM is very good in most cases. The SVM classifier has been used by many researchers in dynamic areas such as medical image classification [40–42], fruit classification [43], and face recognition [44]. Comparative study of SVM variants has not been conducted on Raspberry Pi yet, and choosing the optimum variant is still an open issue. The accuracy achieved by our experiments are comparatively better and investigation of all the other variants is beyond the scope of this paper.

3. Proposed methodology

Raspberry Pi cloud-based face detection and recognition is an advanced technology, which can enable law-enforcement agencies to easily identify different suspects locally and remotely in a seamless way. Raspberry Pi cloud based face detection and recognition can be operated through the local system as well as in the cloud. The proposed system will help security agencies to access criminal face images from the stored database for the purpose of identifying criminals. This framework reduces the computational power, storage, and bandwidth cost of the system without affecting the accuracy and performance. However, due to the limited resources provided by Raspberry Pi in terms of computational power and storage, the implementation of fully independent Raspberry Pi based face detection and recognition is not feasible. Therefore, in order to achieve best performance and user experience, Raspberry Pi is combined with the powerful computation capabilities of a cloud server. Heavy computations are assessed and transferred to the cloud in real-time, and returned back to the Pi. Furthermore, cloud based applications are more reliable as their availability in real time is crucial to this system. Face recognition and classification is a computationally expensive task and hence cannot be performed on Pi without affecting the performance and accuracy.

The proposed framework consists of: (1) real-time video streaming from a wireless camera to the Pi, (2) Raspberry-Pi-Cloud with a reliable communication gateway to access faces database (3) face detection and recognition through offloading from Raspberry-Pi to the cloud, and (4) the use of the cloud for classification of different types of criminals, assigning them to their respective classes based on pre-defined criminal classes. An overview of the proposed system is given in Fig. 1.

Please cite this article in press as: M. Sajjad, et al., Raspberry Pi assisted face recognition framework for enhanced law-enforcement services in smart cities, Future Generation Computer Systems (2017), https://doi.org/10.1016/j.future.2017.11.013.

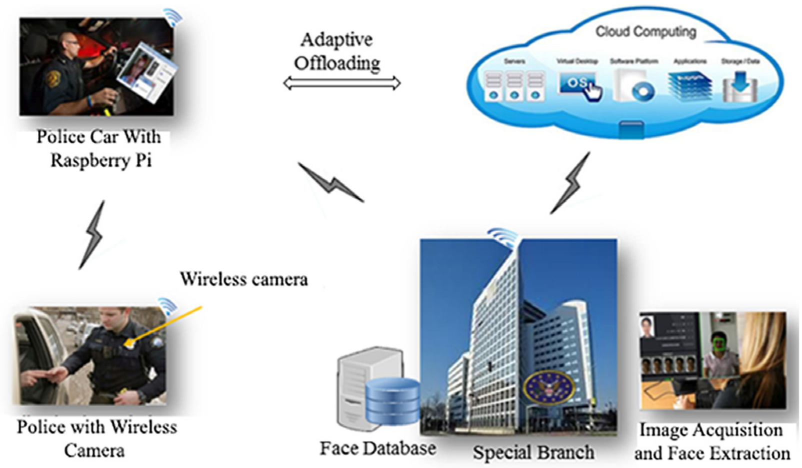

Fig. 1. Overview of the proposed Raspberry-Pi and cloud aided face recognition framework.

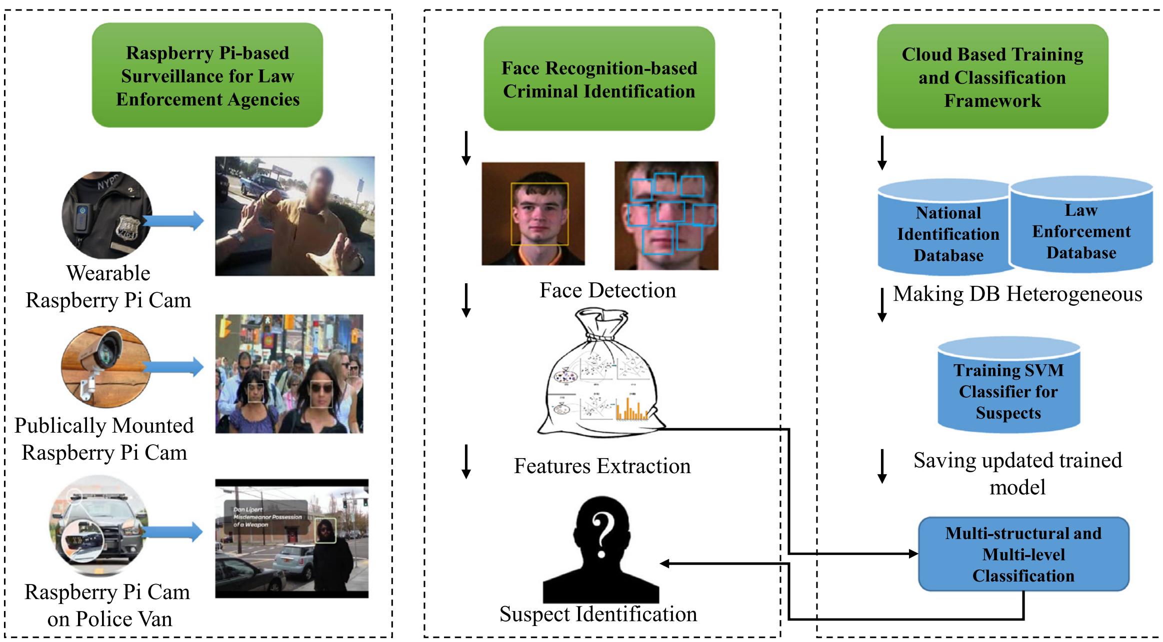

Fig. 2. Detailed view of the proposed face recognition framework for suspects identification.

In this framework, face recognition is achieved with a three step process: (1) face detection in a live video stream using the Viola Jones algorithm, (2) feature extraction using BoF with ORB, and (3) face recognition using a cloud assisted support vector machine (SVM). The proposed method has the competency to easily detect and recognize a face with its corresponding classes. The schematic representation of the proposed method is shown in Fig. 2.

3.1. Real-time face detection

Raspberry Pi can be mounted on the shirt of a police officer, on the police van, or located in public places. In the first step, faces are detected in real-time from the videos captured by the Raspberry Pi camera using the Viola Jones algorithm as shown in Fig. 3. The Viola Jones algorithm is considered to be one of the most efficient algorithms for face detection. There are several other face detection algorithms available that can be used to detect faces in real-time. Detailed analysis of these face detection algorithms is presented in [45]. The Viola Jones framework makes use of Haar-based and LBP approaches. The LBP is used as a binary feature descriptor which is usually represented as an unsigned integer. With this approach the performance of object detection is reduced significantly as binary representation is faster to compute and process. Furthermore, the Viola Jones algorithm proved to be more tolerant of illumination variations. Viola Jones proved to be the best in terms of performance in real-time videos; however, it is intolerant towards rotation and some distortions or noise may produce false positives.

After acquiring the face region, ORB points are extracted from the face. Then the SVM classifier is trained in the cloud through the extracted features for the proposed classification.

3.2. Feature extraction

Bag of Features, also called Bag of Words (BoW), is a standard feature descriptor. In this method, the local features of training images are extracted using Oriented FAST and Rotated BRIEF (ORB).

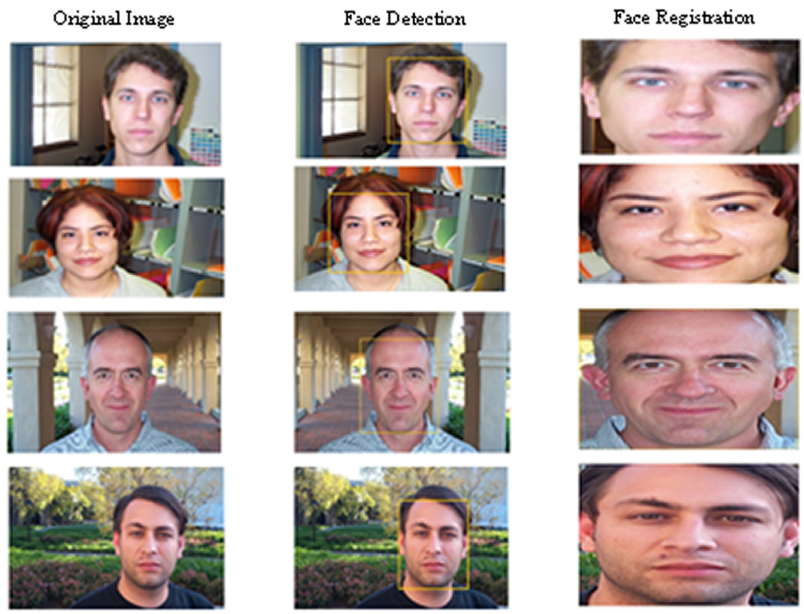

Fig. 3. Face detection and cropping using the Viola Jones algorithm.

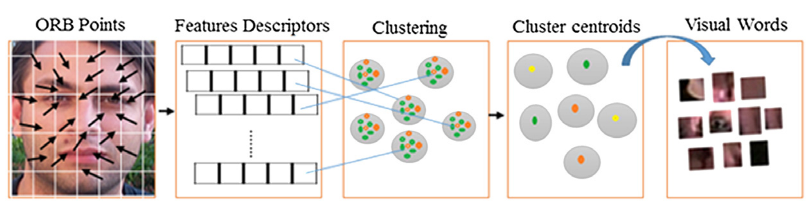

Fig. 4. ORB feature extraction using bag of words.

The reason why we use ORB is that it is fast, robust, and uses a local feature descriptor for object recognition, registration, and classification. The working mechanism of ORB with BoF is similar to SIFT but faster and more robust than SIFT or SURF [46]. Moreover, ORB is less resource intensive in comparison with SIFT and SURF. A detailed comparison of these algorithms are presented in Section 4.

BRIEF, ORB, and BRISK are binary visual descriptors more commonly used. The main advantage of using these descriptors is that they have less computational cost over its vector-based rivals such as SIFT and SURF. The binary feature descriptor uses binary numbers and hamming distance to compute the distance between two bits. The results are calculated by performing a bitwise XOR operation and then counting the acquired result. The end result requires less storage space and has less computational cost as it performs calculations only on bits that can be manipulated by modern systems such as Raspberry Pi, where the hardware support full word instruction, e.g., POPCNT.BRIEF, is a feature descriptor that has been proposed recently. It uses features like SIFT, and it has the same qualities as SIFT. For instance, it is robust in high light situations, distortion of perspective, and blurred images. Besides having all these qualities, ORB is more sensitive towards in-plane rotation.

3.3. ORB (oriented FAST and rotated BRIEF)

ORB makes use of BRIEF descriptors combined with a FAST keypoints detector. BRIEF stands for Binary Robust Independent Elementary Features, and it is a general purpose detector that can be made an arbitrary detector when combined with other point descriptors. Results of BRIEF on geometric and photometric transformed images are usually robust. BRIEF is designed for embedded and small devices as it takes less computational resources and is ideal for real-time image recognition applications [47]. On the other hand, FAST makes use of the Harris corner measurement technique to find top n points. It also produces multi-scale features by using pyramids; however, FAST is not rotationally invariant. The representation of ORB features with bag-of-visual-words is presented in Fig. 4.

For this purpose, ORB introduces few changes to the FAST keypoint descriptor. For rotational invariance, ORB calculates x and y moments in a circular region shaped like a patch of radius r.

$$m_{pq} = \sum_{x,y} x_p y_q I(x, y). \tag{1}$$

To achieve orientation, the intensity weighted centroid is calculated and the vector direction grows towards the centroid from this corner point. A matrix of $2 \times n$ is created for any feature set which contains the pixel coordinates (x_i, y_i), where n is the number of binary tests at a specific location. θ and its rotation matrix is calculated by using orientation of the patch, and S is rotated to get S_θ.

$$s = \frac{m_{10}}{m_{00}}, \frac{m_{01}}{m_{00}}. \tag{2}$$

ORB computes and increments the angle by 12 degrees $(2\pi/30)$ at a time and maintains a lookup table. This lookup table contains the already computed patterns of BRIEF. If the orientation of θ across the views is consistent, the descriptors will be computed according to the correct set of S_θ points.

$$\theta = a\tan 2(m_{00}, m_{10}). \tag{3}$$

3.4. Cloud-based training

Cloud computation and storage provides ubiquitous access to service, store, and utilize these resources from a remote location with the least amount of concern regarding mobility or security. With the revolution of big data, a massive demand of computation, energy, internet bandwidth, and storage is created more than ever before. On the other hand, smart phones, tablets, and other smart devices are often small in size, having less computation power, storage, and limited energy. To overcome these challenges, hybrid approaches are used in which smart devices make use of cloud services for heavy computations such as machine learning model trainings, classifications, and pattern recognitions [16]. There are several cloud vendors, including Google and Microsoft.

Machine learning algorithms generally require large amounts of computation power, memory, and storage other than hardware resources. Besides the resources, these algorithms need a large amount of training datasets for accuracy [29]. However, a large training dataset cannot be loaded into smart devices such as Raspberry Pi, tablets, or smartphones. In order to avoid any damage to the device and improve user experience, a resource aware hybrid-approach is proposed, where the cloud is used as a service to reduce computation cost. The cost of classification is higher than the pre-calculated threshold *T (Tau)*. The formulation of the threshold has already been tested in our previous work [48].

$$\mathrm{T} = e^{-(\sqrt{BW^2+B^2})} * U. \tag{4}$$

The bandwidth (BW) is usually the key aspect in calculating the overall utilization of energy and resources. The available battery (B) is also considered as we must be aware of the available resources in hand. In our previous work we concluded that the threshold is inversely proportional to the BW and B. Small values of T will prove to be more efficient in terms of resource utilization. All resources are measured from 1 to 0, i.e., maximum battery will be indicated by 1 and minimum will be counted as 0. The user preference U is a critical variable. It gives control to the user for better utilization of resources, i.e., if user is aware of available resources then he can adjust the user preference accordingly.

Using this threshold, additional computational cost is offloaded to the cloud thereby reducing resource usage on the Raspberry Pi. In machine learning, some classifiers offer more robust and accurate classification procedures due to their global properties such as ANN [30] and SVM [31,32]. These techniques become more complex and expensive to process large datasets on smart devices such as Raspberry Pi [33]. In the current technological age, there are various distributed machine learning methods which can be trained on multiple local computers or on a single powerful cloud server. Once trained, these models can be accessed for classification purposes in both local as well as remote locations.

4. Results and discussion

As discussed earlier, the wireless video camera mounted on police officers' uniforms captures real-time video and streams it back to the Raspberry Pi. The stream of the video is processed frame-by-frame, and the face region is extracted from the real time video using the Viola Jones algorithm [49]. After face detection, the face image is stored locally and forwarded to feature extraction module. Bag of Words descriptor is used to extract ORB points. Once the features are extracted, we determine the cost of the resources needed to classify it locally or on the cloud. The SVM classifier is trained using the same extracted features. This model resides on the cloud and is acceptable using the Google Cloud API provided by most services

4.1. System configuration

The Raspberry Pi device was used to acquire a video stream from the wireless camera. The device was used with the following specification and configuration and hardware details are also given in Table 1. The Raspberry Pi has a Broadcom BCM2837 system on a chip which includes an ARM Cortex-A53, 1.2 GHz processor, Video Core IV GPU, and an SD card slot. The GPU of the Raspberry Pi is capable of video playback using H.264 which can play Blu-ray quality videos at 40MBits/s. OpenGL ES2.0 and OpenCV libraries are used to access fast 3D cores. There are several ports present on the Raspberry Pi 3 Model B board including HDMI, 2×2 USB Ethernet, and several others.

Raspbian is the default operating system of the Raspberry Pi and it has more support than any other operating system for the device. Furthermore, the community support for Raspbian is appreciable. As Raspbian is built on the flavor of Debian, it naturally has all the features and compatibilities required for the project. Python 2.7 and 3.5 is already part of the Raspbian operating system and therefore a separate installation is not necessary. The reason that we chose Python 2.7 is because it has more resource community support available and unlike Python 3.5 it is fully compatible with OpenCV 3 and above. The project requires some external Python libraries that need to be installed separately. We have also installed some other performance measurement libraries to evaluate the performance of the code.

4.2. Repeatability measurement

Point-to-point matching of two different images is measured in terms of repeatability, which corresponds to the mean number of points matched in two images.

$$Cr_{12} = \frac{C(I_1, I_2)}{mean(m_1, m_2)}. \tag{5}$$

Repeatability measurement is computed using the above equation, where $C(I_1, I_2)$ shows the corresponding number of points represented in couples, and m_1 and m_2 are means of the total detected points of two images.

These images are evaluated with another evaluation measurement technique called RANSAC [50]. This technique is used to remove inconsistent matches, and it takes into account only those points that are inliers. Inliers are those points whose corresponding points are matched in both images. The goal of this technique is to accept all inliers and ignore the outliers. The probability of the algorithm to never get any inlier points in set is 1-P.

$$1 - P = (1 - w^m)^k. \tag{6}$$

Here, m is the minimum number of points needed to analyze a model, w is the probability of RANSAC selecting the inliers and k is the number of inputs required [50]. The proposed system has been tested with different types of distortions and noise to test the accuracy of the repeatability measurement of the ORB points. Fig. 5 presents the proposed distortions and noises.

Please cite this article in press as: M. Sajjad, et al., Raspberry Pi assisted face recognition framework for enhanced law-enforcement services in smart cities, Future Generation Computer Systems (2017), https://doi.org/10.1016/j.future.2017.11.013.

Table 1
Raspberry Pi software specification for the proposed framework.

Name	Configuration
OS	Noobs (Raspbian)
Programming language	Python 2.7
Libraries	Numpy, sciPy, pyLab, matplotlib, RPI.GPIO
Imaging libraries	OpenCV 3.1.0, scikit-Learn, scikit-image, MATLAB support package for raspberry Pi
Performance monitoring utilities	BCMStat, CFML, CommandBox, ContentBox, line profiler

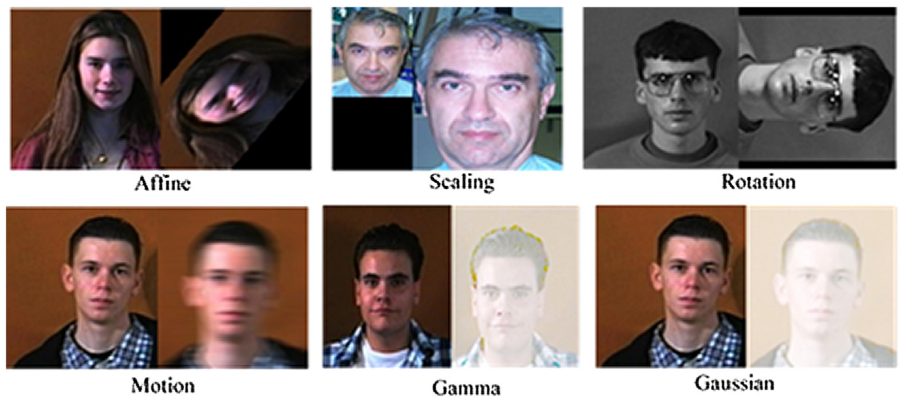

Fig. 5. As test images we used affine transformed images along with rotation, scaling, gamma, and three types of blurred images. All these general deformations are included by the OpenCV and the same sets of images were used for testing the three different feature extraction techniques.

4.3. Face-96, face-95 and frontal dataset

The Face-96 directory consists of 140 individual face images at 196 × 196 pixels. The only difference in face-95 and face-96 is the change in the background and scale of the face. The background in the face-96 dataset is very complex. The Face-95 dataset consists of 72 male and female individual face images with a red background. Most images are of the frontal face, some with minor side movement, and some of these images consist of some translation. The dataset also contains images with lighting variations and some facial expressions. The resolution of each image is 180 × 200 pixels and they are stored in a JPEG format. The frontal dataset is created by the California Institute of Technology and it contains a total number of 450 face images at a resolution of 896 × 592 pixels. The dataset consists of face images of 27 individuals, and the images are stored in a JPEG format. These face images have lighting variations, facial expressions, and different backgrounds.

4.4. Repeatability measurement against noise and distortion

Images with varying gamma values were used to compare the methods and the computed results are presented. For images with varying intensity values, SIFT provides the best matching rate, while ORB has the least. The computational time requirement for ORB is the lowest (See Fig. 6).

The influence of blur is measured on the images and results were compared in the tables below. Consistent with the previous experiments, the first ten matches were considered. The radius of Gaussian blur was gradually increased from 0 to 9.0, and the results were measured. As shown in the graph below, the proposed method performs well and has the most correct matches. Besides the Gaussian blur, Motion and Median blur were also tested, and the number of matches were higher in the proposed ORB method. An increase of Gamma has no effect on both SURF and SIFT, while it enhances the matching ratio of ORB up to the value of 2.5 Gamma (See Fig. 7).

The repeatability measurement of algorithms were tested against different kinds of blurs and the points collected by SIFT were more accurate than any other method. The main problem with SIFT was that the number of points collected were not enough to effectively train a model. The only method whose collected points were nearly good to train the model was ORB. The number of points collected by ORB were more than SURF, and it helped the model to be more accurate than SURF.

In this experiment, we evaluate the performance of the proposed system by using scale invariance. As shown in Fig. 8, the number of matches for all three algorithms are clear. Consistent with the previous experiment, the number of matches is based on the first 10 whose distance is the least. As the scale of the image is changed, we observe that the proposed method outperforms the SIFT or SURF. The data is presented as the number of matches with the increase in number of images. Further, the set of images were tested and the influence of rotation is analyzed. As shown in Fig. 8, the images were rotated by 5 to 10 degrees, and then the first ten matches are observed.

SIFT performs well in terms of rotation and had the most stable results. On the other hand, SURF did not perform well and hence has the least number of matches. The number of matches for the proposed system is not better than SIFT, and hence it can be improved by tuning the parameters. In another experiment, the stability of the methods is evaluated when the affine transformation is changed. This transformation is usually important where the images need to be stitched together, e.g., in a panorama. The results are measured in terms of transformation ratio as it is increased from 0 to 50 degrees. SURF and SIFT work well when this ratio is small; however, for larger numbers the proposed method is significantly better (See Fig. 9).

Changes in the perspective and geometric transformation of the image affect the algorithm performance. We tested the same sets of images with different deformations. The results suggest that a change in affine affects ORB the most, and the number of matches reduced to less than 55%. On the other hand, the results of SURF and SIFT were better. Similarly, in the case of rotation, ORB performed moderately better while SIFT shows promising results. We test the images against both scaling up and scaling down to see if there is any significant change between the results. As we can see by scaling up, the performance of ORB is significantly better than SIFT or SURF, while on scaled down images the performance is inconclusive.

Please cite this article in press as: M. Sajjad, et al., Raspberry Pi assisted face recognition framework for enhanced law-enforcement services in smart cities, Future Generation Computer Systems (2017), https://doi.org/10.1016/j.future.2017.11.013.

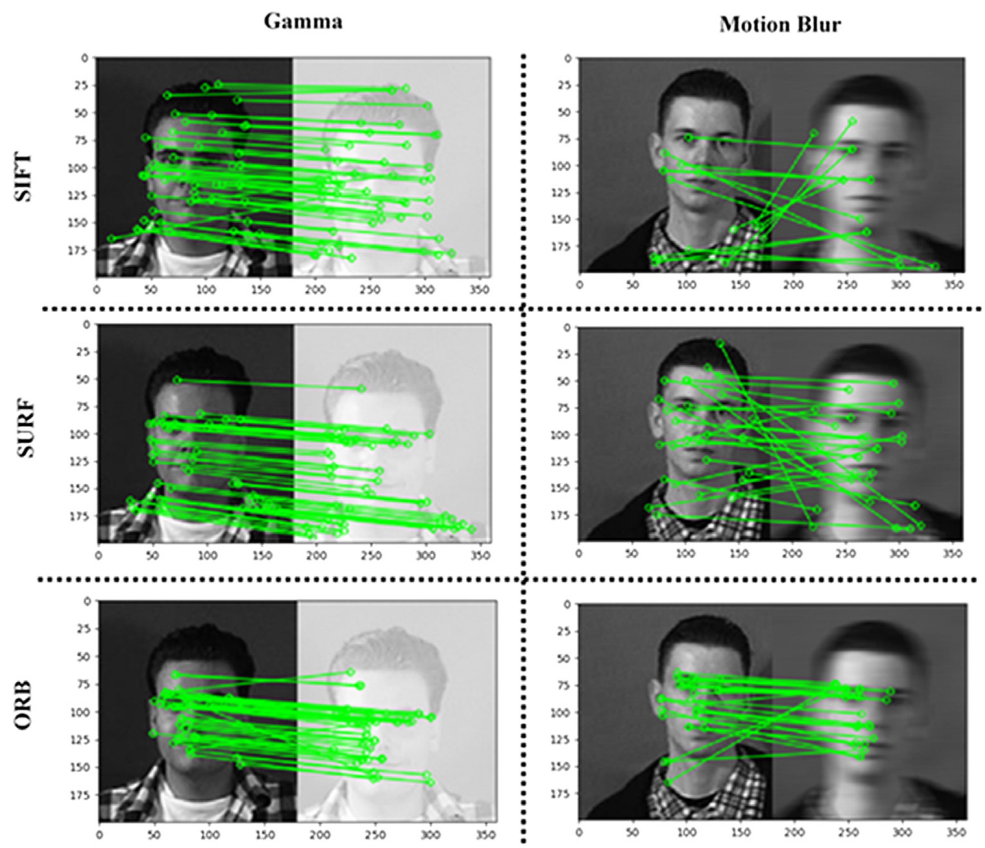

Fig. 6. Visual results of Gamma and Motion blur.

4.5. Time analysis of SURF, SIFT and ORB

Evaluation of time is always relative as it depends on multiple factors, e.g., the size, quality, and texture of the image. It also depends on the settings and parameters of the algorithm for instance the size of k or the distance ratio etc. Fig. 10 shows the average amount of time spent to detect the first ten matches. All images are sized 300 × 240 and are captured from the live video stream of the Raspberry Pi camera. Initial parameters of each algorithm are set as default meaning as proposed in their respective original papers.

Time is measured for both feature detection and matching. As mentioned in Fig. 10, the proposed method is relatively fast.

4.6. Experimental evaluation

The proposed face recognition system is tested on a benchmarked dataset discussed earlier. The grid size for feature selection is 8 × 8, and the block width is [32, 64, 96, 128] pixels. For the feature quantization, the number of clusters used are 500 and 250 with cross validation 0.7 and 0.3, i.e., 0.7 for training and 0.3 for testing. The experiment was conducted on frontal images from Face 95 and Face 96 face datasets. From the given dataset, only the faces were extracted and classified into their respective class. The results were then compared with the originals to calculate the accuracy of the proposed face recognition technique.

The results of all experiments on test images are shown in Tables 2–6. There is no single method that performs best in all deformations. Hence, choosing the right feature extraction method strictly depends on the type of data and the performance of the method. In our case, the results of these experiments were not constant, varying according to the image texture, size, color intensity, scaling, and transformation effects. The results also varied when the size of the clusters were altered or the parameters of RANSAC were changed.

The number of features collected by SIFT is huge, and hence the matching success is also satisfactory because of the reduced localization errors. However, the problem with using SIFT on Raspberry Pi is the time and memory it took to compute these features. On the other hand, SURF outperforms SIFT in time, and the matching ratio of SURF collected points were far better than SIFT. The only issue with SURF points was that it did not perform in both Gamma variation as well as with blurred images. As surf uses Fast-Hessian detectors the collection speed of SURF is almost 3 times as fast compared to SIFT [51]. ORB among all three performs best in regard to time. Its feature extraction time is almost 3 times as fast as SIFT and twice as fast as SURF. Furthermore, the SVM model trained with collection of points extracted by ORB were significantly better than SIFT or SURF. The time complexity and lower computational resource requirement makes this method ideal for small devices like Raspberry Pi.

5. Conclusion

Real-time suspect detection and recognition without interaction with the subject is a challenging task. Face recognition technology and the embedded processing capabilities of portal devices such as Raspberry Pi can significantly help law enforcement agencies in the identification of suspects in a cost effective manner. This necessitates the requirement of an efficient framework for simplifying the suspect recognition process. With this motivation, we have proposed an efficient suspect identification framework using cloud services and Raspberry Pi, which can extract suspect's face from the video stream captured by a uniform-mounted camera from the police officer. Raspberry Pi not only provides an expedient

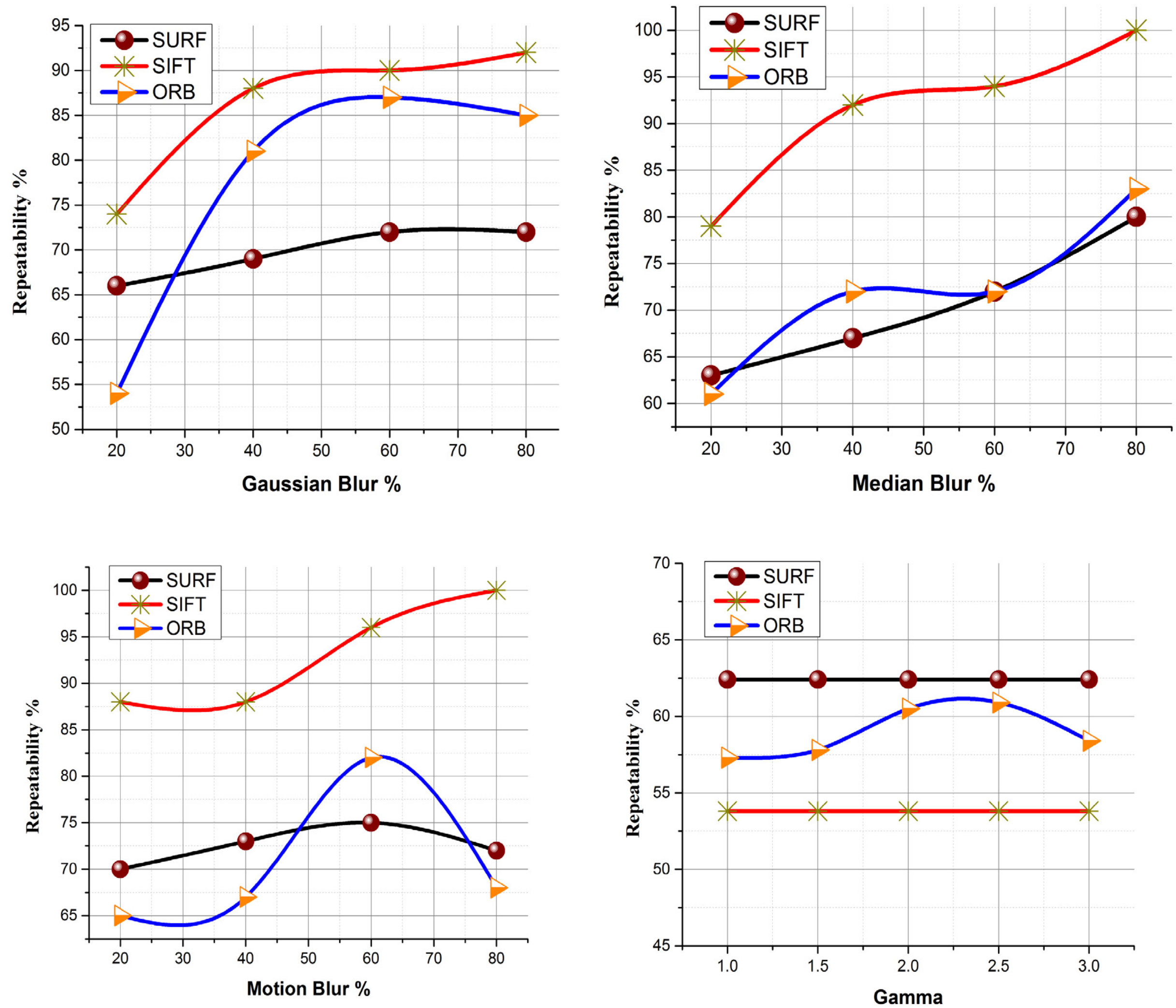

Fig. 7. Noise analysis of the three methods.

Table 2
Results of the proposed method on face-95 with different number of images, cross validation size, and k-size.

No: classes	Training	k-size	Cross validation	No: of features	Average accuracy
70	30	500	0.7	364 320	100
70	30	500	0.3	850 080	99
70	05	500	0.7	60 720	92
70	05	500	0.3	121 440	89.3

Table 3
Results of the proposed method on face-95 with different cross validation and k-size.

No: classes	Testing	k-size	Cross validation	No: of features	Accuracy %
70	30	500	0.3	179 162	96.8
70	30	500	0.7	422 163	98.4
70	05	500	0.3	32 219	86.3
70	05	500	0.7	61 417	88.7

Table 4
Results of the proposed method on face-95 with different no. of images and cross validation and k-size.

No: classes	Training	k-size	Cross validation	No: of features	Accuracy %
33	20	500	0.7	858 000	98.7
33	20	500	0.3	330 000	95.0
33	05	500	0.7	132 000	89.1
33	05	500	0.3	66 000	79.1

platform for detection and feature extraction, but also reliably communicates with the cloud for assistance where necessary. The proposed framework automatically extracts the face using the Viola Jones algorithm, followed by feature extraction using the

Please cite this article in press as: M. Sajjad, et al., Raspberry Pi assisted face recognition framework for enhanced law-enforcement services in smart cities, Future Generation Computer Systems (2017), https://doi.org/10.1016/j.future.2017.11.013.

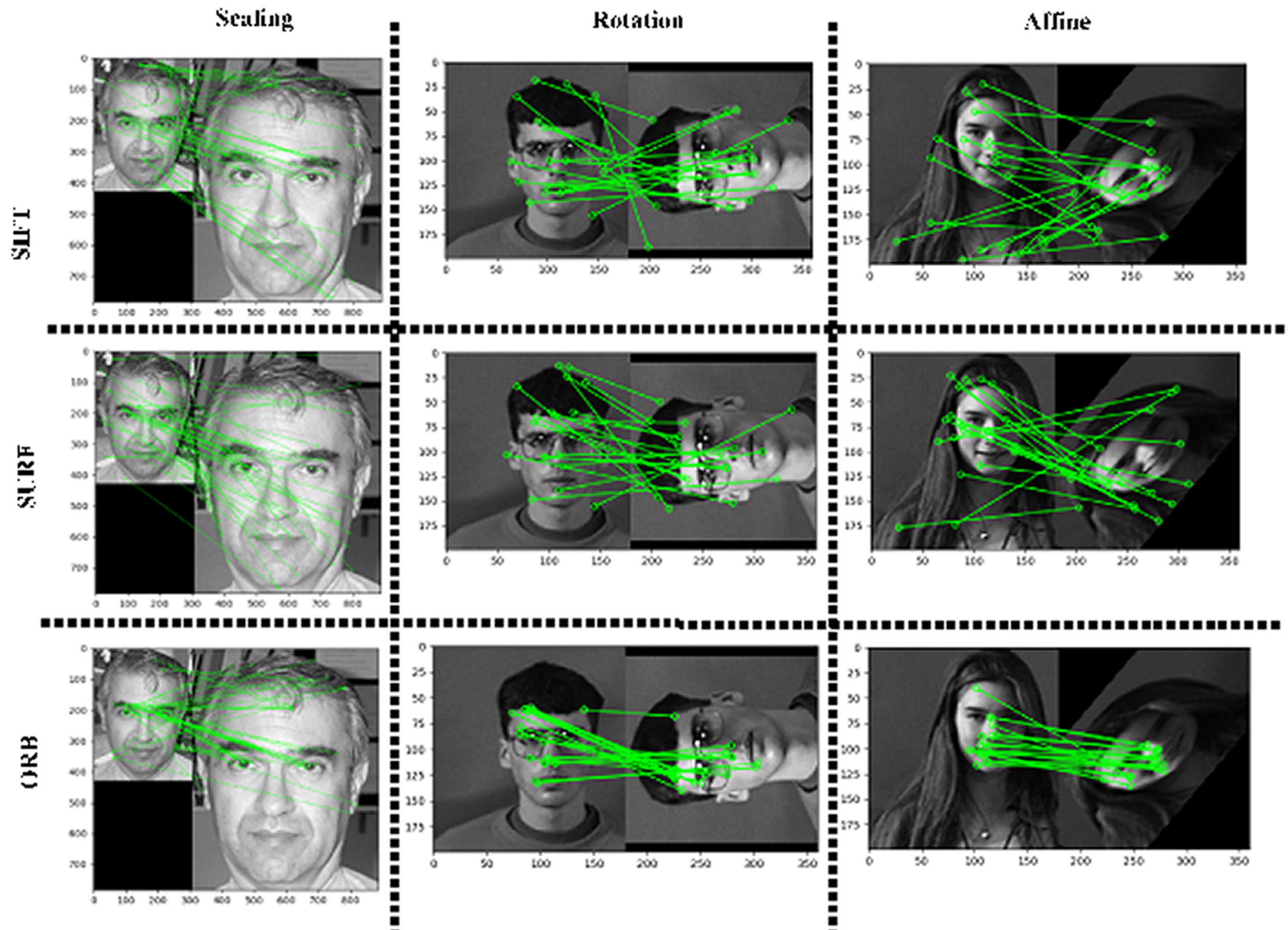

Fig. 8. Visual results of scale, rotation and affine transformation invariance.

Table 5
Results of the proposed method on face-95 with different no. of images and cross validation and k-size.

No: classes	Training	k-size	Cross validation	No: of features	Accuracy %
70	30	250	0.7	427 639	98.3
70	30	250	0.3	164 393	96.2
70	05	250	0.7	43 266	83.1
70	05	250	0.3	21 346	71.2

Table 6
Perspective transformation and its effects on the proposed method.

Method	Noise effects		Perspective transformation			Other
	Blurring effect	*Gamma variations*	*Scale variations*	*Rotational changes*	*Affine transformation*	*Time analysis*
SURF	Ordinary	Ordinary	Ordinary	Ordinary	Good	Good
SIFT	Good	Ordinary	Good	Good	Good	Ordinary
Proposed	Best	Best	Good	Ordinary	Best	Best

ORB algorithm, which is significantly better than SURF and SIFT as proved in our experiments. The cost of computing features of the face region is calculated and used as a threshold for adapting offloading. A binary SVM model is trained and a portion of it is stored locally to classify suspects. The experimental evaluation suggests that ORB has significant advances over SIFT and SURF as it is more robust and is ideal for processors with limited capabilities. The performance of the proposed system is further analyzed by introducing different noises and variations. Quantitative and qualitative evaluation using three different datasets validate the robustness of the proposed framework for enhancing the effectiveness of law-enforcement services in smart cities.

In the future, we will investigate convolution neural networks and deep belief networks and their performance on Raspberry Pi for suspect identification. Furthermore, we are planning to conduct detailed analysis of face detection algorithms on real-time video streams and its performance on the Raspberry Pi device. The use of a better classifier will definitely increase the performance of the algorithm, and in the future we will investigate different variants of SVM and present a comparative analysis on Raspberry Pi.

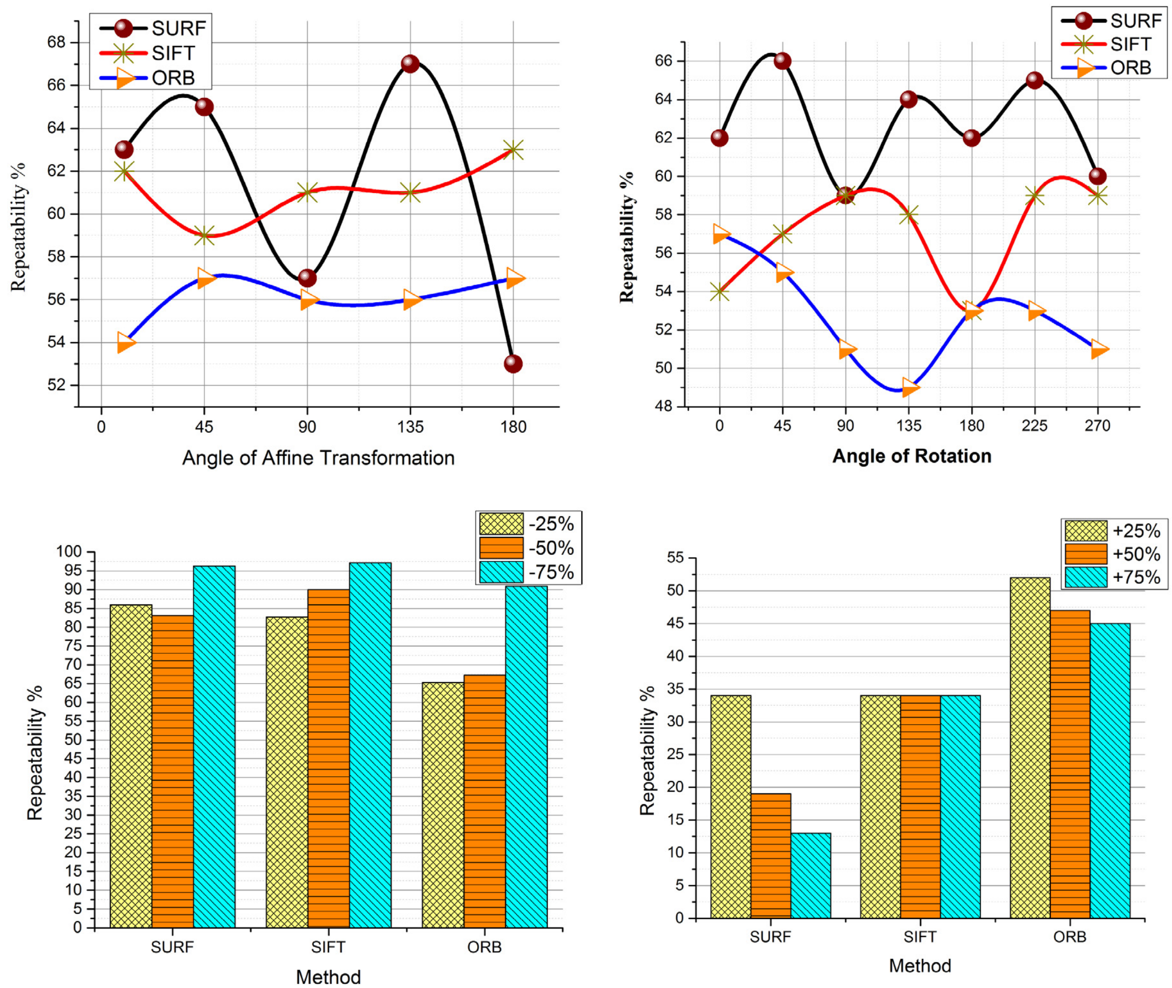

Fig. 9. Comparative analysis of SURF, SIFT and ORB on scaling.

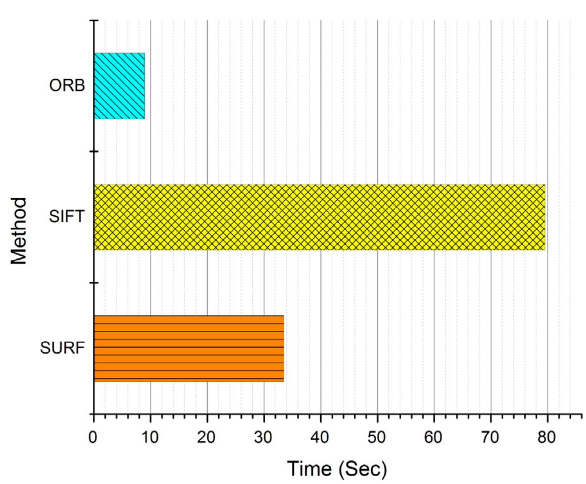

Fig. 10. Time analysis of SURF, SIFT and ORB.

Acknowledgments

This research is supported by: Start-up Research Grant Program through Research and Development Division (R & D Division) funded by Higher Education Commission of Pakistan (21-1498/SRGP/R&D/HEC/2016) and National Research Foundation of Korea (NRF) grant funded by the Korean government (MSIP) (No. 2016R1A2B4011712).

References

[1] Y. Wang, R. Chen, D.-C. Wang, A survey of mobile cloud computing applications: Perspectives and challenges, Wirel. Pers. Commun. 80 (4) (2015) 1607–1623.
[2] K. Biswas, V. Muthukkumarasamy, Securing smart cities using blockchain technology, in: 2016 IEEE 18th International Conference on High Performance Computing and Communications; IEEE 14th International Conference on Smart City; IEEE 2nd International Conference on Data Science and Systems (HPCC/SmartCity/DSS), IEEE, 2016.
[3] A. Nguyen, J. Yosinski, J. Clune, Deep neural networks are easily fooled: High confidence predictions for unrecognizable images, in: Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition. 2015.
[4] B. Mandal, et al., A wearable face recognition system on google glass for assisting social interactions, in: Asian Conference on Computer Vision, Springer, 2014.
[5] X. Wang, et al., Computerized-eyewear based face recognition system for improving social lives of prosopagnosics, in: 2013 7th International Conference on Pervasive Computing Technologies for Healthcare (PervasiveHealth), IEEE, 2013.
[6] S. Chen, A. Pande, P. Mohapatra, Sensor-assisted facial recognition: an enhanced biometric authentication system for smartphones, in: Proceedings of the 12th Annual International Conference on Mobile Systems, Applications, and Services, ACM, 2014.
[7] D.N. Parmar, B.B. Mehta, Face recognition methods & applications. arXiv preprint arXiv:1403.0485, 2014.
[8] S.H. Houmb, An integrated security verification and security solution design trade-off analysis approach. Integrating Security and Software Engineering: Advances and Future Visions/Mouratidis, Haralambos, 2007: pp. 190–219.

[9] J. Yang, et al., Two-dimensional PCA: A new approach to appearance-based face representation and recognition, IEEE Transactions on Pattern Analysis and Machine Intelligence 26 (1) (2004) 131–137.
[10] M.S.S. Kumar, R. Swami, An improved face recognition technique based on modular LPCA approach. 2011.
[11] M. Yang, et al., Monogenic binary coding: An efficient local feature extraction approach to face recognition, IEEE Transactions on Information Forensics and Security 7 (6) (2012) 1738–1751.
[12] P.M. Corcoran, C. Iancu, Automatic Face Recognition System for Hidden Markov Model Techniques, INTECH Open Access Publisher, 2011.
[13] P. Sermanet, Overfeat: Integrated recognition, localization and detection using convolutional networks. arXiv preprint arXiv:1312.6229, 2013.
[14] H. Zhang, et al., Svm-knn: discriminative nearest neighbor classification for visual category recognition, in: 2006 IEEE Computer Society Conference on Computer Vision and Pattern Recognition, IEEE, 2006.
[15] J. Wang, et al., Locality-constrained linear coding for image classification, in: 2010 IEEE Conference on Computer Vision and Pattern Recognition (CVPR), IEEE, 2010.
[16] M. Sajjad, S. Khan, Z. Jan, K. Muhammad, H. Moon, J.T. Kwak, ... , I. Mehmood, Leukocytes classification and segmentation in microscopic blood smear: a resource-aware healthcare service in smart cities. IEEE Access 5 (2007) 3475–3489.
[17] M. Sajjad, et al., Mobile-cloud assisted framework for selective encryption of medical images with steganography for resource-constrained devices, Multimedia Tools Appl. 76 (3) (2017) 3519–3536.
[18] K. Muhammad, M. Sajjad, S.W. Baik, Dual-Level security based cyclic18 steganographic method and its application for secure transmission of keyframes during wireless capsule endoscopy, J. Medical Syst. 40 (5) (2016) 114.
[19] K. Muhammad, et al., A novel magic LSB substitution method (M-LSB-SM) using multi-level encryption and achromatic component of an image, Multimedia Tools Appl. 75 (22) (2016) 14867–14893.
[20] P. Viola, M. Jones, Rapid object detection using a boosted cascade of simple features, in: Proceedings of the 2001 IEEE Computer Society Conference on Computer Vision and Pattern Recognition, 2001. CVPR 2001, IEEE, 2001.
[21] P. Jones, P. Viola, M. Jones, Rapid object detection using a boosted cascade of simple features, in: University of Rochester. Charles Rich, Citeseer, 2001.
[22] L. Wolf, Deepface: closing the gap to human-level performance in face verification, in: 2014 IEEE Conference on Computer Vision and Pattern Recognition (CVPR), IEEE, 2014.
[23] Y. Taigman, Deepface: Closing the gap to human-level performance in face verification, in: Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition. 2014.
[24] R. Varun, et al., Face recognition using hough transform based feature extraction, Procedia Computer Science 46 (2015) 1491–1500.
[25] M. üge Çarıkçı, F. Özen, A face recognition system based on eigenfaces method, Procedia Technology 1 (2012) 118–123.
[26] S. Xie, et al., Learned local Gabor patterns for face representation and recognition, Signal Process. 89 (12) (2009) 2333–2344.
[27] G.S. Yaji, et al., Dwt feature extraction based face recognition using intensity mapped unsharp masking and laplacian of gaussian filtering with scalar multiplier, Procedia Technology 6 (2012) 475–484.
[28] S. Yang, et al., Effective face recognition using bag of features with additive kernels, J. Electron. Imaging 25 (1) (2016). 013025.
[29] L. Juan, O. Gwun, A comparison of sift, pca-sift and surf, International Journal of Image Processing (IJIP) 3 (4) (2009) 143–152.
[30] N. Chowdhury, S. Nooman, S. Sarker, Access control of door and home security by Raspberry Pi through internet, Int. J. Sci. Eng. Res 4 (2013) 550–558.
[31] Z. Xu, et al., Raspberry Pi based intelligent wireless sensor node for localized torrential rain monitoring, Journal of Sensors 2016 (2016).
[32] D. Shah, IoT based biometrics implementation on Raspberry Pi, Procedia Computer Science 79 (2016) 328–336.
[33] N. Agrawal, S. Singhal, Smart drip irrigation system using raspberry pi and arduino, in: 2015 International Conference on Computing, Communication & Automation (ICCCA), IEEE, 2015.
[34] J.J. Atick, P.A. Griffin, A.N. Redlich, Continuous video monitoring using face recognition for access control. 2000, Google Patents.
[35] D. Sethia, S. Singh, V. Singhal, et al., ABE based raspberry pi secure health sensor (shs), in: R. El-Azouzi (Ed.), Advances in Ubiquitous Networking 2: Proceedings of the UNet'16, Springer Singapore, Singapore, 2017, pp. 599–610.
[36] A. Imteaj, An IoT based fire alarming and authentication system for workhouse using Raspberry Pi 3, in: 2017 International Conference on Electrical, Computer and Communication Engineering (ECCE). 2017.
[37] W. Chungki., et al. Auto charging platform and algorithms for long-distance flight of drones. in 2017 IEEE International Conference on Consumer Electronics (ICCE). 2017.
[38] V. Zdraveski, et al., Dynamic load balancing and reactive power compensation switch embedded in power meters, IEEE Transactions on Circuits and Systems II: Express Briefs 64 (4) (2017) 422–426.
[39] J. Chorowski, J. Wang, J.M. Zurada, Review and performance comparison of SVM-and ELM-based classifiers, Neurocomput. 128 (2014) 507–516.
[40] Y. Zhang, et al., Magnetic resonance brain image classification via stationary wavelet transform and generalized eigenvalue proximal support vector machine, Journal of Medical Imaging and Health Informatics 5 (7) (2015) 1395–1403.
[41] Y. Zhang, et al., Preclinical diagnosis of magnetic resonance (MR) brain images via discrete wavelet packet transform with Tsallis entropy and generalized eigenvalue proximal support vector machine (GEPSVM), Entropy 17 (4) (2015) 1795–1813.
[42] Y.D. Zhang, et al., Magnetic resonance brain image classification based on weighted-type fractional Fourier transform and nonparallel support vector machine, Int. J. Imaging Syst. Technol. 25 (4) (2015) 317–327.
[43] Y. Zhang, L. Wu, Classification of fruits using computer vision and a multiclass support vector machine, Sensors 12 (9) (2012) 12489–12505.
[44] P.J. Phillips, Support vector machines applied to face recognition. in: Advances in Neural Information Processing Systems. 1999.
[45] I.R. Fasel, J.R. Movellan, A comparison of face detection algorithms, in: International Conference on Artificial Neural Networks, Springer, 2002.
[46] P. Panchal, S. Panchal, S. Shah, A comparison of SIFT and SURF, International Journal of Innovative Research in Computer and Communication Engineering 1 (2) (2013) 323–327.
[47] E. Rublee, et al., ORB: an efficient alternative to sift or surf, in: 2011 IEEE International Conference on Computer Vision (ICCV), IEEE, 2011.
[48] I. Mehmood, M. Sajjad, S.W. Baik, Mobile-cloud assisted video summarization framework for efficient management of remote sensing data generated by wireless capsule sensors, Sensors 14 (9) (2014) 17112–17145.
[49] P. Viola, M.J. Jones, Robust real-time face detection, Int. J. Comput. Vis. 57 (2) (2004) 137–154.
[50] A. Vinay, et al., Feature extractionusing ORB-RANSAC for face recognition, Procedia Computer Science 70 (2015) 174–184.
[51] E. Karami, S. Prasad, M. Shehata, Image Matching Using SIFT, SURF, BRIEF and ORB: Performance Comparison for Distorted Images. Faculty of Engineering and Applied Sciences, Memorial University, Canada.

Muhammad Sajjad received his Master degree from Department of Computer Science, College of Signals, National University of Sciences and Technology, Rawalpindi, Pakistan. He received his Ph.D. degree in Digital Contents from Sejong University, Seoul, Republic of Korea. He is now working as an assistant professor at Department of Computer Science, Islamia College Peshawar, Pakistan. He is also head of "Digital Image Processing Laboratory (DIP Lab)" at Islamia College Peshawar, Pakistan, where students are working on research projects such social data analysis, medical image analysis, multi-modal data mining and summarization, image/video prioritization and ranking, Fog computing, Internet of Things, virtual reality, and image/video retrieval under his supervision. His primary research interests include computer vision, image understanding, pattern recognition, and robot vision and multimedia applications, with current emphasis on raspberry-pi and deep learning-based bioinformatics, video scene understanding, activity analysis, Fog computing, Internet of Things, and real-time tracking.

Mansoor Nasir received his M.S. degree in Computer Science from Institute of Management Sciences, Peshawar, Pakistan. He is currently pursuing Ph.D. course from Islamia College, Peshawar, Pakistan. His research interest include, Network Security, Distributed Systems and Trusted Computing.

Khan Muhammad (S'16) received the bachelors degree in computer science from Islamia College, Peshawar, Pakistan with research in information security. He is currently pursuing M.S. leading to Ph.D. degree in digitals contents from College of Software and Convergence Technology, Sejong University, Seoul, Republic of Korea. He has been a Research Associate with the Intelligent Media Laboratory (IM Lab). His research interests include image and video processing, wireless networks, information security, image and video steganography, video summarization, diagnostic hysteroscopy, wireless capsule endoscopy, deep learning, computer vision, and CCTV video analysis. He has authored over 30 papers in peer-reviewed international journals and conferences, such as Future Generation Computer Systems, the IEEE ACCESS, the Journal of Medical Systems, Biomedical Signal Processing and Control, Multimedia Tools and Applications, Pervasive and Mobile Computing, SpringerPlus, the KSII Transactions on Internet and Information Systems, the Journal of Korean Institute of Next Generation Computing, MITA 2015, PlatCon 2016, and FIT 2016.

Please cite this article in press as: M. Sajjad, et al., Raspberry Pi assisted face recognition framework for enhanced law-enforcement services in smart cities, Future Generation Computer Systems (2017), https://doi.org/10.1016/j.future.2017.11.013.

Siraj Khan received his BCS degree from University of Peshawar, Pakistan in the field of computer science. Currently, he is doing Master degree in computer science from Islamia College Peshawar, Pakistan. He is an active member of Digital Image Processing Lab, Department of Computer Science, Islamia College Peshawar. His research interests include image processing, image segmentation, image classification and healthcare services.

Zahoor Jan is currently holding the rank of an associate professor in computer science at Islamia College Peshawar, Pakistan. He received his M.S. and Ph.D. degree from FAST University Islamabad in 2007 and 2011 respectively. He is also chairman of Department of Computer Science at Islamia College Peshawar, Pakistan. His areas of interests include image processing, machine learning, computer vision, artificial intelligence and medical image processing, biologically inspired ideas like genetic algorithms and artificial neural networks, and their soft-computing applications, biometrics, solving image/video restoration problems using combination of classifiers using genetic programming, optimization of shaping functions in digital watermarking and image fusion.

Arun Kumar Sangaiah has received his Doctor of Philosophy (Ph.D.) degree in Computer Science and Engineering from the VIT University, Vellore, India. He is presently working as an Associate Professor in School of Computer Science and Engineering, VIT University, India. His area of interest includes software engineering, computational intelligence, wireless networks, bio-informatics, and embedded systems. He has authored more than 100 publications in different journals and conference of national and international repute. His current research work includes global software development, wireless ad hoc and sensor networks, machine learning, cognitive networks and advances in mobile computing and communications. Also, he was registered a one Indian patent in the area of Computational Intelligence. Besides, Prof. Sangaiah is responsible for Editorial Board Member/Associate Editor of various international journals.

Mohamed Elhoseny completed his B.S. in Computer and Information Sciences from Mansoura University, Faculty of Computers and Information, Egypt. Then, Dr. Elhoseny received his Ph.D. in Computer and Information Sciences from Mansoura University Egypt (in a scientific research channel with Department of Computer Science and Engineering, University of North Texas, USA). His Ph.D. thesis was awarded the best Ph.D. thesis prize (2016) at Mansoura University. Dr. Elhoseny is currently an Assistant Professor at the Faculty of Computers and Information, Mansoura University, Egypt where he also teaches several courses such as Security in Computing, "Mobile Computing", and Information Theory. Collectively, Dr. Elhoseny authored/co-authored over 50 International Journal articles, Conference Proceedings, Book Chapters, and 1 Springer brief book. His research interests include Network Security, Cryptography, Machine Learning Techniques, Internet of Things, and Quantum Computing. He has several publications in reputed and high impact journals published by IEEE, Elsevier, Springer, and others.

Sung Wook Baik received the B.S. degree in computer science from Seoul National University, Seoul, Korea, in 1987, the M.S. degree in computer science from Northern Illinois University, Dekalb, in 1992, and the Ph.D. degree in information technology engineering from George Mason University, Fairfax, VA, in 1999. He worked at Datamat Systems Research Inc. as a senior scientist of the Intelligent Systems Group from 1997 to 2002. In 2002, he joined the faculty of the College of Electronics and Information Engineering, Sejong University, Seoul, Korea, where he is currently a Full Professor and Dean of Digital Contents. He is also the head of Intelligent Media Laboratory (IM Lab) at Sejong University. His research interests include computer vision, multimedia, pattern recognition, machine learning, data mining, virtual reality, and computer games. He is a member of the IEEE.

Please cite this article in press as: M. Sajjad, et al., Raspberry Pi assisted face recognition framework for enhanced law-enforcement services in smart cities, Future Generation Computer Systems (2017), https://doi.org/10.1016/j.future.2017.11.013.