Future Generation Computer Systems 83 (2018) 553–563

Contents lists available at ScienceDirect

Future Generation Computer Systems

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

Monitoring of pet animal in smart cities using animal biometrics

Santosh Kumar *, Sanjay Kumar Singh

Department of Computer Science & Engineering, Indian Institute of Technology (B.H.U.), Varanasi-221005, India

HIGHLIGHTS

- A pet recognition system is proposed for the monitoring of pet animals (dogs) in the smart cities.
- The system recognizes the individual dogs based on their biometric facial features
- The proposed system uses the one-shot similarity and distance metric based learning methods for matching of facial features of pet animals (dog).
- We also developed a prototype for evaluating the accuracy of the recognition system.
- The efficacy of proposed pet animal recognition system is 96.87% recognition rate.

ARTICLE INFO

Article history:
Received 28 July 2016
Received in revised form
11 November 2016
Accepted 5 December 2016
Available online 14 December 2016

Keywords:
Animal biometrics
Pet animal
Face recognition
Smart city
Security
Monitoring
Dog
OSS
FLPP
LBP
SURF
LDA

ABSTRACT

Monitoring of pet animal in smart city is a big challenge for authorities concerned. The classical animal identification and monitoring methods fail to provide the required level of security and management of pet animals. Animal biometrics based recognition systems are considered a good alternative for the health management, tracking, identification, and security of pet animals. In this paper, we propose a low-cost system for monitoring of pet animals (dogs) based on their primary animal biometric identifiers. The proposed recognition approach uses the one-shot similarity and distance metric based learning methods for matching and classifying the extracted features of face images for recognition of pet animals (dog). We also developed a prototype for evaluating the accuracy of the recognition system. The efficacy of proposed pet animal recognition system is evaluated under identification settings yields 96.87% recognition rate.

1. Introduction

Smart cities include various kinds of intelligent devices with efficient functions and systems [1], that can be accessed remotely by the users [2]. The main objective of the smart city is to provide an enhanced comfort, saving of resources, efficient retrieval of information, fast communication, better security for its residents and pet animals [2,3].

According to available literature, the total population of pets (dogs) in the throughout wold is more than 700 million [4], and 7 million dogs enter the animal shelters in the United States every year. Only 10% of the total population of pets are adopted or make it back to their owners or parentage in the smart cities [5].

According to Ref. [6], in the USA, there is one pet animal for every three humans, and the increasing rate of domestic animals (i.e., canine breeds), and other pets ownership keeps rising continuously. Based on the current report of pet animals in 2015–16, the total number of pets is about 153,000 (especially dogs) in the city of Seattle which is greater than the number of children of each family (*e.g.*, 107,000 *children*).

Similarly, New York City also recorded a rapid increase in the number of production of dog breeds, and in owners of pet animals (*e.g.*, 600,000 *dogs*) which is greater than the previous year [7]. It is a huge problem in the monitoring and recognition of huge population of pet animals using existing approaches and traditional identification systems in the smart cities of the United States.

* Corresponding author.
E-mail addresses: santosh.rs.cse12@iitbhu.ac.in (S. Kumar), sks.cse@iitbhu.ac.in (S.K. Singh).

http://dx.doi.org/10.1016/j.future.2016.12.006
0167-739X/

In a similar direction, author Maroto [7] reported that more than 50,000 starving stray pet animals (dogs) swarmed Detroit when the pets owners left the bankrupt city leaving their pet animals behind. Based on the current survey of pet animals, the average number of pets per household varies in different countries, generally depending on the total population.

Still, there is no record, database or any documentation available for the average number of pet animals per household in the smart cities throughout the world. However, the UK have an average of 3.7 pet animals, in contrast to the USA states, which have an average of 3.9 [8]. The values depict more than 4 billion pet animals are living with people [8]. Further, in the UK nearly 4 million dogs and around 3 million cat owners take their pet animals away, when enjoying a short break, or attending a different kind of conferences for business away from their home or city [8,9].

The recognition and monitoring of the huge population of pet animals (e.g., dogs and other pet animals) are major problems in the smart cities throughout the world [7,10,11]. For the recognition of missed, or swapped of pet animals, monitoring and verification of false insurance claims, no animal biometric recognition systems are found in the literature or public domains to solve these major challenging problems of pet animals [7]. These major problems cannot be neglected by computer vision scientists, professionals, animal experts, and different research communities to provide to the consistent efforts for the design, and development of a non-invasive, cost-effective and automatic system for the monitoring of pet animals.

Due to the failure of the traditional animal recognition systems for solving the major challenging problems of pets, there is a requirement to develop an animal biometrics based recognition system for pet animal to recognize and monitoring of individual pet animals in the smart cities.

The pet animal recognition system can help to identify the owners or parentage of pet animals after matching of their facial image with stored database. The recognition systems also provide a way to control the wide spread of critical diseases in animal livestock [11]. It can provide efficient methods to ensure the quality food for the pet animals. It can also perform the validation process to verify and check the various sources of food productions, processes, and their exports. In the available literature, classical animal recognition approaches are applied to recognize and monitor the pet animals in the smart cities [12]. The classical animal recognition methodologies are ear-tagging, freeze-branding, ear-tattoos, ear-tipping or notching and embedding of microchips in the body of pet animals for their recognition purpose [10,13]. These are invasive approaches for the recognition of individual pet animal (dogs). However, classical methodologies are more susceptible to huge vulnerability to losses, illegibility. It has always more security issues for the recognition and monitoring of pet animals [14,15].

In the conventional animal recognition systems, monitoring and recognition of pet animal can easily be done using ear-tags, embedding microchips in their body [15]. However, integrated ear-tags and microchips became damaged, lost or stolen easily [11,16,17]. The embedded unique number in the ear-tags can also be duplicated and forged. Therefore, ear-tagging and microchips based techniques have more vulnerability due to losses and cause major security issues [18].

Moreover, in the current state-of-the-art based animal biometric-based recognition systems [19,20], only manual recognition systems are available [21]. The animals are verified and identified using only these techniques to solve the major problems such as missing, swapped animal, false insurance claims by cutting their ear or snatch the labeled ear tags or notches from the animals ear by different governmental and private animal insurance organizations [11,22].

Further, for the recognition of pet animals, various emerging technologies and Internet of Things (IOT) devices have been investigated to provide the better solutions for recognizing, monitoring and tracking problems of pet animals in the smart cities [23]. The technologies mainly include GPS positioning, Bluetooth or Wi-Fi-networks, and RFID techniques [24]. However, it is reported that during the practical implementation, these techniques are more problematic to attach or embed the IOT based devices to pet animals [25,26]. Various apps are also reported in the literature for monitoring of pet animals [6].

Animal biometrics is a pattern recognition based system for recognizing the species or an individual animal based on their primary biometric characteristics [19,27]. Recently, recognition systems are gaining more attention and proliferation due to a variety of applications and use for registration and monitoring of pet animal in the smart city throughout the world [20,28].

In this paper, we proposed a recognition system for pet animal (dogs) to recognize individual dogs using their facial images in the smart city. The dog face image consists of discriminatory biometric features. Moreover, face recognition-based solutions provide efficient recognition of individual pet animal in the smart city in the real-time.

To solve this major problem and provide efficient solutions, the proposed recognition system uses surveillance cameras for automatic capturing the dog face images in the smart city. The deployed surveillance cameras have continuously performed the recording of videos and capture the movements of pet animal (dogs).

The proposed automatic recognition system provides effective solutions for recognizing and monitoring of pet animals (dogs) and to help the smart cities to cope with the rapidly rising population of pets across the world. These solutions can also provide the better platform for their recognition, registration, monitoring, and traceability in the real-time scenario.

The benefits of the proposed system are cost-effective, non-invasive, automatic, easy to acquire the biometric data for the monitoring of pet animals in the smart city in real time scenario. The proposed system does not need any extra hardware like RFID-tags, embedding microchips, hot iron, freeze-branding and sensors. The proposed recognition system provides a non-contact, cost-effective, and robust recognition system for the pet animals. Thus, there is no requirement to mount or embed any invasive artificial marking or microchips identifiers to the pet animals for the recognition and monitoring purpose.

The proposed pet animal recognition system can replace the classical recognition and monitoring approaches. The recognition system is good for easy to acquire images, accurate, and also humane [19,20,29].

•Research contributions

Following are the major contributions of this research:

1. In this paper, we propose an automatic pet recognition system as a prototype for the recognition and monitoring of pet animals (dogs) in the smart cities. The proposed recognition system recognizes the individual dogs based on their biometric facial features of pet animals (dogs). The recognition system performs the preprocessing of captured video frames (set of image sequence) by removal and filtering of noises which increase the image quality and enhance the contrast of dog face images.
2. We propose a Fisher Linear Projection and Preservation (FLPP) feature extraction and representation approach for unique recognition of pet animals (dogs) by maximizing the inter-class (between-class) scatter feature matrix by minimizing the intra-class (within-class) scatter matrix of dog face images database to improve the recognition accuracy.

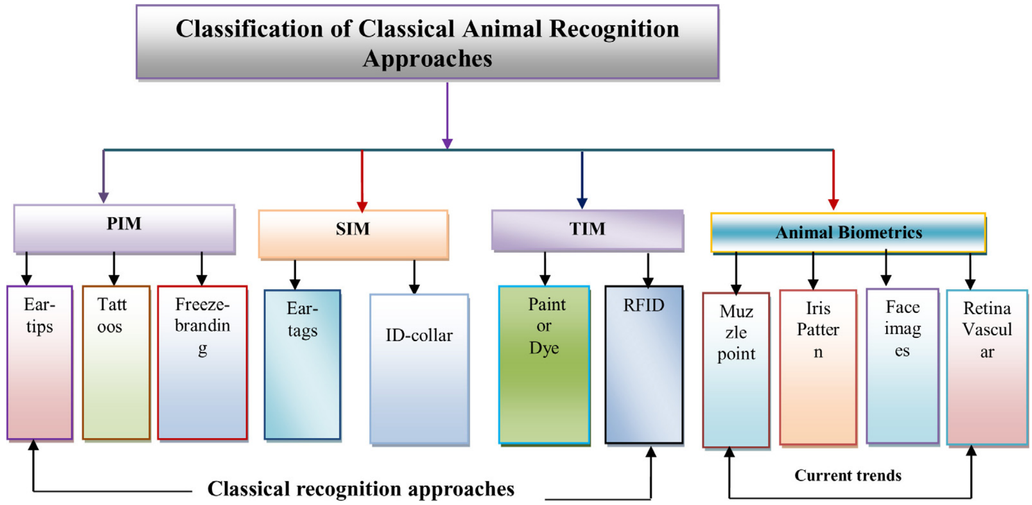

Fig. 1. Classification of classical animal recognition approaches.

3. The proposed approach uses the One-Shot Similarity (OSS) via distance metric based learning with online incremental support vector machine to classify the extracted features of face image database of pet animals (dogs). We use the OSS matching, and the distance matrices based learning technique for the matching of the feature vector of dog facial images with a stored template database of pet animals (dogs).

The remaining sections of this paper are as follows: Section 2 presents the literature review, existing techniques for monitoring, and identification of animal methods. Section 3 illustrates database description of dog face images. Section 4 demonstrates the proposed system for recognition and monitoring of pet animal (dogs). Section 5 illustrates the proposed feature extraction and representation approach of face image of pet animal (dogs). Section 6 presents experimental results, and analysis. Finally, Section 7 explains conclusion and future directions.

2. Related work

The dog is first pet animals to be domesticated in our society. They shared a common environment with humans for over ten thousand years. The pet animal (dogs) (e.g., Canis dog breeds) plays vital roles in the protection of increased number of industries and organizations [30–32].

The classical animal recognition approaches can be classified broadly into the following groups, namely: (1) Permanent Recognition Method (PRM), (2) Semi-permanent Recognition Method (SRM), and (3) Temporary Recognition Method (TRM) [13] as shown in Fig. 1. The examples of permanent recognition techniques are ear-tattoos, embedding microchips, ear-tipping or notching, hot ironing, and freeze-branding based marking and recognition of pet animals [12–14,33].

In the semi-permanent approaches, ear-tagging and id-collar based recognition techniques are applied for identification of pet animals in the smart city. However, ear-tagging based recognition, embedding tags disintegrate the animal ear for long term usages. Therefore, a lot of critical diseases occurred to animals [34]. The temporary recognition techniques include extra hardware for the identification of pets [13,34].

The collar-id and GPS-enabled sensor devices provide the efficient solutions as compared to embedding microchips or RFID for monitoring of pet animals in the smart city. However, due to weak signal, management of GPS-enabled devices is a challenging problem [10,16,35]. Therefore, the traditional animal recognition and monitoring systems do not provide the required level of control and security of pets [11,13,14,36–38].

The animal biometrics has provided a new paradigm for the recognition and monitoring of pet animals in the smart cities [37]. In [39], author Own et al. [40] proposed an intelligent pet animal care system (e.g., automatic pet doors and pet feeder systems) using the Internet of Things (IOT) techniques for the monitoring and feeding of pet animals [40,41]. The proposed system overcomes the limitation of traditional products and meets the requirements of pet owners to certain levels. However, the significant disadvantage of the proposed system is that the infrared detectors can be disturbed efficiently, which degrades the performance of the animal care system.

The author Chen et al. [42] proposed a novel biometric-based recognition framework to identify the pets (especially for cat breeds) using their nose pattern [42]. The identification of pets is performed on prepared cat data of 700 cat nose image pattern from the 70 different subjects (cat breeds). In this method, representative dictionary based learning techniques with data locality constraint approach are applied for the identification of cats. However, they have not performed any cross-validation for experimental results.

Polimeno et al. [43] proposed a recognition system for identifying the lost pet animals. The system has performed the identification of pet animal using their biometric data (e.g., eyes and nose information).

Recently, Kumar et al. [11] proposed the biometric recognition system for pet animal (dogs)based on their facial images. For the identification of pet animal (dogs), 400 face image database is prepared from 50 dogs races. In this paper, experimental results demonstrated the effectiveness of the proposed biometric system for pet animal as compared to state-of-the-art feature-based algorithms and yield 94.86% identification accuracy for the pet animal.

3. Description of database

This section illustrates the description of prepared face image database of pet animals (dogs). For the preparation of database, facial image of is collected from different websites such as Dogster [44], Catster [45] and dog-space [46]. Additionally, two other social websites (e.g., Google and Flickr image sites) [47] is employed to collect the database of dog face images for the training and testing of the proposed recognition model for identification of pet animal (dogs). The size of prepared face image database of dog

Table 1
Details of dog breeds face image database.

Breeds (dogs)	No. of subjects (dogs)	No. of images
Rajapalayam dog	150	1500
German Shepherd dog	150	1500
English Bulldog	100	1000
Tibetan Mastiff dog	100	1000

Fig. 2. Face images of dogs from the database.

is 5000 face images (i.e., 500 subjects (dogs)) × 10 images of each subject). The size of each face image of the dog is 500 × 500 pixels. The sample detail description of the database is given in Table 1. The face image of the dogs from the database is shown in Fig. 2.

4. Proposed system

In this section, the proposed recognition system for pet animals (dogs) using their facial images is illustrated in detail. The working block diagram of the proposed recognition system is shown in Fig. 3. For the manifestation of recognition of pet animals (dogs), the proposed recognition system uses the surveillance cameras for continuous acquisition of the dog image from the captured video. Further, the recognition system extracts the frames (*e.g.,* dog face images) from the captured video.

After that, it performs the pre-processing and enhancement of extracted frames of pet animals (dogs). The pre-processing is performed by conversion and transformation of captured face images of dogs into grayscale images. The gray scale face images are cropped and re-sized into 200 × 200 pixels. Further, the system performs pre-processing for the mitigation of noise, and blurriness from the grayscale images. The contrast enhances the gray images of dogs between pixel intensity of face images using the Contrast-Limited Adaptive Histogram Equalization (CLAHE) image processing technique [48]. After segmentation of face images, the recognition system extracts the facial features from the segmented dog face images. The pixel intensity and texture features of facial images are extracted from the face images of pet animal (dogs) for the recognition using texture descriptor techniques and appearance feature extraction algorithms.

The test face images of dog are matched with a stored face template database of dog face images of pet animal using One-Shot Similarity (OSS), distance metric based matching techniques, and classifying the extracted features using Incremental Support Vector Machine (I-SVM) learning technique for the recognition of pet animals (dogs).

The proposed recognition system is motivated from the feature extraction, and representation based learning, and distance metric learning based matching technique [49,50]. For the experimentation and encoding purpose, the face database of pet animal (dogs) is divided into two classes: (1) between-class, and (2) within-class of face image database. The main motivation is to achieve the better accuracy for identifying individual pet animals (dogs) by maximizing between-class scatter feature matrices (S_B), and minimizing the within-class scatter feature matrices (S_W) of dog face database. Therefore, it is a need to compute the better separability of the extracted features of dog face images among different respective classes.

To achieve the objective of better separability between classes, we proposed a Fisher Locality Preserving Projections (FLPP) approach which maximizes the between-class scatter by minimizing the within-class scatter of the pet animals (dog) face image database. The proposed FLPP approach is illustrated in detail in the next section.

5. Proposed FLPP feature extraction and representation approach

The proposed Fisher Linear Preserving Projection (FLPP) approach performs computation by determining the directions that maximize the between-class scatter matrix (S_B) and keeping the local geometrical feature (data) in feature space [51,52]. The main advantages of this technique have provided the motivation to propose an improved Fisher Linear Discriminant Analysis (FLDA) feature extraction and representation based technique known as Fisher Locality Preserving Projections (FLPP) [52].

The proposed FLPP approach performs the computation for the global distribution of within-class (S_W) scatter matrix, and between-class (S_B) scatter matrix of the pet animal (dog) face image database locally. The class separability and neighborhood preservation of dog face images are achieved simultaneously using proposed FLPP approach for the feature extraction and representation of face images. The working of the proposed approach [53] is illustrated as follows (shown in Eqs. (1)–(6)):

$$S_B = \sum_{i=1}^{N} (N_i(m_i - m) \times (m_i - m))^T \tag{1}$$

$$S_W = \sum_{i=1}^{N} \sum_{x_k} (N_i(m_i - m) \times (m_i - m))^T \tag{2}$$

$$m = \frac{1}{N} \sum_{i=1}^{N} N_i. \tag{3}$$

In above Eqs. (1)–(3), S_B, S_W and m are defined as a between-class, within-class, and mean of classes of face image database, respectively. The Fisher locality preserving projections (FLPP) approach is applied to compute the between-class (S_B), and within-class (S_W) feature scatter matrix of dog face image database. The proposed approach determine the directions that are efficient for discrimination by minimizing the within-class (intra-class) scatter matrix S_W by maximizing the between-class (inter-class) scatter matrix S_B for compacts representation of extracted features in the feature space.

In order to minimize the misclassification error, we maximize the w to achieve maximum class-separation in the direction w of feature space, term W_{OPT} denotes the maximum separation between class and within-class of face image database of the pet animal (dog).
FLDA computes a projection matrix (W) which is optimized to separate the different classes of face images of dogs. It is denoted by W_{OPT} as follows:

$$W_{OPT} = \underset{w}{\text{argmax}} \frac{u^T S_B}{u} u^T S_W u. \tag{4}$$

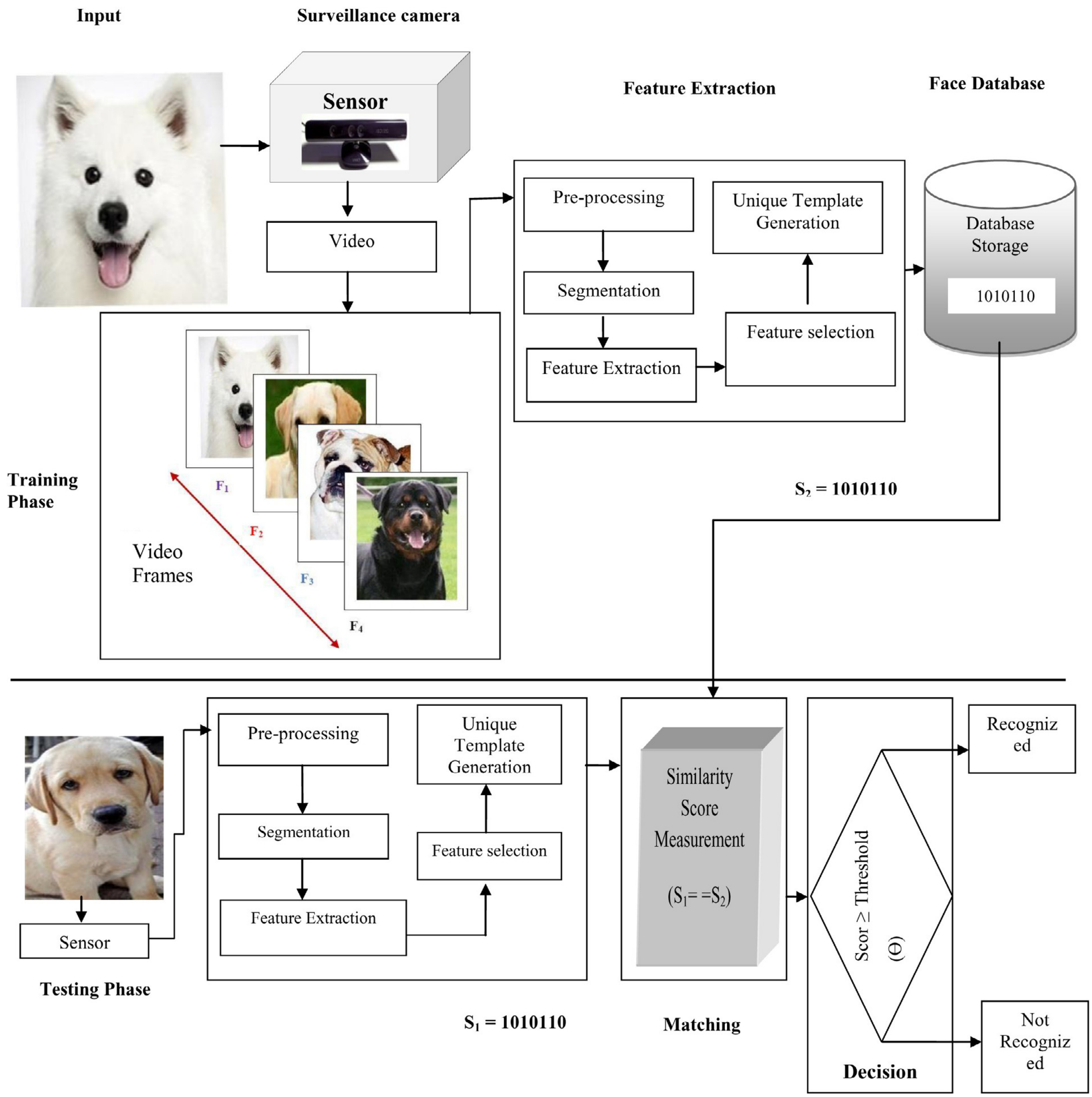

Fig. 3. Proposed block diagram for automatic dog recognition system.

In many cases, within-class (S_W) is usually singular, *e.g.*, the inverse of (S_W) does not exist. The singular equivalent construction method is applied to solve this problem as follows:

$$W_{OPT} = \underset{w}{\text{argmax}} \frac{u^T S_B u}{u^T (S_W + S_B) u} \tag{5}$$

$$W_{OPT} = \underset{w}{\text{argmax}} \frac{u^T S_B u}{u^T (S_R) u} \tag{6}$$

where S_R is defined as total scatter matrix and can be computed as follows:

$$S_R = \sum_{i=1}^{c} \sum_{x_j \in X_i} (x_j - m_i) \times (x_j - m_i)^T. \tag{7}$$

In the above Eqs. (1)–(6), we can notice that Eq. (7) illustrates that S_R only depends on the global mean. It does not compute the complete class means of the database; only it is calculated without having the information of class labels. The criterion, Eq. (6) is formulated into a Generalized Eigenvalue based problem as follows (shown in Eqs. (8)):

$$S_B V_i = \Lambda_i S_R V_i \tag{8}$$

where the Eigen-vector (V_i) is called the ith Fishers linear discriminant. Eq. (8) generalizes the solution (V) of the Eigenvalue problem of dog face image. It retains the most discriminant projection direction in the feature space. The (c) and (n) are defined as the total number of sample images and number of entire classes of the face image of the pet animal (dog) database.

To achieve the maximum separability between the classes of face images, initially, the two graphs are constructed and represented using proposed FLPP approach. The construction and representation of graphs are shown in Algorithm 1. At the beginning, a set of (n) dog face images is represented in the form of $X = (X_1, X_2 \cdots X_n)$ in $\Re^{n \times d}$ [54].

In this case, each face image belongs to one of the c classes such as $x = (x_1, x_2 \cdots x_n)$. The proposed FLPP approach uses an OSS similarity-based matching via distance metric learning with Incremental-SVM (I-SVM)(online) classification model for the classification, and recognition of dog face images [55]. The proposed FLPP approach performs the computation for maximizing the class separability using constructed graphs based representation, which is shown in Algorithm 1.

Algorithm 1 Proposed FLPP Feature Extraction and Representation approach

procedure INITIAL TRAINING

1. Initialize data matrix $X = [X_1, X_2 \cdots X_n]$.
2. Initialize two neighbor sharing ($N_W Xi$), and ($N_B Xi$) for the construction of graphs. Two subsets of neighbor sharing share the similar class label with X_i and G_W.
3. Construct the two graph structures for the compact representation and modeling of the within-class using neighbor sharing (X, S_W), and G_B (X, S_B).
4. The within-class (S_W) compactness is constructed by joining an edge between two nodes (x_i, x_j), if they belong to the same class.
5. Calculate the compactness of within-class (S_W) by computing the G_W(X, S_W) as follows:

$$S_W^{"} = \sum_{(ij)x_i \in N_W}^{N} \sum_{x_j \in N_W(x_(j)} (u^T x_i - u^T x_j) 2u^T \times u(D_W - S_W) \times X^T u \quad (9)$$

where Z = $(D_W - S_W)$ is defined as a Laplacian matrix and D_W is calculated as $D_W = \sum_j S_w$. S_w is the similarity matrix of the within-class graph GW. We have applied the heat kernel function based formulation to calculate the S_w as follows:

$$S_W = \begin{cases} exp(-\frac{(x_i - x_j)^2}{t}), & \text{if } x_i \in N_W(x_(j) and x_j \in N_W(x_(i) \\ 0 & \text{otherwise} \end{cases}$$

Here, t is a constant.
6. Similarity matching: similarity matching is done between-classes G_B (X, S_B) and between-class scatter matrix S_B. The between-class scatter S_B is calculated as follows:

$$S_B = \begin{cases} exp(-\frac{(x_i - x_j)^2}{t}), & \text{if } x_i \in N_W(x_(j) and x_j \in N_W(x_(i) \\ 0 & \text{otherwise} \end{cases}$$

Where, D_B is calculated as follows: $D_B = \sum_j^N S_W$
7. compute the class-separability using defined class graph G_W(X, S_W), and G_B (X, S_B). The class-separability between different classes of dog face images is evaluated by defined class graphs G_W(X, S_W), and G_B (X, S_B). The between-class ($S_B^{"}$) computed as follows:

$$S_B^{"} = \sum_{(ij)x_i \in N_W}^{N} \sum_{x_j \in N_W(x_(j)} (||u^T x_i - u^T x_j||) \times S_B \quad (10)$$

$$= 2u^T \times (D_B - S_B) \times X^T u \quad (11)$$

$$= 2u^T \times T \times X^T u \quad (12)$$

Where, $T = (D_B - S_B^{"})$ is defined as a Laplacian matrix.

End procedure

The proposed FLPP approach computes the projection matrix (W) to separate different classes of dog face images using (S_B'') and (S_W'') (from Eqs. (9) and (10)) which is denoted by W_{new}, (given in Eqs. (13)–(15)) as follows:

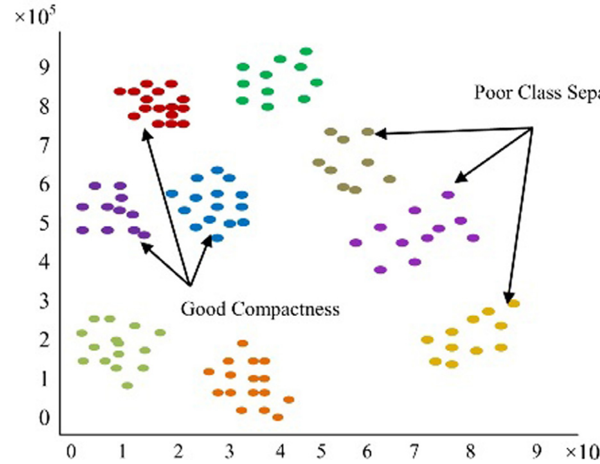

Fig. 4. Scatter plot of 10 different pixel intensity values of face image classes with 250 samples of dog face images using the LLP linear projection, and FLDA supervised classification technique.

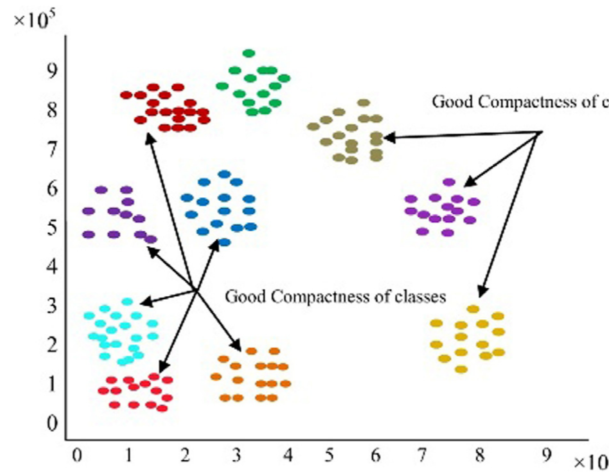

Fig. 5. Representation of scatter plot of 10 different pixel intensity values of face image classes with 250 samples of face images using proposed FLPP approach.

$$W_{new} = \underset{w}{\text{argmax}} \frac{u^T S_B'' u}{u^T S_W'' u} \quad (13)$$

$$W_{new} = \underset{w}{\text{argmax}} \frac{u^T XPX^T u}{u^T XTX^T u} = \underset{w}{\text{argmax}} \frac{u^T XPX^T u}{C} \quad (14)$$

where $u^T XTX^T u = C$, C is a constant. To solve the class separability problem, the proposed FLPP approach is illustrated into a more generalized Eigenvalues to provide better separability as follows:

$$XPX^T W = \lambda XTX^T W. \quad (15)$$

The proposed FLPP approach outperforms the conventional Fisher Linear Discriminant (FLD) and Linear Preserving Projection (LPP) methods. For example, in the case of LPP, proposed FLPP approach yields a superior compaction representation of the within-class (S_W) of dog face image database by minimizing the distances between data (set of features) points and its neighbors of the same classes. The representation of 10 different data classes in the scatter plot of dog face images is shown in Figs. 4 and 5, respectively.

For the comparative analysis of experimental results, we have extracted the texture features of dog face images using texture feature based descriptor techniques. We have applied the

Fig. 6. Representation of Eigen-faces of dog face images using appearance based face recognition approach.

feature descriptor techniques such as Speeded Up Robust Feature (SURF), Local Binary Pattern (LBP), and holistic (appearance) based recognition approaches are applied. A brief description of appearance based feature extraction, and representations, and texture feature descriptor algorithms are given in the next subsection.

5.1. Appearance based and texture based feature extraction algorithm

Appearance-based face recognition algorithms are classical feature extraction and data representation technique. It is widely used in the area of pattern recognition, and computer vision. In this paper, appearance-based feature extraction and representation approaches are used such as Principal Component Analysis (PCA), Linear Discriminant Analysis (LDA) and Independent Component Analysis (ICA) [56,57]. The facial representation of Eigen-face of dog face image is shown in Fig. 6.

The extracted feature of the face image of pet animal (dogs) consists of dense skin texture information. For the extraction of texture features from the dog face images, Speeded Up Robust Features (SURF) [58] and Local Binary Pattern (LBP) [59,60] algorithms are applied to extract the features from the facial images of pet animals (dogs).

The extracted texture features are encoded into a binary pattern for the better matching of the face image. The texture features are extracted from the dog face images using LBP and SURF descriptor techniques, as shown in Figs. 7, 8, and 9, respectively. The higher matching scores of face images enhance the recognition accuracy of pet animal (dogs). The recognition of individual dog is shown in Fig. 10.

Algorithm 2 Matching of the face image of pet animal (dog) using distance metric based learning technique, incremental-SVM and 1-class SVM classification models.

procedure MATCHING
Input : F_1, and F_2 are two face images of pet animal (dog), models of incremental-SVM, and 1-class SVM classification, match scores (S), S_1, S_2, M_i-1 (remaining dog face images), i, N (total face images), and decision threshold (θ), (where i= 2, 3,4...N).
$Incremental - SVM^{F_1}_{online}$:=Update incremental-SVM model with F_1 as positive sample image of faces as training image with remaining face images F_i-1
S_1 = calculation of Euclidean distance from decision boundary of F_2 from $Incremental - SVM^{F_1}_{online}$
$1 - classSVM^{F_2}_{online}$:=Update SVM model online with F_2 as positive sample of dog face image with remaining images F_i-1
S_2 = calculation of Euclidean distance from decision boundary of F_1 from $1 - classSVM^{F_1}_{online}$
Similarity matching : If (S_1 == S_2) **return** similarity scores (S= S_1), **Else**
Update the similarity scores and perform the computation of matching again with test dog face images
output : if(S≥ Threshold (T)) report "genuine" **else** "imposter"
end procedure

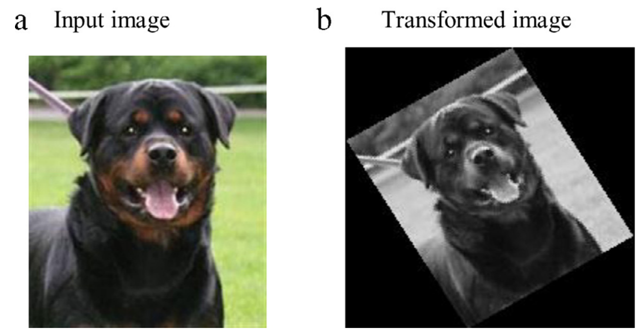

Fig. 8. (a) Input face image, (b) transformed dog face image using SURF descriptor approach.

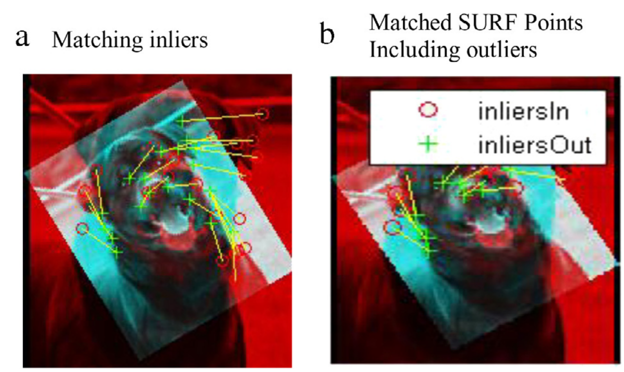

Fig. 9. (a) Matching of inliers points with transformed dog face image, (b) similarity based matching of SURF features including the outerliers using SURF descriptor approach.

Fig. 10. Recognition of dog using texture features of dog face images from the classes of face image database.

5.2. Matching of face images of dogs

In this section, similarity matching techniques such as One-Shot Similarity (OSS) matching, distance metric based learning with Incremental-SVM (I-SVM), and 1-class SVM techniques are applied for the matching of the face images of pet animal (dogs) [61]. The main advantage of I-SVM models in this research work is that it provides the updates regularly to adapt the variations of pixel intensity in the extraction of facial features of pet animal [55]. Further, we customized the batch learning based formulation of 1-class SVM model, and I-SVM model for the increasing or decreasing (online) learning technique. It caters the adequate number of the incremental database of the dog face images with time. The I-SVM learning model successively excludes some histories of sample pictures and restore several new samples from the dog face images. The matching of two face images (based on pixel intensity) is shown in Algorithm 2.

6. Experimental result and analysis

In this section, the experimental results are performed on intel core 2 duo, 2.8 GHz computer with 400 GB of RAM. For performance evaluation of experimental results, we have divided the face images database of pet animal (dogs) into two parts: (1) training part, and (2) testing part. The 6 face images of each dog (e.g., 500 subjects (dogs) $\times$ 6 face images of each subject $=$ 3000) images are applied for the training the pet animal recognition system. For the testing phase, four face images (e.g., 500 dogs $\times$ 4 face images of each dog $=$ 2000) are used as the probe face image for the recognition of dog face using OSS matching technique with stored face images in the database. The evaluation of rank-1 recognition accuracies are computed, and validation of accuracy is computed in 5-times cross-validation.

For the computation of recognition accuracy, texture feature based descriptors algorithms such as SURF [58], LBP [59,60], and appearance-based face recognition algorithms (PCA [62], LDA [63], ICA [56,57]) are applied to the feature extraction, and representation of facial images of dogs in feature space. The experimental results are shown in the form of Cumulative Match Characteristics (CMC) curves. The CMC curve determines the recognition accuracy of pet animal recognition systems.

In this paper, we have performed the experimentation to measure the identification of dog based on their facial images. The CMC curve shows the recognition accuracy of pet animal recognition systems, how well this system discriminates individual by identifying with the registered face image of dogs database on a given test or probe face image of the dogs.

In the case of identification, the input (probe) feature set of dog face image is compared against all templates stored in the face image database of pet animal (dogs) to determine the top best matches. For the matching of query face images, similarity matching techniques e.g., Euclidean distances, One-shot similarity (OSS) and distance metric learning based matching technique are applied. The top best matches are evaluated by determining the matching scores about all the comparisons and provide the recognition of facial template corresponding to the largest matching similarity score.

We can elaborate that does any one of the top P matches of dog face images corresponds to the correct identification of dog? [64, 65]. The rank-P identification rate, R_P illustrates the proportion of times the true identity occurs in the top P matches which are determined by the similarity match score technique. The rank-P based performance evaluation of experimental is demonstrated using the Cumulative Match Characteristic (CMC) curve. The CMC curve plots R_P against P for ($P = 1, 2, \ldots, N$) with N being the number of enrolled subjects (dogs).

In this experiment, the performance of the proposed FLPP approach is evaluated, and its comparison is done with appearance-based recognition technique and texture descriptor algorithms for the identification of pet animal (dogs). The recognition accuracy is illustrated in the form of the number of extracted features of dog face images, and rank basis recognition accuracy (in CMC-curve based representation). The recognition accuracy is shown in Figs. 11, 12 and also summarized in Table 2. The recognition accuracy of pet animal (dog) is illustrated in shown in the Appendix (Table A.4) respectively.

Table 2
Recognition rates (%) of face image images of dogs based on PCA, LDA, ICA, SURF, LBP and proposed approach.

F-sets	PCA	LDA	ICA	LBP	SURF	Prop.
50	74.39	75.57	86.97	78.68	83.40	86.67
100	79.81	80.64	79.92	82.20	62.10	89.78
150	81.89	84.19	78.97	85.92	60.95	93.83
200	75.86	79.95	87.95	92.95	94.57	96.87

Where, Prop. $=$ Proposed approach, F-sets $=$ Feature sets.

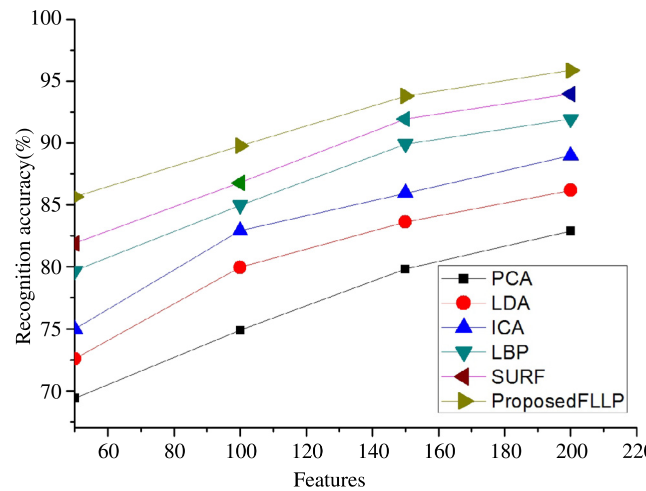

Fig. 11. Recognition accuracy of dogs based on features using PCA, LDA, ICA, LBP, SURF and proposed approach.

6.1. Comparison with appearance-based and texture feature descriptor techniques

The performance of the proposed FLPP approach is compared with appearance-based techniques (e.g., PCA, LDA and ICA), and texture feature descriptor techniques such as LBP and SURF. Table 2 illustrates the experimental results of dog recognition using their face images. It clearly demonstrates that the proposed FLPP approach provides the better recognition accuracy compared to appearance-based face recognition and texture descriptor techniques. The proposed approach is applied to utilize both information of class labels and within-class and between-class graphs to characterize the extreme compactness of samples in the classes while increasing the maximum separation between different classes of dog face images.

The recognition accuracy of LDA algorithm is 79.95%, and minimum recognition accuracy 75.57% using 50 feature vectors, however, PCA techniques yields 75.86% using Eigenvalues with 200 feature sets because PCA-based Eigen-face technique fails to perform the recognition in low illumination and poor quality image cases.

The texture feature descriptors LBP and SURF techniques yield 92.95% and 94.57% recognition accuracy, respectively. The

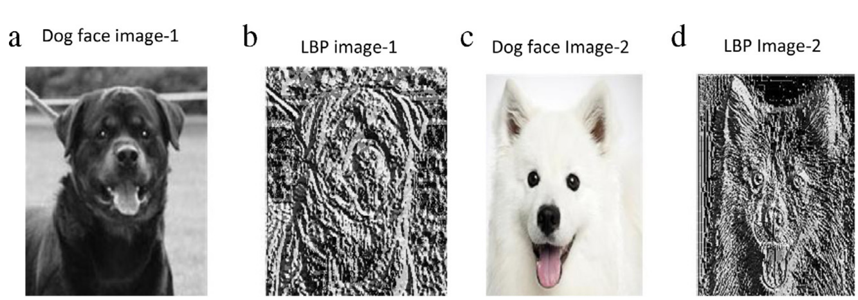

Fig. 7. Representation of texture feature based descriptor of dog face image in (a)–(d) using Local Binary Pattern descriptor.

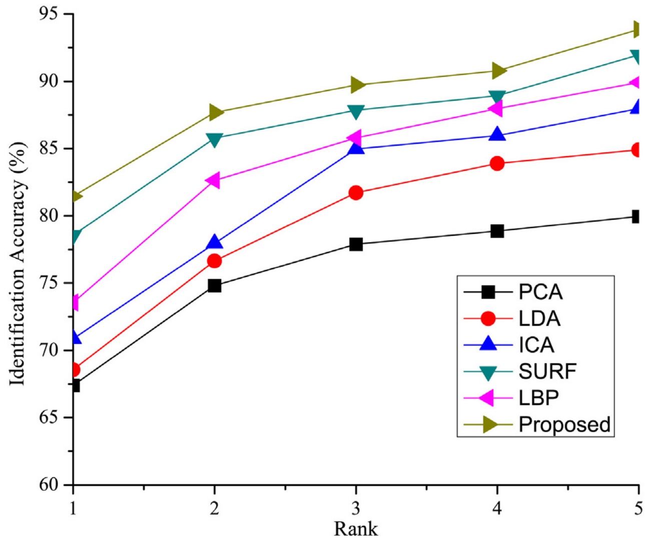

Fig. 12. CMC curve based recognition accuracy of dogs using PCA, LDA, ICA, LBP, SURF and proposed approach.

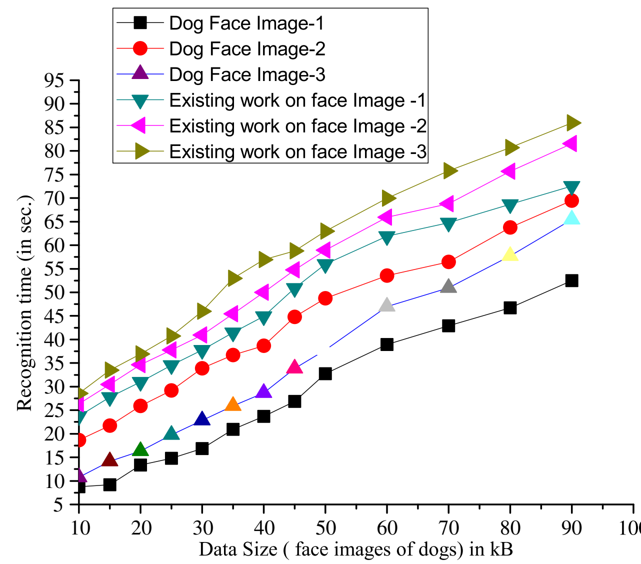

Fig. 13. Impact of recognition time for different size of dog face images.

extracted texture features using descriptors have high extra-class variance (i.e., between-class of dog face images) and low within-class variance. Therefore, LBP and SURF descriptor techniques select the more discriminatory feature vectors from the within-class of dog face image database by minimizing the within-class of dog face images. The recognition accuracy is increased by increasing the number of selected features sets is shown in Fig. 12.

6.2. Impact of recognition time for different dog face images

In the recognition of pet animals, we demonstrated the major impact of dog face images at the required time for the face recognition of individual dogs using the pet recognition system. The recognition time of dog face consists of time taken for enrollment of face images, processing, and matching time during training and testing of dog face images for the recognition of individual dogs.

In the proposed recognition system, the surveillance camera performs the face detection of individual dogs and localize the Region of Interest (ROI) of captured face images of dog. After detection, dog face images (e.g., different size of face image frames) are extracted from captured video. The recognition time for identifying face images of dogs using the proposed recognition system is shown in Table 3. The impact of recognition time for the different face image of individual dogs is shown in Fig. 13. The variation in the data size (face images) as the required time of the recognition system is increased in different size of dog face images.

Fig. 13 illustrates that as the size of dog face image increases, the recognition system takes more time to perform the computation and matching of facial features for the identification of the individual pet animal (dogs). We can observed that during recognition of pet animal dogs, the proposed recognition system takes minimum recognition time for the dog face image-1 as compared to other images because the size of dog face image-1 is less than other dog face images.

Table 3
Recognition time for different face images using proposed approach for pet animal (dog) recognition.

Recognition time (s)		
Dog face image	Image size (kB)	Recognition time
Dog Image-1	10	11.50
Dog Image-2	20	13.25
Dog Image-3	40	14.85
Dog Image-4	50	20.98
Dog Image-5	60	21.78
Dog Image-6	70	22.98
Dog Image-7	75	25.68
Dog Image-8	80	26.98
Dog Image-9	95	27.99
Dog Image-10	100	30.74

7. Conclusion and future directions

In this paper, we demonstrated that monitoring of pet animal in smart cities could be done using animal biometrics. The proposed feature extraction approach extracts the feature from the dog face images for unique recognition by maximizing the inter-class (e.g., between-class) scatter matrix by minimizing the intra-class (e.g., within-class) scatter feature matrix of dog facial images to improve the recognition accuracy.

The proposed recognition approach yields 96.87% recognition rate for identifying the individual pet animal (dogs). With the appearance (holistic) based face recognition and representation, ICA technique yield 87.95% recognition accuracy at the level of 200 feature set. On the other hand, texture features based descriptor techniques such as LBP and SURF yield recognition accuracy of 92.95% and 94.57%, respectively.

The efficacy of the proposed recognition approach for pet animal (dog) is evaluated under identification settings yields 96.87% recognition accuracy for identifying individual dogs. It demonstrates that the recognition system takes 10.25 s for recognizing the individual dogs on 5000 face image database. The proposed system can be deployed in real time scenario for monitoring of pet animal in the smart city.

However, the proposed recognition system for pet animal (dogs) has limitation also. The proposed system is not tested on the real data of pet animals (dogs), captured from the surveillance cameras. In the future, we plan to prepare the real data of pet animals and perform the experimental results for identification and verification of individual pet animals in real time scenario.

In addition, we also plan to design the intelligent pet care and verification systems using the concept of the Internet of Things (IOT), and development of mobile apps for the recognition and monitoring of pet animals in the smart city.

Appendix. Recognition rates (%) of face image images of dogs based on PCA, LDA, ICA, SURF, LBP and proposed approach

Table A.4
Recognition rates (%) of face image images of dogs based on PCA, LDA, ICA, SURF, LBP and proposed approach.

Rank	PCA	LDA	ICA	LBP	SURF	Prop.
1	74.39	75.57	86.97	78.68	83.40	86.67
2	79.81	80.64	79.92	82.20	62.10	89.78
3	81.89	84.19	78.97	85.92	60.95	93.83
4	75.86	79.95	87.95	92.95	94.57	96.87

References

[1] M. Chan, D. Estve, C. Escriba, E. Campo, A review of smart homespresent state and future challenges, Comput. Methods Programs Biomed. 91 (1) (2008) 55–81.
[2] D.H. Stefanov, Z. Bien, W.-C. Bang, The smart house for older persons and persons with physical disabilities: structure, technology arrangements, and perspectives, IEEE Trans. Neural Syst. Rehabil. Eng. 12 (2) (2004) 228–250.
[3] J.H. Lee, M.G. Hancock, M.-C. Hu, Towards an effective framework for building smart cities: Lessons from seoul and san francisco, Technol. Forecast. Soc. Change 89 (2014) 80–99.
[4] T.H.S. of the United States, Pets by the numbers, http://www.humanesociety.org.
[5] G. Valentin, Gestural activity recognition for canine-human communication, in: Proceedings of the 2014 ACM International Symposium on Wearable Computers: Adjunct Program, ACM, 2014, pp. 145–149.
[6] pets population, http://www.slate.com/articles/technology (accessed: 30.06.16).
[7] Is there room for pets in smart cities?, https://pacomaroto.wordpress.com/smart-cities-series/is-there-room-for-pets-in-smart-cities/ (accessed: 30.06.16).
[8] pet animal population Kernel description, https://pacomaroto.wordpress.com/ (accessed: 30.06.16).
[9] pet animal adaptation, https://www.columbus.gov/Residents/Animals-and-Pets.htm (accessed: 29.06.16).
[10] A. Johnston, D. Edwards, Welfare implications of identification of cattle by ear tags, Vet. Rec. 138 (25) (1996) 612–614.
[11] S. Kumar, S.K. Singh, Biometric recognition for pet animal, J. Softw. Eng. Appl. 7 (5) (2014) 470.
[12] A.I. Awad, From classical methods to animal biometrics: A review on cattle identification and tracking, Comput. Electron. Agric. 123 (2016) 423–435.
[13] S. Kumar, S.K. Singh, R.S. Singh, A.K. Singh, S. Tiwari, Real-time recognition of cattle using animal biometrics, J. Real-Time Image Process. (2016) 1–22. http://dx.doi.org/10.1007/s11554-016-0645-4.
[14] S. Kumar, S. Tiwari, S.K. Singh, Face recognition for cattle, in: 3rd IEEE International Conference on Image Information Processing, ICIIP, 2015, pp. 65–72.
[15] S. Kumar, S. Tiwari, S.K. Singh, Face recognition of cattle: Can it be done? Proc. Nat. Acad. Sci. India Sect. A 86 (2) (2016) 137–148.
[16] D. Wardrope, Problems with the use of ear tags in cattle, Vet. Rec. (U. K.) 37 (26) (1995) 675.
[17] S. Ahmed, T. Gaber, A. Tharwat, A.E. Hassanien, V. Snáel, Muzzle-based cattle identification using speed up robust feature approach, in: 2015 International Conference on Intelligent Networking and Collaborative Systems, (INCOS), IEEE, 2015, pp. 99–104.
[18] J.I. Huircán, C. Muñoz, H. Young, L. Von Dossow, J. Bustos, G. Vivallo, M. Toneatti, Zigbee-based wireless sensor network localization for cattle monitoring in grazing fields, Comput. Electron. Agric. 74 (2) (2010) 258–264.
[19] H.S. Kühl, T. Burghardt, Animal biometrics: quantifying and detecting phenotypic appearance, Trends Ecol. Evol. 28 (7) (2013) 432–441.
[20] R.H. Kurvers, J. Krause, D.P. Croft, A.D. Wilson, M. Wolf, The evolutionary and ecological consequences of animal social networks: emerging issues, Trends Ecol. Evol. 29 (6) (2014) 326–335.
[21] P. Briggs, P.L. Olivier, Biometric daemons: authentication via electronic pets, in: CHI'08 Extended Abstracts on Human Factors in Computing Systems, ACM, 2008, pp. 2423–2432.
[22] C. Musgrave, J.L. Cambier, System and method of animal identification and animal transaction authorization using iris patterns, uS Patent 6,424,727 (Jul. 23 2002).
[23] C. Mancini, Towards an animal-centred ethics for Animal-Computer Interaction, Int. J. Hum.-Comput. Stud. 98 (2017) 221–233. http://dx.doi.org/10.1016/j.ijhcs.2016.04.008.
[24] M. Ariff, I. Ismarani, N. Shamsuddin, Rfid based systematic livestock health management system, in: IEEE Conference on Systems, Process and Control, ICSPC, 2014, pp. 111–116.
[25] M. Radenkovic, B. Wietrzyk, Wireless mobile ad-hoc sensor networks for very large scale cattle monitoring, in: Proc. of ASWN, 2006, pp. 47–58.
[26] Q. Zhu, J. Ren, D. Barclay, S. McCormack, W. Thomson, Automatic animal detection from kinect sensed images for livestock monitoring and assessment, in: IEEE International Conference on Computer and Information Technology; Ubiquitous Computing and Communications; Dependable, Autonomic and Secure Computing; Pervasive Intelligence and Computing, CIT/IUCC/DASC/PICOM, 2015, pp. 1154–1157.
[27] A.I. Dell, J.A. Bender, K. Branson, I.D. Couzin, G.G. de Polavieja, L.P. Noldus, A. Pérez-Escudero, P. Perona, A.D. Straw, M. Wikelski, et al., Automated image-based tracking and its application in ecology, Trends Ecol. Evol. 29 (7) (2014) 417–428.
[28] H.-Y. Shin, C.-Y. Teng, The study and application of the iot in pet systems 3, (1), (2013), 1–8.
[29] C. Micklin, Dogtracker: A mobile app engaging citizens and officials in addressing the stray dog crisis, in: Proceedings of the 2014 ACM Workshops on Advances in Computer Entertainment Conference, 2014, pp. 7.1–7:3.
[30] G. Botella, C. García, Real-time motion estimation for image and video processing applications, J. Real-Time Image Process. 11 (4) (2016) 625–631.
[31] J. Duyck, C. Finn, A. Hutcheon, P. Vera, J. Salas, S. Ravela, Sloop: A pattern retrieval engine for individual animal identification, Pattern Recognit. 48 (4) (2015) 1059–1073.
[32] A. Zhelezniakov, et al. Automatic image-based identification of saimaa ringed seals.
[33] F. Housawi, E.E. Abu, Orf infection following ear tagging in goats, Rev. Elev. Med. Vet. Pays. Trop. 44 (3) (1990) 277–278.
[34] E. Leslie, M. Hernández-Jover, R. Newman, P. Holyoake, Assessment of acute pain experienced by piglets from ear tagging, ear notching and intraperitoneal injectable transponders, Appl. Anim. Behav. Sci. 127 (3) (2010) 86–95.
[35] S. Kumar, S.K. Singh, T. Datta, H.P. Gupta, A fast cattle recognition system using smart devices, in: Proceedings of the 2016 ACM on Multimedia Conference, ACM, 2016, pp. 742–743.
[36] G. Goswami, B.M. Powell, M. Vatsa, R. Singh, A. Noore, Facedcaptcha: Face detection based color image {CAPTCHA}, Future Gener. Comput. Syst., 31, 2014, 59–68. special Section: Advances in Computer Supported Collaboration: Systems and Technologies.
[37] C.E. Bugge, J. Burkhardt, K.S. Dugstad, T.B. Enger, M. Kasprzycka, A. Kleinauskas, M. Myhre, K. Scheffler, S. Ström, S. Vetlesen, Biometric methods of animal identification, Course notes, Lab. Anim. Sci. Norw. Sch. Vet. Sci. (2011) 1–6.
[38] G. Badrinath, P. Gupta, Palmprint based recognition system using phase-difference information, Future Gener. Comput. Syst. 28 (1) (2012) 287–305.
[39] C.-M. Own, For the pet care appliance of location aware infrastructure on cyber physical system, Int. J. Distrib. Sens. Netw. (2012).
[40] The pet feeder, http://gadgets.softpedia.com/gadgetsImage/Automatic-Pet-Feeder-1-22503.html (accessed: 28.06.16).
[41] S. Kumar, S.K. Singh, T. Dutta, H.P. Gupta, Poster: A real-time cattle recognition system using wireless multimedia networks, in: Proceedings of the 14th Annual International Conference on Mobile Systems, Applications, and Services Companion, ACM, 2016, p. 48.
[42] Y.C. Chen, S.C. Hidayati, W.H. Cheng, M.C. Hu, K.L. Hua, Locality constrained sparse representation for cat recognition, in: International Conference on Multimedia Modeling, Springer International Publishing, 2016, pp. 140–151.
[43] J. Polimeno, J.J. Polimeno, S.P. Callahan, J.M. Schreiner, R.S. Chang, Facial recognition lost pet identifying system, uS Patent 9,342,735 (May 17 2016).
[44] Dog database Kernel description, http://www.mydogspace.com/ (accessed: 30.06.16).
[45] Dog database, http://www.catster.com/.
[46] Dog database Kernel description, http://www.catster.com/ (accessed: 30.05.16).
[47] Dog database Kernel description, https://www.flickr.com/groups/1648891@N24/.
[48] K. Zuiderveld, Contrast limited adaptive histogram equalization, in: Graphics gems IV, Academic Press Professional, Inc., 1994, pp. 474–485.
[49] R. Giot, M. El-Abed, C. Rosenberger, Fast computation of the performance evaluation of biometric systems: Application to multibiometrics, Future Gener. Comput. Syst. 29 (3) (2013) 788–799. special Section: Recent Developments in High Performance Computing and Security.
[50] F. Monrose, A.D. Rubin, Keystroke dynamics as a biometric for authentication, Future Gener. Comput. Syst. 16 (4) (2000) 351–359.
[51] L. Yan, J.-S. Pan, S.-C. Chu, M.K. Khan, Adaptively weighted sub-directional two-dimensional linear discriminant analysis for face recognition, Future Gener. Comput. Syst. 28 (1) (2012) 232–235.
[52] X. Chen, J. Zhang, A novel maximum margin neighborhood preserving embedding for face recognition, Future Gener. Comput. Syst. 28 (1) (2012) 212–217.
[53] H. Huang, J. Li, J. Liu, Enhanced semi-supervised local fisher discriminant analysis for face recognition, Future Gener. Comput. Syst. 28 (1) (2012) 244–253.
[54] M. Naghibzadeh, Modeling and scheduling hybrid workflows of tasks and task interaction graphs on the cloud, Future Gener. Comput. Syst. 65 (2016) 33–45.
[55] C.P. Diehl, G. Cauwenberghs, Svm incremental learning, adaptation and optimization, in: Proceedings of the International Joint Conference on Neural Networks, Vol. 4, 2003, pp. 2685–2690.

[56] C. Liu, H. Wechsler, Comparative assessment of independent component analysis (ica) for face recognition, in: International conference on audio and video based biometric person authentication, Citeseer, 1999, pp. 22–24.
[57] M.S. Bartlett, J.R. Movellan, T.J. Sejnowski, Face recognition by independent component analysis, IEEE Trans. Neural Netw. 13 (6) (2002) 1450–1464.
[58] H. Bay, A. Ess, T. Tuytelaars, L. Van Gool, Speeded-up robust features (surf), Comput. Vis. Image Underst. 110 (3) (2008) 346–359.
[59] T. Ahonen, A. Hadid, M. Pietikainen, Face description with local binary patterns: Application to face recognition, IEEE Trans. Pattern Anal. Mach. Intell. 28 (12) (2006) 2037–2041.
[60] T. Ojala, M. Pietikäinen, T. Mäenpää, Multiresolution gray-scale and rotation invariant texture classification with local binary patterns, IEEE Trans. Pattern Anal. Mach. Intell. 24 (7) (2002) 971–987.
[61] L. Wolf, T. Hassner, Y. Taigman, The one-shot similarity kernel, in: 12th IEEE International Conference on Computer Vision, 2009, pp. 897–902.
[62] M.A. Turk, A.P. Pentland, Face recognition using eigenfaces, in: IEEE Computer Society Conference on Computer Vision and Pattern Recognition, CVPR'91, 1991, pp. 586–591.
[63] K. Etemad, R. Chellappa, Discriminant analysis for recognition of human face images, J. Opt. Soc. Amer. A 14 (8) (1997) 1724–1733.
[64] A. Jain, P. Flynn, A.A. Ross (Eds.), Handbook of Biometrics, Springer Science & Business Media, 2007.
[65] J. Gonzalez-Rodriguez, D. Ramos-Castro, D.T. Toledano, A. Montero-Asenjo, J. Gonzalez-Dominguez, I. Lopez-Moreno, J. Fierrez-Aguilar, D. Garcia-Romero, J. Ortega-Garcia, Speaker recognition the a tvs-uam system at nist sre 05, IEEE Aerosp. Electron. Syst. Mag. 22 (1) (2007) 15–21.

Santosh Kumar received the B. Tech. degree Computer Science & Engineering, from Uttar Pradesh Technical University (UPTU), in 2008, and M. Tech. in Computer Science & Engineering from Birla Institute of Technology, Mesra, Ranchi (Jharkhand, India) in 2012. Currently he is pursuing Ph.D. from the Department of Computer Science & Engineering, Indian Institute of Technology (Banaras Hindu University) Varanasi-221005, India under the active supervision of Dr. Sanjay Kumar Singh. His research interests span a wide range of spectrum including Computer vision, Pattern recognition, Digital image processing, Digital video processing, Swarm Intelligence, Metaheuristics, Bio-inspired computing, Artificial intelligence. He was a recipient of best poster awards at Institute Day, Indian Institute of Technology (B.H.U.) Varanasi-221005. He is a member of the Computer Society and the Association for Computing Machinery.

Sanjay Kumar Singh completed his B. Tech. in Computer Engg., M. Tech. in Computer Applications and Ph.D. in Computer Science and Engineering. Currently he is an associated professor at the Department of Computer Science and Engineering, IIT (BHU), Varanasi-221005, India. He is a Certified Novell Engineer (CNE) from Novell Netware, USA and a Certified Novell Administrator (CNA) from Novell Netware, USA. He is a member of LIMSTE, IEE, International Association of Engineers and ISCE. His research areas include Biometrics, Computer Vision, Image Processing, Video Processing, Pattern Recognition and Artificial Intelligence. He has over 70 national and international journal publications, book chapters and conference papers. He is also a Guest Editorial Board Member of Multimedia Application and Tools, Springer, and the EURASIP Journal of Image and Vision Processing (Springer). He is a member of the Computer Society and the Association for Computing Machinery.