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Lemur Face Recognition: Tracking a Threatened Species and Individuals With Minimal Impact

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Abstract

Lemurs are a unique and diverse group of primates that are endemic to the island of Madagascar. Unfortunately, they are also the world's most endangered mammals. Habitat loss, hunting pressure, and illegal trafficking for the pet trade are ongoing threats, and population numbers for most lemur species are declining. In order to implement effective conservation strategies, accurate information on population numbers and dynamics is needed, which may be improved by incorporating identification of individual lemurs. Current methods for individual lemur identification are often invasive, which can pose risks to already endangered species. This also makes them impractical for use at large spatial and temporal scales. This paper proposes a method using patch-wise Multiscale Local Binary Pattern features by which computer facial recognition can be used to identify lemurs with a high degree of accuracy (98.7% Rank 1 in closed-set identification). The face recognition system we have developed can be easily integrated into a smartphone application, allowing anyone, not just specialists, to determine the whereabouts of a particular lemur. Experiments demonstrate improvement over existing methods in both accuracy and robustness. We expect to integrate this face recognition software into a citizen science initiative to enhance the public's direct impact on conservation efforts in Madagascar.

1. Introduction

Madagascar has been designated as one of the world's biodiversity hotspots because of high species endemism coupled with a large amount of habitat loss [1]. Lemurs represent one of Madagascar's most enigmatic groups of endemic mammals and comprise 20% of the world's primate species [2]. However, they have also been identified as the world's most endangered group of mammals [2]. A shrinking habitat is one of the primary threats to lemur species. Forest cover in Madagascar is only 10-20% of its former area, and continues to decline [2]. Lemurs are also threatened by human hunting [3] and illegal trafficking for the pet trade [4], making conservation initiatives a high priority in Madagascar.

Figure 1. Red-bellied lemurs. The individual on the left is male, the other is female.

Successful implementation of conservation strategies requires knowledge of species' conservation status and methods for monitoring changes over time. Accordingly, it is necessary to obtain accurate information on population numbers, demography, and factors related to survival and reproduction throughout life. However, current primate survey methods (such as line transects [5]) may not yield accurate assessments, in part because population density estimates may be imprecise (i.e., over-/under-estimating populations [6]), and because we often lack long-term data.

Individual identification can reduce these errors and facilitate more accurate methods for determining population numbers [7]. Individual identification also facilitates the collection of demographic and life history information (e.g., survival rates for different age groups, reproductive rates, and lifespans), which is essential for modeling population growth and decline. Furthermore, long-term research of known individuals is critical for understanding population dynamics and how individuals respond to environmental change, but such research is hindered by disruptions to data collection (e.g., differences in methods between studies, lack of research funds, loss of animals from the study site), particularly in long-lived species.

Current methods for individual identification of larger-bodied lemurs ($>$ 2 kg) often involve either capturing animals and placing unique combinations of colored-collars and tags around their necks [8], or relying on researchers' knowledge of individual differences [9]. The former method has several advantages, such as enabling the collection of data that would otherwise be impossible (e.g., blood samples, ectoparasites), but can be expensive and is impractical for use in studies conducted over large spatial and/or temporal scales. Furthermore, capturing and collaring may pose additional risks to already threatened species. For example, such methods have been shown to cause acute stress responses in other primates [10] and have influenced group dynamics and reproduction in other vertebrate species [11, 12]. The second method, which takes advantage of variation in individual appearance is less invasive, and therefore removes some of the potential risks associated with capturing and collaring, but, this method requires substantial training and may be difficult to integrate data across multiple researchers [9].

The development of an improved method of non-invasive individual identification that mitigates these disadvantages would greatly facilitate long-term research and conservation efforts on lemurs. An ideal method for lemur identification would require little to no training, allow comparable data collection across researchers, and be available at low cost. Such a system could ideally be deployed by researchers, students, and local villagers to enable large-scale and long-term data collection on lemur populations. Here, we propose the use of computer facial recognition software that can run on low-power smart mobile devices to fulfill these needs.

Facial recognition technology has made great strides in its ability to successfully identify humans [13]. However, this aspect of computer vision has much untapped potential. Facial recognition technology has only just begun to expand beyond human applications. While limited work has been done with non-human primates [14, 15], facial recognition of lemurs is particularly underexplored. Many lemur species possess unique facial features (e.g., hair (pelage) patterns) that make them appropriate candidates for applying modified techniques developed for human facial recognition.

In an earlier study, we demonstrated limited success in lemur facial recognition, achieving 73% rank-one accuracy in individual identification for red-bellied lemurs (shown in Figure 1) [9]. However, this performance leaves much room for improvement. Additionally, our previous system required substantial computer storage for the feature representations of individuals, making it impractical for use in the field.

The proposed system significantly improves upon our previous algorithm's performance and is designed to run on a smartphone, allowing researchers to quickly and easily catalog individuals they see in the field and correlate this information with GPS coordinates and time of sighting. Ultimately, we aim to use this recognition system to generate a photographic database of red-bellied lemurs to facilitate longitudinal research and more accurate population assessments in this species. Furthermore, this system will eventually be incorporated into a citizen science initiative, whereby local villagers, as well as tourists and tourist guides, can use this technology to participate in biodiversity research and monitoring. Finally, by using open-source software, we will make the technology adaptable for use across multiple taxa both in and outside Madagascar.

2. Lemur Habitat and Species

2.1. Lemur Habitat

Lemurs are endemic to Madagascar and distributed across the island's varied landscape. A rain-shadow effect concentrates rainfall in the eastern part of the island, resulting in very different forest habitats along the eastern and western regions. Forests in the west are generally characterized as dry and deciduous, whereas more humid rainforests are found along the eastern side of the island. Dry conditions are also found in the south, which is often described as "Spiny forest" due to the prevalence of thorny vegetation [16]. Lemurs occur in all forest types, and many lemur species are restricted to a single habitat type [16].

2.2. Lemur Species

Recent estimates suggest there may be over 100 lemur species in Madagascar, 94% of which are threatened with extinction [2]. Figure 2 illustrates some of the observed diversity across lemur species. These species vary in their current conservation statuses, ranging from the Near Threatened red-fronted brown lemur (*Eulemur rufifrons*) to the Critically Endangered indri (*Indri indri*) and black-and-white ruffed lemur (*Varecia variegata*) [17]. As a whole, lemurs occupy a variety of ecological niches, varying in activity patterns (nocturnal, cathemeral, and diurnal), diet (e.g., frugivorous, folivorous, insectivorous), and habitat use (e.g., deciduous forest, lowland rainforest, high altitude rainforest) [16]. They also range in size from small noctur-

Table 1. Lemur Tracking Methods

Method	Advantages	Disadvantages
Collaring	Precise location of animal known at all times (for GPS collar)	Invasive, poses risk to animal, expensive
Manual Identification	Non-invasive	Substantial training, difficult collaboration, less data collected, error-prone, sparse data
Face Recognition	Non-invasive, minimal user training, better collaboration	Sparse data

nal mouse lemurs (weighing as little as 30 g) to the largest living lemur, the indri (6-10 kg) [16].

2.3. Red-Bellied Lemurs

Red-bellied lemurs (*Eulemur rubriventer*) are medium-sized, frugivorous primates [16]. They are among the majority of threatened lemurs and are currently listed as Vulnerable with a decreasing population trend [17]. This species is endemic to Madagascar's eastern rainforests [16] (see Figure 3 A). Despite their seemingly wide distribution, however, the rainforests of eastern Madagascar have become highly fragmented [18], resulting in an apparent patchy distribution for this species. Red-bellied lemurs are also found at low population densities [19], although density data for specific populations across their range are lacking, making it difficult to accurately estimate remaining population numbers.

Research on this species suggests populations are vulnerable to habitat disturbances (e.g., logging), which appear to negatively impact red-bellied lemurs in the forms of increased stress and higher infant mortality [20, 21]. Consequently, this species appears to have little flexibility in the face of environmental changes, which are currently impacting Madagascar as a whole in the forms of illegal logging, mining, and agricultural land use [17, 2]. In certain areas, this species is also hunted for meat consumption [3]. Where red-bellied lemurs have been studied more extensively (i.e., Ranomafana National Park, see below), their populations have declined over time [22, 23], and this is consistent with its global population decline [17]. These results are particularly alarming, as *E. rubriventer* is an important seed disperser [24] and entire families of plants may rely on this species to disperse seeds [25]. As a result, loss of this single species from a lemur community could have broader implications and trigger additional local (or global) extinctions. This taxon's vulnerability, coupled with the limited data on population numbers throughout its range, make it an important target for conservation efforts in Madagascar.

2.4. Ranomafana National Park

Data collection for this study was concentrated on the population of red-bellied lemurs in Ranomafana National Park (RNP). RNP is approximately $330km^2$ of montane rainforest in southeastern Madagascar [26, 23] (see Figure 3 B). Red-bellied lemurs in RNP have been the subject of multiple long-term research projects [27, 28, 20].

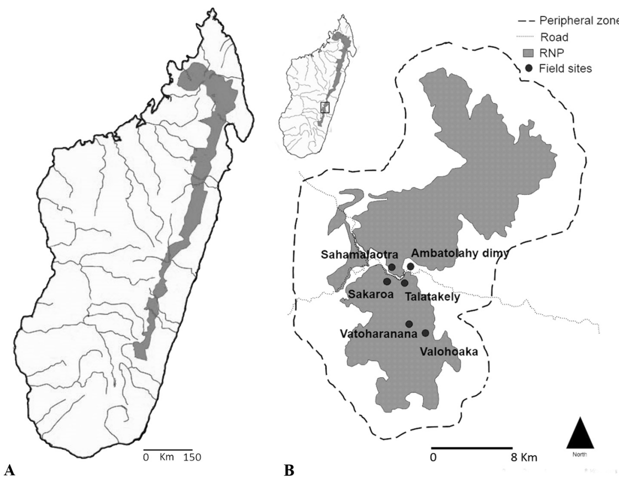

Figure 3. A. Range map for *Eulemur rubriventer*. B. Map of Ranomafana National Park depicting all photograph collection sites.[2]

2.5. Dataset

Our dataset consists of 462 images of 80 red-bellied lemur individuals. Each individual had a name (e.g., Avery) or code (e.g., M9VAL) assigned by researchers when it was first encountered. Four individuals are from the Duke Lemur Center in North Carolina,[3] while the remainder are from Ranomafana National Park in Madagascar. There are varying numbers of images (1-21) per individual. The dataset only includes images that contain a frontal view of the lemur's face with little to no obstruction or occlusion. Figure 4 contains a histogram of the number of images available per individual. Photos from Ramonafana were captured using a Canon EOS Rebel T3i with 18-55 and 75-300mm lenses. Lemurs were often at heights between 15-30 meters, and photos were taken while standing on the ground. The images from Duke were captured with a Google Nexus 5 or an Olympus E-450 with a 14-42mm lens. Lemurs were in low trees (0-3 meters), on the ground, or in enclosures, and photos were taken standing on

[2]A is modified from the IUCN Red List (`www.iucnredlist.org`) and B is modified from [29]

[3]`http://lemur.duke.edu/`

Figure 2. Examples of different lemur species. Photos by David Crouse, Rachel Jacobs, and Stacey Tecot.

the ground.

The majority of the images taken in Madagascar were captured from September to December 2014, however, some individuals had images captured as early as July 2011, giving a limited longitudinal perspective to our dataset. The Duke images were captured in July 2014. Due to the longer duration of the image collection in Madagascar, there was some difficulty establishing whether certain individuals encountered in 2014 had been encountered previously. In three cases, there are photographs in the dataset labeled as belonging to two separate individuals which might actually be of the same individual. These images were treated as belonging to separate individuals when partitioning the dataset for experiments, but if images that might belong to a single individual were matched together, it was counted as a successful match.

Figure 5 illustrates the facial similarities and variations present in the dataset. Figure 5 (a) illustrates the similarities and differences between individuals (inter-class similarity), while Figure 5 (b) shows different images of the same individual (intra-class variability).

In addition to the database of red-bellied individuals, a database containing lemurs of other species was assembled. In addition to 52 images of 31 individuals from Duke Lemur Center, 138 images of lemurs were downloaded based on an online image search. These images were used to expand the size of the gallery for lemur identification experiments. Examples of these individuals are illustrated in Figure 6.

3. Identification of Lemur Faces

The work outlined in Jacobs et al. [9] was used as a starting point to develop an improved lemur face recognition system. The goal of this improvement was to simultaneously increase the recall performance and reduce the dimensionality of the extracted facial features to reduce the template size and therefore facilitate porting the facial recognition software to mobile devices. Figure 7 illustrates the operation of our improved recognition system. This system

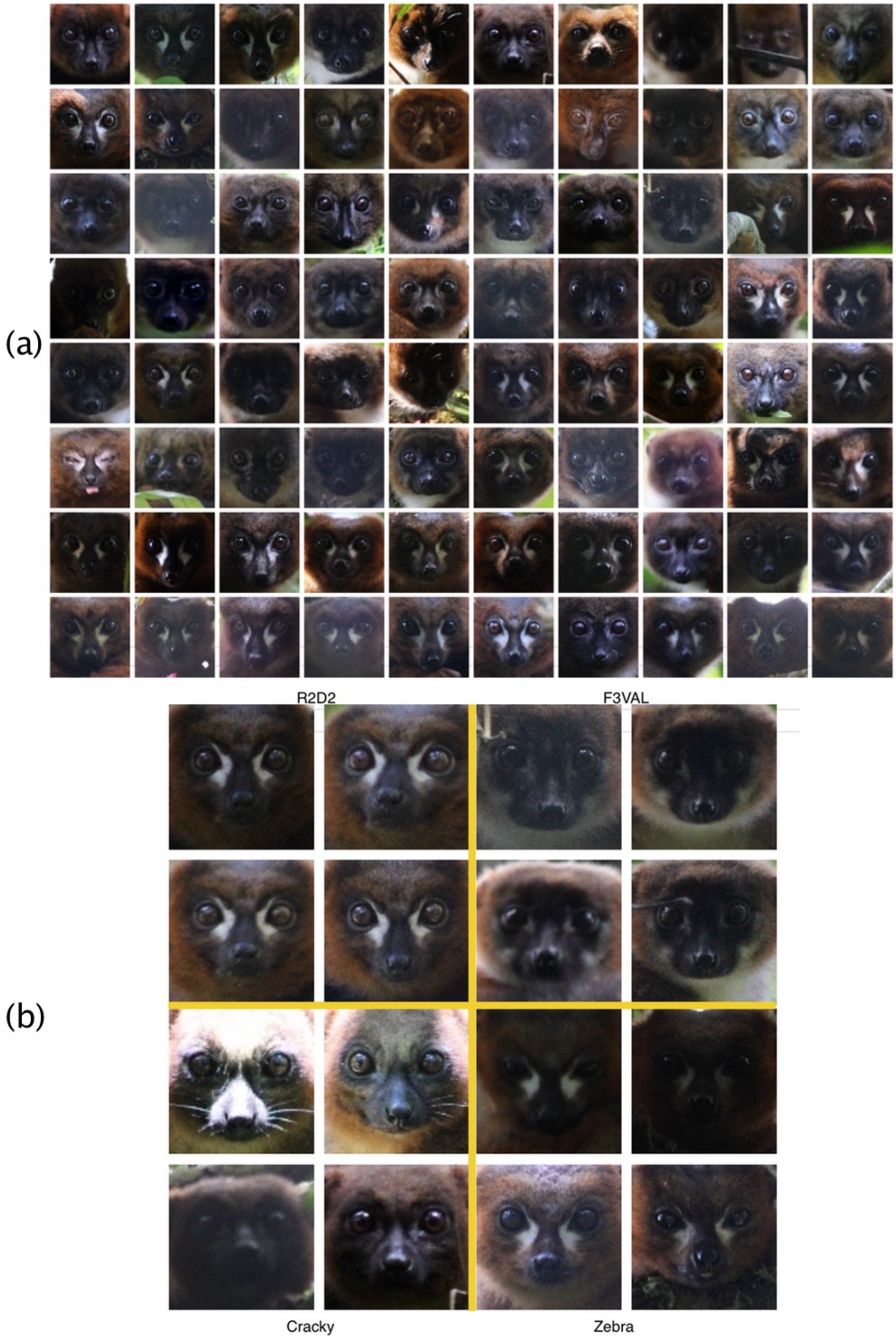

Figure 5. Variation in lemur face images. (a) inter-class similarity , (b) intra-class variation.

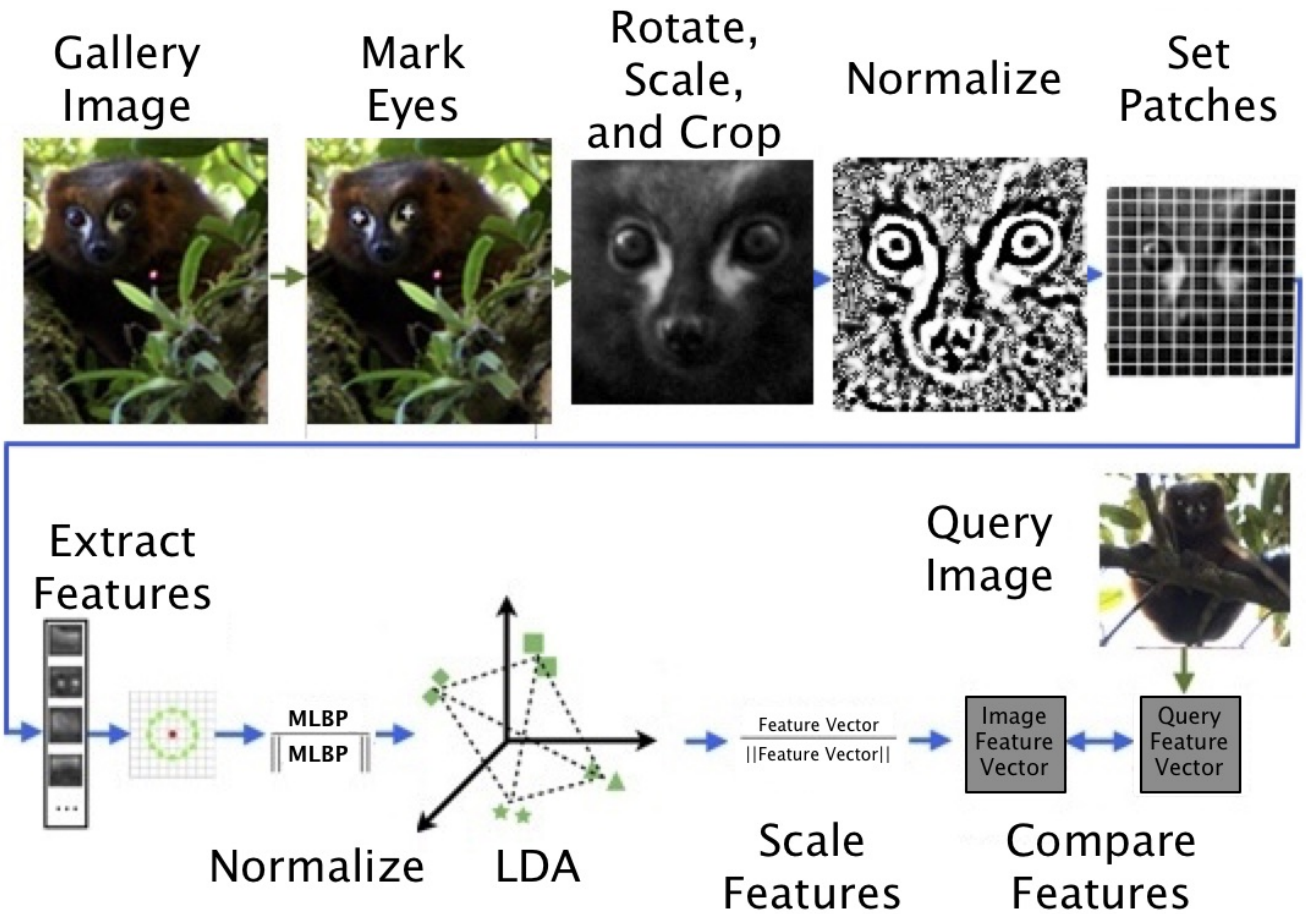

Figure 7. Flowchart of the proposed lemur face recognition system.

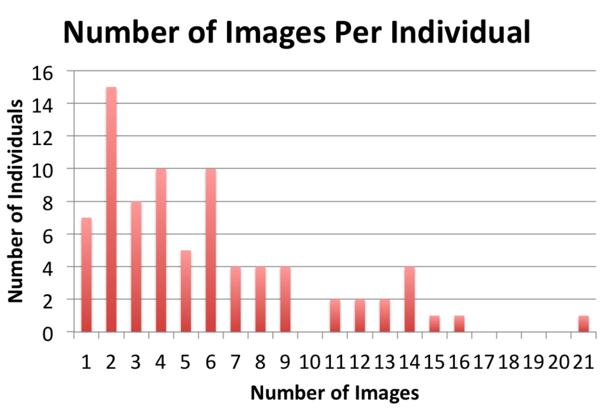

Figure 4. Number of images per individual.

was implemented using the OpenBR framework [30] [4].

3.1. Pre-Processing

Eye locations have been found to be critical in human face recognition [13]. Given the lack of a sufficiently large dataset, we have not been able to train a robust eye detector for lemurs. For this reason, for now we resort to manual eye location. Prior to matching, the user marks the locations of the lemur's eyes in the image. Using these two points, with the right eye as the center, a rotation matrix M is calculated to apply an affine transformation to align the eyes horizontally. Let lex, ley, rex, and rey represent the x and y coordinates of the left and right eyes, respectively. The affine matrix is defined as:

$$M = \begin{bmatrix} 0 & 0 & rex \\ 0 & 0 & rey \\ 0 & 0 & 1 \end{bmatrix} \times \begin{bmatrix} cos(\theta) & -sin(\theta) & 0 \\ sin(\theta) & cos(\theta) & 0 \\ 0 & 0 & 1 \end{bmatrix} \times \begin{bmatrix} 0 & 0 & -rex \\ 0 & 0 & -rey \\ 0 & 0 & 1 \end{bmatrix}$$

$$\theta = atan(\frac{ley - rey}{lex - rex})$$

The input image is rotated by the matrix M, then cropped based on the eye locations. Rotation is applied prior to cropping so that the area cropped will be as accu-

[4] openbiometrics.org

Figure 6. Example faces from the database of non-red-bellied lemur individuals.

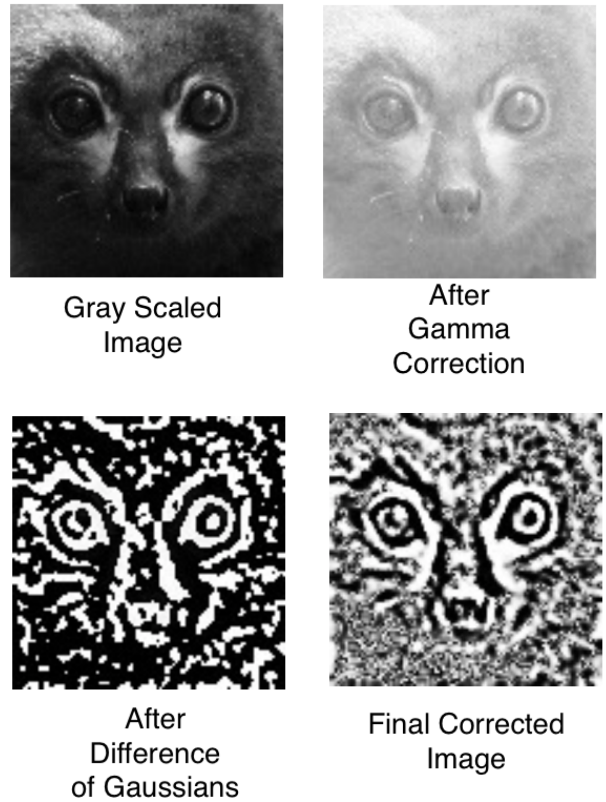

Figure 9. Illumination normalization of a lemur image.

rate as possible. The Inter-Pupil Distance (IPD) is taken as the Euclidean distance between the eye points. The image is cropped so that the eyes are $\frac{IPD}{2}$ pixels from the nearest edge and $0.7 \times IPD$ pixels from the top edge, with a total dimension of $IPD \times 2$ pixels square. This image is then resized to final size of 104×104 pixels, which facilitates the patch-wise feature extraction scheme described below. This process is illustrated in Figure 8. Following rotation and cropping, the image is converted to grayscale and normalized.

Since the primary application of the face matcher is to identify lemurs from photos taken in the wild, the results must be robust with respect to illumination variations. To reduce the effects of ambient illumination on the matching results, a modified form of the illumination normalization method outlined by Tan and Triggs [31] is applied. The image is first convolved with a Gaussian filter with $\sigma = 1.1$, and is then gamma corrected ($\gamma = 0.2$). A Difference of Gaussians operation [31] (with parameters σ_1 and σ_2 corresponding to the standard deviations of the two Gaussians) is subsequently performed on the image. This operation eliminates small-scale texture variations and is traditionally performed with $\sigma_1 = 1$ and $\sigma_2 = 2$. In the case of lemurs, there is an ample amount of hair with a fine texture which varies from image to image within individuals. This fine texture could confuse the matcher, as changes in hair orientation would result in increased differences between face representations. To reduce this effect in the normalized image, σ_1 is set to 2. The optimal value of σ_2 was empirically determined to be 5. The result of this operation is then contrast equalized using the method outlined in Tan and Triggs [31], producing a face image suitable for feature extraction. Figure 9 illustrates each step of the pre-processing for a single lemur image.

3.2. Feature Extraction

Local Binary Pattern (LBP) representation is a method of characterizing local textures in a patch-wise manner [32]. Each pixel in the image is assigned a value based on its relationship to the surrounding pixels, specifically whether each surrounding pixel is darker than the central pixel or not. Out of the 256 possible binary patterns in a $e \times 3$ neighborhood, 58 are defined as uniform (having no more than 2 transitions between “darker” and “not darker”) [32]. The image is divided into multiple patches (which may or may not overlap), and for each patch a histogram of the patterns is developed. Each of the 58 uniform patterns occupies its own bin, while the non-uniform patterns occupy a 59th bin [32].

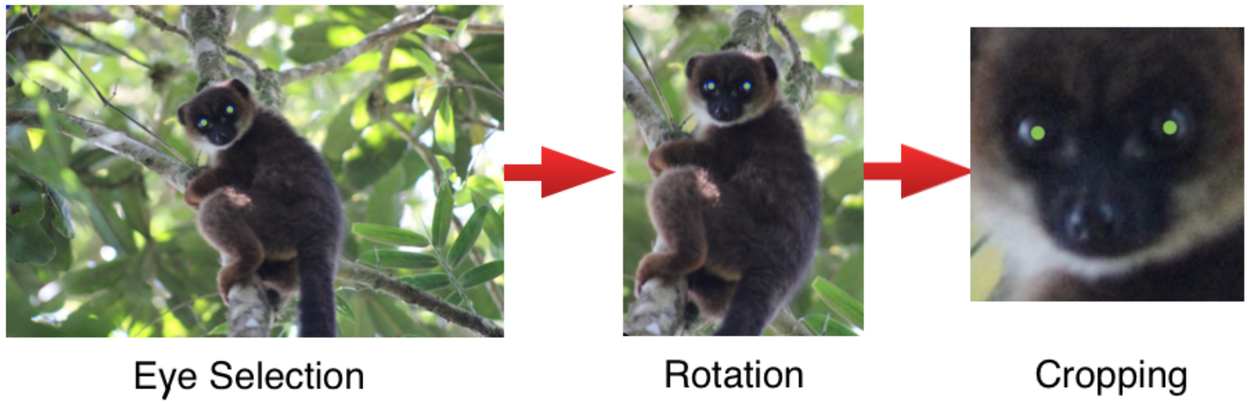

Figure 8. Eye selection, rotation, and cropping of a lemur image.

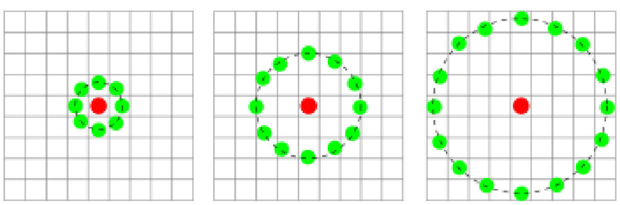

Figure 10. Local Binary Patterns of radii 1,2, and 4. [5]

This histogram makes up a 59-dimension feature vector for each patch. In our recognition system, we use 10×10 pixel patches, overlapping by 2 pixels on a side. This results in 144 total patches for the 104×104 face image.

Multi-scale Local Binary Pattern (MLBP) features are a variation on LBP which use surrounding pixels at different radii from the central pixel [32], as shown in Figure 10. For this application, we used radii of 2, 4, and 8 pixels. Hence, each patch generates 3 histograms, one per radius, each of which is normalized, then concatenated together and normalized again, both times by L2 norm. This results in a 177-dimensional feature vector for each 10×10 patch. Figure 11 shows an example of three face images of the same individual with an enlarged grid overlaid. As demonstrated by the highlighted areas, patches from the same area in each image will be compared in matching.

To extract the final feature vector, Linear Discriminant Analysis (LDA) is performed on the 177-dimensional feature vector for each patch. LDA transforms the feature vector into a new, lower-dimensional feature vector such that the new vector still captures 95% of the variation between individuals, while minimizing the amount of variation between images of the same individual. For this transformation to be robust, a large training set of lemur face images is desirable. LDA is trained on a per-patch basis to limit the size of the feature vectors considered. The resulting vectors for all the patches are then concatenated and normalized to produce the final feature vector for the image. Because each patch undergoes its own dimensionality reduction, the final dimensionality of the feature vector will vary from one training set to another.

In Jacobs et al. [9], Scale Invariant Feature Transform (SIFT) features [33] are used in addition to MLBP features to build the per-patch feature vector. SIFT features are sensitive to local gradients, so the resultant feature representation is sensitive to local hair patterns and hence was not very effective in lemur face recognition. The SIFT feature vector has a higher dimensionality than those generated by LBP, leading to a larger per-patch feature representation (128 dimensions for SIFT vs 59 for LBP). The use of a reduced-length feature vector, combined with more training data available to us compared to [9] (166 images of 41 individuals), enables our method to eliminate the random binning approach for LDA used in [9]. This significantly reduces the mean size of the resultant image features from a 396,850 dimensions to 7,305 dimensions.

3.3. Face Matching

In preparation for matching, a gallery (a database of face images and their identities against which a query is searched) is assembled containing feature representations of multiple individual lemurs. The Euclidean distance d between feature vectors of a query image and each image in the gallery is calculated. The final similarity metric is calculated as $[1 - log(d + 1)]$, where higher values indicate more similar images. A query can consist of 1 or more images, all of which must be of the same lemur. For each query image, the highest similarity score for each individual represents that individual's match score. The mean of these scores is calculated to obtain the final individual scores. The

[5] http://upload.wikimedia.org/wikipedia/commons/c/c2/Lbp_neighbors.svg

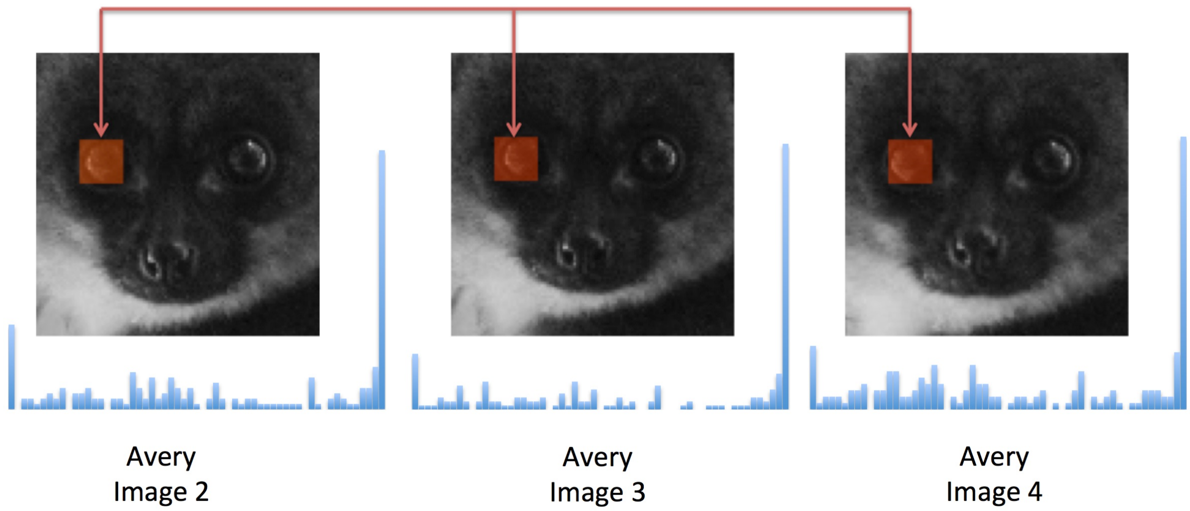

Figure 11. Example of how patches and their corresponding Local Binary Pattern histograms are compared across different images of a single lemur, Avery.

rank 1-5 results are the individuals with the 5 highest scores, in descending order. We evaluated matching with 1 and 2 query images.

Figure 12 (a) shows score histograms for genuine (comparing 2 instances of the same lemur) vs impostor (comparing 2 instances of different lemurs) match scores with 1 query image. Figure 12 (b) shows score histograms with fusion of 2 query images. Note that the overlap between genuine and impostor match score histograms is substantially reduced by the addition of a second query image.

In closed-set identification mode (where it is assumed that the query lemur is represented in the gallery), the closest matches, regardless of their quality, are always reported. This is useful for identifying a lemur in a captive situation, where an individual is guaranteed to be known to the system. To allow for conditions encountered in the wild, where individuals may be encountered that have not been seen before (novel individuals not present in the gallery), open-set identification mode is used. This includes an option to consider a lemur as novel and hence not present in the gallery. Queries whose fused match score is lower than a certain threshold are classified as containing a novel individual.

4. Experiments

The proposed matcher was evaluated on our dataset in both open-set and closed-set modes. These were compared with results from the matcher proposed in Jacobs et al. [9], which was retrained and re-evaluated on our larger dataset, using the same methodology as was used for our proposed identification system.

The accuracy of the matcher was determined by conducting 100 trials over random splits of the dataset (462 images of 80 red-bellied lemurs). In order to determine the response of the recognition system to novel individuals, the LDA must be trained on a disjoint set of individuals (known as the training set) from those used to evaluate matching performance (called the test set). To satisfy this condition, the dataset was divided into training and testing sets via random split. Two-thirds of the 80 individuals (59 individuals) were designated as the training set, while the remainder (27 individuals) comprised the test set. In the test set, two-thirds of the images for each individual were assigned to the gallery and the remainder were assigned to the probe. Individuals with fewer than 3 images were placed only in the gallery. The gallery was then expanded to include the secondary dataset of other species to increase its size.

Testing was performed in both open-set and closed-set identification scenarios. For open-set testing, one-third of the red-bellied individuals in the gallery were removed. Their corresponding images in the probe set therefore made up the set of novel individuals. For open-set, the mean gallery size was 266 images, while for closed-set the mean size was 316 images. Across all trials of the proposed matcher, the mean probe size was 42 images.

Figure 13 characterizes the open-set performance on the dataset by plotting the Detection and Identification Rate (DIR) versus the False Accept Rate (FAR). DIR is characterized as the proportion of non-novel individuals which were correctly identified at or below a given rank, and FAR is characterized as the number of novel individuals incorrectly matched to a gallery individual at or below a given rank.

Rank 1 results for closed-set operation are reported in

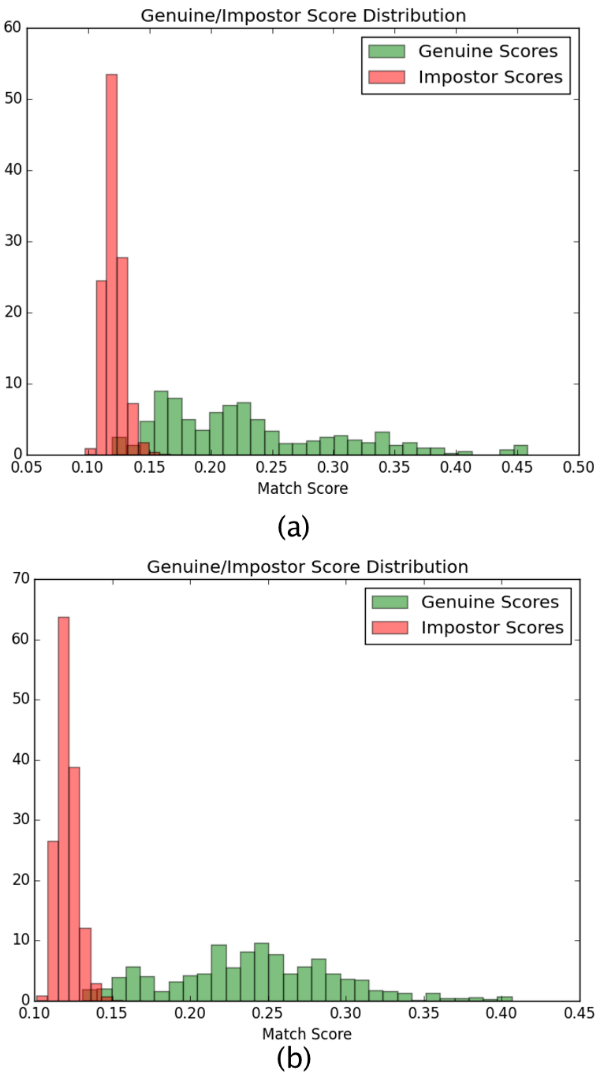

Figure 12. Histograms of genuine (correct match) vs impostor (incorrect match) scores: (a) shows results with only one query image (4,265 genuine, 831,583 impostor), (b) shows results with 2 query images (4317 genuine, 841743 impostor).

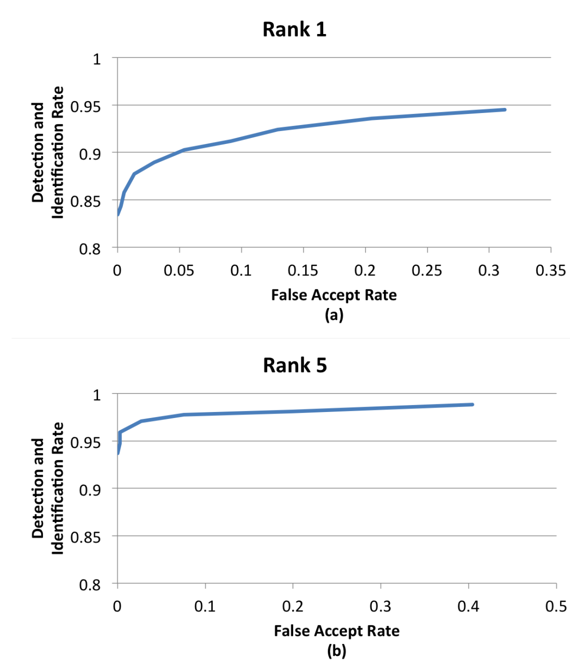

Figure 13. Detection and Identification Rate (DIR) Curve for Open-Set Matching with 2 query images at (a) rank 1 (a) and (b) rank 5. These plots show what proportion of in-gallery lemurs were correctly identified (Detection and Identification Rate) versus what proportion of novel individuals were matched to a gallery individual (False Accept Rate).

Table 2, and the Cumulative Match Characteristic (CMC) curve for 2-image fusion is shown in Figure 14 (a). This plot shows the proportion of correct identifications at or below a given rank. We also applied the method in Jacobs et al. [9] to our dataset for use as a baseline, the CMC curve for this evaluation is shown in Figure 14 (b). While the larger size of the new dataset improves the performance of the previous method, the proposed method still shows significant improvement over prior work. In addition to its better overall performance, the proposed closed-set method also has less variation between folds than the baseline, evidenced by its significantly smaller standard deviation. Fusion of 2 query images improves results further, as is demonstrated in Figure 15. Figure 16 illustrates different performance cases of the matcher, showing queries that were matched successfully at different ranks.

Table 2. Face Matcher Evaluation Results (Rank 1, closed-set). True Accept Rate is the percentage of correct matches. Standard deviation is computed over 100 random splits

Method	Mean True Accept Rate	Standard Deviation
Jacobs et al. [9]	81.5%	6.68%
2 query images	98.7%	1.81%
1 query image	93.3%	3.23%

5. Conclusions and Future Work

In this paper, we have presented a significant improvement to the state of the art in the machine identification of lemurs by facial features. Our improved illumination normalization reduces the effect of hair and ambient lighting on identification, and our feature set is simultaneously more discriminative and more compact than in our previous work. Future work will be focused on enlarging the dataset, as well as increasing open-set performance by improving the feature representation to provide better separation between scores for in-gallery and novel individuals. Additionally, an automatic lemur face detector and eye locator will be

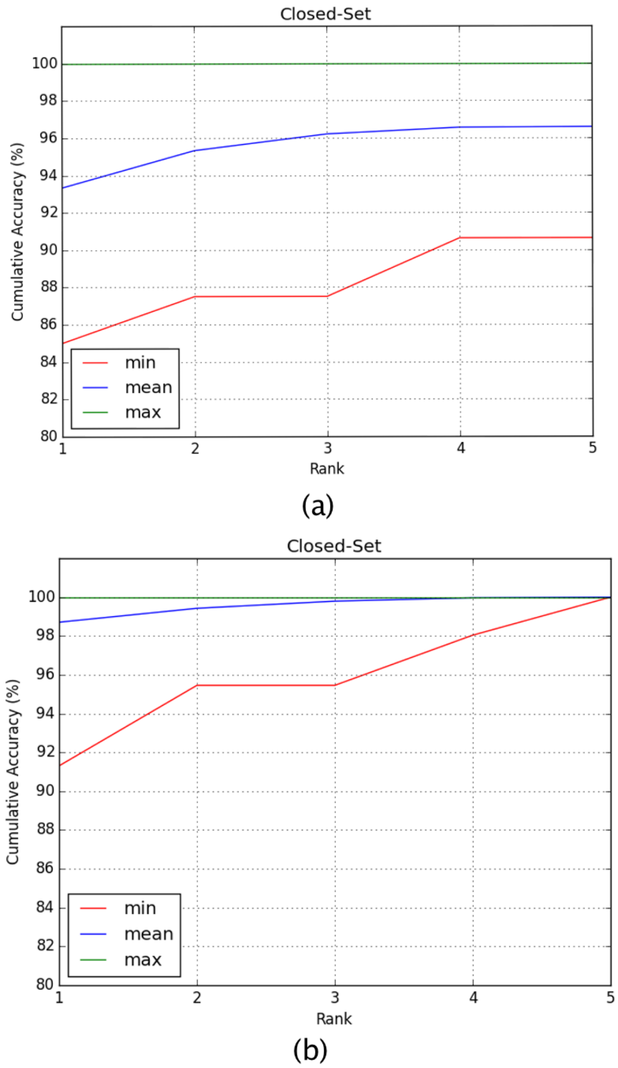

Figure 14. Cumulative Match Characteristic curves for Closed-Set performance. (a) illustrates performance of our proposed method with 1 image as query. (b) illustrates our proposed method with 2 images as query. This indicates the percentage of correct matches at each rank and below.

developed. The identification system will be ported to a smartphone application allowing users to instantly identify lemurs in the field. This application will be integrated into a citizen science initiative in Madagascar to provide more data on the habitat and behavior of red-bellied lemurs.

6. Acknowledgements

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Figure 15. Three examples where a single image is matched incorrectly at Rank 1, but adding a second results in a correct match. Evaluated on gallery containing red-bellied individuals only.

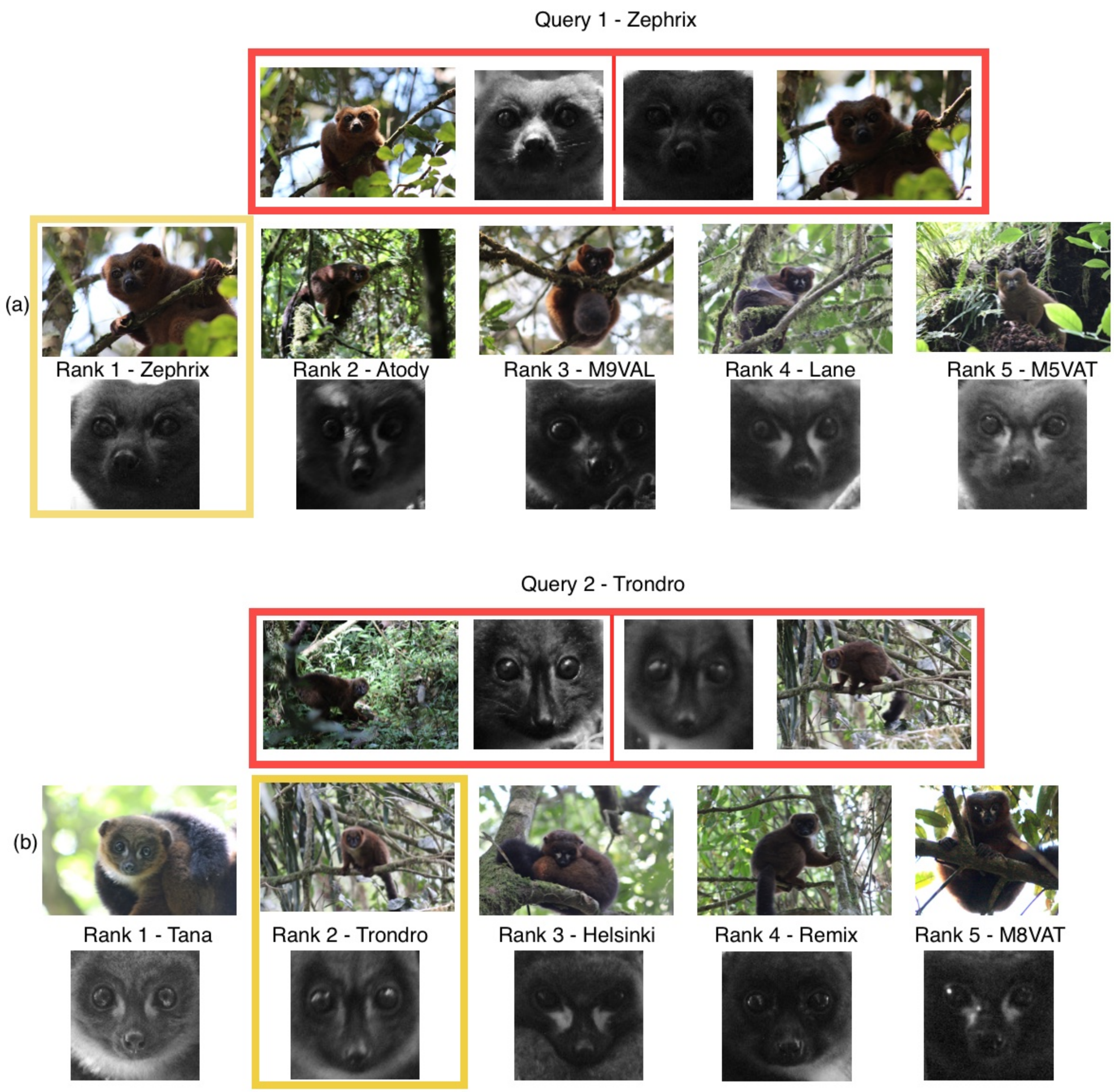

Figure 16. Query images with matches at Rank 1 (a) and Rank 2 (b). Each query involves 2 images of interest (indicated by a red box). The correct match is indicated by a yellow box. Evaluated on gallery containing red-bellied individuals only.