Segmentation of Saimaa Ringed Seals for Identification Purposes

Artem Zhelezniakov[1,3], Tuomas Eerola[1(✉)], Meeri Koivuniemi[2], Miina Auttila[2,4], Riikka Levänen[2], Marja Niemi[2], Mervi Kunnasranta[2], and Heikki Kälviäinen[1,5]

[1] Machine Vision and Pattern Recognition Laboratory, School of Engineering Science, Lappeenranta University of Technology, Lappeenranta, Finland
a.zheleznyakof@yandex.ru, {tuomas.eerola,heikki.kalviainen}@lut.fi
[2] Department of Biology, University of Eastern Finland, Joensuu, Finland
{meeri.koivuniemi,riikka.levanen,marja.niemi,mervi.kunnasranta}@uef.fi
[3] Department of Computer Technologies and Control Systems, ITMO University, Saint Petersburg, Russia
[4] Parks and Wildlife Finland, Metsähallitus, Savonlinna, Finland
Miina.Auttila@metsa.fi
[5] School of Information Technology, Monash University Malaysia, Bandar Sunway, Selangor, Malaysia
heikki.kalviainen@monash.edu

Abstract. Wildlife photo-identification is a commonly used technique to identify and track individuals of wild animal populations over time. It has various applications in behavior and population demography studies. Nowadays, mostly due to large and labor-intensive image data sets, automated photo-identification is an emerging research topic. In this paper, the first steps towards automatic individual identification of the critically endangered Saimaa ringed seal (*Phoca hispida saimensis*) are taken. Ringed seals have a distinctive permanent pelage pattern that is unique to each individual making the image-based identification possible. We propose a superpixel classification based method for the segmentation of ringed seal in images to eliminate the background and to simplify the identification. The proposed segmentation method is shown to achieve a high segmentation accuracy with challenging image data. Furthermore, we show that using the obtained segmented images promising identification results can be obtained even with a simple texture feature based approach. The proposed method uses general texture classification techniques and can be applied also to other animal species with a unique fur or skin pattern.

1 Introduction

Wildlife photo-identification (Photo-ID) provides a tool to study and monitor animal populations over time based on captured images of individuals. It has various applications in studying key aspects of the populations such as survival,

G. Bebis et al. (Eds.): ISVC 2015, Part II, LNCS 9475, pp. 227–236, 2015.
DOI: 10.1007/978-3-319-27863-6_21

dispersal, site fidelity, reproduction, health, population size and density. Due to its non-invasive nature the photo-ID is a great alternative to more destructive techniques, such as tagging that requires catching the animal and may cause stress to the animal, as well as, change its behavior or increase mortality. The identification of individuals is based on distinctive permanent characteristics, such as fur patterns, pigmentations, scars, or shape. Traditionally, the identification has been performed manually by researchers. However, due to the rapid increase in the amount of image data, there is a demand for automated methods. Computer vision techniques provide an attractive tool to replace the laborious and time-consuming manual work.

This work focuses on the Saimaa ringed seal (*Phoca hispida saimensis*) which is a critically endangered subspecies of ringed seal only found in Lake Saimaa, Finland. At present, around 300 seals inhabit the lake, and some 60 pups are born annually. This small and fragmented population is threatened by various anthropogenic factors, especially by-catch and climate change [1]. The long-term and accurate assessment of the population is needed for conservation purposes and camera trapping has recently launched as a new monitoring tool for the Saimaa ringed seal [2,3]. Camera trapping is especially effective method for Saimaa ringed seal monitoring due to high site fidelity of the seals. The pelage of the Saimaa ringed seal has a distinctive patterning of dark spots surrounded by light gray rings (see Fig. 1). These patterns are unique to each seal enabling the identification of individuals over their whole lifetime. Photo-ID data of the Saimaa ringed seal is mostly collected by game cameras during the molting season in spring. The camera trapping produces large number of seal images, which have been identified manually until these days.

Fig. 1. Saimaa ringed seal

In this work, a novel supervised segmentation method for the ringed seal is proposed. The method starts with unsupervised segmentation to produce a set of superpixels and proceeds to the superpixel classification to obtain two segments: the seal and background. Furthermore, a simple identification method exploiting texture features is proposed. The methods are evaluated with challenging image data consisting wide range of different images, such as images captured using camera traps and various camera types. The obtained results indicate a high segmentation success rate. Also, the preliminary identification results can be considered promising.

2 Related Work

Several approaches for automatic image-based animal identification can be found in the literature. Methods have been developed, for example, for polar bears [4], cattle [5], newts [6], giraffes [7], salamanders [8], snakes [9], insects [10], and marine mammals [11]. All of these methods use image processing and pattern recognition techniques to identify individuals. Most of the studies consider the identification of a certain animal species or species groups. For example, in [7], the effectiveness of wild-ID [7] software in identifying individual Thornicroft's giraffes from a dataset of 552 images was studied. The approach uses a Scale Invariant Feature Transform (SIFT) algorithm [12] to extract and match distinctive image features regardless of scale and orientation.

In [6], the suitability of biometric techniques for the identification of the great crested newt was investigated. Distinctive belly patterns were used to compare images of newts with an image database. Two different methods were used for the comparison: (1) the correlation coefficient of the gray-scale pixel intensities, and (2) the Hamming distance between the binary image segments.

Most of the current methods are developed for one species only and are not generalizable to other animals. However, there have been also research efforts towards creating an unified approach applicable for identification purposes for several animal species. For example, in [13], HotSpotter method to identify individual animals in a labeled database was presented. This algorithm is not species specific and has been applied to Grevy's and plains zebras, giraffes, leopards, and lionfish. HotSpotter uses viewpoint invariant descriptors and a scoring mechanism that emphasizes the most distinctiveness keypoints and descriptors. In [14], a species recognition algorithm based on sparse coding spatial pyramid matching (ScSPM) was proposed. It was shown that the proposed object recognition techniques can be successfully used to identify animals on sequences of images captured using camera traps in nature.

3 Methodology

The proposed method for the identification of Saimaa ringed seals has two main parts: the segmentation and identification (Fig. 2). First, the segmentation is applied to detect the seal and to eliminate the background that could complicate the identification process. Saimaa ringed seals tend to use same sites or areas inter-annually for molting and haul out, and the images are captured using static camera traps. herefore, the same seal is often captured with the same background increasing the risk that a supervised identification algorithm learns to "identify" the background instead of the actual seal if the full image or bounding box around the seal is used. This may further leads to a system that is not able to identify the seal in a new environment making the separation of the animal from the background (segmentation) important. After the segmentation, the seal is identified based on texture features computed from the pelage pattern.

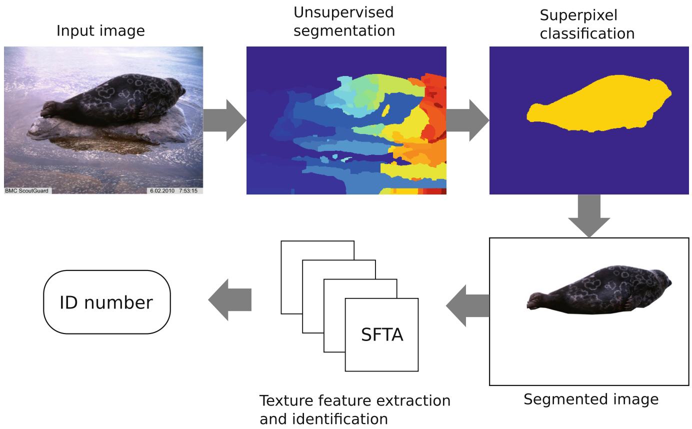


Fig. 2. The proposed method.

3.1 Segmentation

Automatic segmentation of animals is often difficult due to the camouflage colors of animals, i.e. the coloration and patterns are similar to the visual background of the animal. This makes it difficult to define a single criterion to distinguish the animal from the background. The proposed method to segment ringed seals start with unsupervised segmentation step to divided image into segments or superpixels. After this, the superpixels are classified into two different classes: seal or background. Similar approach have been used, for example, to segment the optical disc in retinal images [15]. Ideally, superpixels should be completely inside or outside the object, i.e. there should not be such superpixels that contain both seal and background pixels. Furthermore, superpixels should be large enough to make the classification possible. Generally, the larger the superpixels are the better as long as they fulfill the first criterion.

In this work, the method proposed in [16,17] is used for unsupervised segmentation. The method has shown to produce the state-of-the-art performance in the Berkeley Segmentation Dataset [18]. It combines Globalized Probability of Boundary (gPb) detector, Oriented Watershed Transform (OWT), and Ultrametric Contour Map (UCM) to produce a weighted contour image that can be thresholded to produce superpixels. The size of the superpixels can be controlled by varying the threshold value. By selecting a proper value, both criteria mentioned above can be fulfilled.

After the unsupervised segmentation step, texture features are computed from the superpixels and each superpixel is classified into the seal or background class in a supervised manner. In this work, blur invariant Local Phase Quantization (LPQ) features [19] and support vector machine (SVM) classifier were used for superpixel classification. The LPQ descriptor uses locally computed phase information and decorrelated low-frequency coefficients to create a code word histogram that can be used for the texture classification. Since the low-frequency phase components are ideally blur invariant, and the phase information is invariant to uniform illumination changes, the LPQ texture descriptor is a good choice for processing camera trap images which often are out of focus and suffer from large illumination changes between day and night time. After the superpixel classification step, all the superpixels that are classified to the seal class are combined to form the seal segment for identification purposes.

3.2 Identification

The identification of Saimaa ringed seals is based on the unique pelage pattern of the individuals. The ring pattern forms a texture making the texture classification techniques an apparent choice for the identification.

In this work, the identification of seal is performed using segmentation-based fractal texture analysis (SFTA) features [20] computed from the seal segment. SFTA features are calculated by decomposing the segmented image into a set of binary images and by computing fractal dimension from the regions of the each binary image. The identification is formulated as a classification problem and solved using a naive Bayesian classifier. Given the vector of SFTA features $\mathbf{x}$, posterior probabilities

$$p(C_k|\mathbf{x}) = \frac{p(C_k)p(\mathbf{x}|C_k)}{p(\mathbf{x})} \tag{1}$$

are computed for each class C_k representing earlier identified individual in a database. Class priors $p(C_k)$ are calculated by assuming equiprobable classes. Posterior probabilities are used to rank classes, i.e., individual animals in the database, from most likely to less likely. Finally, a set of most likely matches can be presented to an expert for the final decision making.

4 Experiments

4.1 Data

To evaluate the method, a unique photo-ID database of Saimaa ringed seal images collected by University of Eastern Finland was used. The database contained total of 785 images of 131 individual seals. Most of the images contains one individual Saimaa ringed seal, and only few images contains two or more individuals. Example images from the database are shown in Fig. 3.

The database contained images of individual seals from the right and left sides because both flanks of the ringed seal have different pelage patterns. In addition, the database contained images from belly and back sides of the seals. However, most of the individual seals in the database had only one or few images making the training of the identification method practically impossible. Therefore, the seals with less than 5 images were omitted from the experiments. Also, images with multiple seals or too low quality for identification purposes were screened out from the data set. The final data set contained 40 ringed seal individuals and total of 363 images with reasonable quality.

Fig. 3. Examples from the Saimaa ringed seals database.

The seals were identified from the images by experts to form the ground truth for identification. The segmentation ground truth was constructed by manually drawing the contour of the animals.

4.2 Segmentation

The gPb-OWT-UCM segmentation algorithm [17] selected for the unsupervised segmentation allows to choose the threshold value that effects on the size of the superpixels obtained as an output. The success of the ringed seal segmentation depends highly on the selected threshold value. To select the value, two criteria should be considered: (1) superpixels that contains both seal and background pixels should be minimized, and (2) the size of the superpixels should be as large as possible without violating the first criteria to make the superpixels classification as robust as possible.

The evaluation of the UCM thresholds was carried out using 121 images. A superpixel was considered as bad superpixel if the percentage of background pixels inside the superpixel was more than 0.1 and less than 0.9. The number of bad superpixels was computed for each image using the ground truth information. The results of the experiment are presented in Fig. 4. Based on the results a threshold value of 0.3 was selected for the further experiments.

In order to train and test the superpixel classification methods, the unsupervised segmentation was performed to all images, and resulting superpixels were manually labeled into two classes: seal and background. The images were divided into training and test set randomly. The training set contained 343 images and the test set 20 images. LPQ features were compared to SFTA and Local Binary Pattern Histogram Fourier features (LBP-HF) [21]. SVM classifier was compared to Naive Bayes and k-NN ($k = 9$) classifiers. The segmentation accuracy was measured as percentage of images that were successfully segmented. Image was considered as successfully segmented if the percentage of pixels that were correctly classified was higher than 95 % (Table 1).

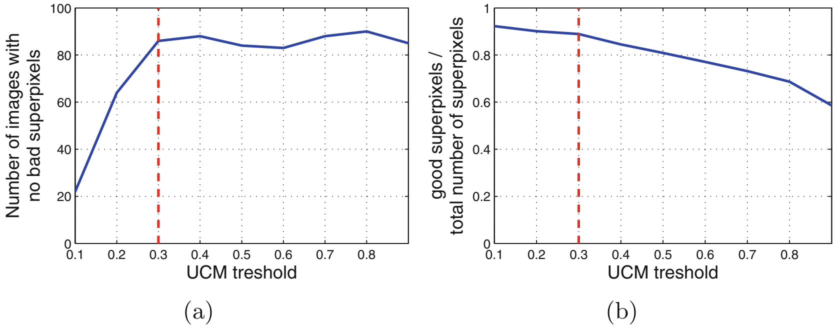


Fig. 4. The effect of UCM threshold: (a) Number of images with no bad superpixels; (b) Portion of good superpixels over all images.

Table 1. Segmentation accuracy with different texture features and classifiers.

Features/classifier	k-NN ($k = 9$)	Naive Bayes	SVM
SFTA	0.24	0.52	0.44
LBP-HF	0.32	0.00	0.28
LPQ	0.60	0.00	0.81

The results shows that the LPQ texture features and SVM classifier outperform the other feature-classifier combinations. Examples of the segmentation results with the LPQ features and the SVM classifier are shown in Fig. 5.

4.3 Identification

The identification was studied using a set of 40 seals. One image of each seal was randomly selected to test set and rest of the images (323) were used as training set. The identification algorithms ranked the seals in the training set from most likely to least like match to the seal in each test image. The performance of different texture features and ranking methods for identification were measured using Cumulative Match Score (CMS) histogram commonly used in the face recognition research [22]. It measures how well the identification system ranks the identities in the database with respect to input image. The Nth bin in the CMS histograms tells the percentage of test images where the correct individual seal was in the set of N best matches proposed by the identification algorithm.

The proposed SFTA texture features for identification were compared with the LBP-HF and LPQ features. For each set of features, the raw feature set was compared with sets of features reduced using Principal Component Analysis (PCA), and the feature set producing the best results was used. The posterior probability provided by the Bayesian classifier was compared to class scores provided by k-NN and SVM classifiers. The results are shown in Fig. 6.

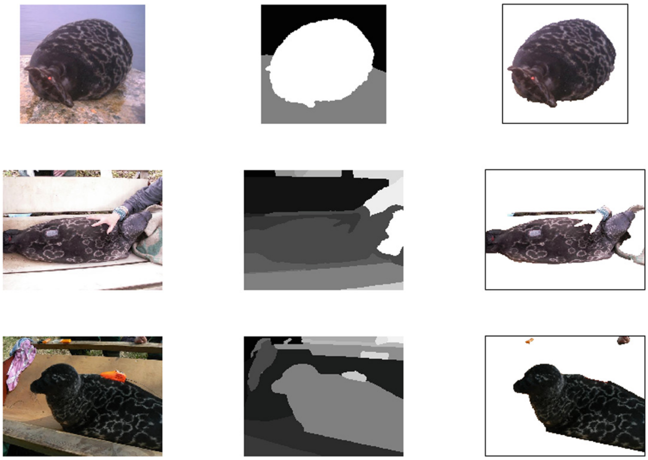
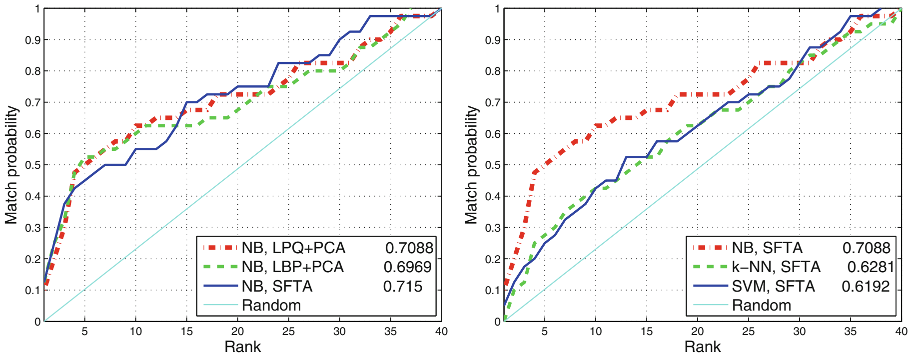


Fig. 5. Segmentation results (from the left to the right): the input image, unsupervised segmentation (superpixels), the segmentation result.



(a) (b)

Fig. 6. Cumulative match score histograms (CMSH) with the areas under CMSH curve for identification methods: (a) Comparison of feature extractors with naive Bayesian classifier; (b) Comparison of classifiers with SFTA features.

The SFTA features have the highest area under CMS histogram value. However, there are no significant differences in the performance between different texture features. Posterior probabilities provided by Naive Bayesian classifier, on the other hand, outperforms all the other ranking methods. The correct seal was in the set of 15 best matches in 70 % of the cases. Although, the identification performance is not yet good enough for most practical applications, the fact that the results were obtained using rather simple texture classification methods with no preprocessing besides the segmentation suggests that the automatic identification when further developed has potential to become a useful tool for studying the Saimaa ringed seal.

5 Conclusions

In this paper, a segmentation method for Saimaa ringed seals using unsupervised segmentation and texture based superpixel classification was proposed. Different texture features and classification techniques were compared and the proposed combination of LPQ features and SVM classifier was shown to produce the best segmentation results. Furthermore, a simple texture based approach for the ringed seal identification was evaluated. The best identification results were obtained using SFTA features and posterior probabilities provided by a Bayesian classifier. Although, the identification performance is not yet good enough for most practical applications, the results of this pilot study can be considered promising.

Acknowledgements. The authors would like to thank the Wildlife Photo-ID Network funded by the Finnish Cultural Foundation.

References

1. Kovacs, K.M., Aguilar, A., Aurioles, D., Burkanov, V., Campagna, C., Gales, N., Gelatt, T., Goldsworthy, S.D., Goodman, S.J., Hofmeyr, G.J.G., Härkönen, T., Lowry, L., Lydersen, C., Schipper, J., Sipilä, T., Southwell, C., Stuart, S., Thompson, D., Trillmich, F.: Global threats to pinnipeds. Mar. Mammal Sci. **28**, 414–436 (2012)
2. Auttila, M., Niemi, M., Skrzypczak, T., Viljanen, M., Kunnasranta, M.: Estimating and mitigating perinatal mortality in the endangered saimaa ringed seal (phoca hispida saimensis) in a changing climate. Annal. Zool. Fenn. **51**, 526–534 (2014)
3. Koivuniemi, M., Auttila, M., Niemi, M., Levänen, R., Kunnasranta, M.: Photo-ID as a tool for studying and monitoring the critically endangered saimaa ringed seal. (2015) manuscript under review
4. Anderson, C.J.: Individual identification of polar bears by whisker spot patterns. Ph.D. thesis, University of Central Florida, Orlando, Florida (2007)
5. Tharwat, A., Gaber, T., Hassanien, A., Hassanien, H.A., Tolba, M.F.: Cattle identification using muzzle print images based on texture features approach. In: Proceedings of the Fifth International Conference on Innovations in Bio-Inspired Computing and Applications, pp. 217–227 (2014)
6. Hoque, S., Azhar, M., Deravi, F.: ZOOMETRICS-biometric identification of wildlife using natural body marks. Int. J. Bio-Sci. Bio-Technol. **3**, 45–53 (2011)
7. Halloran, K.M., Murdoch, J.D., Becker, M.S.: Applying computer-aided photo-identification to messy datasets: a case study of Thornicroft's giraffe (Giraffa camelopardalis thornicrofti). Afr. J. Ecol. **53**, 147–155 (2014)
8. Bendik, N.F., Morrison, T.A., Gluesenkamp, A.G., Sanders, M.S., O'Donnell, L.J.: Computer-assisted photo identification outperforms visible implant elastomers in an endangered salamander, Eurycea tonkawae. PLoS One **8**, e59424 (2013)
9. Albu, A.B., Wiebe, G., Govindarajulu, P., Engelstoft, C., Ovatska, K.: Towards automatic modelbased identification of individual sharp-tailed snakes from natural body markings. In: Proceedings of ICPR Workshop on Animal and Insect Behaviour, Tampa, FL, USA (2008)

10. Yılmaz Kaya, L.K., Tekin, R.: A computer vision system for the automatic identification of butterfly species via gabor-filter-based texture features and extreme learning machine: GF+ ELM. TEM J. **2**, 13–20 (2013)
11. Adams, J.D., Speakman, T., Zolman, E., Schwacke, L.H.: Automating image matching, cataloging, and analysis for photo-identification research. Aquat. Mammals **32**, 374 (2006)
12. Lowe, D.G.: Distinctive image features from scale-invariant keypoints. Int. J. Comput. Vis. **60**, 91–110 (2004)
13. Crall, J., Stewart, C., Berger-Wolf, T., Rubenstein, D., Sundaresan, S.: Hotspotter - patterned species instance recognition. In: IEEE Workshop on Applications of Computer Vision (WACV), pp. 230–237 (2013)
14. Yu, X., Wang, J., Kays, R., Jansen, P., Wang, T., Huang, T.: Automated identification of animal species in camera trap images. EURASIP J. Image Video Process. **2013**, 52 (2013)
15. Cheng, J., Liu, J., Xu, Y., Yin, F., Wong, D.W.K., Tan, N.M., Tao, D., Cheng, C.Y., Aung, T., Wong, T.Y.: Superpixel classification based optic disc and optic cup segmentation for glaucoma screening. IEEE Trans. Med. Imaging **32**, 1019–1032 (2013)
16. Arbelaez, P., Maire, M., Fowlkes, C., Malik, J.: Contour detection and hierarchical image segmentation. IEEE Trans. Pattern Anal. Mach. Intell. **33**, 898–916 (2011)
17. Arbelaez, P., Maire, M., Fowlkes, C., Malik, J.: From contours to regions: An empirical evaluation. IEEE Conf. Comput. Vis. Pattern Recogn. **2009**, 2294–2301 (2009)
18. Martin, D., Fowlkes, C., Tal, D., Malik, J.: A database of human segmented natural images and its application to evaluating segmentation algorithms and measuring ecological statistics. In: Proceedings of the 8th International Conference on Computer Vision vol. 2, pp. 416–423 (2001)
19. Ojansivu, V., Heikkilä, J.: Blur insensitive texture classification using local phase quantization. In: Elmoataz, A., Lezoray, O., Nouboud, F., Mammass, D. (eds.) ICISP 2008 2008. LNCS, vol. 5099, pp. 236–243. Springer, Heidelberg (2008)
20. Costa, A., Humpire-Mamani, G., Traina, A.: An efficient algorithm for fractal analysis of textures. In: 25th Conference on Graphics, Patterns and Images vol. 2012, pp. 39–46 (2012)
21. Ahonen, T., Matas, J., He, C., Pietikäinen, M.: Rotation invariant image description with local binary pattern histogram fourier features. In: Salberg, A.-B., Hardeberg, J.Y., Jenssen, R. (eds.) SCIA 2009. LNCS, vol. 5575, pp. 61–70. Springer, Heidelberg (2009)
22. Phillips, P.J., Moon, H., Rauss, P.J., Rizvi, S.: The feret evaluation methodology for face recognition algorithms. IEEE Trans. Pattern Anal. Mach. Intell. **22**, 1090–1104 (2000)