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Author(s) :Eduardo Mendoza, Pierre R. Martineau, Elliott Brenner and Rodolfo Dirzo
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Note

A Novel Method to Improve Individual Animal Identification Based on Camera-Trapping Data

EDUARDO MENDOZA,[1,2] *Department of Biology, Stanford University, Stanford, CA 94305, USA*
PIERRE R. MARTINEAU, *Department of Psychiatry and Behavioral Sciences, Stanford University, Stanford, CA 94304, USA and Martineau & Associates, Menlo Park, CA 94025, USA*
ELLIOTT BRENNER, *Department of Biology, Stanford University, Stanford, CA 94305, USA*
RODOLFO DIRZO, *Department of Biology, Stanford University, Stanford, CA 94305, USA*

ABSTRACT We present a novel method to improve individual identification of animals based on camera-trapping data. The method combines computer tools and human visual recognition to help multiple users to reach identification agreement. Application of this method to a bobcat (*Lynx rufus*) picture database from the Jasper Ridge Biological Preserve resulted in a progressive increase in identification agreement between 2 users, as measured by the adjusted Rand index (ARI). An initial ARI value of 0.28 increased to a final value of 0.84 (1 = maximum agreement). In contrast, comparisons involving random picture groupings consistently rendered low ARI values ($\leq$0.05). The numbers of individuals named by the 2 users decreased from initial values of 46 and 43 to final values of 25 and 29, respectively. The tool presented here will help researchers and wildlife managers to identify individual mammals and monitor populations. © 2011 The Wildlife Society.

KEY WORDS adjusted Rand index, animal natural marks, bobcat, camera-trapping, individual identification, jasper ridge biological preserve, *Lynx rufus*.

The use of camera-trapping to survey wildlife fauna is undergoing an explosive expansion (Cutler and Swann 1999, Kays and Slauson 2008, Kelly 2008, Rowcliffe and Carbone 2008). Factors underlying its increasing use include: amenability of picture-derived data for quantitative analysis, low labor costs in comparison to traditional inventory methods (e.g., transects), and low environmental invasiveness (Kays and Slauson 2008, Rowcliffe et al. 2008). Yet the most advantageous characteristic of camera-traps is likely its effectiveness in producing information on highly cryptic species occurring in hard-to-access terrain (Jackson et al. 2005, Tobler et al. 2008).

Presence of natural marks such as fur spot patterns (Jackson et al. 2005, Heilbrun et al. 2006), skin blotches (Bhupathy 1991), tail marks (Swanepoel 1996), stripe patterns (Karanth 1995), body coloration patterns (Church et al. 2007), and injury scars (Langtimm et al. 2004) makes individual identification feasible, when based on camera-trapping data. Individual identification has numerous applications in ecological and behavioral studies. For example, it allows for building of presence–absence matrices, which can be analyzed with mark-recapture models to generate estimates of population abundance (Karanth 1995, Heilbrun et al. 2006). This analytic approach produces more accurate population estimates of wild fauna while avoiding the need to capture and mark animals, which can harm them or be logistically unfeasible.

Recent studies have shown that to produce sounder camera-trapping data and unbiased population estimates, several methodological aspects are important to consider, including: the spatial array of cameras with respect to species' habitat use (Wallace et al. 2003, Karanth et al. 2004, Trolle et al. 2007, Rowcliffe et al. 2008), compliance with the assumptions of mark-recapture models (Karanth and Nichols 1998, Trolle and Kery 2003, Heilbrun et al. 2006), sampling intensity (Trolle and Kery 2003), the potential interaction between camera presence and an animal's behavior (Séquin et al. 2003), and the adequate selection of animal marks to be used to distinguish among different individuals (Karanth 1995, Heilbrun et al. 2003, Trolle and Kery 2003, Trolle et al. 2008). However, less attention has been paid to the need to reduce subjectivity in the process of visually identifying individuals, despite that it has been shown that misidentification can produce significant biases in population estimates (Trolle et al. 2008, Yoshizaki et al. 2009).

There are 2 main ways, not mutually exclusive, in which misidentification and its potential impacts on population estimates can be addressed. First, when misidentification cannot be reduced but its source and approximate magnitude are known, models can be built to explicitly incorporate such effects into population estimations. For example, Yoshizaki

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[1]*E-mail: mendoza.mere@gmail.com*
[2]*Present Address: Centro de Investigación en Ecosistemas, Universidad Nacional Autónoma de México, Morelia, Michoacán C.P. 58190, Mexico.*

et al. (2009) modeled the effect that over counting caused by evolving natural marks (i.e., natural marks that change with time) would have on populations estimates. Yoshizaki et al. (2009) found that models not accounting for misidentification resulting from evolving marks consistently overestimated population size. Second, efforts can be focused on improving the process leading to the individual identification itself by using tools to automate the identification process. This option is particularly useful when working with large picture databases, which could be time-consuming and prone to error. For example, Kelly (2001) used a 3-dimensional computer-matching system to aid in classifying nearly 10,000 photographs of Serengeti cheetahs (*Acinonyx jubatus*). The results of applying such a computer-based method were promising in terms of their accuracy and capacity to process a large database, however, the method's performance was clearly affected by picture quality and skewed camera angles. Other attempts to apply computer-assisted matching have been found to be successful in analyzing large picture databases (approx. 24,000 pictures) of mammals such as humpback whales (*Megaptera novaeangliae*). Yet, these attempts still strongly rely on the expert's opinion to make pictures amenable to be matched (Mizroch and Harkness 2003). The many challenges that arise when dealing with individual identification (e.g., variable camera angles and a variety of natural marks) have precluded development of a fully automated method to identify individuals. Consequently, picture-based individual identification is largely based on ad hoc protocols, which tend to strongly rely on human visual inspection of pictures. This has slowed the development of a standardized protocol for data quality control, although studies on cetacean photo-identification have made important progress in this regard (Hammond 1986, Friday et al. 2000, Mizroch and Harkness 2003).

We developed a novel method to improve individual identification based on computer-aided tools and visual recognition of pictures. We tested our method by having two independent users (hereafter classifiers) apply the method to a database consisting of 1,072 pictures of bobcat (*Lynx rufus*) we collected during two years of fieldwork. Central to this method was that it allowed multiple people to work in parallel in a cooperative process aimed to interactively refine and reach consensus on individual identification. Our goal was to evaluate to what extent the application of our method resulted in an increased agreement between identifications made by the independent classifiers (assumed to be indicative of a more accurate identification) as compared to randomly generated bobcat picture groupings. We hypothesized that the application of our method would result in an increase in picture classification agreement between classifiers greater than would be expected just by chance.

STUDY AREA

Our picture database was a product of a camera-trapping study carried out at the Jasper Ridge Biological Preserve (JRBP) in California, USA. The JRBP was operated by Stanford University and covered an area of 481 ha encompassing a variety of vegetation types, including chaparral scrubland, woodland, serpentine grassland and redwood forest patches, all co-occurring in a Mediterranean-type climate (Field et al. 1996, Human and Gordon 1996).

METHODS

In March 2006, we set up a grid over the JRBP composed of 12 camera-trapping stations. Stations consisted of 2 posts (10 m apart) each holding a waterproof Sure Shot A-1™ film camera (Canon, Lake Success, NY) connected to a TrailMaster™ TM15500 active infrared monitoring system (Goodson and Associates, Inc., Lenexa, KS). All camera-trap stations operated continuously for 2 years (Mar 2006 to Apr 2008) with the support of a team of trained field assistants.

We sent all film rolls obtained from the camera-traps to a commercial vendor to be developed, scanned to the highest available resolution, and digitally stored on compact discs. We then uploaded the digital pictures onto a relational database (MySQL, Inc., Cupertino, CA) and stored them on a web-accessible file server. The picture uploading process included the automated extraction of the date and time (hr and min) data directly from the scanned pictures, as this information was only available as a yellow printed time stamp on each individual picture. We developed a custom image processing code to automatically locate and parse time stamps. Essentially, the code searched each scanned image for patterns matching the time stamp format in a narrow yellow spectral band. We wrote the code in Matlab (The MathWorks, Inc., Natick, MA) using mathematical morphology functions.

We stored pictures in the database and conducted further processing using an interface designed in Access 2000 (Microsoft Corporation, Redmond, WA). During this processing we verified the extracted date and time information and entered additional data regarding species identity and number of individuals depicted in each picture. For the rest of our study we focused on the individual identification of bobcats from the 1,072 pictures mentioned above.

As a first step towards identifying individual bobcats, we applied an automatic procedure to group pictures into clusters based on the camera-trap station, date, and time of their occurrence (hereafter, picture time clusters). We used a 3-min cut-off time to group pictures within a time cluster. We selected this cut-off time based on the observation that in a histogram showing the distribution of time intervals between consecutive pictures at each site, 3 min corresponded to the point where the distribution had a marked drop.

As a result of applying the 3-min limit criterion, we generated 487 picture time clusters with an average size of 2.2 pictures per cluster and a range of 1 to 16 pictures. We carried out a second phase of merging by focusing on pictures separated by >3 min but that seemed to belong to the same picture sequence. Such situations might have occurred as a result of the clocks of the 2 cameras at one station being marginally desynchronized. This subsequent processing reduced the number of picture time clusters to 464.

We created an online web interface to allow internet access to the bobcat picture time clusters and their associated information of time, date, and camera-trap station. This web interface consisted of 2 main modules and provided tools to help in individual identification. We developed the first module (Bobcat identification tool) to help in the naming of picture time clusters (see Supporting Information Video 1: available online at www.onlinelibrary.wiley.com). A particularly relevant characteristic of this module is that it allowed classifiers to independently name bobcats in a parallel, mutually blind procedure. Two classifiers visually inspected individual pictures to identify the same bobcat in different pictures. Separate picture time clusters containing pictures identified as the same bobcat were exclusively labeled with the same name (e.g., Bobcat01) from a predefined list of names (hereafter, named picture time clusters or named clusters). We assumed all pictures within a picture time cluster to be of the same individual. If multiple individuals were in the same picture, we focused upon and named the more recognizable bobcat.

Prior to individual naming we used the visualization capabilities of the bobcat identification tool to apply the protocol employed by Mizroch et al. (1990) to categorize bobcat pictures in terms of their quality. Using a computer spreadsheet each classifier categorized pictures within clusters into 3 levels (poor, medium, and excellent) based upon: 1) their image quality and 2) their potential to help in individual identification by showing clear views of distinctive natural marks. We compared how classifiers categorized pictures differently with correlation analysis. Individual identification by the classifiers was based on presence of the dark spots observed on the bobcats' sides, ears, and tails in conjunction with those observed on the front and back of legs (see Fig. 1). Patterns of spots in bobcats' fur have been used as a reliable trait for individual identification as they are distinctive and do not show evident change over time (Heilbrun et al. 2003). We implemented a second module (Bobcat reconciliation tool) to help form a consensus between the classifications generated by different classifiers (see Supporting Information Video 2: available online at www.onlinelibrary.wiley.com). Following the initial, independent individual identification, each of the classifiers used the bobcat reconciliation tool to compare already named picture time clusters. We allowed the classifier using the reconciliation tool to compare their classifications with that of the second, independent classifier. We provided each classifier with the option to modify their classifications by naming previously unnamed picture time clusters or renaming already named picture time clusters. After finishing the comparison of classifications, both classifiers went through all of the bobcat pictures to do a final inspection to try to ensure the uniqueness of all named individuals.

By assigning names to pictures, each classifier created their own de facto partition between all named and unnamed picture clusters. We assessed the level of agreement between classifiers by comparing the picture clusters that were in the named partitions of both classifiers. To evaluate the level of agreement between classifiers, we calculated the adjusted Rand index ARI (Hubert and Arabie 1985). This index compares the level of similarity between 2 partitions (i.e., 2 different classifications of picture clusters, in this case). This comparison considers only picture clusters named by both classifiers. Furthermore, the ARI has 2 specific traits that make it particularly useful (Milligan and Cooper 1986). First, the ARI considers that some level of agreement between partitions might arise by chance. Accordingly, the ARI is adjusted in the sense that it results in a value of zero when the index equals its expected value. Second, the ARI has an upper bound of one, which makes interpretation of the level of agreement straightforward; the closer the ARI is to one, the greater the similarity between 2 partitions (Hubert and Arabie 1985). The ARI can also produce negative values indicating that the agreement between partitions is worse than expected by chance. There is no lower bound for the ARI.

The formula to calculate the ARI for 2 partitions is:

$$\mathrm{ARI} = \frac{\sum_{i,j}\binom{n_{ij}}{2} - \left[\sum_i \binom{n_{i.}}{2} \times \sum_j \binom{n_{.j}}{2}\right] \Big/ \binom{n}{2}}{\frac{1}{2}\left[\sum_i \binom{n_{i.}}{2} + \sum_j \binom{n_{.j}}{2}\right] - \left[\sum_i \binom{n_{i.}}{2} \times \sum_j \binom{n_{.j}}{2}\right] \Big/ \binom{n}{2}}$$

with n = total number of items being classified, n_{ij} = num-number of items in both partitions, and $n_{i.}$ and $n_{.j}$ = number of items in partitions i and j, respectively. In parentheses are denoted the possible combinations of 2 items that can be taken from the various sets of items described before. We calculated the ARI at 3 different times during the processing of the pictures: first, just after the classifiers finished the first round of picture naming; second, after one of 2 classifiers finished using the reconciliation tool; third, when both of the classifiers finished using the reconciliation tool.

To contrast the levels of consensus reached by classifiers to those that can be achieved by random processes, we carried out a series of Monte Carlo simulations to generate a set of random partitions of the picture clusters. We constrained partitions from the Monte Carlo simulations to have the same number and size of picture clusters as those actually produced by each classifier at each stage of naming. For example, to compare with the results of the first round of naming by classifier A, we generated a set of 100 random partitions of the picture clusters fixing the number and size of picture clusters at each Monte Carlo simulation to correspond with those of the classification created by classifier B after their first round of naming. We carried out the same ARI comparisons we made between classifiers but this time instead used the corresponding Monte Carlo generated partition. For each comparison, we recorded maximum ARI values.

Finally, we were interested in evaluating whether the number of pictures included in the clusters influenced the probability of them being named by the classifiers. Therefore, we compared the distribution of sizes of picture clusters named by each classifier at the beginning and at the end of the study with the initial distributions of sizes of the clusters available for naming using contingency tables. Differences in the distributions of sizes of original picture clusters and named picture clusters would be indicative of size-based

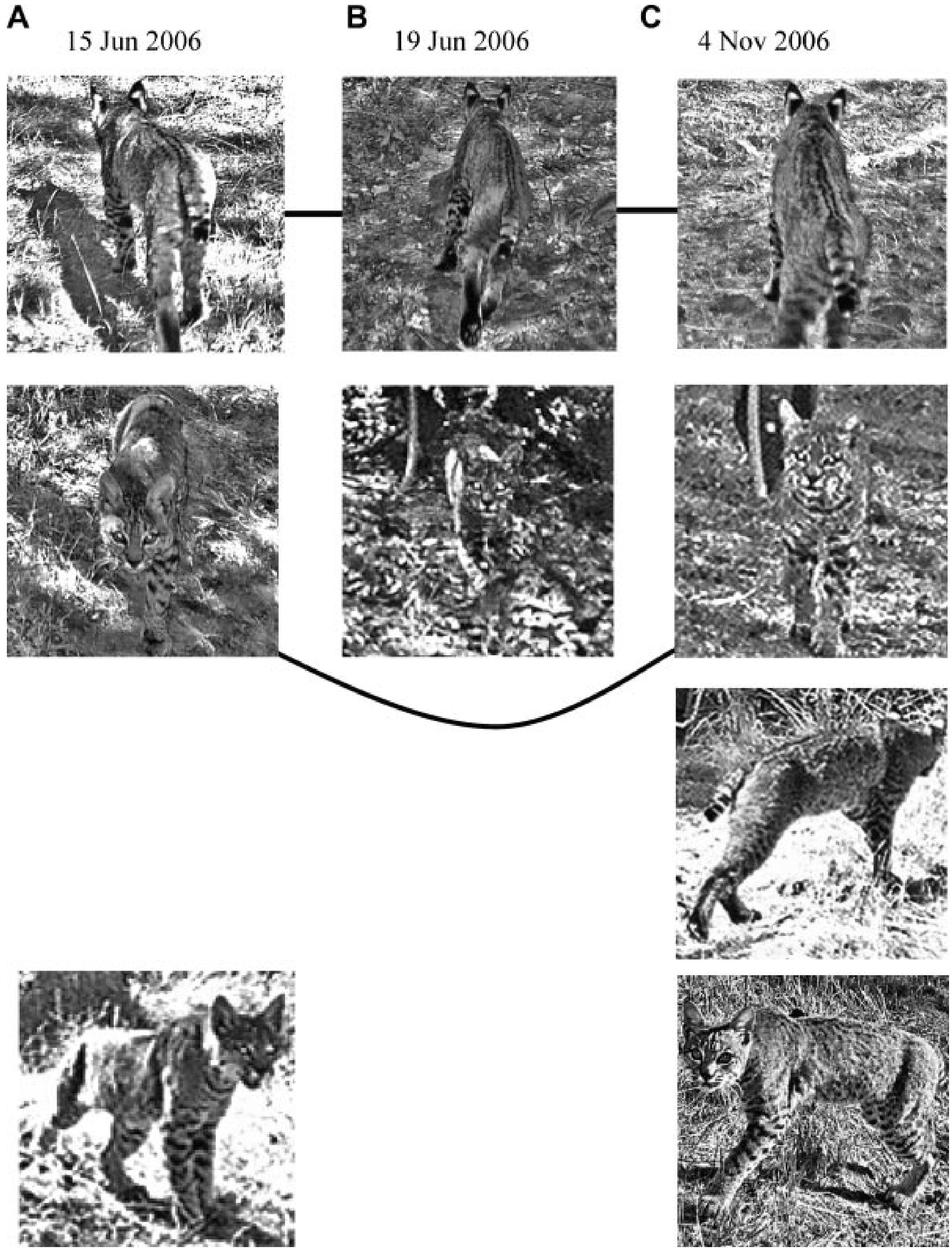

Figure 1. Picture time clusters showing (vertically) the same individual bobcat recorded at the Jasper Ridge Biological Preserve, California, at 3 different dates in June and November 2006. Lines connect pictures allowing identification. The individual is identified by the fur patterns on the tail, back, ears, and rear views of the front left legs and rear left and right legs. Use of picture clusters instead of individual pictures helps to link pictures that otherwise would be hard to match together as belonging to the same individual due their low image quality or because of the absence of clear views of natural marks.

biases in the selection of picture clusters to be named (e.g., clusters with more photos may be more likely to be named).

RESULTS

From the 464 picture clusters analyzed, 90 were deemed by the 2 classifiers as solely containing poor pictures both in terms of picture quality and recognition quality. Single pictures constituted most of these picture clusters (76%). There were 106 clusters with various image quality scores that were deemed by both classifiers as poor in terms of the potential of those clusters to help in individual identification. There was little agreement between classifiers in terms of their categorization of picture quality (Pearson correlation = 0.32), but greater agreement existed in terms of their categorization of the potential of pictures to help in individual recognition (Pearson correlation = 0.56). As the overall process of picture identification progressed, the number of names assigned by each classifier reduced. Classifier A passed from originally assigning 46 different names to assigning 25. Similarly, classifier B originally assigned 43 names but ended up assigning 29 names. In turn, the number of named individuals by each classifier dropped by 45.6% and 33.6%, respectively (Fig. 2).

In contrast to the concurrence observed in the reduction of the number of named bobcat individuals, there was a discrepancy between classifiers in the proportion of picture

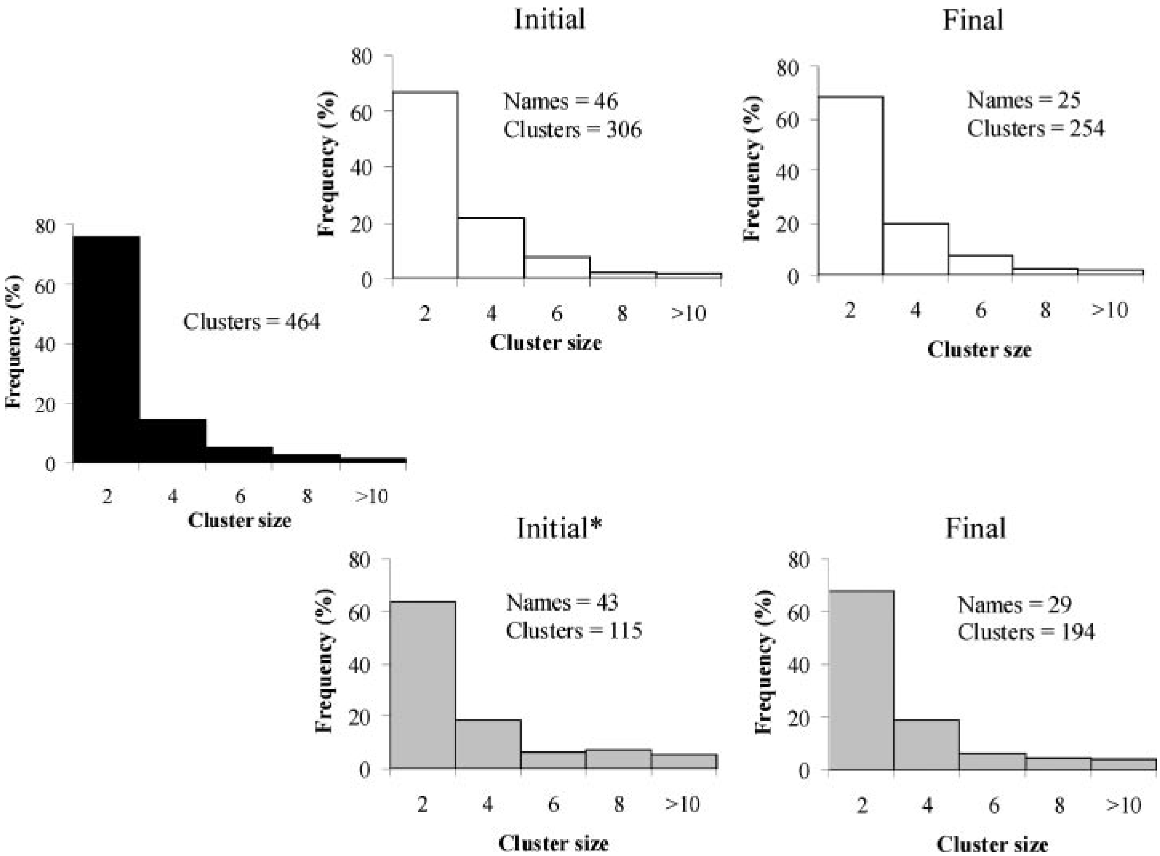

Figure 2. Comparisons among distribution of sizes of bobcat picture clusters recorded between March 2006 and April 2008 at the Jasper Ridge Biological Preserve, California. The initial distribution of picture clusters is shown with black bars. Distributions of picture clusters generated by classifier A and classifier B after their first and second round of naming are shown in white bars and gray bars, respectively. The asterisk indicates classifier's picture cluster distribution that statistically differs from the initial cluster distribution.

clusters that received a name. Classifier A passed from initially naming 306 picture clusters (66% of the total number of picture clusters) to naming 254 (55% of the total). In comparison, classifier B increased the number of picture clusters named by passing from 115 to 194 (25% and 42% of the total, respectively). When we adjusted these figures by discounting clusters not suitable to be identified and named, final success reached in naming picture clusters was 71% and 54% for classifier A and B, respectively. Overall, classifiers identified and named 32 different bobcats from which 22 (69%) were common to both classifiers through shared picture clusters.

We identified evidence of an initial disagreement between the original distribution of sizes of picture time clusters and the distribution of sizes of clusters named by classifiers ($\chi^2 = 11.82$, df $= 5$, $P = 0.03$). This discrepancy was caused by a slight overrepresentation of intermediate-sized clusters among named clusters by one of the classifiers after the first round of inspection (Fig. 2). This difference, however, did not continue in the subsequent round of naming.

The level of agreement between classifiers quickly increased, as measured by the proximity of the ARI values to 1 (Fig. 3). Values of the ARI passed from an initial value of 0.28 (before any of the classifiers used the reconciliation tool) to an intermediate value of 0.49 (after one of the classifiers used the reconciliation tool) and finally to a value of 0.84 (after the 2 classifiers finished the reconciliation process). This represented an increase of 300% in the ARI value at the end of the study (Fig. 3).

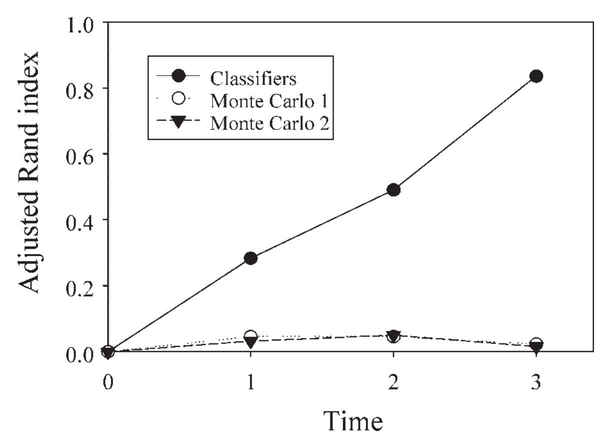

Figure 3. Similarity of bobcat picture groupings created by two classifiers (A and B) and Monte Carlo simulations. Bobcat pictures were recorded from March 2006 to April 2008 at the Jasper Ridge Biological Preserve, California. Similarity between groupings is measured with the adjusted Rand index (ARI). ARI values close to 1 indicate greatest similarity. Times 1 to 3 correspond to successive rounds of picture classification. Comparisons between Monte Carlo simulations and classifiers A and B are indicated as Monte Carlo 1 and Monte Carlo 2, respectively.

We observed marked contrast between the results of the comparisons of agreement between classifiers and the comparisons of agreement between classifiers and Monte Carlo simulations. Comparisons involving Monte Carlo simulations rendered consistently low ARI values. Even when focused on maximal ARI values, comparisons between classifiers and Monte Carlo picture partitions generated ARI values $\leq$0.05. Even the lowest ARI value resulting from the comparison between classifiers (0.28) was 5.6 times greater than the maximal value reached by the ARI in comparisons involving Monte Carlo simulations (Fig. 3).

DISCUSSION

We found that the application of our individual identification method resulted in a marked increase (300%) in agreement between classifiers, as measured by the ARI, after just 2 rounds of classification. The increase in the level of agreement reached by classifiers was much greater than the agreement resulting from comparisons between classifications we generated via Monte Carlo simulations. Therefore, we confirmed our initial hypothesis indicating the utility of our approach to improve individual identification based on camera-trapping data. In conjunction with our computer-based tools, the companion ARI measure of classification agreement was an effective parameter to evaluate changes in identification agreement.

The distribution of sizes of picture time clusters named by the classifiers reflected the original picture cluster distribution of sizes indicating the lack of bias in the likelihood to name a picture time cluster depending on its size. We found, however, slight differences between classifiers in terms of the number of picture clusters they named at the end of the study. These differences are probably related to differences between classifiers in terms of their appreciation of picture quality and a picture's potential to assist in individual recognition, as is suggested by our comparison of the picture categorizations carried out by both classifiers. The different number of picture clusters named by different classifiers highlights the risk of individual identification resulting in a different number of named individuals, when a consensus agreement is missing. To increase standardization of evaluation criteria among classifiers and assist in the formation of a classification agreement, it is highly desirable to carry out practice trials prior to individual identification.

Our approach is a promising tool to improve the individual identification of wild fauna based on camera-trapping studies. Given that the database available for our analysis consisted of scanned film, we needed to include in our approach tools to extract information from images (e.g., date and time) that otherwise would have been directly available from digital metadata. The existence of many databases still consisting of film pictures, as well as ongoing studies that continue using film-based camera-traps, warrants the application of tools such as those we applied here to manipulate scanned pictures. Yet, our protocol will clearly benefit from future modifications to fully exploit new technological developments such as digital camera-traps and Global Positioning System (GPS)-derived data. The flexibility of the platform in which we based our tools provides great adaptability to incorporate applications derived from these technologies.

A more comprehensive process of evaluation would help to maximize the potential of our approach. Aspects that should be of relevance to include in such an evaluation include: 1) the impact that the increase in the number of classifiers has on the process and level of agreement reached, 2) the comparison of our method with a fully automated method (Kelly 2001), and 3) the application of our method to pictures where individual identities are reliably known in advance to assess identification accuracy. Because one of the ultimate goals of individual identification is helping to generate population size estimates, it would be relevant to evaluate the effect that applying our method has on the calculation of population estimates. We consider that the combined application of methods such as ours with other modeling approaches that account for sources of misidentification, such as evolving natural marks (e.g., Yoshizaki et al. 2009), will lead to the emergence of a more robust approach to animal individual identification.

Management Implications

The approach we present in this paper can be easily implemented in a diversity of wildlife communities by researchers and preserve managers to increase the accuracy of monitoring of populations of species with distinctive, detectable marks. Moreover, our approach can be used by instructors to teach novice users to carry out individual identification and to achieve homogeneous criteria within teams working on mammal population monitoring. For example, classifier teams can include local people living in remote areas, as long as access to internet in nearby locations is possible.

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