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Animal Reidentification using Restricted Set Classification

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Abstract

Individual animal recognition and re-identification from still images or video are useful for research in animal behaviour, environment preservation, biology and more. We propose to use Restricted Set Classification (RSC) for classifying multiple animals simultaneously from the same image. Our literature review revealed that this problem has not been solved thus far. We applied RSC on a koi fish video using a convolutional neural network (CNN) as the individual classifier. Our results demonstrate that RSC is significantly better than applying just the CNN, as it eliminates duplicate labels in the same image and improves the overall classification accuracy.

Keywords: Individual animal recognition, Reidentification, Restricted Set Classification

1. Introduction

Consider an environmental project where the scientist is interested in wild animal behaviour, and is monitoring the movements of a group of animals on a daily basis. In order to study the behaviour and the dynamic within the group, each animal has to be identified with a unique tag or name. As recording and processing 24-hour video footage is impractical, time-lapse

7 footage can be used instead. This modality will render tracking methods
8 infeasible and will require other methods for re-identification of the animals
9 in the group images. Individual animal recognition has made significant
10 advances [1, 2, 3, 4]. Interestingly, the current approaches try to identify
11 each animal individually, disregarding the possibility that several animals
12 from the same group can be present in the image. Having several animals
13 in the same image poses an instant constraint on the classification task.
14 Suppose that four subimages were extracted from an image, each containing
15 an individual animal. In classifying those four individuals, we will have the
16 extra knowledge that they all have *different* identities. Taking this restriction
17 into account is expected to improve on the individual classification accuracy.

18 In this study we propose a methods for re-identification of animals from
19 images using Restricted Set Classification (RSC) [5, 6, 7]. RSC belongs to
20 the general area of weak supervision and non-standard classification [8]. A
21 *set* of objects are classified together so that each object receives a unique
22 label but the relationship between the objects (the context) is also taken
23 into account. Our experiments with a video of a fish pond demonstrate that
24 the classification accuracy increased compared to that of the naive approach
25 where each object is classified individually.

26 The rest of the paper is organised as follows. Section 2 gives an overview
27 and categorisation of the computer vision methods for animal recognition and
28 reidentification. RSC is explained in Section 3. The experiment is reported
29 in Section 4 and our conclusions are given in Section 5.

30 **2. Methods and approaches for animal recognition**

31 Past methods for animal identification such as physical branding, tagging,
32 tattooing or radio frequency identification (RFID) were accurate but often

33 invasive or at least intrusive to the animal [9, 10, 11]. Computer vision has
34 been gaining momentum as an inexpensive and non-intrusive alternative.

35 2.1. Tasks

36 A substantial amount of research has been devoted to automatic analysis
37 of camera-trap images in order to find out whether there is an animal in the
38 camera view and also to identify the species [3, 12, 13, 14].

39 On the other hand, individual animal identification and re-identification
40 are of great interest to the animal behaviourist. Started as hand-drawn pat-
41 terns and descriptions of re-captured animals (e.g., swan bill patterns [15]),
42 visual biometrics now dominate the research landscape of animal re-identi-
43 fication. Burghardt and Campbell [16] point out in 2007 that while tools for
44 human re-identification from images abound, animal re-identification does
45 not enjoy the same level of attention. Nonetheless, there are many studies,
46 especially recent ones, that propose adapted or new methodologies for animal
47 re-identification. One of the matching directions between human and ani-
48 mal re-identification is face/head identification in the image and subsequent
49 recognition, predominantly for primates [17, 18, 19] but also for other animals
50 such as cats, tigers, pandas, foxes, cheetahs [20], lions [21], lemurs [22] and
51 cows [23]. The main interest, however, lies in the identification of the unique
52 coat/skin pattern such as spots, stripes, creases, etc. [24, 25, 26, 16, 27].

53 In *tracking* animals in video footage, the main focus is on the trajectories
54 of the movements of the individual animals [28, 29, 30, 31]. The animals
55 have to be re-identified in each frame of the video. This is typically done
56 based on two sources of information: the predicted position of the animal
57 and the appearance. The leading source is the former, especially in the case
58 when the animals are very similar in appearance such as fruit flies or ants.

59 In this study, we are interested in identification of individual animals from
60 separate images (e.g. from time-lapse video footage), which may not form a
61 succession suitable for tracking. Thus, the appearance of the animal is the
62 only source of information.

63 Notably, the task of *group recognition* has not been approached thus far
64 in the literature. Such groups exist in many of the studies, as can be seen
65 by the published images, for example, a group of primates [19], piglets [32],
66 cows [33] or African penguins [34]. Here we argue that taking the group into
67 account will improve on the accuracy of the individual recognition.

68 2.2. Machine Learning and Computer Vision methods

69 The overwhelming majority of the literature on animal identification is
70 concerned with what Schneider et al. [3] name *feature engineering*. This is a
71 collective term for methods from *Computer Vision* for extracting informative
72 features from images and videos. *Machine Learning* has been widely applied
73 in studying animal behaviour [35] but it can offer a lot more, specifically
74 to animal re-identification. Typically, animal re-identification relies on a
75 database of stored images and a comparison of a candidate image with the
76 database to retrieve the closest match. This approach is the same as the
77 nearest-neighbour classifier in machine learning. The use of state-of-the-art
78 machine learning is handicapped by the relatively small number of images of
79 a single individual in the database. This is the case in many applications,
80 especially those relying on crowd sourcing for collecting images of individual
81 animals. Even though the database may have a substantial size, containing
82 data for thousands of animals, training accurate classifiers will be impossible
83 due to the small count of images per animal. In our scenario, a group of
84 animals is observed over a period of time, allowing for collecting an adequate

85 number of samples for each individual. In this case, advanced classification
 86 methods could be applied.

87 Recently, deep neural networks (DNN) have established themselves as
 88 the preferred tool for various tasks in animal re-identification [36, 37, 13, 14].
 89 While most of the applications are about detecting bounding boxes, face
 90 matching and similarity evaluation [36], with a sufficient number of images
 91 per individual in the data set, DNN can be used as a high-accuracy classifier.
 92 We use a DNN classifier in the experiment in this study. We show that taking
 93 advantage of the group context improves the classification accuracy of the
 94 DNN classifier.

95 3. Restricted Set Classification

96 3.1. Definitions

97 **Definition 1.** The *restricted set classification problem* is defined as follows
 98 [5, 7]. Let $X = \{\mathbf{x}_1, \dots, \mathbf{x}_m\}$ be a set of instances such that at most k_i
 99 instances come from class $\omega_i \in \Omega$, where $\Omega = \{\omega_1, \dots, \omega_c\}$ is the set of class
 100 labels (animal identities). The task is to find labels for all elements of X so
 101 that the restriction holds.

102 Note that $k_1 + \dots + k_c = k \geq m$.

103 **Definition 2.** A *base classifier* D is a classifier that assigns a class label to
 104 an instance $\mathbf{x} \in \mathbb{R}^n$

$$D : \mathbb{R}^n \rightarrow \Omega. \quad (1)$$

105 We also require that D provides estimates of the posterior probabilities
 106 $P(\omega_1|\mathbf{x}), \dots, P(\omega_c|\mathbf{x})$.

For the animal re-identification problem, we assume that there is a group of c animals that we wish to monitor. The c animals are the classes of interest. Assuming that there are no newcomers to the group, in any given image, there may be at most c different animals. This problem is a version of the restricted set classification problem, which we termed “who-is-missing” [6]. In this case, $k_1 = k_2 = \dots = k_c = 1$, and $m \leq c$. Classifier D will output the probabilities for the c classes for a given animal sub-image $\mathbf{x}$.

Definition 3. A *super-label* for set X is any collection of m labels from Ω so that any instance $\mathbf{x} \in X$ receives a single label. A super-label will be called *consistent* if it satisfies the requirement that at most k_i labels are equal to ω_i , $i = 1, \dots, c$.

Denote by $\mathcal{S}$ the set of all possible super-labels of X . For cardinality $|X| = m$, $\mathcal{S}$ has $\frac{c!}{(c-m)!}$ elements. Let $P = [p_{ij}]$ be a matrix of size $m \times c$ that contains the posterior probability estimates obtained from the base classifier D applied to X . Entry p_{ij} is the estimate of $P(\omega_j | \mathbf{x}_i)$. Let $\mathcal{P}$ be the set of all matrices P .

Definition 4. A *set classifier* D_{set} assigns a super-label to any set X using the output of classifier D , that is

$$D_{\text{set}}(X, D) : \mathcal{P} \rightarrow \mathcal{S}. \quad (2)$$

3.2. Evaluation of accuracy of a set classifier

We consider two type of estimates of the accuracy of D_{set} for a given set X :

- A_T , total accuracy: $A_T = 1$ if *all* labels are correctly assigned to the instances in X , and $A_T = 0$, otherwise;

- A_P , partial accuracy: A_P is the *proportion* correctly labelled instances across the whole set of instances (identical to classification accuracy).

3.3. Three set classifiers

We consider here the following set classifiers:

(1) *Independent set classifier (Baseline)* D_{set}^i . This classifier takes the labels suggested by D without any modification and collates them to make the super-label of X . Note that this approach does not guard against having multiple labels of the same animal for different objects in X (sub-images). Thus, the super-label is not guaranteed to be consistent.

In D_{set}^i , all instances are labelled independently. Assuming that D 's accuracy is p , the accuracy measures of D_{set}^i are

$$A_T(D_{\text{set}}^i) = p^{\mathbb{E}[m]}, \quad (3)$$

where $\mathbb{E}[m]$ is the expected value of the cardinality of X , and

$$A_P(D_{\text{set}}^i) = p. \quad (4)$$

(2) *Greedy set classifier* D_{set}^g . The input to this set classifier are the posterior probabilities $P(\omega_i|\mathbf{x})$ produced by classifier D for $i = 1 \dots, c$ for the given $\mathbf{x} \in \mathbb{R}^n$. The Greedy Set Classifier labels X according to the following algorithm:

1. Initialise a set $V = \emptyset$ to store the assigned object-class pairs.
2. Identify the largest posterior probability $P(\omega_j^*|\mathbf{x}_j^*)$ among the objects and classes not assigned so far.
3. Remove ω_j^* from the list of available classes, and $\mathbf{x}_j^*$ from the list of available objects, and add the pair to set V .

151 4. If there are no objects left, stop and return V . Else, continue from
 152 step 2.

153 The Greedy set classifier guarantees consistent super-labels. It can be
 154 formally proved [7] that for two-class problems, and 2 instances in each image,

$$A_P(D_{\text{set}}^g) > A_P(D_{\text{set}}^i) . \quad (5)$$

155 (3) *Hungarian set classifier* D_{set}^h . Here we propose to use this set classifier
 156 for the animal re-identification problem. It is based on the Hungarian as-
 157 signment algorithm further developed by Kuhn and Munkres, also known as
 158 Kuhn-Munkres algorithm [38]. Proposed originally for $c \times c$ matrices, the
 159 Hungarian algorithm has been extended for rectangular matrices [39]. Be-
 160 low we demonstrate the mathematical rationale behind the Hungarian set
 161 classifier.

162 We shall assume that the objects in X are drawn independently from
 163 their respective classes, that is, $\mathbf{x}_i$ is drawn from the distribution of class ω_i ,
 164 independently of the remaining $m - 1$ objects. It can be argued that the ap-
 165 pearance of a given animal in the image does not depend on the appearances
 166 of the other animals. For example, one chimpanzee’s face could be in full
 167 frontal view in the image while another’s could be in semi-profile. However,
 168 animals interact in certain ways, and there may be patterns of interactions
 169 that will correlate the animals’ appearance. For example, all animals can be
 170 on high alert and looking in the direction of the approaching danger. Also,
 171 they may all be looking at a food source. Correlated appearances may be
 172 used to improve the accuracy of the set classifier. For such correlated appear-
 173 ances to be evaluated and used, we need a large amount of data. While this
 174 is an interesting research line, for the purposes of this study, we will assume
 175 independent appearances.

176 With this assumption in place, the likelihood of a super-label $S = \langle s_1, \dots, s_m \rangle$,
 177 $s_i \in \Omega$ is

$$L(S|X) \propto \prod_{i=1}^m P(s_i|\mathbf{x}_i) . \quad (6)$$

178 The optimal super-label S^* will be the one maximising L (equivalently $\log(L)$),
 179 that is

$$S^* = \arg \max_{S \in \mathcal{S}} \sum_{i=1}^m \log(P(s_i|\mathbf{x}_i)) , \quad (7)$$

180 It can be shown that the Greedy set classifier D_{set}^g will not guarantee
 181 the optimal solution. We can cast the problem defined by Equation (7) as
 182 a linear programming problem (LP). Let T be a reward matrix with entries
 183 $t_{i,j} = P(\omega_i|\mathbf{x}_j)$. Introducing the unknowns $r_{(i,j)} \in \{0,1\}$, $i = 1, \dots, m$,
 184 $j = 1, \dots, c$, the LP is

$$\max \sum_{i=1}^m \sum_{j=1}^c r_{(i,j)} \log(t_{i,j}),$$

185 subject to

$$\begin{aligned} \sum_{i=1}^m r_{(i,j)} &\leq 1, \quad j = 1, \dots, c, \\ \sum_{j=1}^c r_{(i,j)} &= 1, \quad i = 1, \dots, m. \end{aligned}$$

186 The Hungarian assignment algorithm provides the solution to this LP
 187 problem, guaranteeing that the obtained super-label is S^* .¹

¹MATLAB code for the Restricted Set Classification with the three set classifiers is available at <https://github.com/LucyKuncheva/Restricted-Set-Classification>.

188 4. Experiment

189 4.1. Data

190 Koi is an informal group name of the coloured variants of the Amur carp
191 (*Cyprinus rubrofuscus*) that are kept for decorative purposes. We sourced a
192 video from Pixabay to use as an example with multiple animals in the same
193 frame. The video consists of 536 frames with 9 fish in total. We named the
194 fish randomly (regardless of their true gender): Catherine, Dwayne, Florence,
195 Humphrey, JP, Jack, Ruby, Selwyn and Siobhan. Each frame of the video
196 was manually segmented by defining a bounding box around the visible part
197 of the fish. Each sub-image was stored with the respective name tag. By
198 segmenting the video manually, we bypass the main bottleneck of animal
199 re-identification. We did this on purpose, because the claim in this study
200 concerns the last stage of the classification.

201 Overall, 1640 sub-images were cropped from the 536 frames, each one
202 containing one fish individual. Table 1 shows the distribution of the classes
203 as well as examples from each class.

204 4.2. The Independent classifier D

205 The Independent classifier D used in this experiment was a deep neu-
206 ral network (Convolutional Neural Network, CNN) from the Deep Learning
207 Toolbox of MATLAB, version 12.1 (R2019a). We chose this model because
208 of the overwhelming evidence in the literature reviewed in Section 2 in favour
209 of deep learning models. Since we have nine classes, and the data set is not
210 very large compared to standard deep learning set-ups, we kept the CNN as
211 simple as possible using its default structure and training choices:

- 212 • Structure:

Table 1: Distribution and examples of the classes (nine individual fish).

Name	Number	Examples
Catherine	103 (6.28%)
Dwayne	228 (13.90%)
Florence	145 (8.84%)
Humphrey	152 (9.27%)
JP	233 (14.21%)
Jack	161 (9.82%)
Ruby	265 (16.16%)
Selwyn	94 (5.73%)
Siobhan	259 (15.79%)
Total	1640 (100.00%)	

- 213 – an input layer with colour images sized 56-by-56 pixels
 - 214 – a convolution layer with 10 filters of size 5-by-5
 - 215 – a RELU layer
 - 216 – a max pooling layer with pool size [2, 2] and stride [2, 2]
 - 217 – a fully connected layer for 9 classes
 - 218 – a softmax layer returning the posterior probabilities for the classes.
- 219 • Training parameters: We used the default stochastic gradient descent
 - 220 with momentum (SGDM) optimiser with 30 maximum number of epochs
 - 221 and initial learning rate 0.0001. The data was shuffled after each epoch.
 - 222 • Data Augmentation:
- 223 In view of the relatively small data size, we opted for augmentation.
- 224 Each image in the data set was processed twice with random aug-
- 225 mentation, thereby tripling the training data size. MATLAB func-
- 226 tion `imageDataAugmenter` was applied with the following augmenta-
- 227 tion choices:
- 228 – random rotation at an angle between 0 and 360 degrees. This
 - 229 transformation was deemed reasonable because the fish were swim-
 - 230 ming in any direction in the video.
 - 231 – random scaling on the x-axis and a separate random scaling on
 - 232 the y-axis at a ratio between 0.8 and 1.
 - 233 – random shear on the x-axis and a separate random shear on the
 - 234 y-axis at an angle between -20 degrees and 20 degrees.
 - 235 – random translation on the x-axis and a separate random transla-
 - 236 tion on the y-axis at ± 4 pixels.

237 The experiments were carried out on a HP Pavilion Laptop 15-cs1xxx with
238 graphics card NVIDIA GeForceGTX 1050 with Max-Q Design and operating
239 system Windows 10 Home 64-bit.

240 We considered the classification accuracy sufficient for the purposes of
241 this study.

242 4.3. An example

243 The expected improvement on the classification accuracy by using RSC
244 is illustrated by the following example. Figure 1 shows the original image
245 containing five fish and Catherine’s head. Catherine was not segmented in
this frame because she would not be identifiable from such a small part.

Figure 1: Original image with five recognisable fish.

246
247 Figure 2 shows the labels assigned by the Independent set classifier. This
248 classifier labelled two fish as Jack and mistook Humphrey for Florence.

249 The two proper set classifiers guarantee that the restriction is observed
250 (no repeated labels). The Greedy set classifier (Figure 3) resolves the conflict

Figure 2: Labelling by the Independent set classifier. Correct labels are marked with a yellow bounding box, repeated labels with red, and wrong (non-repeated) labels, with blue.

251 by relabelling the bottom “Jack” to “Catherine”, which is also largely white
 252 in colour. It, however fails to recover the correct label of “Florence”.

253 Finally, the Hungarian set classifier reassigns the labels to their correct
 254 values as shown in Figure 4.

255 4.4. Cross-validation experiment

256 To compare the independent set classifier with the two proposed variants,
 257 we ran a 2-fold, 3-fold, 5-fold and 10-fold cross-validation by splitting the set
 258 of *frames* into folds. We then retrieved the objects in the training frames to
 259 collate a training set of *objects* for D . The objects in the testing frames were
 260 pooled to create the testing data set. Care should be taken when preparing
 261 training and testing data from a video. The individual fish images cropped
 262 from consecutive frames will be very similar. Thus, if two consecutive frames
 263 are randomly assigned to the training and the testing part, respectively, the

Figure 3: Labelling by the Greedy set classifier. Correct labels are marked with a yellow bounding box and wrong labels, with blue.

264 classifier may achieve a deceptively high accuracy. Therefore, we carried out
 265 the cross-validation by splitting the video into time intervals. For example,
 266 in the two-fold cross-validation experiment, the first 268 frames were taken
 267 as the first fold and the remaining 268 frames, as the second fold. All cross-
 268 validation and data shuffle experiments were carried out in this manner.

269 The classification accuracies A_P and A_T , averaged across the folds, are
 270 shown in Tables 2 and 3, respectively. The last column in Table 2 shows
 271 the number of frames with repeated labels in the testing set. These numbers
 272 show how many chances there have been for the RSC to improve on the
 273 Independent set classifier. As D becomes more accurate with the growing
 274 size of the training data, the number of frames with repeated labels declines.

275 Tables 2 and 3 show that the best option is the Hungarian set classifier
 276 for both A_P and A_T . Naturally, the total accuracy is lower than the partial
 277 accuracy, as it requires that *all* objects in the frame are correctly labelled.

Figure 4: Labelling by the Hungarian set classifier. Correct labels are marked with a yellow bounding box.

278 A_T is more affected by the training sample size than A_P . In the 2-fold cross-
 279 validation the training sample contained 820 objects on average, while in the
 280 10-fold cv, this size was 1476.

281 Statistical validation of these results is only feasible for the 10-fold cross-
 282 validation experiment. Table 4 shows the relationship between the set clas-
 283 sifiers. The probabilities were calculated using a Bayesian correlated t-test
 284 proposed by Benavoli et al. [40]. The paper argues that the p-value based
 285 statistical analyses are inaccurate and misleading. The proposed alternative
 286 directly answers the question of ‘what is the probability that classifier A
 287 is better than classifier B?’ For two classifiers and one data set, the authors
 288 propose using a cross-validation and a Bayesian correlated t-test as a replace-
 289 ment of the conventional t-test or even the corrected t-test due to Nadeau

Table 2: Partial accuracy A_P for the cross-validation experiment and the three set classifiers. The last column shows the number of frames with repeated labels.

	Hungarian	Greedy	Independent	Repeated labels
2-fold	0.4257	0.4063	0.4248	206
3-fold	0.5204	0.4856	0.4613	250
5-fold	0.4819	0.4743	0.4701	177
10-fold	0.6243	0.6138	0.6039	165

Table 3: Total accuracy A_T for the cross-validation experiment and the three set classifiers

	Hungarian	Greedy	Independent
2-fold	0.1856	0.1819	0.1726
3-fold	0.2559	0.2236	0.1593
5-fold	0.1611	0.1739	0.1412
10-fold	0.2502	0.2481	0.2219

290 and Bengio [41].² Again, the Hungarian set classifier is substantially better
 291 than the Greedy set classifier and the Independent classifier in view of both
 292 partial accuracy and total accuracy.

293 To illustrate the difference in the performances of H and I, we com-
 294 pare their partial accuracy A_P . Based on the number of folds of the cross-
 295 validation and the number of repeats, a distribution of the paired differences
 296 between the classification accuracies was calculated and plotted in Figure 5.
 297 It is an extended Student distribution with degrees of freedom $N - 1$, where

²Python library `baycomp` contains the functions for this analysis <https://github.com/janezd/baycomp>. Here we used a MATLAB version available at <https://github.com/LucyKuncheva/Bayesian-Analysis-for-Comparing-Classifiers>.

Table 4: Probabilities from the Bayesian correlated t-test for A_P . The value in cell (i, j) is the probability that Method i (the row) is better than Method j (the column).

	Partial accuracy A_P			Total accuracy A_T		
	H	G	I	H	G	I
Hungarian	0.0000	0.9221	0.8581	0.0000	0.9884	0.9988
Greedy	0.0779	0.0000	0.7282	0.0116	0.0000	0.9989
Independent	0.1419	0.2718	0.0000	0.0012	0.0011	0.0000

Note: The column headings are abbreviated as H (Hungarian set classifier), G (Greedy set classifier) and I (Independent classifier)

298 N is the number of differences, the mean is equal to the sample mean $\hat{x}$, the
299 variance is

$$v = \left(\frac{1}{N} + \frac{\rho}{(1 - \rho)} \right) \hat{\sigma}^2$$

300 where $\rho = 1/K$ for a K -fold cross-validation and $\hat{\sigma}^2$ is the sample variance.
301 The larger shaded area to the right of 0 indicates that the differences are
302 mostly positive, and the Hungarian set classifier is better than the Indepen-
303 dent set classifier.

304 Based on these results, we recommend the Hungarian set classifier for the
305 problem of individual animal recognition from images containing groups of
306 animals.

307 4.5. *Data-shuffle experiment*

308 This part of the experiment examines the effect of the training set size
309 on the improvement offered by the set classifiers. We carried out 100 runs
310 of training and testing with a given proportion split. As explained earlier,
311 we kept the testing set as a time-contiguous part of the video with a random

Figure 5: Distribution of the difference $A_P(D_{\text{set}}^h) - A_P(D_{\text{set}}^i)$ [40]. Most values lie to the right of zero (orange line). The shaded area to the right of zero gives the probability 0.8581 that the Hungarian set classifier is better than the Independent classifier.

312 starting point. We ran experiments with split proportions $\{0.5, 0.7, 0.9\}$.
 313 The accuracies A_P and A_T for the three methods are shown in Tables 5 and
 314 6, respectively.

Table 5: Partial accuracy A_P for the data shuffle experiment and the three set classifiers for splitting proportions P . The last column (R) shows the number of frames with repeated labels.

P	Hungarian	Greedy	Independent	R
0.5	0.3823	0.3624	0.3350	131.7100
0.7	0.4216	0.4079	0.3696	74.0500
0.9	0.5862	0.5783	0.5675	15.1300

315 The results ascertain again the advantage of the RSC classifiers over the
 316 independent labelling of the objects. Notably, there is a dramatic fall in
 317 the classification accuracy for smaller training data sizes. Further statistical
 318 analyses using the Bayesian correlated t-test also unequivocally select the

Table 6: Total accuracy A_T for the data shuffle experiment and the three set classifiers for splitting proportions P .

P	Hungarian	Greedy	Independent
0.5	0.1155	0.1132	0.1001
0.7	0.0659	0.0641	0.0494
0.9	0.1427	0.1414	0.1071

319 Hungarian set classifier as the best of the three alternatives. The dominance
 320 of the Hungarian set classifier is even more prominent compared to the cross-
 321 validation experiment. For all split proportions, for both A_P and A_T , the
 322 probability that the Hungarian set classifier is better the Greedy and the
 323 Independent set classifiers was evaluated at 1. Similarly, The Greedy set
 324 classifier dominated the Independent set classifier in all experiments with
 325 probability evaluated at 1.

326 The *rate* of improvement was not affected much by the training sample
 327 size, unlike the accuracy itself. While accuracy A_P drops by over 20% (in
 328 absolute units) when 50% of the data is used for training compared to 90%
 329 of the data, the improvement offered by the RSC methods is within 5% for
 330 both training proportions. Still, the less accurate individual classifier for the
 331 50% split leaves more room for improvement. To illustrate this, we show two
 332 box-plots in Figure 6. The three methods were plotted next to one another
 333 for split proportions 0.5 and 0.9. In both plots, the box for the Hungarian
 334 set classifier is higher than the other two boxes. The dotted line marks the
 335 median of the Independent set classifier taken as baseline.

336 While the improvement achieved by the Hungarian and the Greedy set
 337 classifiers is visible, the *rate* of improvement is similar between the two pro-
 338 portions. The reason for this is that if the independent classifier D is not

339 very good (the case with the smaller training data), then there are too many
 340 mistakes. For example, a frame containing fish that is labelled wrongly but
 341 there are no repeated labels, will receive the same labels from all set classi-
 342 fiers. Therefore, the potential of correcting the repeated labels through any
 343 set classifier is limited by the accuracy of D .

344 Fine-grained classifiers based on more complex CNN architectures may
 345 be accurate, provided there is enough data for training. In this case, the
 346 effect of RSC may be too small to warrant its use.

Figure 6: Box-plots of the classification accuracies A_P for split proportions 0.5 and 0.9. The dashed horizontal line indicates the median of the baseline method (the Independent set classifier).

347 Table 7 shows the computational times of the data shuffle experiments.
 348 The table also shows the number of *frames* in the training data as well as the
 349 average number of images in the training data (after augmentation) and the
 350 average number of frames with repeated labels. The times are calculated as
 351 the average of the 100 runs and are shown in seconds. The CNN training takes
 352 the bulk of the time. Testing is a small fraction of the training time, and the
 353 add-ons through the RSC classifier are also relatively small. The Hungarian
 354 set classifier is slightly more expensive than the Greedy set classifier and can

355 be used as a viable extension of the individual CNN in the RSC setting.

Table 7: Computational times in seconds for the data shuffle experiment (100 runs with each proportion split). P is the proportion of the video for training; N is the number of individual training sub-images per run; R is the number frames with repeated labels per run.

P (frames)	N	R	Times (s)			
			Train	Test	Hungarian	Greedy
0.5 (268)	2151.0	131.7	15.2	0.120	0.027	0.021
0.7 (375)	3309.0	74.0	20.8	0.088	0.016	0.013
0.9 (482)	4146.0	15.1	28.8	0.055	0.005	0.005

356 5. Conclusion

357 In this study we advocate using a Restricted Set Classification instead of
 358 independent classification for individual animal recognition. We demonstrate
 359 that RSC can correct mistakes when there are more than one animal in the
 360 same image assigned to the same individual label. The best RSC version
 361 was the Hungarian set classifier which assigns the most probable labels while
 362 observing the restriction of no repeated labels in the same frame.

363 Note that no further labelling is needed for RSC to work. The only
 364 information that it uses is that the set of sub-images that are labelled together
 365 come from the same frame.

366 We observed that the potential of correcting repeated labels through a set
 367 classifier is limited by the accuracy of the base classifier. It would be inter-
 368 esting to prove the limits of the improvement and determine how calibration
 369 of posterior probabilities affects it.

370 This study bypasses the considerable problem of image segmentation by
371 assuming that the correct bounding boxes and labels are available. The
372 result from any classification will be preconditioned by the accuracy of the
373 segmentation. If the segmentation is accurate, then the classifier (CNN)
374 could be good on its own. This means that the individual classification
375 accuracy will be high, and the benefits from RSC may not be that great.
376 The proposed approach will be most useful when the individual accuracy
377 leaves room for improvement. It will be interesting to study the effect of
378 automatic segmentation on the improvement potential of RSC.

379 While the results in favour of the RSC classifier are compelling, we have
380 used only one data set (the koi fish video). We could not find another suitable
381 annotated and labelled data set with multiple individual animals to expand
382 our experiment. We are currently preparing a second data set from a video
383 containing a group of pigeons.

384 An important future line of research is accommodating objects from
385 classes that were not represented in the training data. In other words, the
386 individual classifier D should be able to realise its own competence by out-
387 putting a probability vector that does not necessarily sum up to 1. The
388 ‘leftover’ probability will allow for assigning label ‘don’t know’ to accom-
389 modate unseen classes. The set classifier should be modified accordingly.
390 Further on, constrained clustering can be used to label the objects in the
391 ‘don’t know’ category into different classes (individuals). The constrained
392 version of the clustering will ensure that the RSC restrictions are in place,
393 that is, there cannot be more than one individual with the same class label
394 in a single image.

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