A Distribute Approach for Classifying Anuran Species Based on Their Calls

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Abstract

In this work, we evaluate the performance of a distributed classification system in a Wireless Sensor Network for monitoring anurans. Our aim is to study how to take advantage of the collaborative nature of the sensor network to improve the recognition of anuran calls. To accomplish this, we evaluate four low-cost techniques (majority vote, weighted majority vote, arithmetic and geometric combinators) to combine three classifiers commonly used in sensor applications (Quadratic Discriminant Analysis, Naive Bayes, and Decision Trees) and trained to identify anuran calls. We investigate how the environment perceptions of the sensors can be used to discard confusing scenarios, i.e., scenarios in which there are multiple calls from different species at same time. Our best combination strategy achieved a gain of about 11% over a sensor taken in isolation. We also found that, by using the entropy of the species estimates, the sensor committee is able to effectively identify confusing scenarios, increasing gains over the isolated sensor to about 20%.

1. Introduction

Accounting amphibian populations, specifically anurans (frogs or toads), is a common tool used by biologists as an early indicator of environmental stress. The reason is that anurans are closely related to the ecosystem [5]. Several data sources may be used for monitoring these animals. Among them, anuran calls represent, an interesting alternative because anuran calls lead to a non-intrusive data acquisition strategy. The state-of-the-art of amphibians monitoring systems, employing automatic classification methods and Wireless Sensor Networks (WSNs), may help estimate long-term changes in amphibian populations and, consequently, determine the causes of such changes.

WSNs are usually composed of low-cost sensor motes, allowing the spread of a large amount of sensors over the desired areas [2]. Nonetheless, the low cost hardware imposes restrictions, such as lower processing power and batteries with reduced lifetime [17]. The wireless communication ability enables collaboration between sensors by exchanging information [13].

From a WSNs standpoint, we can consider each anuran call as an event which is detected and processed by the sensor committees (or clusters). Thus, if we disseminate L sensors in a certain area, each of them will have its own opinion about the detected event. Later, by combining these possibly different opinions, we can decide the underlying species with a higher degree of certainty.

This problem can be viewed as the Machine Learning task of creating an 'Ensemble of Classifiers' (Figure 1). Therefore, we can assume that there are L equal classifiers[1] receiving slightly different signals (by effect of noise and attenuation) and the data fusion is accomplished by means of a probabilistic combination rule [15, 11].

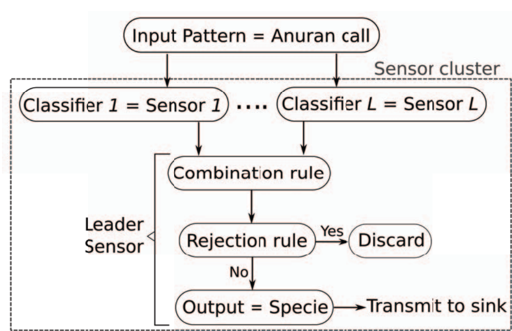

Figure 1: Viewed as an ensemble of classifiers, each sensor in the WSN plays the role of a member (base classifier) of a decision committee, where a central node (sink node) is in charge of the final decision by combining decisions from other members.

[1] Although sensors with different classifiers could provide more independent opinions, which would be more appropriate for combination, we assume that in a realistic scenario, sensors belonging to a same cluster will be deployed with the same classifiers.

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In real situations, sensors will face many scenarios where random noises, other animal vocalizations and even different species of anurans are present. Thus, in order to provide reliable estimates, in many applications, it can be interesting that the sensors are able to identify and discard such confusing scenarios. To accomplish this, the sensors can colaborate to recognize, for instance, disagreements and discrepant estimates.

In this work, we model the problem of recognizing anuran calls by using a sensor network as an ensemble of classifiers. We also propose and evaluate a rejection technique on the *a posteriori* species probability vector to discard confusing scenarios. In summary, our contribution consists in verifying two hypotheses: (1) The decision provided by a sensor committee is better than the one provided by a single sensor and (2) A rejection technique can reduce the misclassification rate.

To test the first hypothesis, we compare the performance of the sensor committee with a single sensor, and to test the second hypothesis, we compare the error rate as the methods reject scenarios they identified as confusing. To test these hypotheses, we simulate scenarios where one or two anuran species vocalize at the same time in an environment with attenuation and Gaussian noise. In addition, we analyze the impact of using three classification techniques (Decision Tree, Naive Bayes and Quadratic Discriminant Analysis - QDA) and four ways of combining the classifiers (majority vote, weighted majority vote, arithmetic probability rule and geometric probability rule [15, 11]). Results show that sensors using QDA classifiers combined by arithmetic voting obtained a gain of about 11% over a single sensor. Moreover, the sensor committee is able to increase such gain to about 20% when confusing scenarios are discarded.

The remainder of this paper is organized as follows. Section 2 presents an overview of the related work. Sections 3 and 4 summarize the combination and rejection techniques. The parameters and experimental protocol employed are described in Section 5. The experiments and results are presented in Section 6. Finally, conclusions and outlook are discussed in Section 7.

2. Related Work

Collins and Storfer [6] shows that amphibians are directly affected by environmental changes. This observation has motivated many researchers to combine WSN with automatic classification to monitor amphibian population, mainly by using vocalizations [1, 7, 16, 9].

The general idea consists in treating the problem of recognizing a vocalization as a classification task. Thus, each vocalization is represented by a set of features (measurements taken from the sound wave that characterizes it according to its amplitude, frequency, duration, etc). The task is to determine the class (species) of a new vocalization sample (test instance), given a set of vocalizations previously identified (training examples).

In most of these previous work, the set of features used to represent bio-acoustic signals is transmitted to the sink node, where the classification is performed. Thus, if more than two sensors receive signals form related sources, the amount of information transmitted may be redundant, and, consequently, the collaborative network capacity is not fully used, increasing the cost of transmission.

A different strategy to reduce the transmission cost is to compress the audio before transmission [1, 8]. Aide et al. [1] propose the use of a lossless compression codec *FLAC*, while Diaz et al. [8] used a framework based on *compressive sensing*. In these cases, the amount of information transmitted is smaller and, as additional benefit, it is possible to recover the audio in the sink. The recovered audio allows for a more exhaustive control over the classification outcome. Anyway, the collaborative network capacity is not harnessed.

As a workaround, Ribas et al.[14] grouped the sensors in clusters by similarity and performed the classification on the own motes. They used the *Mahalanobis* distance as a classification technique and the majority vote to combine the classifiers. Performing these operations *in situ* increases the processing in the sensor motes but decreases the amount of information transmitted in the network.

This last work leaves an open question: What is the impact on the classification effectiveness using others ensemble methods different from a simple voting mechanism? Unlike previous work, we will make an effort to answer this question evaluating four different combination techniques, as well as approaches to reject confusing situations, which can be useful to reduce transmission costs and increase network lifetime.

3 Combination Techniques

To take advantage of the collaboration capability of a WSN, we must decide which classification method and combination technique to apply. Given the hardware restrictions, such techniques should have a low computational cost. For this reason, we choose to compare the Naive Bayes Classifier [15], the Quadratic Discriminant Analysis (QDA) [10] and the Decision Tree [15].

For each sensor, two steps are necessary for the classifying task: (a) the *training*, where the stored samples are used to create the classification model. Since this is the most expensive step, the model is created offline, outside the sensor; and (b) the *prediction*, where the classifier captures the vocalization, calculate its features, and uses the classification model to estimate the probability of such vocalization belonging to each class. This step takes place within the sensor mote.

In the Naive Bayes classifier, the features are assumed to be independent of each other, as well as the classes. Thus, given a vocalization x represented by features $F_{i,1\leq i\leq n}$ (from a set of features F), the probability of x belongs to species w_j (from a set of species W) can be estimated by $P(w_j|x) = P(w_j|F)$. Thereby, the species of x is given as follows:

$$\textit{class}(x) = \text{argmax}_j \; \eta P(w_j) \prod_{i=1}^{n} P(F_i|w_j)$$

where η is a normalization constant, $P(w_j)$ is the probability of class w_j and $P(F_i|w_j)$ is an estimate of feature F_i regarding species w_j.

In the QDA method, the classes are separated by quadratic boundaries. This method assumes that each class (w_j) has a multivariate normal distribution with different covariance matrices (Σ_j) [12]. To check this assumption, we applied the Box's M test [3]. The discriminant function result for the unknown features vector x in each class is:

$$\delta_j(x) = -\frac{1}{2}\log|\Sigma_j| - \frac{1}{2}(x-\mu_j)^T\Sigma_j^{-1}(x-\mu_j) + \log(\pi_j)$$

where π_j and μ_j are the prior probability and the vector with mean values of the features for each class j respectively. Thereafter, the decision rule is given by: $argmax_j\ \delta_j(x)$.

Finally, in the Decision Tree method, a decision tree is built from the examples. In the resulting tree, each internal node indicates a feature, each branch corresponds to a feature value and each leaf node assigns a class. The training data is split by using the feature values. The split process is repeated recursively until it is no longer possible to divide the feature space. The decision rule is to reject the classes until we reach an accepted class [15].

Since a single sensor classifies vocalizations based on the partial information available, it may fail even if it uses the best classification strategy. To cope with this problem, we can use the complementary information that resides in the other sensors to minimize the classification error rate. Thus, we adopted four strategies to combine the individual outputs to reach the final decision.

The first combination strategy is a simple majority vote (MV), that is, the final decision is the most common among the base classifiers. Therefore, to estimate the final class we use the following rule:

$$l_c = \begin{cases} L/2+1 & \text{if } L \text{ is even} \\ (L+1)/2 & \text{if } L \text{ is odd} \end{cases}$$

where L is the number of sensors. According to this rule, we decide in favor of the class with at least l_c classifiers agreeing on the class label of the unknown pattern. This rule is very popular because of their simplicity and robustness, but is not good enough when the classifiers have different accuracy.

In our scenario, when the classification is performed, some sensors can receive signals with more attenuation than others because of the proximity to the source. In this case, if the source is too close to one of the sensors, probably the decision of the majority will be wrong and the classifier will choose a wrong label.

To overcome this problem, it is reasonable to give more importance or weight to the classifiers who are closer to the source. Thus, we implemented a weighted majority vote (WMV), where the power of the received signal is used as weight. Then, the most probable output label w_j for class j is obtained through the following equation:

$$\text{argmax}_{w_j} \sum_{i=1}^{L} PW_i d_{ij}$$

where $PW_i = \frac{1}{N}\sum_{n=1}^{N} x_i^2[n]$ is the power of the signal x received by the sensor i, N is the window length and d_{ij} is equal to 1 for the voted class j.

A different way to combine classifiers is by using *a posteriori* probability output of each class. To do this, we used two rules: the geometric average rule, based on the KullbackLeibler (KL) probability distance measure, and the arithmetic average rule, using the alternative KL distance formulation [15].

According to the geometric rule (GV) we must choose the class that maximizes the following product:

$$\text{argmax}_{w_j} \prod_{i=1}^{L} P_i(w_j|x)$$

where P_i is the *a posteriori* probability of the *jth* class (w_j) computed by the *ith* sensor. This rule may lead to less reliable results when the outputs of some of the sensors result in values close to zero [15].

An alternate way is to replace the product of the previous equation by a sum, like in the following equation:

$$\text{argmax}_{w_j} \frac{1}{L}\sum_{i=1}^{L} P_i(w_j|x),$$

according to the arithmetic rule (AV).

Although there are other combination techniques beyond the previously explained, we chose these ones due simplicity and low computational cost. In next section, we explain how to discard cases, found after combining the indvidual decisions, where the uncertainty about the underlying event is large.

4 Rejection Technique

The combination (or voting) is performed by the sink node (the leader node of the cluster of sensors) and the result of this process is a vector with posterior normalized probabilities. The higher the entropy of this set of probabilities, the greater the uncertainty about the identified specie. On the other hand, when the probabilities are concentrated into an unique class the classifiers reach agreement. Thus, it is possible to reject confusing cases just by finding out an apropriate entropy threshold level. The entropy threshold is computed as:

$$\text{H(x)} = -\sum_{j=1}^{|W|} P(w_j) \log P(w_j).$$

For instance, assume two scenarios i and j, where the sink node obtained the vector probabilities $P(W|x_i) = [0.01; 0.97; 0.02; 0]$ and $P(W|x_j) = [0.3; 0.3; 0.2; 0.2]$, respectively. In first scenario, the sensors clearly agree with class w_2, whereas, in the second, they do not. Thus, by selecting thresholds $H(x_i) = 0.06$ and $H(x_j) = 0.57$, the second scenario is discarded, since overall uncertainty is very large.

By using this threshold, we can transform the classification problem of j classes into a binary problem. That is, our scenario is *confusing* when the values of entropy are high or *not confusing* when the values are low. Thus, we can use accuracy to infer if the received signal was generated by more than one species. It is crucial to find the best threshold value to decrease the false negative rate (and test the second hypothesis).

5 Parameter Settings on Experiments

We simulate a 10x10 m^2 sensor field spread in a grid with a normal random perturbation at each position with zero mean and variance equal to 1 m (Figure 2). Our sound database has nine different anuran species and every sound record includes background noise from the forest. Before composing the dataset, the vocalizations have been segmented into smaller units called syllables (cf. Colonna et al. [7] for a detailed explanation of the syllable segmentation we carried out).

At each iteration of our simulation, we perform the following steps: (a) the scenario (one or two anurans) is

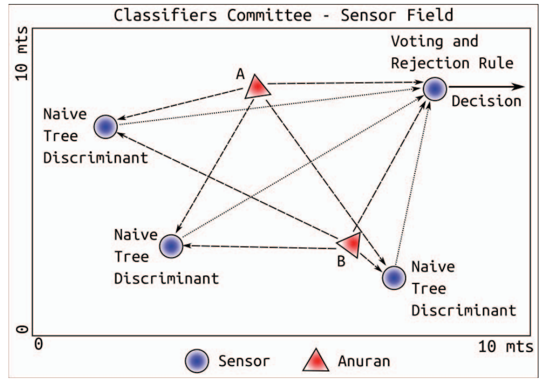

Figure 2: Example of sensor field with two random anuran.

randomly selected with equal probability. The scenario consists of the positions of sensors and anurans. If two anurans are selected, they belong to different species; (b) one syllable of each selected species is separated from the dataset which contains 2939 samples, to ensure that data from the training set will not be used in the test set. This syllable will be used in the test set while the remaining ones in the training set; (c) the bioacoustic signals of the syllables are attenuated according to the distance (to each sensor) and linearly combined to represented a mixed sound; (d) features are extracted from these mixed sounds and classified by four classifiers representing the four sensors. These classifiers were previously trained to recognize the individual vocalizations of the species according to described in [7]; (e) at the end, the classifier decisions are combined and the entropy of the decisions are saved to a posterior rejection analysis.

In step (c) the signals are attenuated and combined by applying Eq. 1.

$$\text{Signal} = \textit{atte}_1 S_1 + \textit{atte}_2 S_2 \tag{1}$$

where S_1 and S_2 are the syllables, *atte* $= 1/10^{\frac{\alpha d_i}{20}}$, d_i (m) is the distance from source to each sensor and α (dB/m) is an atmospheric absorption constant [14]. Note that $atte_2$ is zero in the scenario with a single anuran.

In this work, the extracted features (step d) are the 12 Mel-Cepstral Fourier Coefficients (MFCCs), because they are little affected by noises and frequently applied in bioacoustic signal classification [4, 16, 7, 14].

To evaluate the classifiers, we use the error rate, calculated according to Eq. 2:

$$e = 1 - \frac{\text{TP} + \text{TN}}{\text{TP} + \text{TN} + \text{FN} + \text{FP}}, \tag{2}$$

where TP accounts true positive decisions, TN true negative decisions, FN false negative decisions, and FP false positive decisions. For all error rates in this work, we calculated confidence intervals considering a 95% confidence level.

6 Results

We first compare the decision of combined sensors with the decision of a single sensor. All sensors have the same classifiers: QDA, Naive Bayes, or Decision Tree. The sensors are combined by using four differente voting strategies: majority, weighted majority, geometric rule, and arithmetic rule. To evaluate how such combined classifiers deal with confusing scenarios (more than one species vocalizing at same time), we filtered out the most confusing cases according to the entropy of the species' probability estimates. This comparison is presented in Table 1, where error rates are used to assess the classifier performances. The classifiers taken in isolation are used as baselines. Each line in this table corresponds to the proportion of scenarios that were rejected according to their entropy.

When we consider the situation where no scenario is rejected (RR = 0%), all combination strategies involving the QDA classifier outperform the single sensor (IS). The Naive Bayes outperforms the baseline in all cases, except when combined by using majority voting (at RR = 0%). The weakest performance was achieved by Decision Trees that outperform the single sensor in just two cases. In general terms, QDA obtained the smallest error rates among the three classifiers we tested. Amongst the combination strategies, the arithmetic voting was the best combining strategy for QDA and Decision Trees while geometric voting was the best with Naive Bayes.

Thus, results confirm that we can improve the vocalization recognition by combining the sensor decisions. However, the best gain obtained was moderate (10.8% for QDA combined using arithmetic voting). This moderate gain was due to the fact that the sensors provide little independent information since they use the same classifiers and almost the same input.

We now evaluate the entropy of the species estimates as a metric to reject confusing scenarios where the sensors are more likely to fail (RR $>$ 0%). To accomplish this, we analyse the performance of the sensors when they avoid classifying the scenarios of high entropy.

As expected, the error rate for the isolated sensor decreases as it rejects the cases of high entropy. The same is observed for most of the combination strategies. The exception is the geometric voting, for which the entropy was not able to discriminate confusing from not confusing cases. This happens because, as a result of the geometric combination, all the estimates tend to be flattened. Since the geometric combination is a conjunction, if sensors disagree, all the estimates get low. With similar (low) values, the entropy decreases even for confusing cases.

QDA Error

RR	IS	MV	G(%)	WMV	G(%)	GV	G(%)	AV	G(%)
0%	36.9	34.6	**+8.1**	34.2	**+7.2**	34.1	**+7.7**	33.8	**+10.8**
10%	32.9	31.8	**+6.0**	30.7	**+7.8**	34.1	**-3.1**	30.1	**+9.0**
20%	29.7	28.9	**+2.4**	28.6	**+2.4**	35.1	**-22.0**	26.1	**+9.4**
30%	28.3	28.9	**+1.1**	24.4	**+15.2**	35.1	**-23.7**	23.7	**+18.7**
40%	25.1	28.9	**-11.6**	22.3	**+12.4**	36.5	**-43.4**	20.8	**+20.3**
50%	23.3	22.8	**+5.6**	20.0	**+14.2**	37.9	**-58.8**	19.7	**+18.5**

Naive Bayes Error

RR	IS	MV	G(%)	WMV	G(%)	GV	G(%)	AV	G(%)
0%	44.2	44.1	0	42.4	**+4.3**	42.5	**+4.7**	42.3	**+3.7**
10%	43.2	43.3	0	41.8	**+4.7**	42.5	+2.3	41.4	**+4.6**
20%	41.5	40.6	**+2.4**	41.4	0	41.8	0	39.6	**+4.9**
30%	39.4	40.6	**-2.6**	38.9	+2.6	41.8	**-5.2**	38.6	**+2.6**
40%	37.4	38.9	**-2.7**	37.3	0	41.0	**-10.8**	37.2	-0.4
50%	35.6	38.9	**-8.6**	36.3	-2.9	41.0	**-17.1**	35.9	0

Decision Trees Error

RR	IS	MV	G(%)	WMV	G(%)	GV	G(%)	AV	G(%)
0%	63.2	63.5	-0.8	60.9	**+4.8**	63.9	0	60.2	**+5.0**
10%	61.0	63.3	**-3.3**	59.9	+3.3	62.6	**-1.6**	58.8	**+4.8**
20%	59.2	61.5	**-3.4**	58.5	+1.7	62.7	**-5.7**	56.9	**+4.6**
30%	52.4	58.9	**-11.7**	56.8	**-7.7**	61.1	**-17.3**	55.4	**-5.8**
40%	53.5	58.9	**-9.4**	53.4	0	61.1	**-15.1**	52.0	**+1.9**
50%	51.7	58.9	**-13.7**	50.8	+2.0	61.1	**-19.6**	50.2	**+2.0**

Table 1: Error rates for classifiers Quadratic Discriminant Analysis (QDA), Naive Bayes, and Decision Trees taken in isolation (IS) or combined using majority (MV), weighted majority (WMV), geometric (GV) and artithmetic (AV) voting. RR stands for Rejection Rate. Column G shows the gains over IS. Gains shown in bold face represent statistically significant ($p < 0.05$) differences to the baselines.

On the other hand, the entropy was very effective in filtering confusing scenarios when used along with the arithmetic and weighted voting. This suggests these strategies were better for capturing disagreements among the sensors that indicate multiple vocalizations. In such cases, the greater the number of rejected cases, the greater the gain of the combined sensors over the single one.

7 Conclusion and Outlook

In this paper, we evaluated colaborative strategies to recognize anuran species by using a sensor network. In particular, we evaluated the performance of the Quadratic Discriminant Analysis, Naive Bayes, and Decision Trees classifiers; combined by using the majority vote, weighted majority vote, arithmetic rule and geometric rule; for classifying anuran species. To evaluate these methods, we considered scenarios where one or two anurans vocalize at the same time. Besides evaluating the performance of the combined classifiers, we also assessed the sensors capability of identifying confusing scenarios. As a result, we found that sensors using classifiers based on Quadratic Discriminant Analysis, combined with an artihmetic voting strategy outperformed a single sensor with a gain of about 11%. By using the entropy of the species estimates, this same sensor committee was able to effectively identify confusing scenarios, achieving gains of 20% over the single sensor.

As a future work, we first intend to improve our simulation considering more complex scenarios (a large number of species) and to investigate how sensors could be dinamically selected to take part of the sensor committe in an adaptative fashion. We also intend to study how to apply advanced ensemble methods, such as bagging and boosting, in the context of sensor fusion. In a broader view, we want to investigate how to adapt the general theory of ensemble of classifiers to particular aspects of sensor networks, such as missing committee members (sensors), unreliable information due to events such as low energy, and resource constraints (processor capability, memory and energy). Also, we will evaluate if the independence of several classifiers justifies the deployment of sensors using different classification techniques.

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References

[1] T. M. Aide, C. Corrada-Bravo, M. Campos-Cerqueira, C. Milan, G. Vega, and R. Alvarez. Real-time bioacoustics monitoring and automated species identification. *PeerJ*, 1:e103, 2013.

[2] I. F. Akyildiz, W. Su, Y. Sankarasubramaniam, and E. Cayirci. Wireless sensor networks: a survey. *Computer Networks*, 38(4):393–422, 2002.

[3] G. E. P. Box. A general distribution theory for a class of likelihood criteria. *Biometrika*, 36(3/4):317–346, 1949.

[4] J. Cai, D. Ee, B. Pham, P. Roe, and J. Zhang. Sensor network for the monitoring of ecosystem: Bird species recognition. In *3rd International Conference on Intelligent Sensors, Sensor Networks and Information*, pages 293–298. IEEE, Dec. 2007.

[5] C. Carey, W. R. Heyer, J. Wilkinson, R. Alford, J. W. Arntzen, T. Halliday, L. Hungerford, K. R. Lips, E. M. Middleton, S. Orchard, and S. Rand. Amphibian declines and environmental change: Use of remote-sensing data to identify environmental correlates. *Conservation Biology*, 15(4), 2001.

[6] J. P. Collins and A. Storfer. Global amphibian declines: sorting the hypotheses. *Diversity and Distributions*, 9:89–98, 2003.

[7] J. G. Colonna, A. D. Ribas, E. M. Dos Santos, and E. F. Nakamura. Feature subset selection for automatic frog calls classiication applied to monitoring system based on sensor network. *International Joint Conference on Neural Networks (IJCNN)*, June 2012.

[8] J. Diaz, J. Colonna, R. Soares, C. Figueiredo, and E. Nakamura. Compressive sensing for efficiently collecting wildlife sounds with wireless sensor networks. In *Computer Communications and Networks (ICCCN), 2012 21st International Conference on*, pages 1–7, 2012.

[9] W. Hu, V. N. Tran, N. Bulusu, C. T. Chou, S. Jha, and A. Taylor. The design and evaluation of a hybrid sensor network for cane-toad monitoring. In *4th International Symposium on Information Processing in Sensor Networks.*, pages 503–508. IEEE, Apr. 2005.

[10] W. J. Krzanowski, editor. *Principles of multivariate analysis: a user's perspective*. Oxford University Press, Inc., New York, NY, USA, 1988.

[11] L. Kuncheva. *Combining Pattern Classifiers: Methods and Algorithms*. Wiley, 2004.

[12] G. J. McLachlan. *Discriminant Analysis and Statistical Pattern Recognition*. Wiley Series in Probability and Statistics. Wiley, 2005.

[13] E. F. Nakamura, A. A. F. Loureiro, and A. C. Frery. Information fusion for wireless sensor networks: Methods, models, and classifications. *ACM Comput. Surv.*, 39(3), 2007.

[14] A. D. Ribas, J. G. Colonna, C. M. S. Figueiredo, and E. F. Nakamura. Similarity clustering for data fusion in wireless sensor networks using k-means. In *Neural Networks (IJCNN), The 2012 International Joint Conference on*, pages 1–7, 2012.

[15] S. Theodoridis and K. Koutroumbas. *Pattern Recognition*. Elsevier Science, 2008.

[16] G. Vaca-Castaño and D. Rodriguez. Using syllabic mel cepstrum features and k-nearest neighbors to identify anurans and birds species. In *Signal Processing Systems (SIPS), 2010 IEEE Workshop on*, pages 466–471, 2010.

[17] G. Xing, X. Wang, Y. Zhang, C. Lu, R. Pless, and C. Gill. Integrated coverage and connectivity configuration for energy conservation in sensor networks. *ACM Transactions on Sensor Networks*, 1(1):36–72, 2005.