# Sparse Representation Classification of Dolphin Whistles Using Gabor Wavelets


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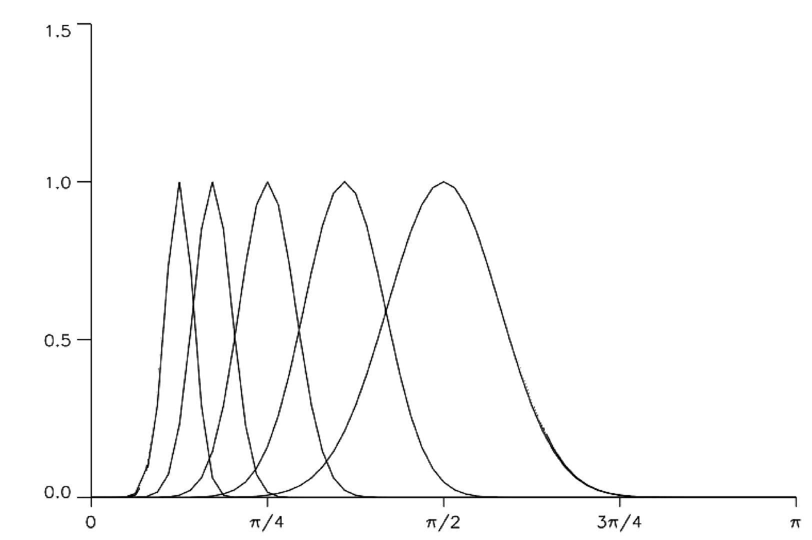
## MOTIVATION

- A major task in bioacoustic research is analyzing recorded repertoires of various species to either be associated with a behavior or determine animal identity.
- Bottlenose dolphins can produce whistles that are narrow-band long duration sounds from 1 kHz up to 24 kHz.
- Marine mammal vocalizations are usually corrupted by different acoustic sources making the pre-processing task necessary and costly.
- Most feature extraction techniques require tracing the contour of whistles in order to obtain distinguishing information for recognition purposes.

## METHODOLOGY

Pre-processing Contour tracing → Feature extraction → Classification

- Pre-processing stage may implement band-pass filtering with cut-off frequencies at 4 kHz and 16 kHz as well as spectral denoising.
- If needed to contour tracing, the highest frequency peak of isolated fundamental whistle is picked at each time instance.
- Feature extraction methods can be relied on the whistle contour or not.
- **Contour-based:**
  - Time-Frequency Parameters (TFPs)
  - Fourier Descriptors (FDs)



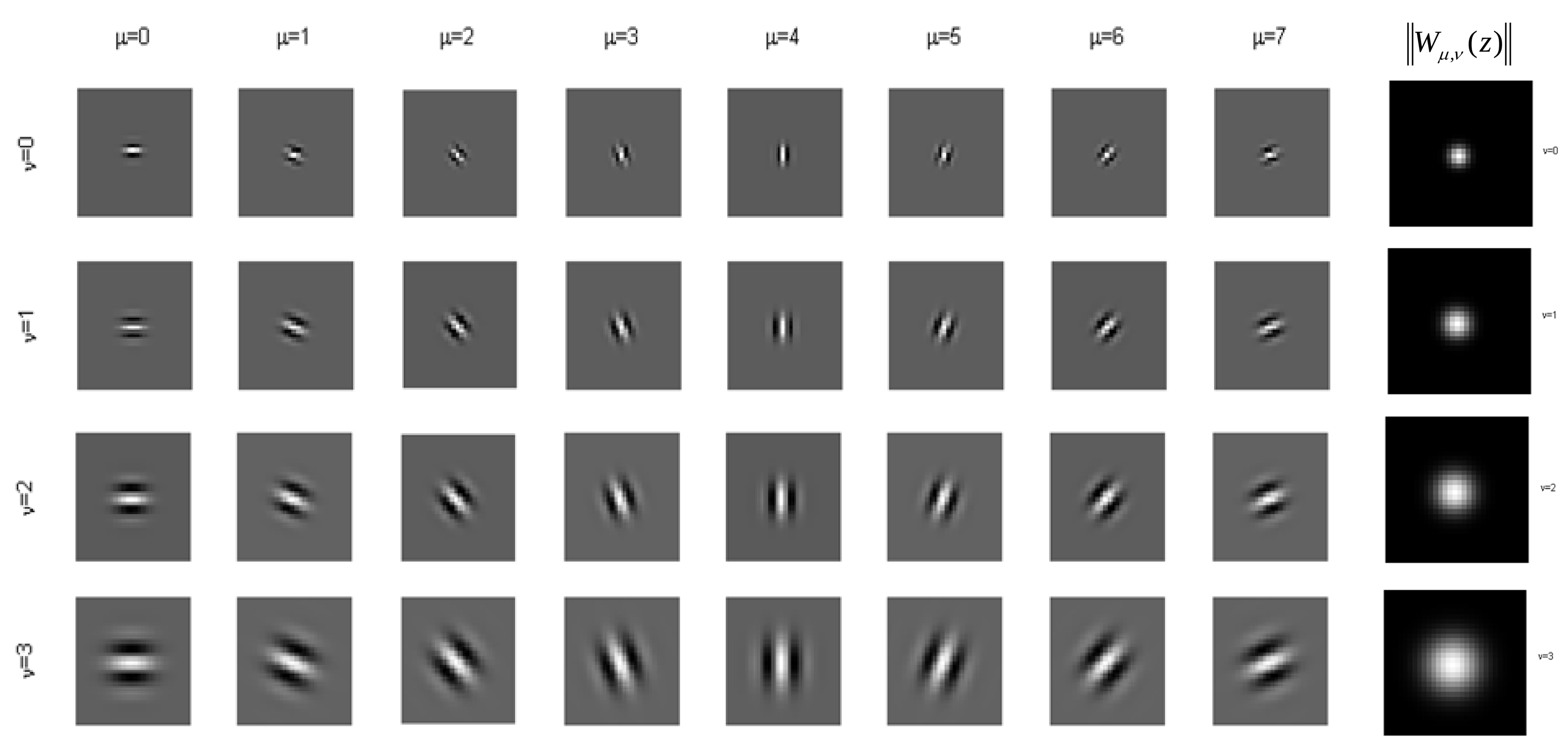

$$k_\nu = \frac{\pi/2}{\sqrt{2}^{\nu}} \quad for\ \nu = 0,1,2,3$$

✓ Fourier transform of all kernels where variations inside the critical frequency range between $\pi/16$ and $\pi/2$ are small.

The Gabor wavelet representation is the convolution of the spectrogram with a family of Gabor kernels:

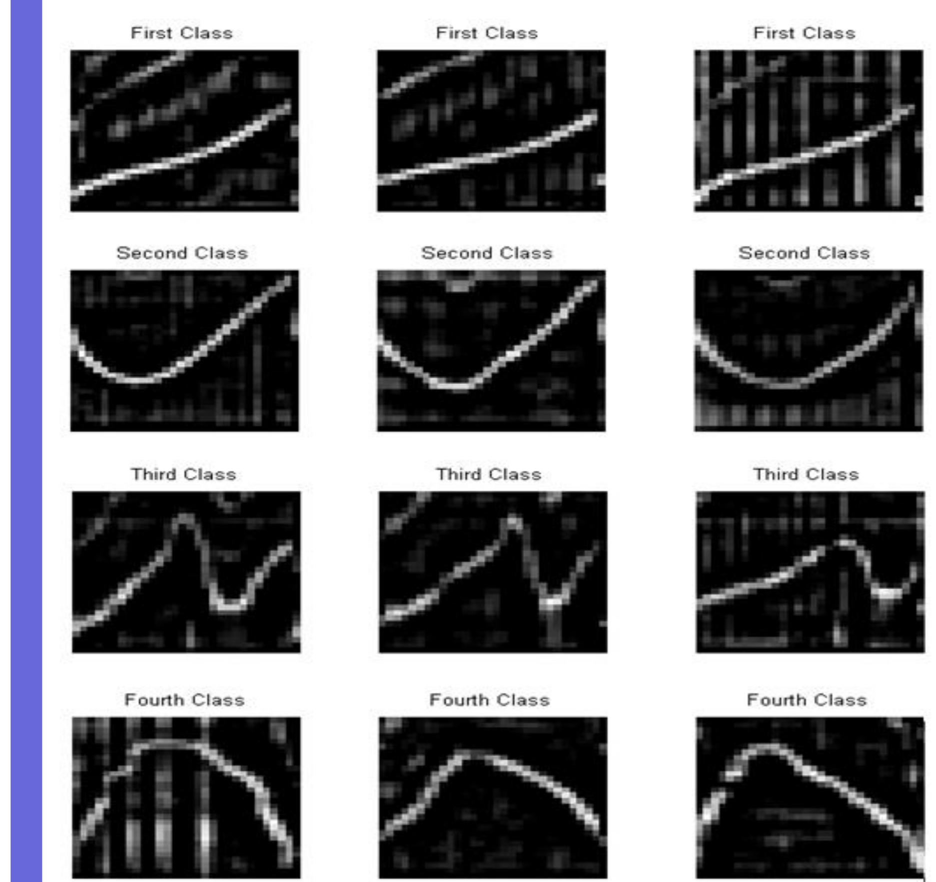
$$W_{\mu,\nu}(z) = I(z) * \psi_{\mu,\nu}(z)$$

$I(z)$ denotes the spectrogram image.



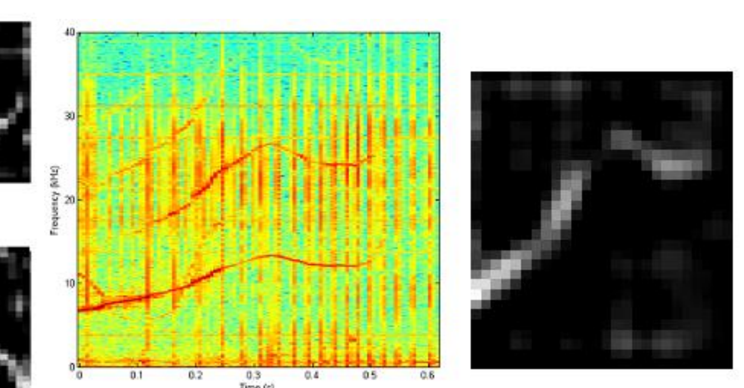

## RESULTS

**Examples of Gabor wavelet outputs:**




**Confusion matrix of SRC+Gabor (98%)**

| | First class (%) | Second class (%) | Third class (%) | Fourth class (%) |
|---|---|---|---|---|
| 1st class | 100 | 0 | 0 | 0 |
| 2nd class | 0 | 100 | 0 | 0 |
| 3rd class | 0 | 0 | 92 | 8 |
| 4th class | 0 | 0 | 0 | 100 |


(a) (b)

**Confusion matrix of SRC+TFPs (92%)**

| | First class (%) | Second class (%) | Third class (%) | Fourth class (%) |
|---|---|---|---|---|
| 1st class | 85 | 15 | 0 | 0 |
| 2nd class | 0 | 100 | 0 | 0 |
| 3rd class | 0 | 0 | 83 | 17 |
| 4th class | 0 | 0 | 0 | 100 |

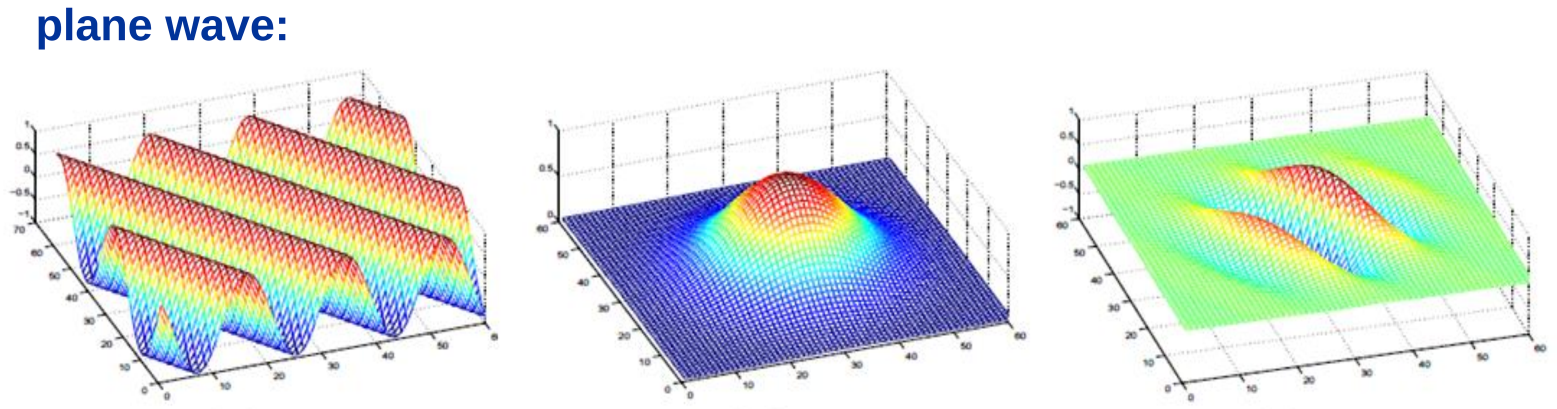
**Confusion matrix of SRC+FDs (88%)**

| | First class (%) | Second class (%) | Third class (%) | Fourth class (%) |
|---|---|---|---|---|
| 1st class | 100 | 0 | 0 | 0 |
| 2nd class | 0 | 94 | 0 | 6 |
| 3rd class | 33 | 0 | 58 | 9 |
| 4th class | 0 | 0 | 0 | 100 |

## FEATURE EXTRACTION

- **Non-contour-based:**
  - Gabor wavelets:

2-D Gabor filter is a Gaussian kernel function modulated by a sinusoid plane wave:


(a) (b) (c)

$$\psi_{\mu,\nu}(z) = \frac{\|k_{\mu,\nu}\|^2}{\sigma^2} e^{-\frac{\|k_{\mu,\nu}\|^2\|z\|^2}{2\sigma^2}} [e^{ik_{\mu,\nu}z} - e^{-\sigma^2/2}]$$

$$\phi_\mu = \pi\mu/N \qquad k_\nu = k_{\max}/f^{\nu} \qquad k_{\mu,\nu} = k_\nu e^{i\phi_\mu}$$

$\mu, \nu$ : the orientation and scale of Gabor filer, respectively.
$Z=(x,y)$ : the Cartesian coordinate.
$k_{\mu,\nu}$ : the wave vector.
$k_{\max}$ : the maximum frequency and $N$ is the number of orientations.
$f$ : spacing factor in between kernels in the frequency domain.
$\sigma$ : standard deviation of the Gaussian window .

**Parameter selection:**

$\mu \in \{0,1,2,3,4,5,6,7\}$ ; $\nu \in \{0,1,2,3\}$ ; $\sigma = \pi$ ; $f = 2$^0.5 ; $k_{max} = \pi/2$

## CLASSIFICATION METHOD

**Sparse Representation Classifier (SRC)**

The application of compressive sensing to classification has been recently emerged where sparse representation of the test sample is obtained using a training data set.

➢Consider a dictionary $U = [U_1, U_2, \ldots, U_d]$ where each class consists of $n_i$ training vectors $U_i = [u^1, u^2, \ldots, u^{ni}]$ for $i = 1,2,\ldots,d$. A test sample $y$ from $i$-th class can be represented as a linear combination of all training samples from $d$ distinct classes as:

$$y = \sum_{i=1}^{n_1}\beta_1^i u_1^i + \sum_{i=1}^{n_2}\beta_2^i u_2^i + \ldots + \sum_{i=1}^{n_d}\beta_d^i u_d^i \quad \text{or} \quad y = U\alpha_0$$

In this case, all the elements of weighting vector $\alpha_0$ should be zero but those associated with the same class:

$$[0,\ldots,0,\beta_i^1,\ldots,\beta_i^{n_i},0,\ldots,0]$$

➢Now the signal $y$ is deduced to be sparse in domain $U$ and the convex optimization problem can be solved:

$$\bar{\alpha} = \arg\min \|\alpha_0\|_1 \quad subject\ to \quad \|y - U\alpha_0\|_2 \le \varepsilon$$

➢Once the sparse solution is obtained, the classification procedure of SRC is summarized as follows:

1) For each class, find the residual between the reconstructed sample and the test sample:

$$r_i = \|y - U_i\bar{\alpha}_i\|_2 \quad for \quad i = 1,2,\ldots,d$$

2)The class of test sample is determined by:

$$class(y) = \arg\min_i (r_i)$$

## CONCLUSIONS

- A new algorithm that combines a compressive-sensing based technique called Sparse Representation Classifier and a feature vector set derived from Gabor wavelets was developed and applied to the classification of dolphin whistle types.
- The proposed approach avoids the need for tedious preprocessing and contour tracing steps while achieving a superior classification performance in comparison with two other contour-based feature extraction techniques.
- The accuracy obtained by combination of Gabor wavelet and SRC classifier is comparable with the accuracy achieved with LBP and SVM classifier reported in an earlier paper by authors.

## REFERENCES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## ACKNOWLEDGMENT


•This project was partially supported by SNMREC.
• The data used in this research was provided by Woods Hole Oceanographic Institution (WHOI).