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Fabien Millioz, Nadine Martin. Reassignment Vector Field for Time-Frequency Segmentation. ICSV 2007 - 14th International Congress on Sound and Vibration, Jul 2007, Cairns, Australia. hal-00200220

**HAL Id: hal-00200220**

**<https://hal.science/hal-00200220>**

Submitted on 20 Dec 2007

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# ICSV14

Cairns • Australia  
9-12 July, 2007



## REASSIGNMENT VECTOR FIELD FOR TIME-FREQUENCY SEGMENTATION

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### Abstract

In this paper, we propose to use the phase information of the Short Time Fourier Transform (STFT) to improve a time-frequency segmentation based on the statistical features of the STFT, and proposed by the authors in 2006.

If the resolution of the STFT is too low, close components may be segmented in a single pattern. The idea is to add phase information provided by the reassignment principle in order to determine if there are more than one component in a pattern instead of two.

Reassignment, originally proposed by Kodera et al. in 1976, is a non-linear method which creates a new time-frequency representation by moving the spectrogram values away from their computation place. Reassignment focuses energy components by moving each time-frequency location to its group delay and instantaneous frequency, that represent more accurately the component energy. The obtained reassignment vector field associated to a given spectrogram describes how time-frequency locations are reassigned.

We propose to use the reassignment vector field not to modify the time-frequency representation, but to give information on the signal structure. We compute local reassignment vectors on patterns segmented by the method mentioned above. Given that spectrogram tends to spread the time-frequency patterns, whereas reassignment method moves back energy to a pattern's point, reassignment vectors aim at the pattern. That leads to a pattern's boundary information, which is used to determine how many components are embedded in a single segmented pattern. Moreover, this information describes the boundaries of frequency modulations as well as wide band signal, and extends the use of the reassignment principle to wide band signals.

This principle is finally applied to the shaft's vibrations of a three phase AC induction engine, in order to separate the different harmonics embedded in a single pattern.

## 1. INTRODUCTION

Time-Frequency Representations (TFR) are useful tools in nonstationary signal analysis. It describes the spectral energy varying along time. A segmentation task helps such analysis, by highlighting time-frequency areas containing the signal's energy.

We have already proposed a segmentation algorithm [[1],[2]], based on the Short Time Fourier Transform (STFT), defined as

$$F_x^{(h)}(t, f) = \int_{-\infty}^{+\infty} x(t - \tau)h^*(\tau)e^{-2\pi f\tau} d\tau, \quad (1)$$

where  $h(t)$  is the window function.

We have taken as signal model  $x(t)$  a nonstationary signal  $s(t)$  embedded in a white Gaussian noise of variance  $\sigma^2$

$$x(t) = s(t) + n(t). \quad (2)$$

We have derived the time-frequency coefficients distribution from this model, in order to segment the TFR in classes, corresponding to different signal patterns.

However, this segmentation may be not ideal. Two different signal patterns may be segmented in a single class. In this paper, we propose to use reassignment information to determine if there is more than one signal pattern in a single class or not.

The first section presents quickly the TFR segmentation algorithm.

In the second section, the reassignment principle, originally proposed by Kodera *et al.* in 1976 [3] and reintroduced in 1993 by Auger and Flandrin [4], is presented. Reassignment is a non-linear method which creates a new time-frequency representation by moving the spectrogram values away from their computation place. Its goal is to focus component energy by moving each  $(t, f)$  location to the local gravity center of the signal distribution around  $(t, f)$ . This new location may be equivalently defined as the  $(t', f')$  site, where  $t'$  and  $f'$  are the estimated group delay and instantaneous frequency respectively. Reassignment can be thus considered as a use of the phase information of the STFT.

Here, only the phase of the reassignment vectors is used to determine the pattern boundaries [5].

Finally, an example of merge of these two approaches is shown in section three. The boundary detection is applied on a class foremost segmented by the segmentation algorithm [1, 2] in the time-frequency domain. We thus determine if there is one or more signal components in this class.

## 2. STATISTICAL TIME-FREQUENCY SEGMENTATION

The segmentation algorithm used in this paper is based on the statistical features of STFT coefficients, defined in equation 1. We summarize here quickly the segmentation principle, more details are given in [1, 2].

For  $(t, f)$  location containing no part of the signal  $s$  energy, the real and imaginary parts

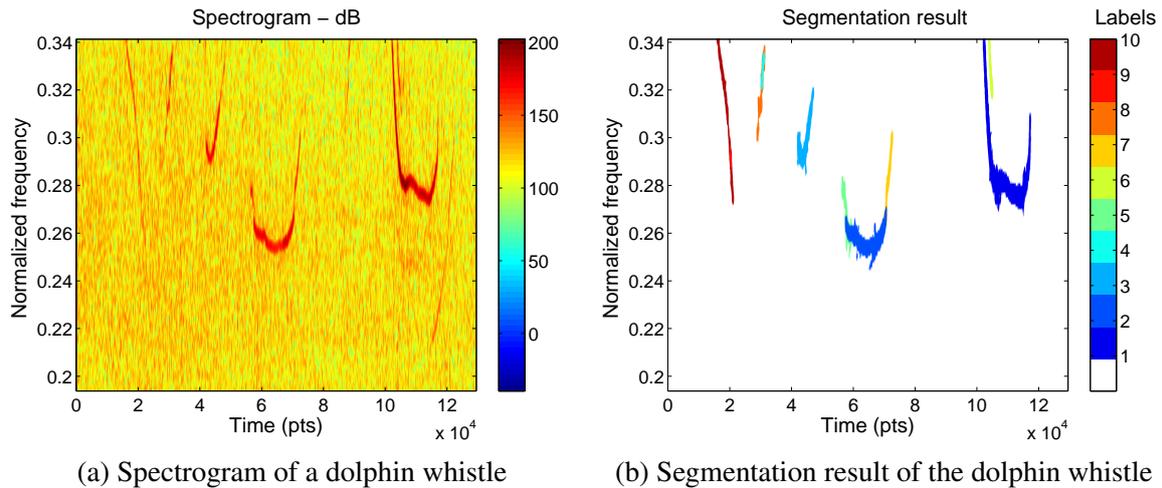


Figure 1. Whistle of a dolphin in underwater acoustic noise. The spectrogram (a) is limited to the normalized frequency  $[0.2, 0.34]$  to have a white Gaussian noise on the coefficients. The segmentation (b) gives signal nine classes labeled from one to ten. The eleventh region labeled 0 is the set of points containing noise only.

of the STFT coefficients have both a zero mean Gaussian distribution. For locations containing both noise energy and signal energy, the coefficients have no more a zero mean Gaussian distribution. However, such locations have a higher second order moment than locations containing noise only. The segmentation principle is to detect the highest second order moments in order to agglomerate them with a neighbourhood criterion in the TFR.

The segmentation algorithm is iterative, with each iteration made of three phases. First, the noise level is estimated on the non-segmented locations. Given that for locations containing both noise and signal, the second order moment is higher than for locations containing only noise, the noise level is overestimated. Second, the second order moments of all time-frequency locations are estimated. Given a probability of false alarm, we apply a Neyman-Pearson strategy to detect locations supposed to contain signal, which are called candidates to the segmentation. Last, a region growing algorithm is used on the candidates set, in order to create the spectral patterns, associated to a given label. When a given percentage of candidates are segmented, we stop the iteration, in order to re-estimate the noise level without the new segmented points.

The algorithm stops when the kurtosis estimated on the non-segmented points reaches a given threshold, meaning that non-segmented points have a Gaussian distribution. In other words, we stop the algorithm when non-segmented points are noise only.

Figure 1 shows an example on a dolphin whistle. Given that underwater acoustic noise is non-white, the frequency band is limited in order to consider white noise only. Spectral patterns are enough separated on the TFR to be segmented in ten different classes.

Three parameters control the segmentation, the probability of false alarm  $p_{fa}$  in the Neyman-Pearson detection, the proportion  $p_{cand}$  of candidates segmented at each iteration, and the threshold  $t_k$  on the kurtosis. An optimal choice of parameters may be difficult, depending on the signal. A bad choice of parameters may segment several components in a single class.

In this paper, we propose to use the reassignment vector field in order to determine if there is one or several components in a single segmented pattern, as a validation of the parameters set.

### 3. BOUNDARIES DETECTION OF TIME-FREQUENCY PATTERNS

#### 3.1. Reassignment method

In order to reassign the spectrogram  $S_x^h$ , which is the square modulus of the STFT, we use another definition of the spectrogram

$$S_x^h(t, f) = \int_{-\infty}^{+\infty} \int_{-\infty}^{+\infty} W_x(\tau, \nu) W_h(\tau - t, \nu - f) d\tau d\nu, \quad (3)$$

where  $W_x(t, f)$  and  $W_h(t, f)$  are the Wigner-Ville distributions (WVD) of the signal  $x(t)$  and the window  $h(t)$  respectively, defined as

$$W_x(t, f) = \int_{-\infty}^{+\infty} x(t + \tau/2) x^*(t - \tau/2) e^{-j2\pi f\tau} d\tau. \quad (4)$$

This definition means that the spectrogram of a signal  $x(t)$  is its WVD, smoothed by the WVD of the spectrogram's window.

This smoothing spreads the energy coming from the WVD. The reassignment idea is to focus the spectrogram energy, by moving the energy at the location  $(t, f)$  to a new  $(t', f')$  point, center of gravity of the signal's WVD  $W_x(t, f)$ , in a neighborhood defined by the smoothing function  $W_h(t, f)$  [6]

$$t'(t, f) = \frac{1}{S_x^h(t, f)} \int_{-\infty}^{+\infty} \int_{-\infty}^{+\infty} \tau W_x(\tau, \nu) W_h(\tau - t, \nu - f) d\tau d\nu \quad (5)$$

$$f'(t, f) = \frac{1}{S_x^h(t, f)} \int_{-\infty}^{+\infty} \int_{-\infty}^{+\infty} \nu W_x(\tau, \nu) W_h(\tau - t, \nu - f) d\tau d\nu \quad (6)$$

The reassignment vector field  $\mathbf{r}(t, f)$  is defined as

$$\mathbf{r}(t, f) = (t'(t, f) - t, f'(t, f) - f)^T. \quad (7)$$

An example of such a reassignment vector field is shown on figure 2.

#### 3.2. Boundaries detection

The spectrogram may be considered (equation 4) as the convolution of the WVD of the signal with a smoothing window. As a result, a spectrogram's pattern fills a larger area in the time-frequency representation than in its counterpart in the WVD.

We define here the boundary of a pattern as the difference between the patterns' supports in the spectrogram and in the WVD.

Reassignment moves the energy spread by the spectrogram to the local center of gravity of the time-frequency representation. On a pattern boundary, spectrogram energy will be moved inward the pattern. Consequently, all reassignment vector located on a pattern boundary will aim at the pattern. Considering that the boundaries variations are smooth enough, we assume that reassignment vectors are locally parallel.

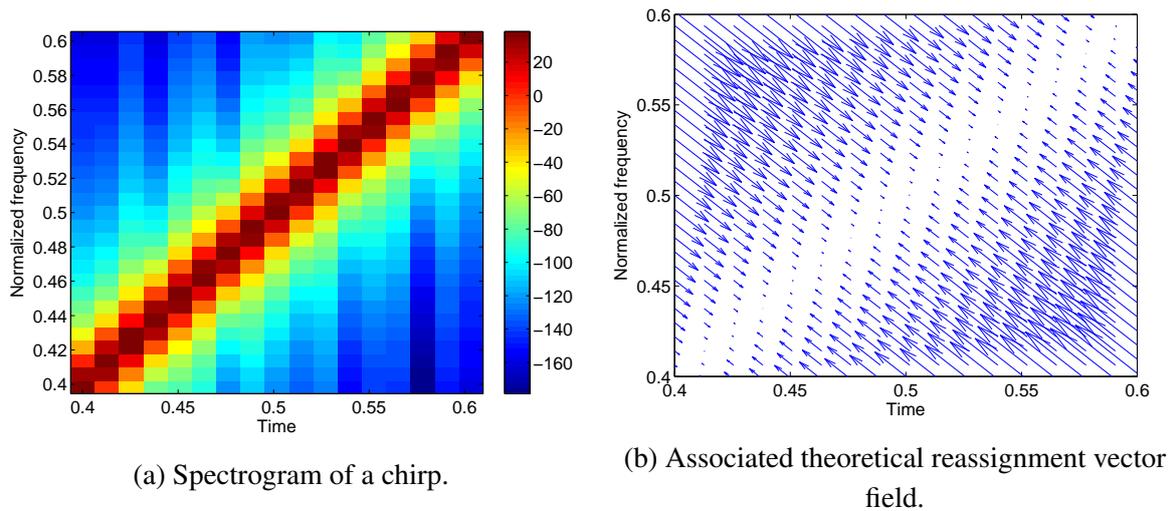


Figure 2. Example of a linear chirp reassignment. The energy contained in the whole spectrogram (a) is reassigned theoretically on the line  $f = t$  (b).

The idea is to look for time-frequency locations where associated reassignment vectors and all of its neighbours have close angles. Due to the spectrogram discretization, reassignment vectors associated to contiguous time-frequency locations may aim at different points, leading to slightly different angles. In order to avoid this problem, reassignment vectors with close angles means that the absolute difference of their angles is below a threshold  $\theta_0$ . This parameter also allows to track the boundary's variation.

We propose a boundary detector  $\det(t, f)$  such as

$$\det(t, f) = \begin{cases} 1 & \text{if } |\text{angle}(\mathbf{r}(t, f)) - \text{angle}(\mathbf{r}(t', f'))| \leq \theta_0 \quad \forall (t', f') \in N_{t,f}, \\ 0 & \text{otherwise,} \end{cases} \quad (8)$$

where  $\text{angle}(\mathbf{r})$  is the angle of vector  $\mathbf{r}$ ,  $N_{t,f}$  the considered  $l_1 \times l_2$  neighbourhood around  $(t, f)$  and  $\theta_0$  a given threshold.

Note that for  $(t, f)$  locations not moved by the reassignment,  $\mathbf{r}(t, f)$  is null. Consequently, the angle of reassignment vectors associated to such locations is not defined, and these locations are not taken into consideration.

Figure 3 gives two examples of such boundary detection, both with a Gaussian window of 127 points, an overlap of 120 points between two consecutive windows and 512 computed frequencies.

The first signal is a linear chirp time-windowed, displayed on the left of figure 3. The second one is a time and frequency filtered white Gaussian noise, shown on right. At the top are the spectrograms, at the middle the angles of the reassignment vector fields and at the bottom the detection results.

In these two cases, the boundary is detected. Note that for the second case, reassignment vectors inside the pattern aim at locally high realization of noise, and local pseudo-boundaries are detected.

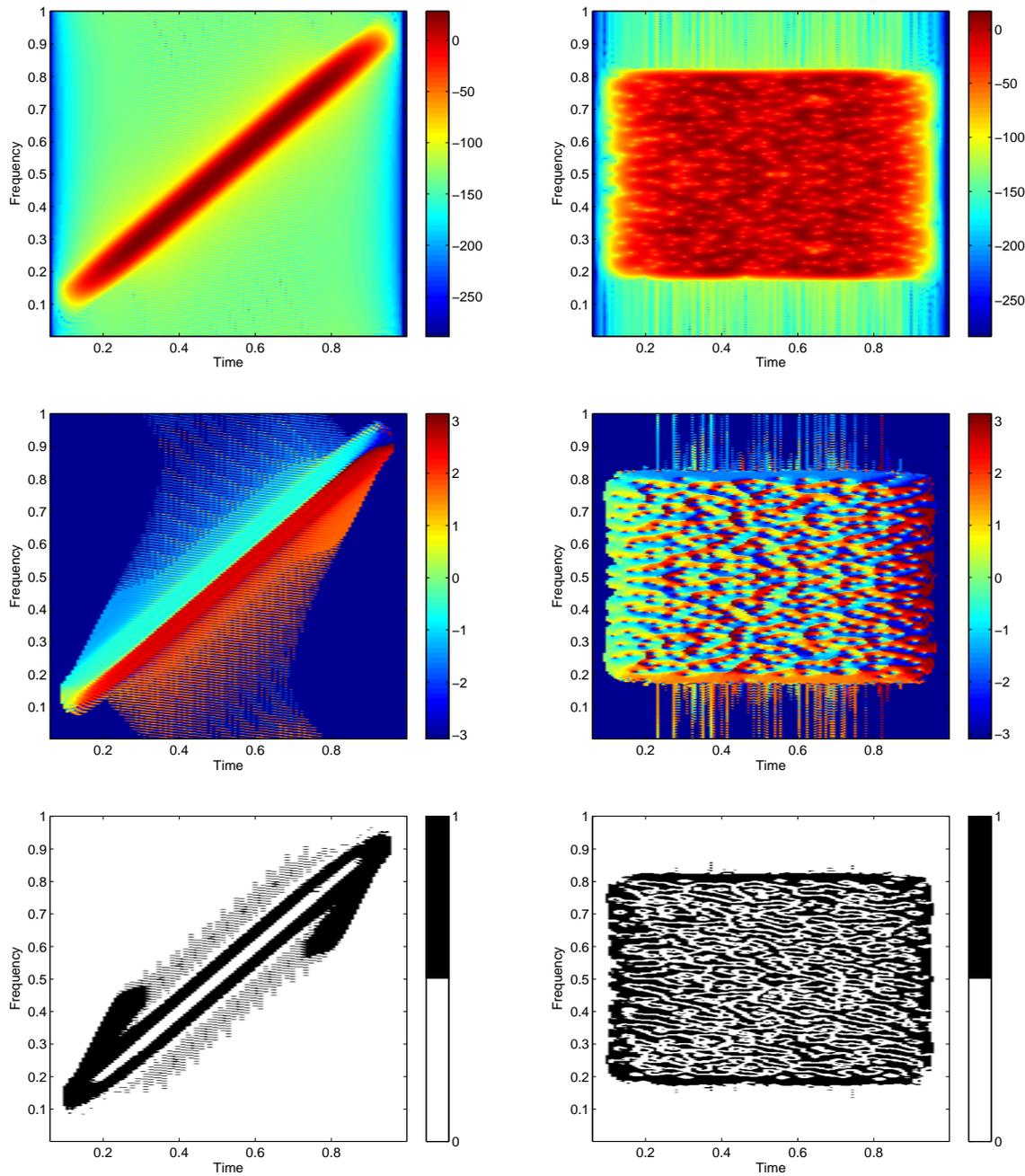


Figure 3. Examples of boundary detection. On the left a linear chirp of equation  $x(t) = e^{i2\pi t^2/2}$ , windowed in time. On the right a white Gaussian noise filtered in time and frequency. Spectrograms are displayed at top, angles of the reassignment vectors coded in color from  $-\pi$  to  $+\pi$  at middle and detection results at bottom.

#### 4. APPLICATION AND MERGE OF THE APPROACHES

We propose in this section to monitor the three-phase AC inductor motor of the test bench GOTIX of the laboratory (<http://www.gipsa-lab.inpg.fr/gotix>). In a first time, we segment the spectrogram of a signal provided by an accelerometer located on the engine shaft. Tracking the time variations of the harmonics allows to monitor the engine's speed.

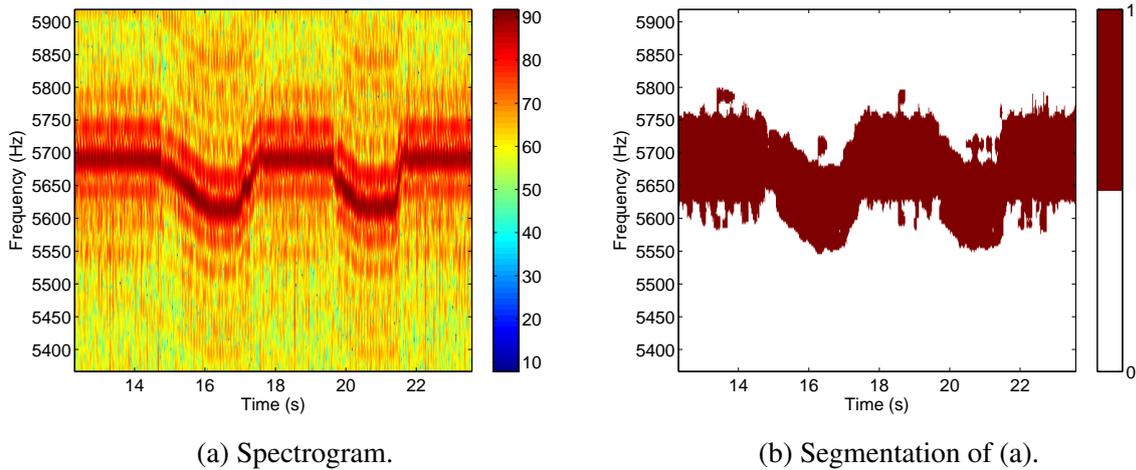


Figure 4. Spectrogram portion of the engine shaft's vibrations (a). The spectrogram is restricted to this portion in order to limit the points number. (b) gives the result of the segmentation algorithm, with  $p_{fa} = 10^{-4}$ ,  $p_{cand} = 0.9$  and  $t_k = 1$ . The main harmonic and its two neighbours are segmented together.

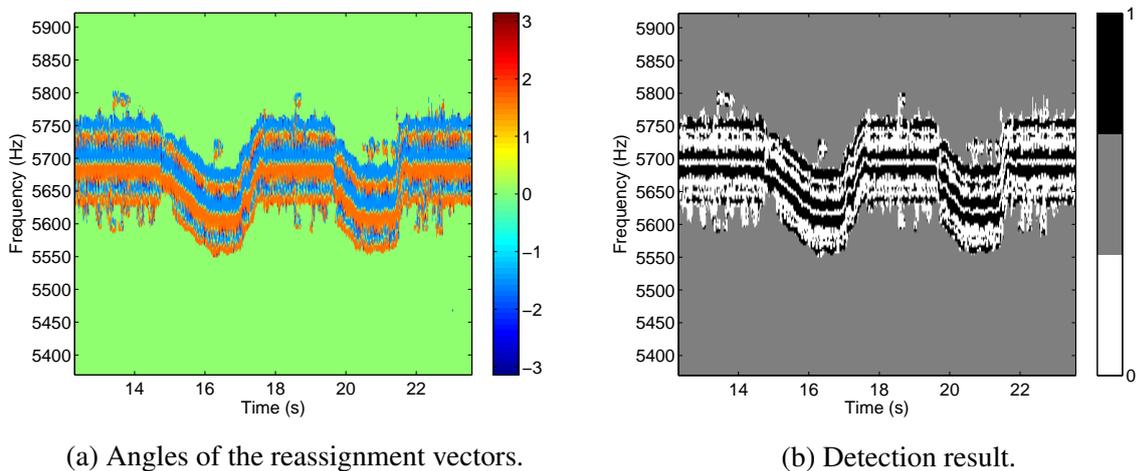


Figure 5. (a) displays the angles of the reassignment vectors of the segmented class (figure 4 (b)). The detection result of equation 8 is shown on (b). Grey points are classified as noise by the segmentation. There are boundaries detected inside the class, and not only on the edges: there is more than one component segmented.

In this application, we want to segment only the main harmonic, in order to recover easily the engine speed. Figure 4(a) shows a portion of the spectrogram of the engine shaft's vibrations. The algorithms are applied only on this restricted spectrogram to limit the point number.

The best monitoring should be when a single harmonic is segmented, which implies a good choice of set of parameters [2]. In an unsupervised segmentation, we take a non-optimal set of parameters, and the segmentation algorithm may merge several harmonics in a single class, as shown on figure 4 (b). In order to improve the segmentation, we apply the boundary detector of equation 8 on segmented patterns.

We then look at the angle of reassignment vectors on this class to determine if the segmented class corresponds to a single narrow-band component, or to several merged harmonics. These angles are displayed on figure 5 (a). The results of detection described in equation 8 are

presented on figure 5 (b). Given that the detected boundaries do not correspond to the segmented class edges, we conclude that the segmentation have merged more than one components in the class. Moreover, we distinct clearly the main harmonic boundary in the middle of the pattern, but the second harmonics boundaries are not as well detected.

The use of the reassignment vectors angles correctly gives a good feedback on the segmentation quality, by showing an estimation of the component number within their boundaries.

## 5. CONCLUSION

A time-frequency segmentation algorithm, based on the statistical features of the STFT may not give ideal results, and more information is needed to determine if there is one or more spectral pattern in a single segmented class.

We add information coming from the reassignment principle. On a pattern's boundary, all reassignment vectors aim at the pattern, consequently there's a continuity of the reassignment vector's angle along the boundary. By looking for local homogeneity in the angle of the reassignment vectors, we detect the pattern boundaries. This extends the use of the reassignment principle to wide-band signals.

Applying this detection on the segmented classes gives information on the spectral content of the classes, and allows to determine if there is one or more signal component segmented together.

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