TEMPLATE MATCHING AND DATA FITTING IN PASSIVE SONAR HARMONIC DETECTION.

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1. ABSTRACT

This paper focuses on an important association problem in passive sonar, associating different frequency tracks from the same noise source. The methods described in this paper concentrate on data recorded using an omnidirectional single sensor passive sonar.

A frequency track is a sequence of detected signals corresponding to a single platform (noise source). Typically each noise source produces several frequency tracks, which collectively form a harmonic set. Physically the relationship between any two harmonics is defined by a fixed ratio over all time.

The algorithm described in this paper exploits this relationship by using a technique known as template matching to directly compare the shape of one frequency track to another. The match is achieved optimally through the minimisation of the least squares error between the frequencies of the template and a transformed data set. The templates are constructed by fitting individual frequency tracks with a cubic B-spline. B-splines are chosen because of their versatility in accurately fitting a vast array of curves.

2. INTRODUCTION

Data association is an important issue in the continued development of passive sonar; the ability to treat collectively data obtained from separate sources (many to one) or to separate data obtained from a single source (one to many) can be a useful tool in many application areas. The methods described in this paper focus on data collected from an omnidirectional single sensor passive sonar. For such sensors it is not possible to derive kinematical (directional or range) information about any targets present from the data recorded without additional sensors being used.

The problem addressed in this paper is that of associating together all of the frequency tracks that are resultant from a common noise source and form a single harmonic set. This will be referred to as the harmonic detection problem.

The algorithm described in this paper uses a novel template matching approach to solve the data association problem and may be regarded as a first step towards the development of an advanced harmonic classification system. Current data association routines within the field of passive sonar tend to be based solely on the kinematical information obtained for each of the noise sources, [1] [2] [3], and hence are not appropriate in this case. The aim of this current research programme is to develop algorithms that are effective in the absence of such information. As such, it is necessary to examine particular features that distinguish one track from another and use these features to group or associate data into harmonic sets.

Work has previously been carried out to solve the harmonic detection problem [4] [5] [6]. However, this new approach offers a potentially more robust and computationally less expensive solution, which can be further developed for implementation in a real time system.

The data that the algorithm is applied to is recorded at a specified sampling rate (in this paper, the sampling rate is 44.1Hz), and then a Fast Fourier Transform (FFT) is applied with a 50% time overlap between successive samples. A tracking algorithm is then used to extract the frequency tracks from the post-FFT data. It is these frequency tracks that form the input for the algorithm described in this paper.

A frequency track belonging to a harmonic set is said to be a harmonic of that set. The features that are common across all of the harmonics in a set are visually obvious to detect. They consist of frequency shifts associated to some alteration in the noise source. For example, the frequency tracks associated with the noise of the propeller of a vessel will show a sharp shift in frequency when the vessel accelerates and the propeller rotates at a higher rate. This type of frequency shift will be evident in all of the harmonics of the set at the same moment in time. However, the magnitude of the frequency shift will not be the same for all harmonics. This is explained by the physical properties governing a harmonic set, which states that

$$f_n(t) = nf_1(t)\ , \qquad (1)$$

where n is a positive integer that defines the n th harmonic of the set. This result shows that there is a known, fixed, ratio between the *n*th harmonic and the fundamental, or lowest, frequency f_1. This result is valid over all time, t, and can be extended to any two harmonics in a set by evaluating

$$\frac{m}{n} f_n(t) = f_m(t)\ , \qquad (2)$$

where *m* and *n* can define any of the harmonics within a set. This is an important result as the fundamental frequency track may not always be present in the recorded data.

The algorithm described in this paper solve the harmonic detection problem using data fitting and template matching techniques to identify tracks with relating features. The types of features that are to associate tracks from the same harmonic set are frequency shifts in the emitted noise at the source and the diffusivity of the tracks. The algorithms also exploit the physical features governing a harmonic set.

3. ANALYSIS PROCEDURE

The algorithm is a batch processing one, which means that the analysis is performed on a group or batch of data representing a number of time updates. The main reason that this method is employed is that analysing a batch of data achieves greater reliability in matching the different tracks to each other. An additional benefit is that it significantly reduces the volume of data to be analysed by only passing the data points representing part of a frequency track into this algorithm, and discarding all the background noise.

The method of analysis employed is a combination of approximation techniques and template matching. Jointly, these are used to determine whether there is a set of tracks present that exhibit the necessary physical properties that characterise a harmonic set. Brief descriptions of these mathematical techniques are given in the following sections followed by an overview of the algorithm itself.

3.1 Template Matching

Template matching, [7], enables a data set to be transformed optimally to match a template (B-spline approximating curve). Optimisation is achieved by minimising the least squares error between the frequencies of the template and the transformed data.

A B-spline function, [8], [9] is a piecewise polynomial, which has good continuity between sections because of imposed conditions. The point where two sections join is called a knot. The use of B-splines is appealing as they allow the sometimes complex shape of the frequency tracks to be approximated using low-order polynomials. This allows a much smoother fit than could be achieved by fitting the entire data set with one high order polynomial, which would exhibit large oscillatory behaviour.

It is possible to allow any type of transformation to occur on the data set, for example translation, rotation or reflection. However, because of the nature of the data obtained using narrowband analysis the only translation required to match one track within a harmonic set to another track from the same set is a scaling in frequency.

Each data set representing a frequency track can be expressed as

$$\{(f_i, t_i)\}_{i=1}^{m} = (\mathbf{f}, \mathbf{t}), \tag{3}$$

where f_i represents the track's i th position in frequency, and t_i the i th sampling time. The template used to match the frequency tracks is represented by the function

$$\{g(t_i)\}_{i=1}^{m} = \mathbf{g}(t). \tag{4}$$

Template matching aims to transform the data set $(\mathbf{f}, \mathbf{t})$ to a new data set $(\hat{\mathbf{f}}, \hat{\mathbf{t}})$, such that any point in the set $\hat{f}_i$ is approximately equal to $g(t_i)$, for $i = 1, \ldots, m$.

Since in this example the only transformation required is a frequency scaling, it can be shown that

$$\left\{\left(\hat{f}_i, t_i\right)\right\}_{i=1}^{m} = \{(Sf_i, t_i)\}_{i=1}^{m}, \tag{5}$$

where S is a scaling parameter. It then follows that

$$\hat{f}_i = Sf_i, \text{ for } i = 1, \ldots, m. \tag{6}$$

To find the optimum fit, the sum of the squares of the errors between the frequencies of the template and the transformed data set are minimised. In effect, the optimal scaling factor, *S*, has a value that minimises these errors. To illustrate this error measure, the error, d_i, between one single data point $\hat{f}_i$ and the template $g(t_i)$ is illustrated in Figure 1.

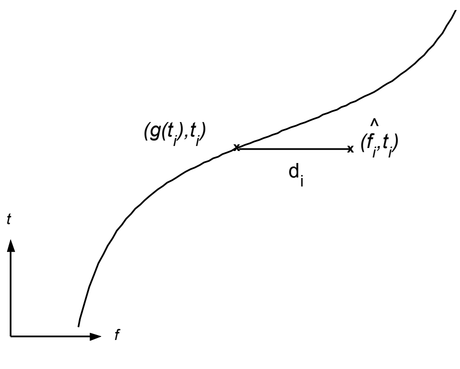

Figure 1 Example of error d_i.

$$d_i = \hat{f}_i - g(t_i). \tag{7}$$

The optimal fit is found by finding the scaling parameter *S* that solves the least squares minimisation problem

$$\min_S \left\{ E = \sum_{i=1}^{m} d_i^{\,2} \right\}. \quad (8)$$

Calculating the transformation that results in the minimisation of *E* can be achieved by differentiating *E* with respect to *S*, and setting the result equal to zero. Defining the vector $\mathbf{d} = [d_1, d_2, \ldots, d_m]^T$, the error function *E* can be expressed as

$$E = \mathbf{d}^T \mathbf{d}\,. \quad (9)$$

Defining the vectors $\mathbf{f} = [f_1, f_2, ..., f_m]^T$, $\hat{\mathbf{f}} = [\hat{f}_1, \hat{f}_2, ..., \hat{f}_m]^T$ and $\mathbf{g}(t) = [g(t_1), g(t_2), ..., g(t_m)]^T$ it can be shown that

$$\mathbf{d} = \hat{\mathbf{f}} - \mathbf{g}(t)\,, \quad (10)$$

and

$$\hat{\mathbf{f}} = S\mathbf{f}\,. \quad (11)$$

Both of these expressions can be substituted into equation (*9*), and differentiated with respect to *S*, to give the so called normal equations

$$\mathbf{f}^T \mathbf{f} S = \mathbf{f}^T \mathbf{g}(t) \quad (12)$$

when set equal to zero. This expression is equivalent to solving *m* simultaneous equations for the parameter *S*, which can be solved to give

$$S = \frac{\sum_{i=1}^{m} f_i g(t_i)}{\sum_{i=1}^{m} f_i^2}\,. \quad (13)$$

A match is said to be positive if the minimum error function, (*9*), is smaller than a pre-defined threshold value. The track is provisionally assigned to a harmonic set and the track is assigned the harmonic set number relating to the template the track has matched. If the match is negative the track remains unmatched and is passed through the algorithm again, using a different template, until a match is found.

3.2 Algorithm Overview

Figure 2 outlines the analysis procedure undergone by each individual batch of data. Each of the different stages depicted are briefly discussed in order. The different stages exploit the physical properties of a harmonic set, either using the fact that one harmonic will exactly match to another of the same set, if scaled in frequency, or using the fact that the scaling parameter is very well defined.

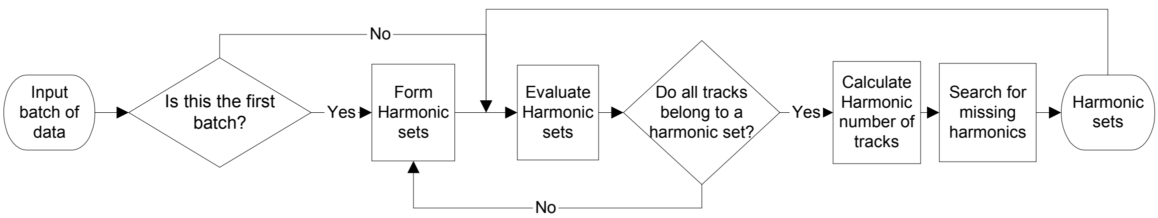

Figure 2: Overview of algorithmic processes.

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3.2.1 Form Harmonic Sets

Provisional harmonic sets are formed by implementing the template matching routine. A template is formed by fitting the lowest occurring frequency track with a B-spline. All the tracks are optimally matched to this template, using the method described in Section 3.1. If the residual error between the transformed data set and the template is below a user defined threshold the track is assigned to the harmonic set defined by the template. This process is repeated for all of the remaining unmatched frequency tracks until they have all been assigned to a harmonic set.

For subsequent batches of data, continuing tracks are identified and initially assigned to the harmonic sets found to be correct during the analysis of the previous batch of data.

3.2.2 Evaluate Harmonic Sets

Stage 1 of the algorithm associates together all of the frequency tracks that have a similar shape. However, it is possible that two or more harmonic sets may exhibit similar characteristics over a single batch of data, particularly if the batch is small. Consequently, it is important to be more rigorous in determining the harmonic sets.

This stage of the algorithm exploits the fact that there is a well defined fixed ratio between all harmonics within a set. Therefore, any tracks found not to conform to this requirement can be expelled from the harmonic set.

3.2.3 Calculate Harmonic Number of Tracks

Having reached this stage of the algorithm the confidence in the harmonic set classification is high. Therefore, it is now possible to determine the harmonic numbers of the frequency tracks within each set. This is achieved by analysing the transformation (scaling) parameters, S, calculated for each of the tracks during the template matching. Physically the scaling parameter can be expressed as

$$S = \frac{n}{N}, \qquad (14)$$

where N is the harmonic number of the template and n is the harmonic number of the frequency track, which are both real, positive integers. N is then the lowest number which results in the values of n satisfying this expression.

3.2.4 Search for Missing Harmonics

This stage of the algorithm checks that no tracks have been missed from the harmonic sets. This is achieved by repeating the template matching for tracks assigned to harmonic sets that comprise a single track only (a single-track harmonic set). However, a positive match is now not determined by the size of the residual error, but by the scaling factors that are calculated to optimise the match. If it is found that a particular track has a scaling factor that is consistent with an existing harmonic set then the track is assigned to this set.

4. NUMERICAL RESULTS

Figure 3 shows a brief breakdown of the way in which the algorithm described in this paper works, and the results which are produced through implementing it. 3a shows the post FFT analysis results, achieved using a 50% overlap. Each frequency cell represents a range of 1Hz. Figure 3b shows the frequency tracks that have been extracted from this data set, it is these tracks that form the input for the algorithm. Figures 3c, 3d and 3e show the output of the algorithm. Each figure illustrates the tracks that have been grouped together by the algorithm to form a harmonic set.

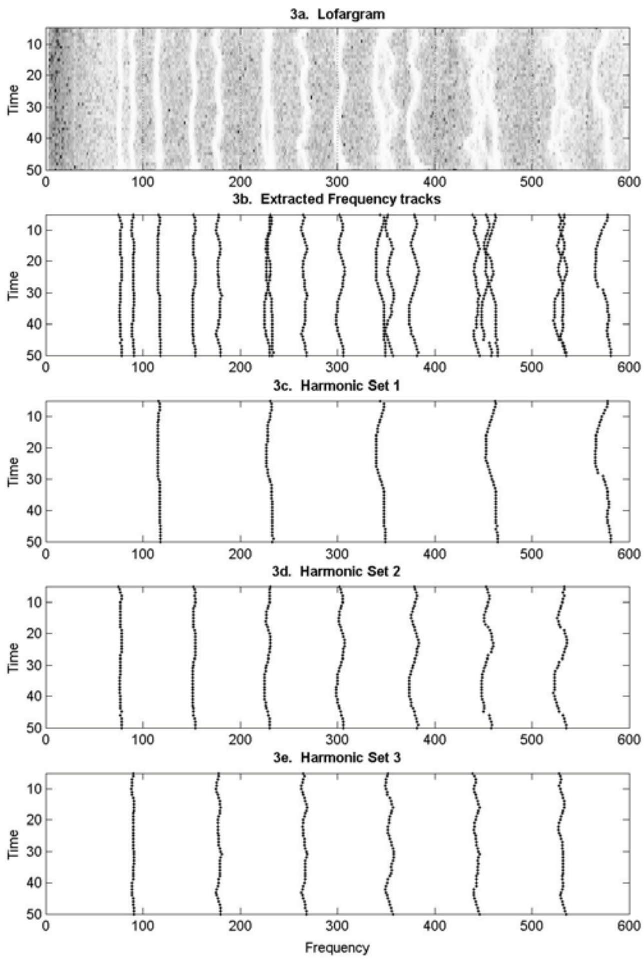

Figure 3: Diagrammatic overview for the results produced for a single batch of data.

5. CONCLUSIONS AND FURTHER DEVELOPMENTS

This paper has described an algorithm to solve the problem of harmonic detection, which is the problem of automatically grouping narrowband frequency tracks into their respective harmonic sets. The algorithm uses batch processing and employs a combination of data approximation and template matching techniques, as well as exploiting the physical properties associated to the frequency tracks within a harmonic set.

The results produced by the algorithm clearly show that the frequency tracks have been successfully grouped into harmonic sets for each of the data samples, and each of the different elements of the algorithm have been shown to work correctly. Testing on other data sets has produced similarly accurate results.

AKNOWLEDGEMENTS

The work has been funded through a CASE award sponsored jointly by EPSRC and Thales Underwater Systems.

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