Exploring EMD for Lung Crackle Detection

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Abstract

This paper presents a two-stage crackle detection algorithm combining Empirical Mode Decomposition (EMD) and a simple energy peak detector. A discussion is presented of the main issues arising in the implementation of the EMD stage and the solutions adopted. The algorithm was implemented in MATLAB® and preliminarily tested on an annotated 10-second respiratory sound file, without any prior systematic training. Applying the energy peak detection to the intrinsic mode function of order 3 (IMF3) generated by the EMD stage, an 87% F performance index was achieved.

1 Introduction

The analysis of pulmonary sounds is an important means of diagnosing respiratory pathologies [1]. The aim is to detect artefacts, generally referred to as *adventitious lung sounds* (ALS), regarded as potential symptoms of lung disease. Signal processing and computing technologies can contribute to improve the diagnosis techniques based on stethoscopy, reducing ALS detection subjectivity.

This paper addresses the automatic detection of *crackles* [2], an important category of ALS, related to pulmonary fibrosis, pneumonia and chronic bronchitis [3]. Crackles are short-duration (<20ms) nonstationary sounds, with a frequency range normally between 100 and 2000 Hz. The energy ratio of crackles to normal respiratory sound is low, resulting in significant waveform distortion. The wide variation in magnitude, explosive nature and broad spectrum observed in crackle waveforms and the fact that they can overlap makes for an intricate signal processing challenge.

Numerous detection methods have been proposed in the literature, applying a variety of algorithms (time-domain analysis, wavelet transforms, fractal dimension filtering, fuzzy logic, neural networks…) and often combining them in more or less complex ways [1]. However, with systematic validation still largely unaddressed, their practical applicability is very unclear; the challenge of reliable automatic crackle detection remains open.

Huang et al. presented Empirical Mode Decomposition (EMD) as a new technique to analyse nonstationary and nonlinear signals [4]. This naturally suggested the possibility of applying it to crackle detection, an idea explored by Charleston-Villalobos et al. [5] and Hadjileontiadis [6].

In contrast to other methods as discussed in [4], EMD offers the advantages of being adaptive, local, intuitive and *a posteriori*.

The core of EMD is an iterative decomposition process, known as *sifting*, whereby data is reduced into so-called *Intrinsic Mode Function* (IMF) components based on local properties.

An EMD-based crackle detection algorithm will comprise two stages:

1) Generation of the IMF components, which maintain the signal's energy distribution and thus the physical meaning of the data;
2) Filtering of the chosen IMFs to find crackle positions.

In the work of Charleston-Villalobos et al. [5], visual inspection of the generated components (particularly IMFs 2 and 3) indicated a good match between the most prominent features and the corresponding signal annotation data. Although encouraging, these results were only qualitative, as stage 2 was not addressed i.e. no automatic method of detecting and counting crackles was implemented. The paper also acknowledged difficulties in telling crackles from basic respiratory sounds and the lack of reliable validation data.

Hadjileontiadis [6] completed the algorithm by combining EMD and Fractal Dimension (FD) filtering. The FD filter stage analyses the temporal evolution of the generated IMF waveform complexity, and this information is used as a pointer to crackle positions.

This paper explores an alternative path to overcoming the limitations of [5], avoiding the hybrid approach of [6], which seems overly complex. Instead, stage 2 is reduced to a simple energy peak detector (based on the premise that the most prominent peaks match crackle positions) and the focus is firmly placed on solving EMD implementation issues in order to fully expose the potential of the technique itself.

2 The EMD algorithm

EMD is an adaptive process that empirically separates the data set into IMFs, applying a time-varying filter. Instantaneous frequency and energy are the relevant global variables of EMD [4].

Each IMF contains an intrinsic oscillatory mode and the instantaneous frequencies can be defined anywhere in this function. The process of signal decomposition into IMFs is called *sifting*. To form an IMF, a time series must satisfy two conditions:

1) Considering the whole data set, the number of local extrema must be equal to the number of zero crossings or differ from it by one;

2) At any point, the mean of the upper and lower envelopes, defined by the local maxima and local minima, respectively, must be zero.

The sifting process is necessary because "misbehaved" signals (such as crackles) may contain multiple instantaneous frequencies at a time. It involves subtracting the higher oscillation modes and iterating on the residual, as illustrated in the flowchart of Figure 1, until signal decomposition is complete.

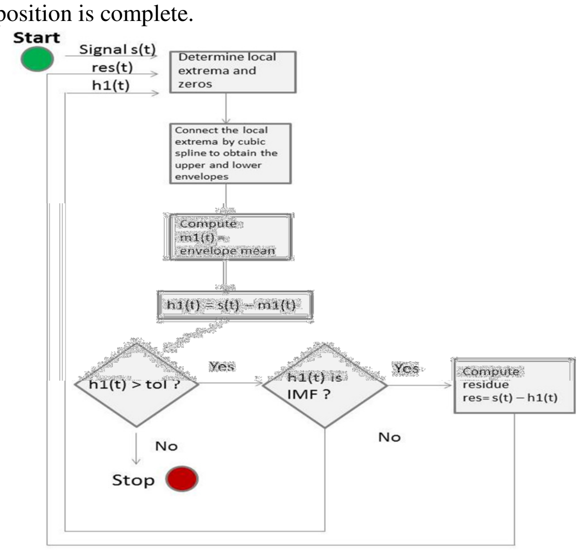

Figure 1: The Sifting process

The end result is a representation of the original signal in terms of a set of N IMFs and a residue:

$$s(t) = \sum_{K=1}^{N} IMF_k(t) + r_N(t)$$

Equation 1: Expansion of a signal s(t) in terms of IMFs

It should be stressed that the physical properties of a time series are maintained when it is expanded into its IMF components; the decomposition is complete, orthogonal, local and adaptive [4].

3 EMD-based crackle detection

The detection algorithm was developed in MatLab®. It takes a respiratory sound file as its input and generates an *annotation file*, recording the detected crackle endpoints sequentially.

Stage 1 implements the sifting process (see Fig. 1), generating IMFs up to the order specified by the user. First, the local extrema (maxima and minima) and zeros of the input signal are obtained. The upper and lower envelopes of the signal are then obtained through interpolation and used to compute the mean. Subtracting this mean from the original signal yields the first IMF candidate, $h_1(t)$; if this new signal verifies the two conditions required (section 2), it forms an IMF and the sifting process continues, taking the residue as a new input signal. Otherwise, the process is repeated taking $h_1(t)$ as the input. This recursive procedure terminates when the required number of IMF components and the respective residue are obtained, forming a complete expansion of the original signal.

The following stage is a straightforward energy peak detector whose operation is illustrated in Fig. 2. It starts by squaring the IMF signal and applying a smoothing convolution filter. The position of the highest peak of the resulting signal is considered the midpoint of a crackle and used to split the signal into two segments. The procedure is then applied to each of them and repeated recursively in order to detect lower amplitude peaks down to a pre-defined energy threshold.

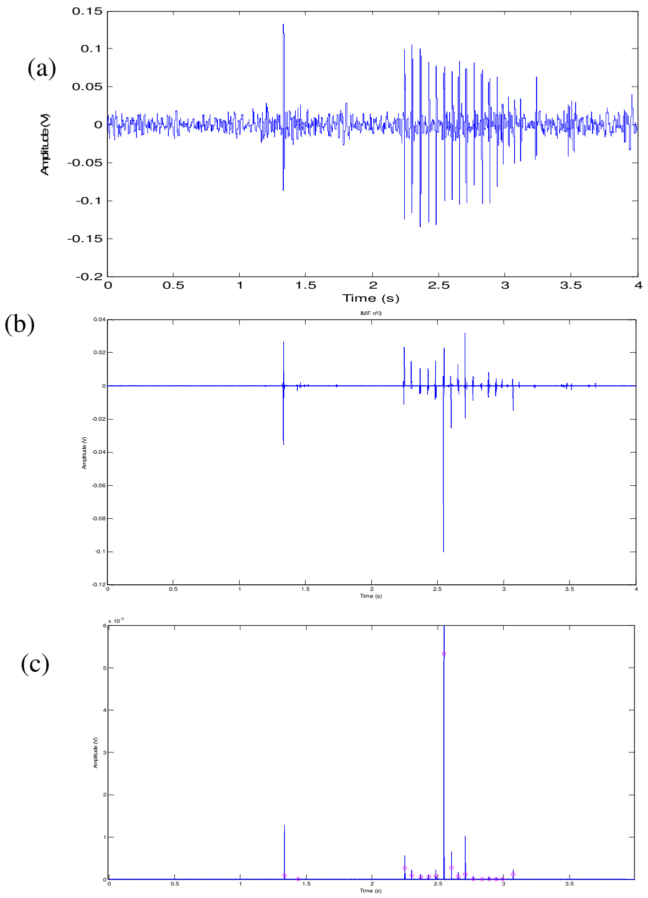

Figure 2: Excerpt of respiratory sound (a) with corresponding IMF3 (b) and crackles indicated by detected IMF3 energy peaks (c).

4 EMD implementation issues

Important issues mentioned (but not explained in detail) in EMD-related literature became apparent in the implementation of this algorithm. One of them was the *end effect* in the spline fitting, extremely notorious in the initial attempts to obtain IMFs. It causes wide variation at the edges of the signal, distorting the decomposition. Boundary conditions were implemented to attenuate this problem: initially, the first and last data points are considered both as minima and maxima, and the remaining extrema of the set are computed. Subsequently, the current values of those first and last minima/ maxima are updated if a result derived from the slope defined by the following/previous points is less/higher than the current value.[7]

Another issue is related to the tolerance and threshold parameters of the sifting algorithm, which need to be adapted (fine-tuned) to the data set under analysis. In this case, the tolerance (parameter *tol* in Fig. 1) was empirically set, based on the maximum absolute value of the signal. Regarding the stopping criteria, the mean criterion proposed by Rilling, G. et al. [8] was applied. This technique, based on two thresholds for an amplitude near zero, considers small global fluctuations and at the same time large local excursions, preventing over iteration.

Several tests led to the conclusion that running both IMF test conditions in the respiratory sound signals took too long and the results obtained by verifying only one of them were identical to those obtained when both were tested. Hence, in order to avoid over-sifting and excessive execution times, the algorithm only observes the mean criterion, which seems to be enough for these specific data sets.

The final issue is the choice of the IMF to be used as input to the peak detector. Visually comparing each IMF with the reference sound data annotated by health professionals, IMF 3 and IMF 4 seemed to provide the best match. Lower and higher order IMFs appeared to contain mostly high frequency and basic respiratory sound noise, respectively. This only partially agrees with the observations of Charleston-Villalobos et al. [5].

5 Results

Preliminary performance tests were carried out on a 10-second respiratory sound file annotated by a health professional, without prior training to optimise the algorithm's parameters. By adjusting only the algorithm's energy peak detection threshold, an F index as high as 92% (harmonic mean of SE=94% and PPV=89%) was achieved.

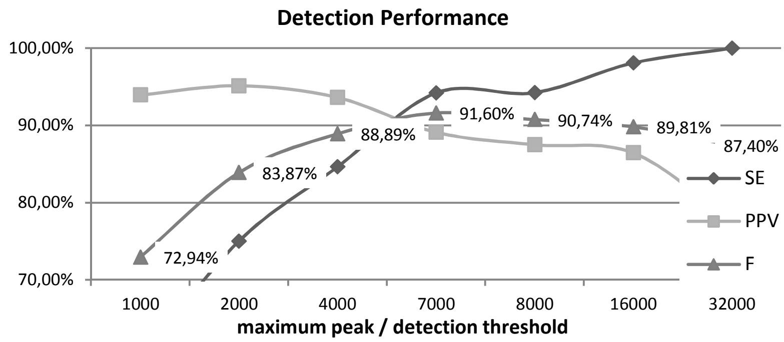

Figure 3: Graph showing the relation between the detection performance and the energy threshold

6 Conclusions and Future Work

This paper explored the application of EMD in automatic respiratory crackle detection systems. Outstanding EMD implementation issues and alternatives to solve them were analysed in this specific application context. A fully functional EMD-based automatic detection algorithm was developed. Highly promising results were achieved in pilot validation tests, calling for further, more systematic performance evaluation on more extensive, multi-annotated test sets. Moreover, numerous algorithm refinement possibilities can be envisaged, including parameter optimisation through training, pre-filtering and combination of different order IMFs and/or IMF derivatives. Since they are associated to different oscillation modes, different order IMFs might also be helpful in fine/coarse crackle classification.

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