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Comparative Study of Pitch Detection Techniques

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Abstract-The purpose of this paper is comparative study of a fast analysis technique for decomposingtime-series into a set of intrinsic mode functions (IMFs) and a residual trend.This decomposing technique, known as the empirical mode decomposition, traditionallyuses cubic-splines in the decomposing process thus creating the need tosolve a system of equations, albeit well-conditioned, at each step. This new method being proposed takes advantage of the theory of matrix-free moving least-squaresapproximation to construct discrete reproducing kernels capable of interpolation toa near natural cubic-spline _t without the need for solving a system of equations. A class of compactly supported radial functions used in constructing the reproducingkernels is also given along with numerical examples validating the robustness of the fast algorithm.

Keywords- IMF, residual, matrix free moving, radial functions, empirical mode decomposition.

I. Introduction

As an adaptive nonlinear decomposition technique referred to as EmpiricalMode Decomposition (EMD), the wide ranging applications this method hasbeen applied to the past few years have varied from analyzing climatology datafor climate variability to the study of white noise characteristics in biologicaldata. Being derived from the simple assumption that any data consists ofsimple unique oscillating modes intrinsic to the data, the EMD is a posteriori in regards to the decomposition of the data into intrinsic modefunctions (IMFs) and does not assume anything about the data, contraryto Fourier methods where data is assumed linear and stationary. Because ofthe adaptive nature of EMD, this method has been shown numerically tobetter describe temporal patterns in nonstationary nonlinear time series thantraditional methods such as Wavelet and Fourier methods [5]. Furthermore,coupled with the Hilbert transform applied to the resulting IMFs (Hilbert-Huang transform), this decomposition method is well localized in the time frequencydomain and reveals important characteristics of the signal. Despitethe success over the past few years of this analysis tool, it still lacks the speedof traditional Wavelet and Fourier methods which have become standards inthe mathematical, statistical, and engineering industry partly due to theirassociated 'fast' transform algorithms and 'black-box' style implementations.

The Empirical Mode Decomposition (EMD) has been proposed recently as anadaptive time–frequency data analysis method. It has been proved quite versatilein a broad range of applications for extracting signals from data generated in noisynonlinear and nonstationary processes. As useful as EMDproved to be, it still leaves some annoying difficulties unresolved.One of the major drawbacks of the original EMD is the frequent appearanceof mode mixing, which is defined as a single Intrinsic Mode Function (IMF) eitherconsisting of signals of widely disparate scales, or a signal of a similar scale residingin different IMF components.Mode mixing is often a consequence of signalintermittency. As discussed by Huang *et al.*, the intermittence could not onlycause serious aliasing in the time–frequency distribution, but also make the physicalmeaning of individual IMF unclear. To alleviate this drawback, Huang *et al.*proposed the intermittence test, which can indeed ameliorate some of the difficulties.However, the approach has its own problems: first, the intermittence test isbased on a subjectively selected scale. With this subjective intervention, the EMDceases to be totally adaptive. Second, the subjective selection of scales works ifthere are clearly separable and definable timescales in the data. In case the scalesare not clearly separable but mixed over a range continuously, as in the case ofthe majority of natural or man-made signals, the intermittence test algorithm withsubjectively defined timescales often does not work very well.To overcome the scale separation problem without introducing a subjectiveintermittence test, a new noise-assisted data analysis (NADA) method is proposed,the Ensemble EMD (EEMD), which defines the true IMF components as the meanof an ensemble of trials, each consisting of the signal plus a white noise of finiteamplitude. Since there is added noise inthe decomposition method, we refer the original data as ‘signal’ in most occasions.This new approach is based on the insightgleaned from recent studies of the statistical properties of white noise, whichshowed that the EMD is effectively an adaptive dyadic filter Banka when applied towhite noise. More critically, the new approach is inspired by the noise-added analysesinitiated by Flandrin *et al.* and Gledhill. Their results demonstrated thatnoise could help data analysis in the EMD.

The principle of the EEMD is simple: the added white noise would populatethe whole time–frequency space uniformly with the constituting components ofdifferent scales. When signal is added to this uniformly distributed white background,the bits of signal of different scales are automatically projected onto properscales of reference established by

the white noise in the background. Of course,each individual trial may produce very noisy results, for each of the noise-addeddecompositions consists of the signal and the added white noise. Since the noise in
each trial is different in separate trials, it is canceled out in the ensemble mean of enough trials. The ensemble mean is treated as the true answer, for, in the end,the only persistent part is the signal as more and more trials are added in theensemble.

A. IMF Satisfies Two Conditions:

1. In whole data set, number of extrema and the number of zero crossings must either be equal or differ at most by one.
2. At many points, mean value of envelope defined by local minima is zero.

B. IMF Properties:

1. Each IMF involves only one mode of oscillation.
2. Each IMF characterizes not only a narrow band but both amplitude and frequency modulation.
3. An imf can thus be nonstationary.

II. EMD

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III. EEMD

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IV. Comparison of EMD and EEMD TECHNIQUE

TABLE 1. COMPARATIVE STUDY OF EMD AND EEMD TECHNIQUES.

EMD	EEMD
In broadband signal, EMD is not effective.	In broadband signal, EEMD is more effective.
EMD does not properly reduce noise.	EEMD reduce noise properly.
Key feature of EMD is to decompose a signal into IMF.	EEMD defines true IMF components as mean of an ensemble of trials.
EMD depends entirely on data itself.	EEMD relies on selection of appropriate wavelet.
Very sensitive to noise in recorded signal.	Less sensitive to recorded signal.

V. CONCLUSION

It has been found that in EMD, any complicated data set is decomposed in infinite set and often small number of components which is a collection of Intrinsic Mode Function (IMF). IMF implies oscillations embedded in data.
Suppose a function is symmetric with respect to local zero mean and have same numbers to extrema and zero crossings. Then a physically meaningful local instantaneous frequency can be discerned from the function. EEMD was introduced to optimize the results of EMD and give better signal quality. Research done only provide oscillations where First condition of IMF is not satisfied. Hence EEMD is better as comparing with EMD and can be used for improving the quality of signal on a network.

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