Empirical Mode Decomposition in Segmentation and Clustering of Slowly and Fast Changing Non-Stationary Telemetric Signals

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Abstract—Empirical mode decomposition (EMD) is a principally new technique, intended to process various types of non-stationary signals by means of decomposing them into a set of certain functions, called “Intrinsic mode functions” (IMFs) or Empirical modes. This paper is dedicated to a newly developed EMD application to Data Mining, namely, to segmentation and clustering problems. Two new algorithms of segmentation are introduced. The first one was devised for slowly changing signals and is capable of extracting monotonous segments (piecewise-polynomial segmentation) as well as other signal patterns. The second one, used for fast changing signals, allows to extract segments with different variances, energies and autoregressive model orders. Both algorithms were tested on various telemetric signals and fuzzy-clustering results of the extracted segments are given. Finally, the advantages and disadvantages of these approaches are described and the possible ways of their further improvement and development are outlined.

INTRODUCTION

Data Mining [1–6]—is a concept which embraces many branches of intellectual analysis of various datasets including signals as their particular case. Among these branches segmentation, clustering, classification, mining association rules, sequential analysis and visualization of multidimensional dataset should be described as the most significant ones. This rather long list of implementations is gradually extending due to the permanently carried out new investigations, new discoveries and regularly arising new tasks and problems in science and technology.

In general, Data Mining intends to extract knowledge from raw data which may be consequently applied to discovering previously unknown regularities, understanding numerous existing phenomena and explaining many hidden facts connected with data. Data Mining techniques are especially efficient when the data's length is large or when several datasets are simultaneously processed for contrastive analysis. The knowledge which is derived from the data via Data Mining techniques must satisfy a number of special requirements:

1. Knowledge must be fresh and non-trivial (that is, unobvious and hidden knowledge is particularly interesting for an expert whereas, regularities easily noticed from visual analysis or other more simple techniques do not justify the waste of technical and human resources).

2. Knowledge must be practically useful (that is, its use in processing new data-sets should lead to perfect results with high reliability), and interpretable by human beings (that is, it should be logically deduced from the well-known patterns and regularities and be completely understandable to a human being).

Provided that all these conditions are fulfilled, the new knowledge should be accepted and taken into account with the intention of its use in different areas of the particular knowledge domain.

In Data Mining knowledge is represented and converted from one form to another by means of different kinds of models. These models, although they are only an approximation of the true structure, are expected to reflect the nature and interconnections in data and, as a matter of fact, they cope with this task. The most widely used models are: sets of segments and clusters, productive rules, decision trees and sequential patterns.

In this paper telemetric signals are considered and all the algorithms described are elaborated for them. This extremely vast class of signals involves the category which describes the conditions of the environment—namely, the changes of temperature, atmospheric pressure, humidity, radiation content and etc. Thus, these signals may be characterized as those connected with monitoring the parameters of the environment. Apart from this group of signals, mechanical parameters (signals) also refer to telemetric. They include velocities and accelerations of various devices.
which are set on different vehicles (spaceships, monitoring systems, etc.).

The most substantial and distinctive feature of all these signals is that they have a big number of samples, sometimes containing a lot of redundancy (repeated values). It is easy to guess that this circumstance may cause serious problems at the step of processing since such processing will be very time-consuming. At the same time it is known that the efficiency and rapidity of processing is indispensable. The problem of telemetric signals classification may be solved in several ways. One of them consists in determining fast and slowly changing ones. The exact definitions of these types of signals will be given below. The main problem of processing such signals, as it has already been stated, is a large number of samples (large volume of the original set of samples), which makes the original signal almost inconceivable and hardly interpretable. Thus, at first we fulfill segmentation which is then followed by clustering. So, the model of a signal will consist of a number of segments (this notion will be revealed later) which possess several features, also called characteristics. Among them the most ubiquitous and effective for the analysis are statistical characteristics including sample mean, variance, kurtosis, skewness, energy, entropy and etc. In addition, it is reasonable to involve spectral analysis and characterize segments in terms of spectral coefficients. In fact, the number of such possibilities is extremely great.

For the sake of forming such models certain algorithms need to be chosen very properly in accordance with the non-stationary nature of signals. This inevitably leads to the necessity of developing adaptive solutions (algorithms). Among them Empirical Mode Decomposition (EMD) is very tempting due to its properties of adaptivity and locality, physical and mathematical clarence and many new opportunities for signal processing.

EMD segmentation and clustering will be demonstrated to succeed in working with various types of telemetric signals obtained from external sources (mainly, sensors which are set on different dynamic objects). Beginning with the next subsection, we are going to introduce in a more detailed way the core of the segmentation problem and a new approach for its solution on the basis of EMD, the offered algorithms, several most vivid and demonstrative examples followed by comments and, finally, delineate the main advantages, disadvantages and further research directions.

SEGMENTATION PROBLEM. SLOWLY AND FAST CHANGING TELEMETRIC SIGNALS. SEGMENTATION CRITERIA

Segmentation may be defined as an automatic partition of a given signal (or, generally, a dataset) into stationary (mainly, weakly stationary) fragments, with the length adapted to the change of local properties in signal’s structure. In other words, segmentation makes an arbitrary signal divided into a set of fragments with homogeneous properties according to a preliminary chosen criterion. Each segment should necessarily have homogeneous characteristics (for example, spectral, statistical, energetic, etc.). The boundaries of the segments must coincide with those points in a signal where the abrupt changes occur. Therefore, the goal of segmentation is to invent methods, which will allow to detect these changes. As a result, a signal will be segmented (partitioned) and the redundancy problem, mentioned at the beginning, will be partially solved. Nevertheless, the problems may arise when the incorrect borders are taken as true ones, for this may cause wrong interpretations at further steps of analysis. Such errors must be eliminated and avoided as they may completely distort the final model of a signal, make it unreliable and spurious.

Let \([a, b]\) be a finite interval of discrete-time signal, where \(a\) and \(b\) denote its initial and final samples, respectively. If \(S\) is a set of all possible values of a signal then each interval is assigned to some value \(s \in S\). In this sense, \(s\) is considered to be a sort of description of the interval \([a, b]\).

At first, it is necessary to select all non-empty intervals \([a_i, b_i]\), which are marked by a particular label (characteristic) \(s_i \in S\). The set \(S\) consists of all the existing labels of the segments which are discovered as a result of segmentation algorithm. These labels describe the properties of the segments therefore, every label is an informative description of the segment. As soon as all the labels are found, it is possible to preserve them (thus gradually forming a warehouse of segments) in order to use afterwards.

Having introduced the main notations, it is now possible to define \([a_1, b_1, s_1], [a_2, b_2, s_2], \ldots\) as a marked (labeled) sequence of intervals (segments) over \(S\), if the following expression is valid:

\[
I_i \cap I_j = \emptyset \quad i \neq j,
\]

where \(I_k = [a_k; b_k]\).

The equation means that segments do not overlap because the intersection of two sets (each denoting one of two adjacent segments) is empty. Thus, when fulfilling the segmentation of a signal, the goal is to map the original signal into the marked sequence of intervals (segments).

Representation of a signal by a sequence of marked intervals helps significantly reinforce the total application effect of such procedures as segmentation, clustering, classification and other methods of intellectual analysis of signals.

All the telemetric signals which are shown further are classified on the basis of slowly and fast changing categories. The first group involves signals which consist of monotonously decreasing and increasing intervals, which alternate (the regularity of alternation is not
obligatory) on the whole duration of a signal. As a rule, the immutability of this alternation is partially hidden from the one’s eye because of the contaminating noise which must be suppressed or filtered before the segmentation procedure. Slowly changing signals do not have wide spectrum, on the contrary, the main energy is usually concentrated in the narrow frequency band. Signals, describing temperature changes of solids, liquids, gases, pressure dynamics, mechanical and angular travels of systems, various velocities and accelerations are usually slowly varying. Unlike the first category, fast changing signals always contain many oscillations with high magnitude and intensity. This group comprises vibrations, acoustic noise, transition and steady-state processes which play an important role in the work of different dynamic objects. Signals which belong to this category do not have the exact upper boundary in frequency domain but it usually varies from several Hz to several hundred or even thousand kHz. The examples of these two categories of signals are shown below, in Fig. 1.

In order to discover and confirm the non-stationary nature of both types of signals and obtain more accurate results of segmentation general approaches must be invented and thoroughly developed. One of such approaches, applied to slowly changing signals, has arisen and has been subsequently developed from an idea based on using an approximation procedure with different time resolution (detailing of local features). That is, several approximations should be calculated for the original signal with different accuracy. In addition, these approximations may be created in such a way that the approximating functions occupy different frequency bands (probably, with overlapping) and the width of these bands is different. The wider the band, the more oscillating the function is. These oscillations are characterized numerically by the total number of extrema and zero-crossings in the approximating function. The more extrema and zero-crossings are in a signal—the more oscillating and broadband it is.

Then, the most steady representation is searched (with respect to the set of extrema or zero-crossings). Finally, the boundaries of segments in the original signal will exactly coincide with the location of extrema (or zero-crossings) in the most steady representation.

Thus, it is possible to formulate the criterion of segmentation for slowly changing non-stationary signals. The main objective of segmentation here is to partition the original signal so that the resulting parts (namely, segments) were monotonous and the monotonicity of any two adjacent segments was different. This monotonicity is often hidden because of noise and outliers which cause local perturbations. And this group of algorithms is intended to reveal this monotonicity. Nevertheless, very often the goal of segmentation is to extract the so-called pattern, i.e. the segments that are encountered several times on the signal’s duration and have high correlation with each other. For example, this may be noticed when segmenting multiharmonic signal (two or more harmonics). Here, the monotonicity of one segment may change several times but this segment is a pattern which has specific form and has the exact copies on the signal’s duration. This fact will be illustrated later.

The second idea, which is applied to fast changing signals, uses the estimate of error function between the original signal and its most informative IMF, which is beforehand subjected to special processing in order to remove all the existing irregularities, outliers and other negative factors. The maxima of this error function are assumed to be the change points (the boundaries of the segments). The criteria of information content are entropy, energy, correlation with the original signal and etc. The criterion of segmentation of fast changing signals is to discover the parts (segments) in the original signal which will have the same energy or entropy. It is also possible to obtain segments with different variance.

Before introducing the approaches based on EMD in details, it is necessary at first to describe the key points of the underlying algorithm (EMD), so that all the rest corollaries became clearer and more natural.
INTRINSIC MODE FUNCTIONS. EMD ALGORITHM. SIFTING PROCESS. POSTULATES OF EMD

The overwhelming majority of signals in practical implementations are non-stationary which means that one or more of their characteristics are time-varying. This is especially typical for those signals which have big length. These time-varying characteristics may be statistical moments and autocorrelation functions of different orders, instantaneous frequency calculated via Hilbert transform.

The classical Fourier approach on the basis of approximating a signal by a finite number of discrete harmonics is reasonable to be applied only to stationary signals because of the corresponding features of the basis functions. As it follows from signal processing theory, rigorous mathematical sense of Fourier coefficients exists only for stationary processes (with constant frequency and statistical moments). However, the basis functions—harmonics—are totally deprived of time locality (because the whole signal is used when calculating the particular Fourier coefficient) and very often a big number of harmonics is needed in order to guarantee the certain accuracy of reconstruction. The signal’s energy is spread over the wide band which makes it difficult to select the areas of its main concentration. In order to improve the reliability of the analysis of non-stationary signals a specific approach should be created which will possess the adaptivity towards the particular signal. In other words, decomposition and further analysis must take into account local features (for example, extrema, zero-crossings) and internal structure (amplitude or frequency modulations, contaminating noise) of the particular signal. These important properties are inherent to Empirical Mode Decomposition which is very perspective for fulfilling such tasks as de-noising, detrending, signals’ extension, analysis of regularity and chaotic state of signals by means of estimating Hurst parameter, time-frequency analysis on the basis of Hilbert-Huang transform (HHT). HHT results in 3-dimensional representation “energy-time-frequency” (or, in other words, “amplitude-time-frequency”) which is very convenient for discovering hidden frequency or amplitude modulations in signals. Along with these applications, multiresolution analysis, similar to that made in terms of wavelet technology, is very advantageous as it allows to separate components which constitute the original complicated signal, classify them on high- and low-frequency, and try to clarify their physical sense.

The main advantage of this approach is adaptivity of all the methods on its basis which guarantee high reliability of the analysis. Further investigation is required for comparing the potential of EMD with that of other adaptive approaches (wavelet technology, singular spectral analysis).

According to the name of the algorithm, empirical modes (IMFs) are the basis components for decomposition of signals. In general, they may have an arbitrary form, be defined analytically (by exact formula) or numerically (by a set of discrete samples) but they must necessarily satisfy two conditions [7–12]:

(1) The total number of extrema on the whole duration of a signal must be equal to the total number of zero-crossings or differ from it at most by one:

\[ N_{\text{max}} + N_{\text{min}} = N_{\text{zero}} \pm 1, \]

where \( N_{\text{max}}, N_{\text{min}}, N_{\text{zero}} \)—the total number of maxima, minima and zero-crossings, respectively. These numbers do not include the starting and final samples of a signal which may be sometimes the only extrema.

(2) The mean value (half-sum) of two envelopes—the upper one which interpolates local maxima, and the lower one which interpolates local minima must not exceed some small value \( \epsilon \) which depends on machine epsilon \( \eta \), sifting criterion (it will be defined below) and errors connected with the acquisition, converting and transmitting signal samples. For interpolation of both envelopes cubic splines are mainly used which will be explained afterwards. The exact equality is impossible to reach due to several reasons: errors caused by extremum definition, calculation errors, bad conditionality of the equations which are used for finding spline coefficients and the influence of a signal itself (for example, end effects). The second property may be analytically written as

\[ \frac{U(k) + L(k)}{2} \leq \eta, \quad k = \frac{1}{2}N, \]

where \( U(k) \) and \( L(k) \)—the values of upper and lower envelopes formed by cubic spline interpolation (K-number of sample), \( \eta \)—threshold value, \( N \)—total number of samples. This half-sum is the so-called local mean of a signal which must be less or equal than the predetermined threshold.

These two conditions have certain interpretations. The first one is the narrowband requirement. The measure of the band for an arbitrary signal in time domain may be evaluated in the following way:

\[ \nu^2 = \frac{(N_{\text{max}} + N_{\text{min}})^2 - N_{\text{zero}}^2}{N_{\text{zero}}^2}. \]

Evidently, this quantity is equal to zero if the numbers of extrema and zero-crossings are the same and it is very close to zero if the difference between them is no more than one.

The second condition also has its physical interpretation. The key sense is that empirical mode is a stationary function with respect to the defined local mean which is less than the predefined threshold. Besides, empirical mode must have positive maxima and negative minima, otherwise the symmetry round the time axis will be violated. Finally, empirical mode is at the same time amplitude and frequency modulated function. The law of the amplitude modulation may be...
defined via the constructed envelopes with the use of splines or by Hilbert transform; the law of the frequency modulation is found by the Hilbert transform.

The term “envelope” for defining an IMF is considered with respect to the chosen kind of interpolation. As it was indicated, cubic splines are mainly used in the algorithm. Splines in general and cubic splines as their particular case possess a number of advantages in comparison with the other functions which also have high degree of smoothness. This property is very important as it facilitates the extraction of the separate components from a signal.

First of all, in comparison with polynomials, splines have less intensive oscillations. Besides, they are continuous (the values in knots are the same) and twice differentiable. These facts mean that splines do not have acute angles (due to the 1st derivative) and its curvature may be defined for every point (due to the 2nd derivative) which allows to estimate the intensity of oscillations for every IMF. But the most important of all is the minimization of oscillation behaviour. It means that among the diversity of continuous and twice differentiable functions \( f(k) \) on the interval \([a; b]\) which interpolate the set of points \( \{(x_i, y_i)\}_{i=1}^{N} \), cubic spline is the least oscillating. This property may be written as

\[
\int_{a}^{b} (S''(x))^2 dx \leq \int_{a}^{b} (f''(x))^2 dx,
\]

provided that \( S'(a) = f'(a), S'(b) = f'(b) \), where \( S(x) \) is a cubic spline, \( f(x) \)—an arbitrary twice oscillating function. This condition is written for continuous-time functions but it is also valid for continuous functions which are defined on the discrete set of samples. The same property may be established for splines of higher orders but their use is often time-consuming and does not improve the results essentially. The examples of empirical modes are shown below in Fig. 2.

**Characteristic modes** are very similar to empirical being their particular case. They always have rigorous analytic expression and hence, they are hardly ever used in practice. At the same time both conditions which were formulated for empirical modes remain valid. Such kinds of models, based on characteristic modes, may be used for approximating empirical modes what often makes further analysis easier. Some examples of characteristic modes are given below:

1. \( s_1(k) = A \cos(w_0k + \varphi) \)—harmonic signal with the parameters \( A, w_0, \varphi \).

2. \( s_2(k) = A \cos\left(w_0k + \frac{\mu k^2}{2} + \varphi\right) \)—chirp signal with the parameters \( A, w_0, \mu, \varphi \).

3. \( s_3(k) = e^{-\alpha k^2} \cos(w_0k + \varphi) \)—Gaussian impulse with the parameters \( A, w_0, \varphi \).

EMD has its so-called postulates, which were deduced from logical reasoning and some evident experimental observations:

1. An IMF, having been multiplied by a constant, still remains an IMF.

2. Changing the mean value of a signal (by centering or adding a constant) does not influence the results of decomposition, but changes only the final residual (a constant or a trend).

3. A time-reserved IMF may be extracted from a time-reserved original signal. EMD algorithm represents any signal with the finite number of samples as a set of empirical modes. At the heart of the algorithm lies the fundamental idea that at every new step (when extracting every new IMF) signal (current residual) is represented as a sum of a fast oscillating component (IMF) and a slowly oscillating one (new residual). This “new residual” is then subjected to further decomposition.

The main steps of the algorithm shown in Fig. 4, are described below.

**Step 1.** The current residual \( r_i(k) \) (\( r_1(k) \)—the 1st residual which is the original signal \( s(k) \)) is considered.

Its maxima and minima are defined and 2 sets are formed:

\[ \{M_i\}, \quad i = 1, 2, 3, \ldots; \quad \{m_i\}, \quad i = 1, 2, 3, \ldots, \]

where \( \{M_i\} \) and \( \{m_i\} \) are the sets of local maxima and minima, respectively.

If there are no extrema in the current residual, numerical differentiation may be used in order to obtain at least one. In this case, when the algorithm is termi-
nated return to the original set of values must be made.
In general, it is possible to consider zero-crossings \( \{Z_i\} \)
instead of extrema so that all the envelopes were con-
structed on them:

\[
\{Z_i\}, \quad i = 1, 2, 3\ldots
\]

Afterwards two envelopes are constructed with the use of cubic spline interpolation:

\[
U_j(k) = f_U(M_j, k), \quad L_j(k) = f_L(m_j, k),
\]

where \(U_j(k)\) and \(L_j(k)\)—upper and lower envelopes, which interpolate local maxima and local minima; respectively, \(j\) is the iteration number of the sifting pro-
cess which will be discussed below.

It is necessary to mention that the constructed enve-
lopes should encompass all the values of the current

\[
\text{residual, that is, every sample must satisfy the follow-

\[
L_j(k) \leq r_p(k) \leq U_j(k), \quad \forall k
\]

However in some cases the phenomena known as
“overshoots” and “undershoots” may cause strong
oscillations at the ends (end effects). In order to reduce
them several methods have been employed: mirroring
extrema which are the closest to the boundary samples,
zero-padding and others.

After that the half-sum of two envelopes is defined
(the time-dependent local mean value):

\[
e_j(k) = \frac{U_j(k) + L_j(k)}{2}
\]

Then transition to a Step 2 is made.

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**Fig. 3.** Representation of signal (a) as a sum of low-frequency, slowly oscillating component (b) and high-frequency, rapidly oscil-
lating one (c).

**Fig. 4.** Illustration of the main steps of EMD algorithm (EMD flowchart).
Step 2. The local mean which was found at step 1 is subtracted from the current residual and the result \( h_j(k) \) is a "candidate" on being an IMF:

\[
h_1(k) = r_p(k), \]
\[
h_2(k) = h_1(k) - e_1(k), \]
\[
h_{j-1}(k) = h_j(k) - e_j(k), \]

where \( p \) — the number of extracted IMF.

Then two necessary conditions of referring a function to the class of empirical modes must be checked. If they are both true, we move to step 3. Otherwise, we move to step 1 replacing the current residual for that obtained at step 2. Thus, the sifting process begins which may be written in the following way:

\[
h_1(k) = r_p(k), \]
\[
h_2(k) = h_1(k) - e_1(k), \]
\[
h_{j-1}(k) = h_j(k) - e_j(k), \]

where \( e_j(k) \) — mean value of the function obtained at the \( j \)-th iteration of sifting, \( h_j(k) \) — current residual at \( j \)-th iteration of sifting.

Iteration with the number \( \text{iter} \) is the last one and it is followed by step 3.

Step 3. As soon as an IMF has been obtained it is subtracted from the current residual and the new residual is formed:

\[
r_{p+1}(k) = r_p(k) - c_p(k), \]

where \( c_p(k) \) — extracted IMF, \( r_p(k) \) — current residual, \( r_{p+1}(k) \) — new residual.

Step 4. Then transition to step 1 is made and further extraction is continued from the new residual \( r_{p+1}(k) \).

The main steps of the algorithm require some commentaries. So far, it does not have rigorous theoretical base like Fourier analysis or wavelet technology. According to the name of the algorithm it has empirical nature. EMD is a non-parametric approach as the model of a signal (the set of IMFs) is obtained adaptively by extracting IMFs from the original signal step by step without imposing any restrictions (for example, like in Fourier analysis where a signal is fitted by harmonic series). There is no proof of EMD convergence for an arbitrary kind of interpolation. But this convergence may be explained by logical reasoning and the underlying ideas of the algorithm. At each step the local mean is calculated and subtracted from the current residual. As a result, the final residual is the monotonous trend component which does not have enough extrema points for further decomposition. Besides, it is also possible to put a limit on the number of the extracted IMFs. It may be done by using special information criteria (Akaike, Rissanen, etc.). They are intended to search optimal model order which gives extremum (either maximum or minimum depending on the particular criterion). This criterion usually has two terms: the first term increases with the increase of the model order and the second, vice versa, decreases. In our task the model order will be the number of IMFs in decomposition and the error will be the certain function calculated as the difference between the original signal and the sum of the selected number of IMFs. Such approach is directed to preserve the most informative components which refer to a signal and exclude those ones which represent noise. The majority of the existing information criteria may be written in the following way:

\[
F(p, D) = N \ln D + f(q, N),
\]

where \( N \) — the number of samples, \( q \) — the model order (the number of IMFs), \( D \) — the variance of the error between the signal and the sum of the selected number of IMFs \( q \). The most widely used criteria are

\[
\text{ICA}(p, D) = N \ln D + 2q
\]

Akaike criterion, where \( f(q, N) = f(q) = 2q \), and

\[
\text{MDL}(p, D) = N \ln D + q \ln N
\]

Rissanen criterion (MDL-criterion, Minimum Description Length criterion) where \( f(q, N) = q \ln N \).

When searching the optimal number of IMFs it is reasonable to start from those which have the biggest numbers (the most low-frequency ones) and travel to those with small numbers (the most high-frequency ones) which have low signal-to-noise ratio.

On the basis of the practical results, an empirical formula was found for estimating the total number of IMFs in the decomposition of an arbitrary signal:

\[
M = \log_2 N \pm 1,
\]

where \( M \) — total number of IMFs, \( N \) — total number of signal samples.

The key role in the algorithm is played by sifting process, which has the iterative nature and is directed to extract an IMF until two necessary conditions mentioned above are satisfied. Its purpose is to avoid riding waves and to make both envelopes more symmetric. Sifting can require a big number of iterations, so the special criteria must be developed in order to organize its termination. Some of them are listed below:

— Sifting process for an IMF stops if the following normalized squared difference is bounded in the interval \([0.2; 0.3]\):

\[
SD = \sum_{k=1}^{N} \frac{[h_j(k) - h_{j-1}(k)]^2}{h_{j-1}(k) + \mu},
\]

where \( j \) and \( j-1 \) — two consecutive sifting iterations; \( h_j(k) \) and \( h_{j-1}(k) \) — values of the empirical function at two consecutive sifting iterations, \( \mu \) — small value (usually \( \mu = 0.00001 \)), which prevents the denominator.
from being equal to zero. The interval for SD was suggested in [7–9]. In general these values can be changed. The most important drawback of this criterion is that it does not submit to the definition of an IMF. Hence, it may happen that the result of sifting will be a non-IMF because of the contradictions with the definition. However, in most cases the final result is a true IMF.

—Sifting process for an IMF stops if the number of extrema and zero-crossings on two consecutive iterations are the same and they are either equal or differ at most by one. If it happens that that the half-sum of two envelopes exceeds the threshold value $\eta$ (the 2nd property of an IMF) the number of iterations may be increased.

When the algorithm is finished the original signal may be reconstructed by using the extracted IMFs. Two formulae are employed for this:

$$s(k) = \sum_{i=1}^{M-1} c_i(k) + r_M(k)$$

for involving all the obtained IMFs (both high- and low-frequency), and

$$s(k) = \sum_{i \in I} c_i(k) + r_M(k)$$

for excluding some IMFs, for example, by information criteria. In this case the upper boundary in the sum is not indicated and the summation index belongs to the so-called index set which is arranged in compliance with the IMFs involved in the sum.

As a result of EMD, a signal is displayed as a set of low and high-frequency components with amplitude and frequency modulations. The received set of IMFs can be also interpreted as a dyadic filter bank [18], which contains filters with overlapping on a frequency band. This collection of filters, once found for one signal, may be stored and subsequently applied to other signals, which refer to the same class according to some criterion. It essentially reduces the amount of time, needed for EMD, therefore it is expected to be a great advantage. The spectral structure of IMFs is marked by several features:

—With the increase of an IMF number the width of its frequency band in Fourier amplitude spectrum decreases which is caused by dynamical reduction of the oscillations number and consequently the average frequency. The least oscillating modes are among the initial ones because of slow signal-to-noise ratio, whereas, the last modes are almost ideally smooth (they represent non-oscillating trend components) as their average frequency gradually tends to zero.

—The total number of extrema and zero-crossings monotonically decreases with the increase in number of IMFs. This circumstance, mainly explained by numerous experimental results obtained on telemetric signals, guarantees the convergence of the algorithm in general.

Furthermore, extrema indicate the degree of regularity. The more extrema are located in a signal the less regular it is. Hence, initial levels are the least regular whereas the last ones are considered to be the most regular. And this observation is valid for any signal.

Finally, this decomposition may be interpreted in terms of multiresolution analysis (similar to wavelet technology) which intends to represent the signal on various scales - from the most coarse to the most fine. Decomposition procedure is characterized by minimal losses of information and an opportunity to understand better the nature of the processes and the components involved.

In the conclusion of this section, it is necessary to say that EMD is often considered not as a separate technique but as a part of Hilbert-Huang technology. This technology consists of two main steps: EMD and Hilbert-Huang transform. EMD is intended to obtain the fundamental components of a signal in terms of IMFs’ properties, and Hilbert-Huang transform uses this information (the IMFs), which was obtained at the first step, in order to construct the distribution in time-frequency domain. As a result, final "amplitude-time-frequency" distribution is obtained which is also called Hilbert spectrum. These two steps, when applied together, allow to acquire new and usually hidden knowledge about the original signal.

EMD SURVIVED INTERVALS SEGMENTATION OF SLOWLY CHANGING TELEMETRIC SIGNALS

In order to get the collection of approximations of a signal with the properties described above, it is recommended to use one of the modifications of classical (global) EMD algorithm—local EMD [14]. This type of decomposition has many advantages in comparison with others, the most essential of which is the improvement of the local properties of IMFs, considered as approximations of a signal. Another advantage is that for some signals it is much more reasonable. Nevertheless, some problems still exist. Mainly they are connected with a big amount of time for the algorithm performance. Initial IMFs always have maximum number and intensity of oscillations, which gradually increases with the increase of the IMF’s number. Such approach is suitable for both slowly changing processes, consisting of monotonously increasing and decreasing fragments (pieces) and fast changing ones which usually have a large number of oscillations in the signal’s set. But for the latter the results are a bit less exact than that obtained by the second algorithm.

EMD is capable of working with both extrema and zero-crossings therefore, it is necessary at first to make the choice, which will affect the final results. All the following formulae and algorithms in the paper are introduced, as if we are working with signal’s extrema.
This is more effective when segmentation is fulfilled on slowly changing processes.

The idea of segmentation procedure is the following. For each decomposition level (each IMF) we determine the boundaries (two successive extrema) where the function’s properties remain the same concerning their monotonous behavior. Each interval on its native level a priori has a life time, equal to 1 (because it will definitely survive on the native level), whereas the whole level has a life time, equal to the total number of the discovered monotonous intervals:

\[ T_{\text{min}} = N_i, \]

where \( T_{\text{min}} \)—the minimum life time of a level, \( N_i \)—the total number of monotonous intervals on the \( i \)-th level. As it follows from the brief description, EMD is very convenient for such signals, as it works with maxima and minima, some of which will become the boundaries of segments.

Then each interval is checked on saving its properties on the next level. Several different cases may occur:

1. The interval survives—that is, the function’s (the 6 IMF’s) behaviour on the next level between the boundaries of the examined interval is quite the same as that on the previous level (either monotonous increasing or monotonous decreasing):

\[ T_{\text{min}} = N_i, \]

This case is reduced to two possible situations, depending on the sequence of monotonously increasing and decreasing fragments.

2. The interval does not survive—that is, monotonous properties on the next level are quite opposite to those on the previous one (increasing is opposed to decreasing or vice versa).

In Fig. 5 there are two typical examples, when the upper intervals (in each part) survive, that is, the monotonous properties remain absolutely the same, even though the functions themselves are quite different. On the left the functions’ behavior is increasing, whereas on the right it is, vice versa, decreasing, but it is absolutely the same for both intervals. Hence, we increase the life times of both upper intervals by 1.

In Fig. 6 the situation is quite the opposite. The upper intervals properties do not remain the same as the lower function’s monotonicity changes once in the left part, generating an extremum, and it absolutely differs in the right part (increasing contradicts to decreasing). Thus, none of these two cases refer to the group of survived intervals, both upper intervals are non-survived.

If the particular interval survives, its life time is immediately increased by 1. Such procedure, as described above, is run for all intervals of each level in order to estimate all the life times. The life time of the total level is the sum of life times of all its intervals and it is bounded by the following values:

\[ T_i = \sum_{k=1}^{q_i} v_k + \sum_{j=1}^{q_{i+1}} w_j, \]

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\[ T_i = \sum_{k=1}^{q_i} v_k + \sum_{j=1}^{q_{i+1}} w_j, \]
where $q_i$, $q_{i+1}$—the number of survived intervals on $i$-th and $i+1$-th level. $v_i$ and $w_i$ denote the survived intervals on each of these 2 successive levels. Obviously

$$N_i \leq T_i \leq 2N_i,$$

where $N_i$ and $N_{i+1}$—the total number of monotonous intervals on the $i$-th and $i+1$-th levels. Left bound corresponds to the case, when neither of the founded intervals survive on the next level, while right bound—when all the founded intervals survive on the next level (which is practically unreal).

Finding monotonous intervals for every level (for every IMF) allows to get different alternatives of segmentation of the original signal. However, the main requirement to the division is considered to be its steadiness, which is defined as the total number of survived intervals on the level. In the meantime, using this value as the final decision criterion is not reasonable because in this case the survival of one of the first 2–3 levels will become inevitable (the total number of intervals at these levels dominates substantially over that at the lower levels). This fact is explained by the feature of decomposition, which states that the number of extrema monotonously decreases with the increase of the IMF’s number, dominating on initial levels (usually first 3 levels) [7–12, 16]. Therefore we introduce the so-called average life time of the level’s intervals, calculated according to the formula:

$$T_i = \frac{\text{Int}_i}{N_i},$$

where $\text{Int}_i$—the accumulated life time of all intervals of the $i$-th level.

Finally, the level (set of segments) is considered to be survived, if it has the biggest average life time of all its intervals. The boundaries of segments are depicted by vertical lines (Fig. 7–11).

The alternative criterion of the best division choice also uses the idea of survived intervals. The difference is that the travel is made from initial to final IMFs, while the average life time of the next level exceeds the same value for the previous one. If this condition is violated then termination is made and the best level (best IMF) is selected.

The example of segmentation is shown in Fig. 7. The segments which are extracted preserve monotonous properties concerning the global trend. The segments extracted are the so-called patterns, which have certain statistical, energetic and other characteristics. For slowly changing signals only some of them are informative. Among them are energy, optimal order of approximating polynomial. As an example, energy is chosen as the most informative characteristic for segments’ description and subsequent clustering.

However, because of the end effects of splines, nuisance noise, trend, misses and outliers the real boundaries may sometimes shift from their true location. That is why initial processing is needed, and the final specification of the boundaries should also be done (by cluster-analysis, discriminate functions). For the sake of specifying these boundaries the special criterion is offered. It consists in boundaries replacing so that the sum of the ranges of two successive segments was maximum:

$$\text{Range}_{\{\text{segment}(i-1)\}} + \text{Range}_{\{\text{segment}(i)\}} \rightarrow \max, \ i \geq 2,$$

where

$$\text{Range}_{\{\text{segment}(i)\}} = |\max\{\text{segment}(i)\} - \min\{\text{segment}(i)\}|.$$

This criterion guarantees that the results of segmentation will improve, that is, the location of the boundaries will be more exact in accordance with their monotonous properties. The result of the criterion application is demonstrated in Fig. 8.

Before showing another example, it is necessary to expound some features of the algorithm which may be
noticed from the previous example. The algorithm's tendency is to proclaim the level with the lowest average frequency (that is, an IMF with a large number) as the survived one. This may be shown from segmentation of multi-harmonic signals when the boundaries are defined on the basis of the least low-frequency component. However, this tendency should not be taken for granted but checked for every particular signal. In addition, the algorithm is very perspective for segmenting signals with different monotonicity—so far, there are no restrictions on its type. Although denoising is required before segmentation, in many cases noise does not affect the outcome of the algorithm. What is needed is boundary specification by means of using some criterion like the one introduced in this paper.

In the beginning, it was indicated that this algorithm is also capable of extracting the so-called patterns which are typical for the particular signal. One example which confirms this statement is shown below. Three harmonics were taken, combined with each other, and the final signal was obtained. The signal and the result of its segmentation are shown below in one figure. There are the typical patterns there which were precisely extracted.

### CLUSTERING

Clustering algorithms are directed to join those segments, which refer to the same class according to some criteria, metrics and initial parameters (if they are required). In other words, we look forward to uniting the similar segments, which may occur in different parts of entire signal. Clustering algorithms may be divided into three big groups:
(1) Algorithms, which use initial parameters and unchangeable number of the finally generated clusters (this number cannot be changed during the algorithm’s performance). Such algorithms as $k$-means, EM, FarthestFirst, CobWeb, Fuzzy $k$-means refer to this vast group. However, they are not very flexible in processing real signals, as the number of clusters often needs to be thoroughly tuned depending on signal’s features. Furthermore, sometimes it is considered to be difficult even to predict the exact number of clusters, necessary for obtaining relevant results. But sometimes, despite all this drawbacks, they may be very efficient, when the number of clusters may be estimated after the visual analysis of the signal. In this case, they work much quicker than all the rest ones.

(2) Algorithms, which work completely automatically or almost automatically with starting initialization (Adaptive Subclasses Selection, EM with cross validation, etc.). Usually they do not require the exact number of clusters and the number of elements in each cluster. As a rule, these quantities are either limited from the top or are confined to a particular range. This group is the most feasible for clustering non-stationary signals.

(3) The last group involves the first two groups, but, unlike them, it uses special performance criteria which make the results far better. These criteria are, for example, minimum of intraclass variance, maximum of intercluster distance and etc. They are also rather spread in various clustering and segmentation applications.

Here an attempt is made to cluster the segments from Fig. 8 with the use of the first group of algorithms, namely, Fuzzy $k$-means algorithm. Before clustering it is necessary to define the characteristics which are calculated or estimated in order to describe each segment. Thus, the set of characteristics will be formed and sub-
sequently used by clustering algorithm. Here, segments will be described in terms of polynomial coefficients. The maximum degree is taken 1 (linear function) since it is feasible for representing monotonicity of the segments. Among the two coefficients the free term is ignored as it is scale-dependent (it depends on the magnitude). So, only one coefficient will be considered: the one at the first-degree term. Finally, the signal will be represented in piecewise-linear form thus, demonstrating the capability of the algorithm to fulfill piecewise-linear segmentation.

The number of clusters is chosen to be 4, and, in the end, we will have the probability membership of each segment to each cluster. It is rather natural here because it becomes possible to compare the probability of belonging to each class and find the most credible case. Besides, the results helps better understand the links which exist among segments.

The results from the table (in bold) show that three segments (the 3rd, 5th and 7th) are most likely to belong to the 1st cluster, two segments (the 4th and 6th)—to the 4th cluster, one segment (the 1st)—to the 2nd cluster and one segment (the 2nd)—to the 3rd cluster. Also on the basis of the table it is possible to estimate the membership of each segment to each cluster.

**EMD APPROXIMATION ERROR SEGMENTATION OF FAST CHANGING TELEMETRIC SIGNALS**

The second approach is based on calculating an error which results from approximating a signal by an IMF which has been found to be the most informative. This method is more adjusted to fast changing signals as it uses the sort of smoothing methods, which fit them well due to a big number of oscillations and irregularities. Among such criteria the following are used:

1) \( \text{err}(j) = \min_{i=1, \ldots, M} \{ \| s(j) - c_i(j) \|^2 \} \),

   \( j = 1, \ldots, N \),

minimal approximation squared error of a signal by an IMF, calculated as the square of Euclidean distance between those two functions.

2) \( E_j = \sum_{j=1}^{N} c_i^2(j) \),

   energy of the \( i \)-th IMF;

3) \( D_j = \frac{1}{N} \sum_{j=1}^{N} (c_i(j) - \overline{c_i})^2 \),

   variance of the \( i \)-th IMF, which characterizes the mean square range of its values (samples) from the mean. The more \( D \) is, the more informative is the IMF itself, because, for example, constant value or slowly varying trend (final residual in decomposition) contains fewer “events” (few different values, low entropy) in comparison with the initial IMFs (many different values, high entropy). But before using this rule it is necessary to eliminate noise which should not affect the values of the variance.

The most informative IMF is supposed to have the largest variance. As far as its energy is concerned it often dominates over all the other IMFs and this IMF provides minimal approximation error.

The error of signal approximation by the chosen IMF is calculated and the set of local maxima of the error function is formed. However, almost all signals contain noise, misses and outliers which may spoil the segmentation results. Therefore, it is necessary at first to apply some kind of filtering procedure to the most informative IMF, which helps remove all irregularities.

Concerning the techniques of filtering, it is possible to use the moving average or moving median, when the samples of the filtered function are equal to the mean or median values of the neighboring points:

\[
c_i^k = \frac{1}{2n+1} \sum_{j=k-n}^{k+n} c'_i,
\]

\[
c_i^k = \text{median}\left( c_i^{k-n + \frac{n}{2}}, c_i^{k+\frac{n}{2}} \right).
\]

Also it is recommended to use overlapping with half length of the moving window. As a result, the IMF becomes represented as a piecewise-constant function. However, the main problem is the inevitable necessity of choosing the step size \( p \). The following estimate may be used for it:

\[
p = \left\lfloor \frac{N}{\log_2 N} \right\rfloor,
\]

where \( \lfloor \rfloor \) — rounding towards minus infinity.

Finally, it is possible now to calculate the approximation error of a signal by its most informative IMF after its transformation (preprocessing):

\[
\text{error}(j) = s(j) - c_i(j).
\]

Then the set of maxima of the error function should be found and subsequently used in defining the segments’ borders. As a signal was represented (approximated) by its most informative component (IMF), it is considered that the transition areas, where a new segment begins, need other IMFs for more accurate approximation, thus the error function here reaches maxima and these maxima indicate the certain segment boundaries.

So the location of the error function’s maxima corresponds to the final boundaries of segments in a signal.

The examples of segmentation are shown in Fig. 10 and Fig. 11. In comparison with the algorithm of survived intervals, in this algorithm the boundary specification is not so urgently needed. Nevertheless, there are some aspects to be thought about: overlapping value,
method of irregularities elimination and etc. The first example is a ion-stationary transition process, containing fragments with changing variance and energy. Concerning the 2nd one, it consists of pieces with various orders of autoregressive (AR) models.

For clustering Fuzzy k-means algorithm is used. The number of clusters is chosen 4 and 2, respectively. The corresponding attributes are energy, standard deviation and AR model order. For fast-changing signals in our examples they are informative because they differ from one segment to another and reflect the properties of the segments.

The results, as it is seen from the Table 2, are absolutely the same, concerning the membership of segments. No matter what the attribute is (either energy or standard deviation)—segments 1, 2, 3, 6, 7 following the probability estimates, are most likely to belong to one cluster, whereas segments 4, 5, 8 are also joined together (the second cluster). Nevertheless, probabilities still differ since the attributes have different physical sense. Both results may be used in further analysis.

### CONCLUSIONS

Data Mining techniques have now become very important in such an extensive area of science as Signal Processing. Due to a very rapid development of Data Mining implementations its use in Signal Processing has become almost indispensable. So far, segmentation and clustering are among the main tasks but at the same time they urgently need new adaptive approaches in order to analyze non-stationary signals with higher reliability.

The approaches introduced in this paper showed good results on non-stationary fast and slowly changing telemetric signals. They allow to reveal monotonous segments (for slowly changing signals), segments-patterns (for example, for multiharmonic signals) and segments with different energies, variances, entropies, AR model orders (for fast changing signals). Thus, both of them and the underlying EMD were demonstrated to be very effective and useful in processing a vast class of

### Table 1. Clustering of slowly changing telemetric signal

<table>
<thead>
<tr>
<th>Segment no.</th>
<th>1st-degree coefficient</th>
<th>1st cluster membership</th>
<th>2nd cluster membership</th>
<th>3rd cluster membership</th>
<th>4th cluster membership</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>0.0007816</td>
<td>0.1468545</td>
<td>0.8426409</td>
<td>0.0093721</td>
<td>0.0011325</td>
</tr>
<tr>
<td>2</td>
<td>-0.0001532</td>
<td>0.0008565</td>
<td>0.0017196</td>
<td>0.0970771</td>
<td>0.0003468</td>
</tr>
<tr>
<td>3</td>
<td>0.0016492</td>
<td>0.6425950</td>
<td>0.2649226</td>
<td>0.0738424</td>
<td>0.0186400</td>
</tr>
<tr>
<td>4</td>
<td>-0.0033551</td>
<td>0.0682249</td>
<td>0.0804699</td>
<td>0.1305631</td>
<td>0.7207421</td>
</tr>
<tr>
<td>5</td>
<td>0.0017972</td>
<td>0.5998190</td>
<td>0.2851356</td>
<td>0.0904263</td>
<td>0.0246191</td>
</tr>
<tr>
<td>6</td>
<td>-0.0016464</td>
<td>0.0164982</td>
<td>0.0217904</td>
<td>0.0554000</td>
<td>0.9063114</td>
</tr>
<tr>
<td>7</td>
<td>0.0011342</td>
<td>0.9399404</td>
<td>0.0527144</td>
<td>0.0062400</td>
<td>0.0011052</td>
</tr>
</tbody>
</table>

### Table 2. Clustering of the 1st fast changing telemetric process

<table>
<thead>
<tr>
<th>Segment no.</th>
<th>Energy</th>
<th>Standard Deviation</th>
<th>1st cluster membership (energy)</th>
<th>2nd cluster membership (energy)</th>
<th>1st cluster membership (st. dev.)</th>
<th>2nd cluster membership (st. dev.)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>5.3801 × 10^5</td>
<td>56.8870</td>
<td>0.9563</td>
<td>0.0437</td>
<td>0.0144</td>
<td>0.9586</td>
</tr>
<tr>
<td>2</td>
<td>3.4076 × 10^5</td>
<td>50.3804</td>
<td>0.7743</td>
<td>0.2257</td>
<td>0.0100</td>
<td>0.9900</td>
</tr>
<tr>
<td>3</td>
<td>3.3826 × 10^5</td>
<td>49.8162</td>
<td>0.7620</td>
<td>0.2380</td>
<td>0.0154</td>
<td>0.9846</td>
</tr>
<tr>
<td>4</td>
<td>1.4683 × 10^5</td>
<td>23.1263</td>
<td>0.0015</td>
<td>0.9985</td>
<td>0.9978</td>
<td>0.0022</td>
</tr>
<tr>
<td>5</td>
<td>0.9978 × 10^5</td>
<td>26.5874</td>
<td>0.0099</td>
<td>0.9901</td>
<td>0.9939</td>
<td>0.0022</td>
</tr>
<tr>
<td>6</td>
<td>4.3109 × 10^5</td>
<td>51.3973</td>
<td>0.0951</td>
<td>0.0049</td>
<td>0.0114</td>
<td>0.9886</td>
</tr>
<tr>
<td>7</td>
<td>5.3256 × 10^5</td>
<td>23.8408</td>
<td>0.0000</td>
<td>0.9604</td>
<td>0.0396</td>
<td>0.9967</td>
</tr>
<tr>
<td>8</td>
<td>1.3421 × 10^5</td>
<td>23.8408</td>
<td>0.0000</td>
<td>1.0000</td>
<td>0.995</td>
<td>0.0005</td>
</tr>
</tbody>
</table>

### Table 3. Clustering of the 2nd fast changing telemetric process

<table>
<thead>
<tr>
<th>Segment no.</th>
<th>Order of AR Model</th>
<th>Clusters (based on AR model order)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>2</td>
<td>1</td>
</tr>
<tr>
<td>2</td>
<td>5</td>
<td>2</td>
</tr>
<tr>
<td>3</td>
<td>2</td>
<td>1</td>
</tr>
<tr>
<td>4</td>
<td>5</td>
<td>2</td>
</tr>
</tbody>
</table>
telemetric signals. Another advantage is that the partition (segmentation) is done completely automatically and the extracted segments are further analyzed with the use of clustering algorithms. Segmentation combined with clustering is intended to find new similarities, regularities and patterns in the original signal and reduce the time in comparison with the direct and exhausting analysis of pure signal samples (for example, by statistics).

The further research of the authors, who have already been working on EMD and EMD-connected tasks for more than 3 years, will be connected with other applications of EMD. The latter may be divided into two big groups:

1. EMD in preprocessing—denoising, detrending, time-frequency analysis, regularity analysis, signals' extension, etc.)

2. EMD in intellectual analysis—on the basis of Hilbert-Huang spectrum which is constructed as a part of Hilbert-Huang technology.

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REFERENCES


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Nikolay Oreshko—the graduate of Kharkov State University (Kharkov, Ukraine, 1972) of Mathematics Department. In 1980 he defended his PhD thesis and is currently working in Research and Scientific Center of Saint-Petersburg State Electrotechnical University (St.-Petersburg, Russia). His scientific work and deep interest has always been connected with Wavelet technology and Statistics. He has significantly developed several applications of Wavelets, including Denoising techniques, multiresolution and multiband analysis. Several new approaches developed by him and his coworkers have contributed to signal processing. He also delivered lectures on Time Series Processing at Kharkov State University. Since the beginning of a very rapid development of time-frequency analysis he has been dedicating a lot of time to its applications. He employed time-frequency distributions and EMD in order to solve some very important tasks in processing telemetric signals. So far, he has taken part in a number of international conferences and workshops including OGRW-2007 (Ettlingen, Germany, 2007), PRIA-2007 (Yoshkar-Ola, Russia, 2007), DSPA-2007 (Moscow, Russia, 2006, 2007). Also, he has submitted several papers to international and home editions (journals Pattern Recognition and Image Analysis, Digital Signal Processing). The outlook for the future is further investigation and development of wavelet technology, time-frequency distributions, time series processing. Much attention is expected to be paid to Data Mining techniques in processing telemetric signals.

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