[Mansoura Engineering Journal](https://mej.researchcommons.org/journal)

Volume 16 | Issue 2 Article 3

8-8-2021

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Recommended Citation

Abou-Chadi, Fatma (2021) "The Importance of Phase in Biological Signals.," *Mansoura Engineering Journal*: Vol. 16 : Iss. 2 , Article 3.
Available at: https://doi.org/10.21608/bfemu.2021.187943

THE IMPORTANCE OF PHASE IN BIOLOGICAL SIGNALS

أهمية طيف الطور فى الاشارات الحيوية

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الخلاصة – يهدف هذا البحث الى توضيح الدور الهام الذى يلعبه طيف الطور فى مجال الاشارات الحيوية . ويبدأ بعرض بعض التقنيات الخاصة بالمعالجة المبدئية لطيف الطور قبل تحليله ودراسته . ثم يعرض عدة تطبيقات توضح كيفية استخدام المتغيرات الاحصائية لطيف الطور فى تحليل بعض الاشارات الفسيولوجية والتسجيلات الوبائية واستخلاص خصائصها .

ABSTRACT- In this paper, the importance of phase in the context of biological signals is highlightened. Techniques for manipulating the phase spectral values prior to its use are illustrated and several approaches to exploit the role of phase statistics in biological signal analysis and feature extraction are discussed.

I. INTRODUCTION

In Fourier representation of signals, spectral magnitude and phase tend to play different roles and in some situations, many of the important features of a signal are preserved if only the phase is retained. A corresponding statement can not in general be made for the spectral magnitude (Oppenheim and Lim, 1981). This observation about phase has been made in a number of different contexts and applications including one-dimensional, two-dimensional and three-dimensional signals. In speech, for instance, it has been shown that the intelligibility of a sentence is retained if the phase of the Fourier transform of a long segment is combined with unity magnitude (Rabiner and Schafer, 1978). It has been reported by Hayes and Oppenhiem, (1980) that many of the features of an original image are clearly identifiable in the phase-only image reconstructed but not in the magnitude-only image. This suggests very strongly the fact that in many contexts the phase contains much of the essential "information " in a signal.

The present paper brings emphasis to the role that phase plays in the context of biological signals: physiological and epidemiological records. Section II demonstrates some techniques for manipulating the raw phase spectral values prior to its use. The importance of phase in pattern detection has a number of important implications with regard to applications. In section III, we review some techniques that have been developed and utilized and we consider some specific applications.

II. PHASE SPECTRAL MANIPULATIONS

The complex Fourier spectrum X(f) of a real signal x(t) is defined as

$$X(f) = \int_{-\infty}^{\infty} x(t)\, \exp(-j2\pi ft)\, dt \qquad (1)$$

where x(t) can be given by

$$x(t) = \frac{1}{2\pi} \int_{-\infty}^{\infty} X(f)\, \exp(j2\pi ft)\, df \qquad (2)$$

In the general case, we deal with waveforms of finite duration, hence

$$x(t) = x(t) \qquad t_1 \leq t \leq t_2 \qquad (3)$$
$$= 0 \qquad \text{elsewhere}$$

In this case the integration in Eq.(1) is limited to the closed interval $[t_1, t_2]$.

The frequency component (harmonic) X(f) is a complex quantity with real and imaginary parts denoted by R(f) and I(f), respectively. X(f) has an amplitude A(f) and phase $\phi(f)$ defined by

$$A(f) = \sqrt{R^2(f) + I^2(f)} \qquad (4)$$

$$\phi(f) = \arctg \left\{ \frac{I(f)}{R(f)} \right\} \qquad (5)$$

In practice x(t) is sampled at an appropriate sampling frequency and the discrete Fourier transform is calculated with the help of the Fast Fourier Transform (FFT) algorithm.

The phase spectrum calculated by Eq.(5) can be considered as contributed by two additive factors: the phase effect due specifically to the shape of the waveform, and those due to the fact that the signal is generally displaced away from its most nearly symmetrical position with respect to zero time in the record. In frequency domain terms, the signal is treated as if it repeats on a time-base equal to the chosen record length; the phase spectrum after "spinning" on its time base to its most symmetrical position is treated as that contributed to the waveform alone. But since in general the main pattern features of a signal exhibit an arbitrary displacement from their temporally most-symmetrical position, this adds a phase shift proportional to the relevant time delay and to harmonic number. The resulting phase angle may then be subject to complication by "wrap-around" into the principle angle range.

II.1 The Wrap-Around Effect

Although the phase components calculated from Eq.(5) can have values in the range $(-\infty, \infty)$, the values of $\phi(f)$ are all mapped in the region $[-\pi,\pi]$. This is due to the periodic character of the arctg function. In fact, $\phi(f)$ should therefore be written as

$$\phi(f) = \text{arctg}\left[\frac{I(f)}{R(f)}\right] + 2k\pi, \quad k = \ldots,-2,-1,0,1,2,\ldots \tag{6}$$

This is known as the wrap-around effect.

The effect of wrap-around can be eliminated by an unfolding (unwrapping) procedure. This can be made by adding or subtracting multiples of 2π to the phase values at appropriate frequencies in order to make all the differences of two consecutive phase spectral values less than π. The removal of the folds in the phase spectrum reveals any trend which may be present. This represents the displacement of the main signal features from their temporally most-symmetrical position. The gradient of the trend is proportional to the relevant time delay and to the harmonic number. It may be positive or negatibve depending on whether the signal is advanced forward or delayed after the onset time. Therefore, the unwrapping procedure must be followed by a linear regression and a trend removal. The whole process is known as "Regression Spinning" (Sutton, 1980).

II.2 Removing The Trend

A least-square error line is fitted to the phase spectrum and the calculated trend is removed -the phase spectrum will then have no increments greater than $\pm\pi$ radians, and no overall trend. Using this method, specially on complex signals, it is often found that the unfolded and trend-removed phase spectrum exhibits phase increments greater than $\pm\pi$ radians, and the reconstructed signal is evidently not centered. The folds produced by the removal of best-fit line occur at points where the signal power is low. At these points, sudden 'jumps' occur in the phase spectrum (Sayers, 1974). Regression spinning surmounts this problem by removing these secondary folds by unfolding the phase spectrum once more, and then removing any further trend that emerges. The resultant phase spectrum can now be considered as that contributed by the the signal pattern features alone and can be utilized for different purposes. Fig.1 shows a typical example of unfolded spun phase spectrum of an arbitrary signal.

III. APPLICATIONS

III.1 Pattern Detection

The existence of any systematic pattern, underlying an ensemble of records is problematical. Some basis for comparison is needed: for instance, by testing the records in question against otherwise similar records that certainly do not contain the pattern. The most objective approach is one that depends upon the proprerties of the phase spectrum of the signal.

An ensemble of random signals will exhibit uniformly random phase spectra for each harmonic and, subject to statistical sampling effects, this can be used for testing purposes, because the presence in all signals of a common pattern imposes a measure of phase aggregation in relevant harmonics. Moreover, if a visibly discernable pattern is present in a record, then the incremental phase spectrum (between successive harmonics) is magnitude-limited, and this also may be usable(Sayers et al., 1974).

III.1.a. Using Phase Aggregation

If the same response pattern was present in each of an ensemble of records, some aggregation should occur in the distribution of the phase-spectral values for individual relevant harmonics as depicted in Fig.2. In the absence of any consistent patterns, a uniform distribution of the ensemble of phases would be expected for each harmonic (Sayers et al., 1974). This method has proved to be of some value in different physiological records where it is required to detect the response of a stimulus. For example, Sayers et al., (1979) and Beagley et al. (1979) have applied this technique to the detection of auditory evoked potentials in the electroencephalography (EEG). Pattern aspects of individual post-stimulus responses were examined by the ensemble distribution of phase values of Fourier spectral components employed to characterize signal pattern. The individual harmonic phase values were distributed approximately uniform for unstimulated EEG, but were demonstrated to be increasingly aggregated for increasingly suprathreshold stimuli. It is approved that a fully objective audiometric technique can be based on this method and that the presence or absence of an auditory-evoked potential (AEP) can be decided without the intervention of the tester, thereby removing the tester bias.

III.1.b Using Ensemble Standard Deviation of Phase

One of the most efficient techniques based on statistical pattern analysis has been developed for measuring hearing threshold (Ross, A. J. 1978). The technique uses the phase standard deviation of harmonic components as a measure of consistent pattern content occurring throughout an ensemble of records. It involves a conventional non-parametric statistical test to decide whether the distribution of phase values for individual harmonic components of a number of post-stimulus EEG records is uniform. If the phase ensemble of a harmonic component exhibits aggregation, the ensemble standard deviation value should be significantly small compared to that of a uniformly distributed ensemble. On the other hand, in the case of no constraint, a large ensemble standard deviation value (about $\pi/3$) is expected (Section III.3).

III.2. Decomposition and Disaggregation

Linear decomposition of a signal into its components can sometimes be done by linear filtering. More often, it is necessary to identify empirically any common or recurrent features and then to isolate them, using knowledge about the identified feature and about its occurrence locations. Disaggregation is a term from statistical epidemiology; it means the operation of splitting a record into known contributory parts, for instance according to the geographical regions from which data is obtained, or by separating the contributions by time (seasonally, say) for separate study. The approach can be illuminating by examining specific signals in which the inspection of the spectral phase values is very useful to this end.

A number of authors have used the phase aggregation concept in order to identify the presence of a common pattern or a standard form in an ensemble of records; epidemiological and physiological (Sayers et al., 1982 and Sayers et al., 1983). This may help in establising a reference representative pattern for the common behavior of the records.

Fig.3 shows an ensemble of postneonatal daily death records due to gastrointestinal causes in Dakahlia governorate over years 1981-1987. The records exhibit long-term (seasonal) variations. Moreover, irregular recurrent short-duration increases in the number of deaths which might be 'noise' or might be due to possible biological origin can be observed. Therefore, each record can be regarded as composed of a long-term seasonal component added to high frequency irregular component. A convenient approach is to separate these components using filtering operations. Accordingly, some basis for choosing the extent of filtering should be sought. It has been reported by Abou-Chadi et al.,(1990) that the record phase spectra have shown a clear phase aggregation in harmonic components (H_1 to H_6) (Fig.4). This indicated the existence of a common pattern in the ensemble of records. This common pattern reflects the seasonal behaviour and was isolated from each record for further investigation (Fig.5).

The same procedure has been also applied to 24-hour adult heart-rate and ambulatory intra-arterial blood-pressure records (Sayers et al.,1982 and 1983). It has been reported that records do exhibit two well known features: very large variability superimposed on a crudely circadian pattern. The circadian pattern reflects the fact that the heart-rate and mean blood pressure seems to drop at night during rest, rising again in the morning; the patterns of rise and fall are rather variable being linked to the sleeping cycle of the subject. The existence of the common circadian pattern is reflected on the phase values of the original records in the form of aggregation in the relevant harmonics. This leads, in turn, to identifying the contributing components to the circadian pattern and thereby its isolation.

However, in the analysis of 24-hour heart-rate in neonates (Abou-Chadi, 1986), the distribution of the phase spectral values for the relevant harmonics have been found to be bimodal (Fig.6). This has been considered as an indication that the common long-term pattern in the neonatal heart-rate signal lies in more than one standard form and that each mode is certainly related to some main features. These results have led to classifying the long-term behavior into three distinct forms. This has been achieved by comparing the phase values of the different records and relate them to the nearest modal values. (Here the term circadian is not valid due to the different sleeping and waking times in neonates).

III.3 Validation of The Occurrence of a Recurrent Pattern

. If a recurrent pattern can be observed as the major component in a signal , it may be possible to establish whether it is a pattern due to some underlying mechanism or it is only fluctuation that can be interpreted as an unwanted "noise" or "oscillation". An example is the residual signal that rewmains after removing the long-term pattern from biological variables, Fig.7 shows the residual signal for postneonatal death records and that of the neonatal heart-rate records. The signal shows short-term recurrences of rise and fall, and therefore, it is important to determine the entity of these transient recurrences.

The phase spectral analysis has been efficiently applied to examine the validation of the occurrence of these transient recurrences as an explicit entity. This has been achieved by reconstructing the residual signal using the original amplitude spectrum of the signal and arandomized phase spectrum derived from uniformly phase values ($-\pi$, $+\pi$). the reconstructed signal is shown in Fig.8 obtained by the present author in a previous work. Comparing the original and resynthesed signals, we see clearly that the signal main features have been altered. This has been proved by comparing the statistical parameters for the transient occurrences (e.g. shape of the average transient pattern, amplitude and inter-event intervals).

III.4. Estimating the Bandwidth of a Signal

In establishing the specification for the instrumental measurement of say, electrocardiographic (ECG) waveforms, it is necessary to determine the signal bandwidth. This cannot be based on observations of the amplitude or power spectrum without a priori estimate of the required answer; it is not warranted to infer the result merely by specifying the highest frequency exhibiting significant power. However, an approach can be made using the statistical variability of the waveform phase spectra.

In order to select individual waveforms of ECG from a continuous record, the starting point of each wave must be identified. This is invariably subject to uncertainty resulting in the addition of a random latency to each waveform. This effect adds a phase shift, proportional to harmonic number and to latency value, into the phase spectrum of the waveform. In the complete ensemble, this effect contributes an ensemble standard deviation of phase which is proportional to frequency, at least for spectral components that are coherently linked to the cardiac beat. For spectral components that are not time-linked in this way, and so not part of the ECG signal, the effect of fluctuating latency amongst the different beats in the ensemble is to contribute random phase shifts that result in total phase values that are uniformly distributed across the available range of phases. The ensemble standard deviation of a random variable which is uniformly distributed over the range from -180 to +180 is calculable to be 103.9^{o} (Bendat and Jansen, 1971).

Therefore, the curve of ensemble standard deviation of phase as a function of frequency rises linearly at low frequencies. It fluctuates around a constant value (which approximates 104^{0} for large ensemble sizes) for spectral components that are not time-locked to the ECG beat (Fig.9). It is easy to set a suitable upper limit to the signal-linked spectrum for such an ensemble, and thus to identify the effective bandwidth specification for the signal (Rompelman et al., 1982 and Abou-Chadi et al., 1990).

IV. CONCLUSION

Some applications of the use of phase spectral values in the context of biological signals have been presented. They are illustrative of ways in which the importance of phase can be exploited. They serve to demonstrate and assert that in a number of contexts the Fourier transform phase contains more "important" information than the Fourier transform magnitude. Similar conclusions have been drawn in speech and image signals, optical holography and X-ray crystallography (Oppenhiem and Lim, 1981).

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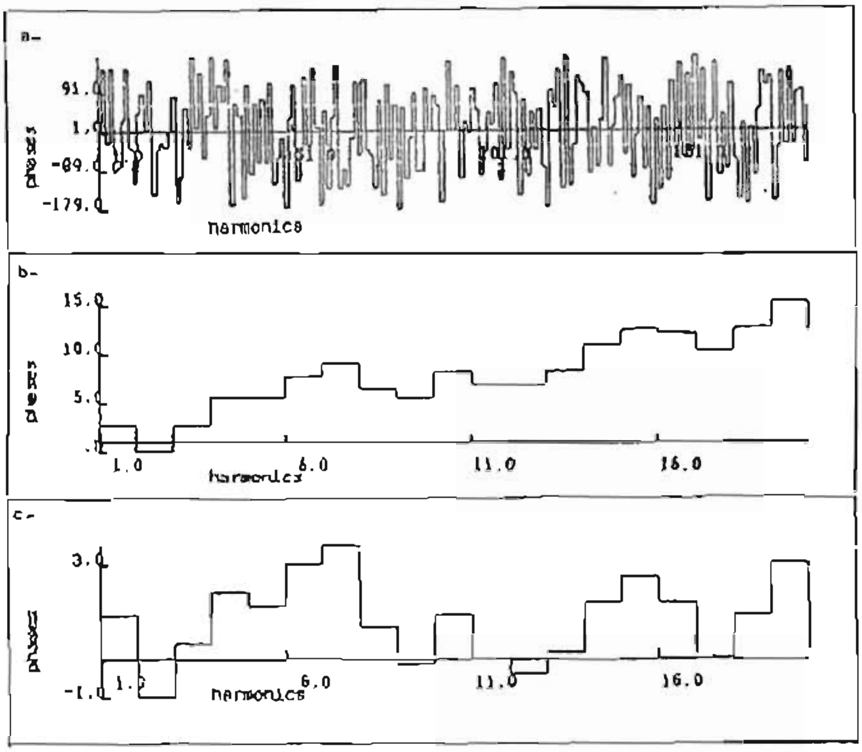

Fig.1 An example of phase spectrum of an arbitrary signal
a- Phase values calculated from the arctg function
b- Unfolded phase values
c- Phase values spun to the signal most-symmetrical position.

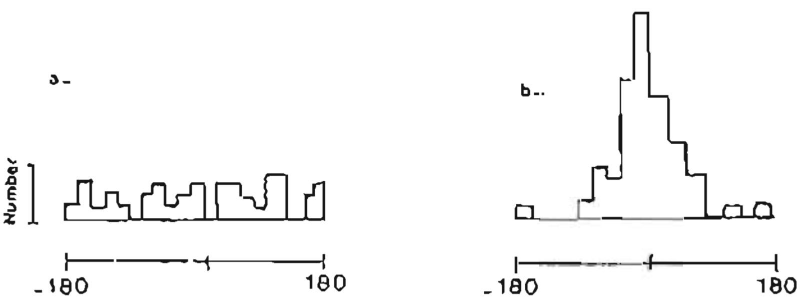

Fig.2 Typical behaviour of phase distributions
a- Uniform distribution
b- Phase distribution in case of aggregation

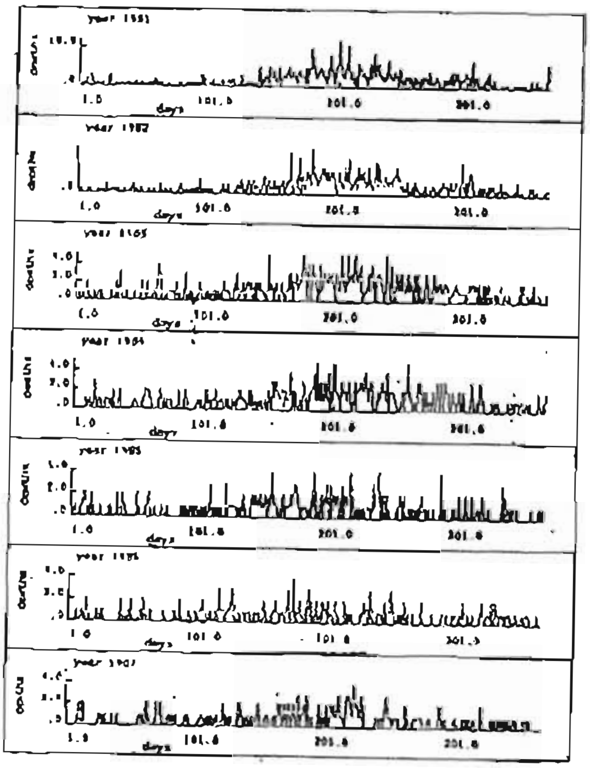

Fig.3 Ensemble of 7 records of postneonatal daily deaths

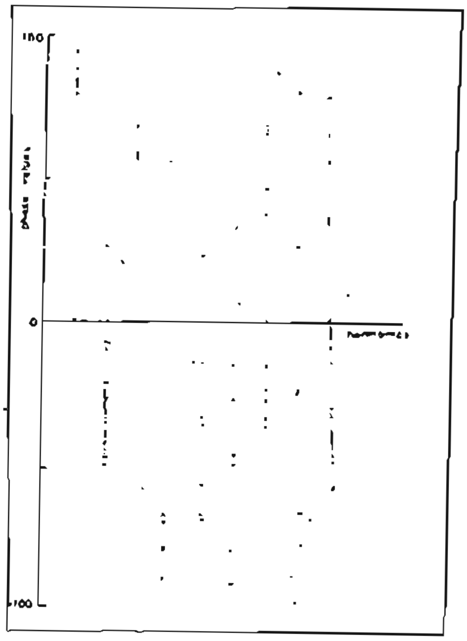

Fig.4 Phase values of harmonics (H_1 - H_{10}) of records in Fig.3

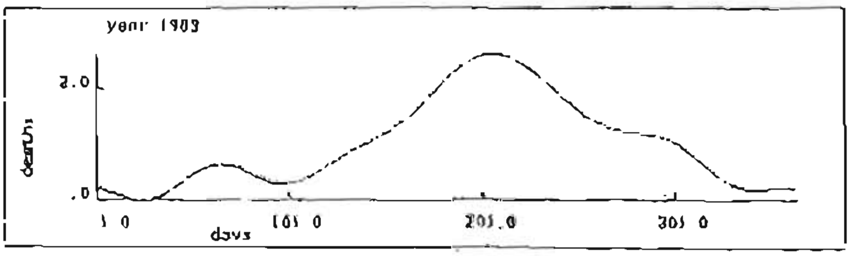

Fig.5 An example of the seasonal common pattern

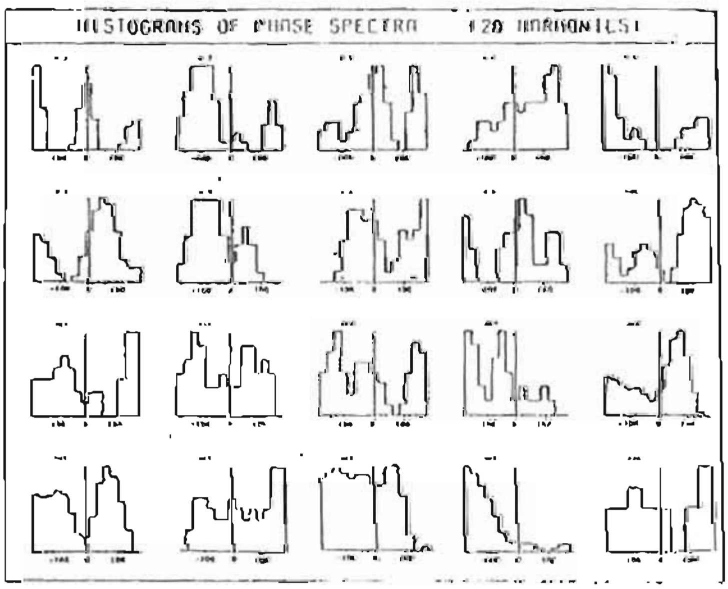

Fig.6 Phase distributions of harmonics (H_1- H_{20}) of neonatal heart rate records

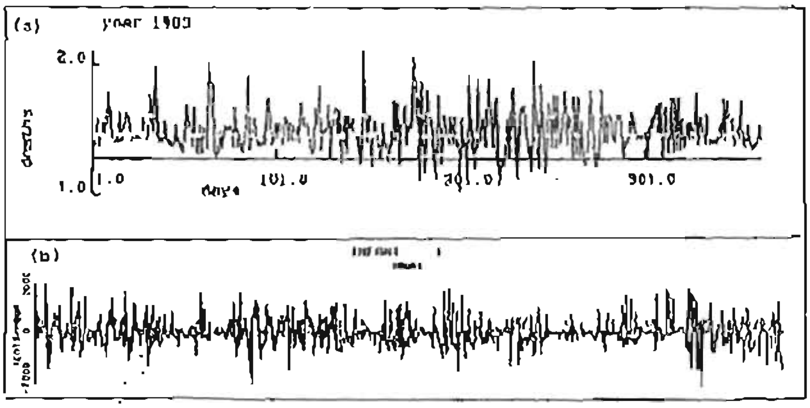

Fig.7 Residual signals (high-pass filtered) of:
a- Postneonatal death records
b- Neonatal heart-rate signal

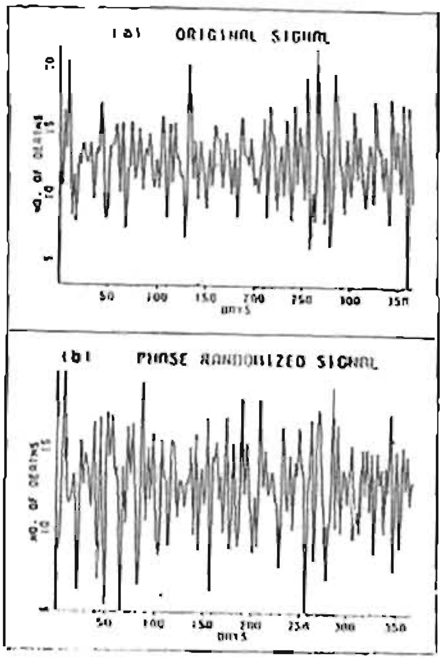

Fig.8 A typical residual signal of postneonatal record
a- Original
b- Reconstructed using randomized phase spectrum

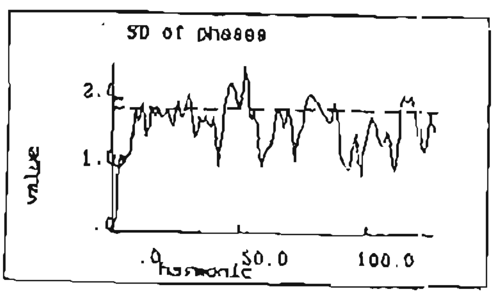

Fig.9 Ensemble standard deviation of phases for an ensemble of ECG beats