Journal of Applied Sciences

ISSN 1812-5654

Journal of Applied Sciences 6 (2): 251-256, 2006
ISSN 1812-5654

Fetal ECG Extraction using Softcomputing Technique

[1]C. Kezi Selva Vijila, M.E., [2]P. Kanagasabapathy and [1]Stanley Johnson
[1]Karunya Institute of Technology, Coimbatore, India
[2]Anna University, Chennai, India

Abstract: The analysis of the fetal electrocardiogram could be a reliable method for diagnosing cardiac diseases, especially fetal arrhythmias and fetal asphyxia. During delivery, accurate recordings can be made by placing an electrode on the fetal scalp. However, during pregnancy other methods should be used due to the inaccessibility of the fetus. Ideally, the fECG recorded from the maternal abdomen is a highly desirable, noninvasive method. But, fECG signals have very low power relative to that of the maternal ECG (mECG) due to several sources of interference. The interference sources can be suppressed with adaptive filters using signal processing. But if the noise phase is same as the original signal then sometimes it also eliminates the desired signal. To avoid this, adaptive noise cancellation is used, which will not affect the desired signal. This study explains how adaptive noise cancellation can be used to extract the fetal ECG from the interference. Output is simulated using neural network and neuro-fuzzy logic techniques. In this study a comparison of noise cancellation using the above techniques is done. Real time analysis is under process.

Key words: fECG, neural network, neuro fuzzy logic technique, adaptive noise cancellation, mECG

INTRODUCTION

One interesting and difficult problem in biomedical engineering is the fetal electrocardiogram extraction (fECG). Since 1960, many different methods[1-4] have been developed for detecting the fECG. Blind source separation (BSS) is one of the methods that were recently investigated[5-8] to measure the fECG. It consists in the extraction of original independent sources from mixtures of methods. In this application, the sources are the fECG, mECG, diaphragm and uterus and the mixers are recorded through electrodes located on the pregnant woman abdomen[9]. Wavelet theory based methods also used to remove noise from the fECG[10,11]. In this study, soft computing techniques like neural network and neuro-fuzzy logic techniques have been proposed for the extraction of the fECG.

ADAPTIVE NOISE CANCELLATION

Noise cancellation is a special case of optimal filtering which can be applied when some information about the reference noise signal is available[12]. The noise cancellation technique has many applications. Some of them are speech processing, echo cancellation in long distance telephone lines, signal enhancement, antenna array processing, biomedical signal and image processing and so on.

The concept of adaptive noise cancelling: The basic noise-canceling situation[13] is shown in Fig. 1. A signal is transmitted over a channel to a sensor that receives the signal plus an uncorrelated noise, n_0. The combined signal and noise, $s+n_0$, form the primary input to the canceller. A second sensor receives a noise n_1, which is uncorrelated with the signal but correlated with some unknown way with the noise n_0.

This sensor provides the reference input to the canceller. The noise n_1 is filtered to produce an output y that is a close replica of n_0. This output is subtracted from the primary input $s+n_0$ to produce the system output, $s+n_0-y$. The reference input is processed by an adaptive filter that automatically adjusts its own impulse response through an LMS algorithm that responds to an error signal dependent, among other things, on the filter's output. Thus with the proper algorithm, the filter can

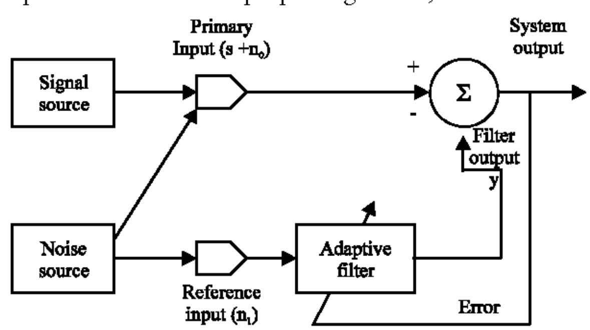

Fig. 1: Adaptive noise cancelling concept

Corresponding Author: C. Kezi Selva Vijila, M.E., Karunya Institute of Technology, Coimbatore, India

operate under changing conditions and can readjust itself continuously to minimize the error signal.

Cancelling the maternal ECG in fetal electrocardiography: Abdominal electrocardiograms make it possible to determine the fetal heart rate and to detect multiple fetuses and are often used during labor and delivery. The background noise due to muscle activity and fetal motion, however, often has amplitude equal to or greater than that of fetal heartbeat. A still more serious problem is the mother's heartbeat, which has an amplitude 2 to 10 times greater than that of fetal heartbeat and often interferes with its recording. The objective is to derive as clear a fetal ECG as possible, so that one could observe not only the heart rate but also the actual waveform of the electrical output. The mother's heartbeat acts as a reference input to the canceller[14]. The combined maternal and fetal heartbeats serves as the primary input. The maternal heartbeat, which dominates the primary input, is suppressed in the noise canceller output.

ADAPTIVE NOISE CANCELLATION USING NEURAL NETWORK (NN)

The main noise contribution in fECG is the maternal electrical activity since its amplitude is much higher than that of the fetus. In addition, the spectra of both maternal and fetal signals overlap. It is not possible to separate them through conventional frequency selective filtering. Different structures can be used for the adaptive filter.

However the structure explained in this paper is the NN adaptive filter because of its ability to generalize from training to test data and to model nonlinear transfer functions of arbitrary order. This section explains an adaptive noise-canceling filter, which uses a neural network as the adaptive element. The general structure of a feed forward MLP neural network is given in Fig. 2[18].

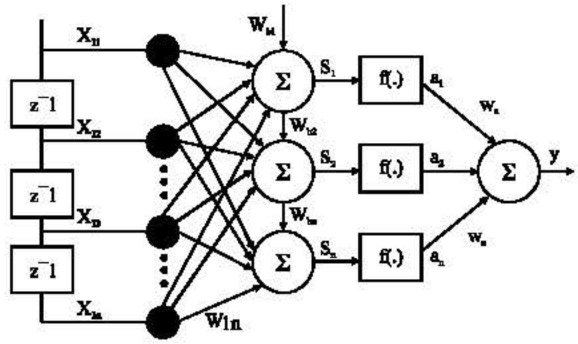

Fig. 2: Feed forward neural network structure

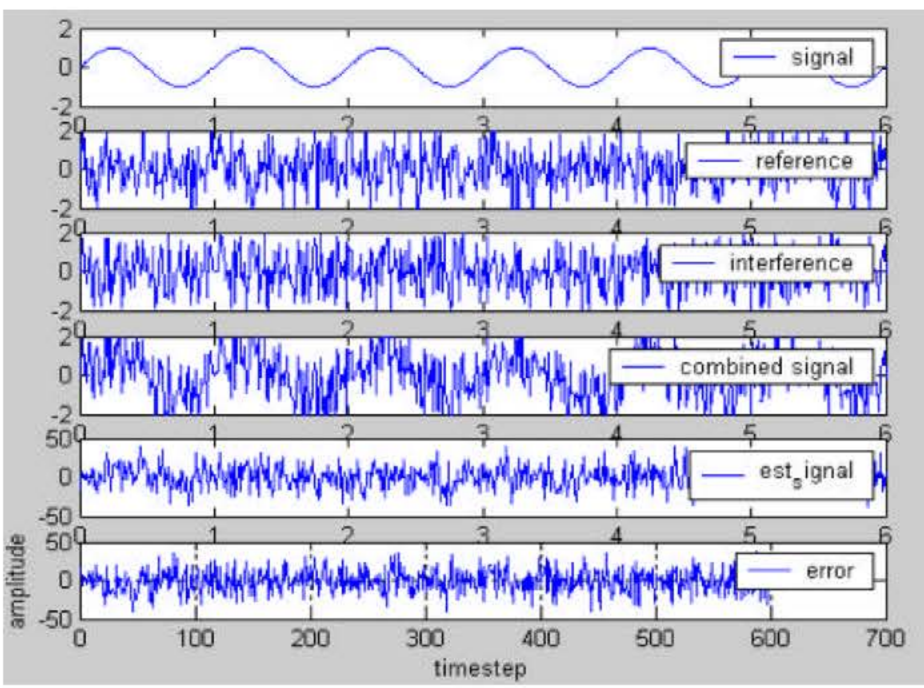

Fig. 3: Adaptive Noise Cancellation using network with sine wave as the information signal (fetal ECG). The labels are interpreted as: Signal: Models the input waveform, i.e., fECG, Reference: Random noise signal that models the mECG, interference: Random noise signal resulting from non-linear disturbances on the interference, Combined: Mixture of signal and interference. Estimated signal: Output of ANFIS. Error: Difference between signal and estimated signal

In Fig. 2, X represents an input vector for the input layer. The input layer is fully connected to the hidden layer through the weight vector W. The hidden layer is connected to the output layer and hyperbolic tangents are used for activation functions. The bias inputs and associated weights, W_{bn}, are also included. During the training phase, the Neural Network weights are updated, from small randomly selected initial values, using the back-propagation algorithm[15]. Noise cancellation using neural network is simulated using MATLAB (Fig. 3).

ADAPTIVE NOISE CANCELLATION USING NEURO FUZZY LOGIC TECHNIQUE

Neural networks recognize patterns and adapt themselves to cope with changing environments. Fuzzy inference systems incorporate human knowledge and perform inferencing and decision-making[19]. This section shows how Adaptive Neuro-Fuzzy Inference System (ANFIS) can be used to identify an unknown nonlinear passage dynamics that transforms a noise source into interference component in a detected signal. Under certain conditions, this approach is sometimes more suitable than noise elimination techniques based on frequency-selective filtering.

Figure 4 shows the schematic diagram of an ideal situation to which adaptive noise cancellation can be applied. Here we have an immeasurable information signal x(k) and a measurable noise source signal n(k); the noise source goes through unknown nonlinear dynamics to generate a distorted noise d (k),which is then added to x(k) to form the measurable output signal y(k). The aim is to retrieve the information signal x(k) from the overall output signal y(k); which consists of the information signal x(k) plus d(k),a distorted and delayed version of n(k). Suppose that we want to measure the fetal ECG x(k) during labor. If we record the signals from a sensor placed in the abdominal region, the obtained signal y(k) is inevitably noisy due to mother's heartbeat signal n(k),which can be measured clearly via a sensor at the thoracic region. However, the heartbeat signal n (k) does not appear directly in y(k). Instead, n(k) travels through the mother's body and arrives delayed and distorted to appear in the overall measurement y(k). In symbols, the detected output signal is expressed as:

$$Y(k)=x(k)+d(k)=x(k)+f(n(k), n(k-1),n(k-2) \quad (1)$$

The function f(.) represents the passage dynamics that the noise signal n(k) goes through. If f(.) were known

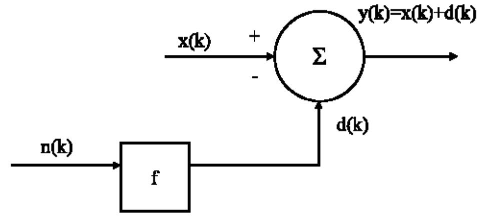

Fig. 4: Schematic diagram of noise cancellation without ANFIS filtering

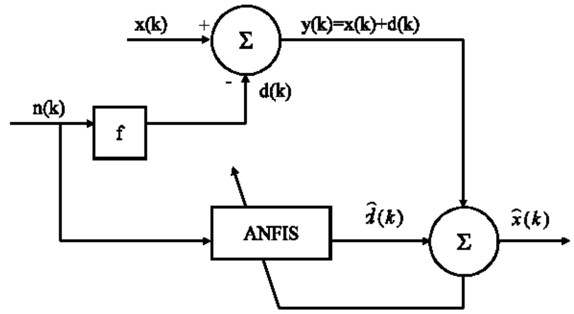

Fig. 5: Schematic diagram of noise cancellation with ANFIS filtering

exactly, it would be easy to recover the original information signal by subtracting (k) from y(k) directly. However, f(.) is usually unknown in advance and could be time varying due to changes in the environment. Moreover the spectrum of d(k) may overlap with that of x(k) substantially, invalidating the use of common frequency domain filtering techniques. To estimate the distorted noise signal d(k), we need to pick up a clean version of the noise signal n(k) that is independent of the information signal. However, we cannot access the distorted noise signal d(k) directly since it is an additive component of the overall measurable signal y(k).

Fortunately, as long as the information signal is zero mean and not correlated with the noise signal n(k), we can use the detected signal y(k) as the desired output for ANFIS training (Fig. 5).

More specifically, let the output of adaptation algorithm be denoted by $\hat{d}(k)$. The learning rule tries to minimize the error.

$$\begin{aligned} \|e(k)\|^2 &= \|y(k)^2 - \hat{d}(k)\|^2 \\ &= \|x(k) + d(k) - \hat{d}(k)\|^2 \\ &= \|x(k) + d(k) - \hat{f}(n(k), n(k-1), \\ &\quad n(k-2), \ldots\|^2 \end{aligned} \quad (2)$$

where, $\hat{f}$ is the function implemented by ANFIS. Taking expectations on both sides and realizing that x(k) is not correlated with $\hat{d}(k)$ yields,

$$E[e^2] = E[x^2] + E[(d - \hat{d})^2] - 2E[x\hat{d}] \quad (3)$$

If x(k) is a random signal with zero mean, then $E[x\hat{d}] = 0$ and we have,

$$E[e^2] = E[x^2] + E[(d - \hat{d})^2] \quad (4)$$

where E $[x^2]$ is not affected when ANFIS is adjusted to minimize $E[e^2]$. Therefore training the system to minimize total error $E[e^2]$ is equivalent to minimizing $E[(d - \hat{d})^2]$, such that function f(.) can be as close as possible to the passage dynamics f(.) in a least square sense.

Conditions under which adaptive noise cancellation is valid:

1. The noise signal n(k) should be available and independent of the information signal x(k).
2. The information signal x(k) must be zero mean.
3. The order of the passage dynamics is known. This determines the number of inputs to the ANFIS filter.

Let ANFIS is applied to nonlinear passage dynamics of order 2. Assume the unknown nonlinear passage dynamics is n2 and the information signal is sinusoidal wave. Assume the measurable noise source is Gaussian with zero mean and unity variance. Due to the nonlinear passage dynamics of f(.) and the large amplitude of d(k),it is hard to correlate y(k) and x(k) in the time domain. In this study, the generalized bell membership function is used. The error cannot be minimized to zero; the minimum error is regulated by the information signal x(k), which appears as fitting noise. Using ANFIS, the estimated information signal can be obtained.

RESULTS AND DISCUSSION

Performance of the ANFIS algorithm for noise cancellation is first tested using a stationary input signal viz., sine wave that models the fetal ECG signal (Fig. 6). The mECG signals and nonlinear interferences are modeled as random noise signals. The combined signal is the mixture of fECG and interference. It is used to represent the ECG signal that is recorded at the abdomen

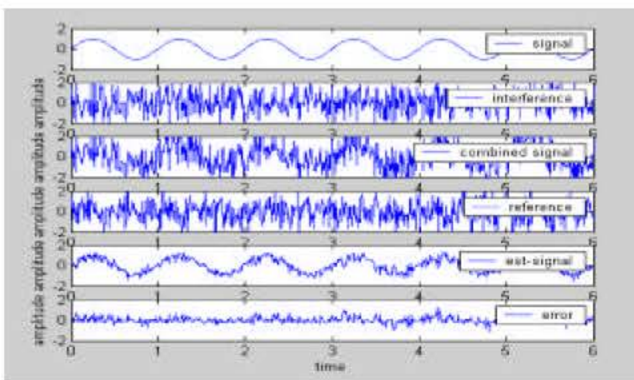

Fig. 6: ANFIS output with sine wave as the information signal

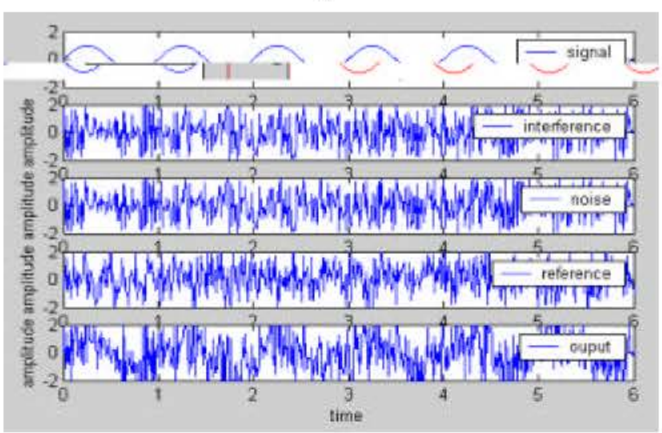

Fig. 7: Adaptive noise cancellation using LMS filter with sine wave as the information signal

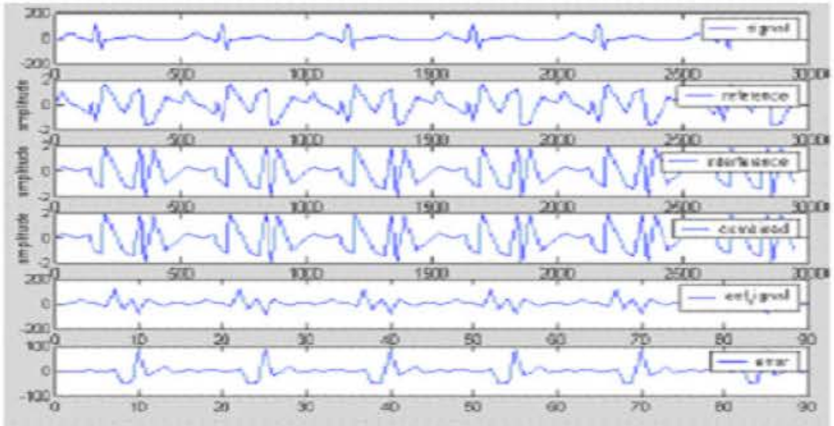

Fig. 8: Adaptive noise cancellation using LMS filter with synthetic ECG waveform as the information signal

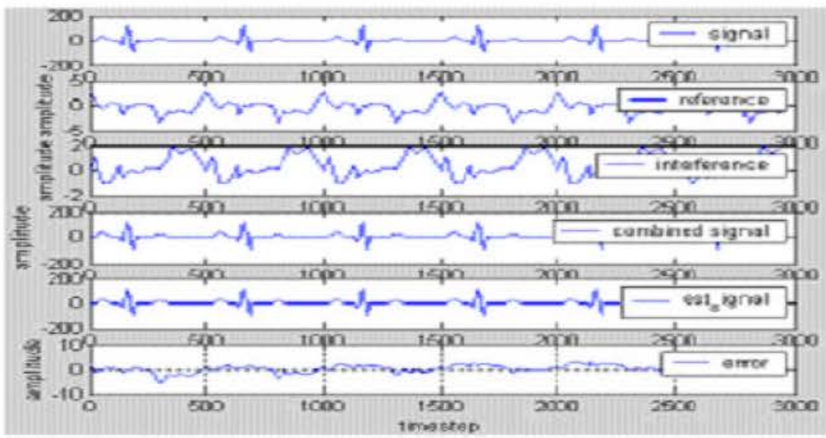

Fig. 9: Adaptive noise cancellation using neural network with synthetic ECG waveform as the information signal

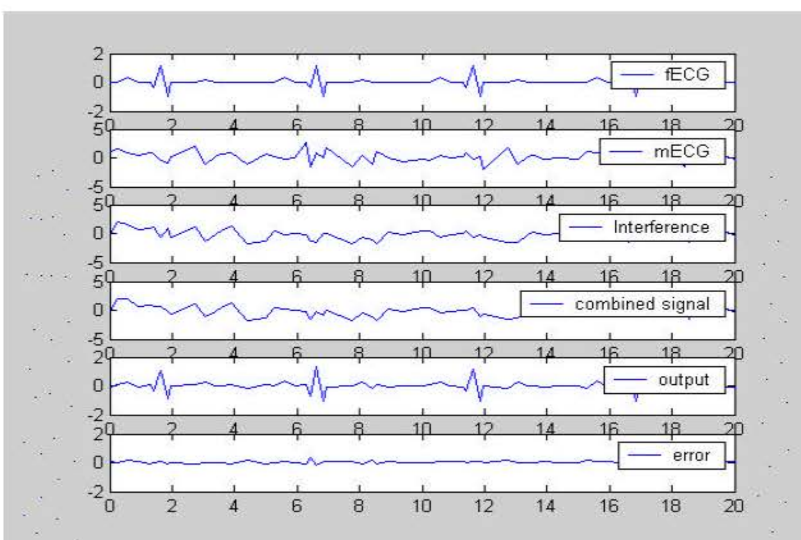

Fig. 10: Adaptive Noise Cancellation using ANFIS with synthetic ECG as the information signal (fetal ECG)

of the mother. The output signal is the estimated fetal ECG that is obtained after the process of noise cancellation. The experimental results obtained are compared with those obtained using a conventional noise cancellation technique viz., Least Mean Squares algorithm (LMS) and neural network as shown respectively in Fig. 6-10. Due to the complexity of ECG waveform, LMS filter gives poor performance compared to the neural network and ANFIS outputs. Generalized bell type membership function is used in ANFIS. The linear and nonlinear parameters and the number of fuzzy rules varies depends on the number of inputs and the type of the information signal.

CONCLUSIONS

Fetal ECG extraction from a mixture of noise can be done by many methods like signal processing, blind source separation and Independent Component Analysis etc. In this study, the performance comparison of noise cancellation using neural network and neuro fuzzy logic techniques is made. From the results obtained, it is inferred that noise cancellation using ANFIS is more efficient than the other techniques. In future, neuro fuzzy technique can be used to get the performance output for a real ECG waveform.

ACKNOWLEDGMENTS

The authors thanks the Founders of Karunya Institute of Technology and Sciences for providing the research facilities. Also, thank Dr. Arun Sam Pradeep MBBS, DCH P. Rajalakshmy and Prof. Rajasekaran for their support.

REFERENCES

1. Bergveld, P. and W.H.J. Meijer, 1981. A New technique for the Suppression of the MECG. IEEE Trans., Biomed. Eng., 28: 348-354.
2. Kanjilal, P.P. and G. Saha, 1997. Fetal ECG Extraction from single-channel maternal ECG using singular value decomposition. IEEE Trans. Biomed. Eng., 44: 785-794.
3. Longini, R.L., 1977. Near-orthogonal basis functions: A real time fetal ECG technique. IEEE Trans. Biomed. Eng., 24: 39-43.
4. Zarso, V., J. Millet-Roig and K. Nandi, 2000. Fetal ECG extraction from maternal skin electrodes using blind source separation and adaptive noise cancellation techniques. Comput. Cardiol., pp: 431-434.
5. Bacharakis, E., K. Nandi and V. Zurzoso, 1996. Fetal ECG extraction using blind source separation methods. Proceeding EUSIPCO'96, Trieste, Italy, pp: 395-398.
6. De Lathuwer, L., B. De Moor and J. Vandewalle, 2000. Fetal electrocardiogram extractraction by blind source subspace separation. IEEE Trans. Biomed. Eng., 47: 567-572.
7. Vrins, F., J.A. Lee, M. Verleysen, V. Vigneron and C. Jutten, 2003. Improving independent component analysis performances by variable selection. Proceedings of the 13th IEEE Workshop on Neural Networks for Signal Processing (NNSP 2003), Toulouse, France, pp: 359-368.
8. Mareossero, D.E., 2003. Independent component analysis for fetal electromagnetism extraction: A case for the data efficient mermaid algorithm. Proceedings of the 13th IEEE Workshop on Neural Networks for Signal Processing (NNSP 2003), Toulouse, France, pp: 359-368.
9. Zarzoso, V. and A.K. Nandi, 2001. Noninvasive fetal electrocardiogram extraction: Blind separation versus adaptive noise cancellation. IEEE Trans. Biomed. Eng., 48: 12-18.
10. Ishikawa, Y. and F. Mochimaru, 2002. Wavelet theory based analysis of high frequency, high resolution electrocardiograms: A New Concept for Clinical Uses. Prog. Biomed. Res., 7: 179-184
11. Mochimaru, F. and Y. Fujimoto, 2002. Detecting the fetal electrocardiogram by wavelet theory-based methods. Prog. Biomed. Res., 7: 185-193.
12. Parsa, V. and P.A. Parker, 1994. Multireference Adaptive Noise Cancellation Applied to Somatosensory Evoked Potentials. IEEE Trans. Biomed. Eng., pp: 41.
13. Widrow, B., 1975. Adaptive noise canceling: Principles and applications. IEEE Trans. Biomed. Eng., 63: 1692-1716.
14. Nitish, V.T. and Z. Yi-Sheng, 2001. Applications of Adaptive Filtering to ECG Analysis: Noise Cancellation and Arrhythmia Detection. IEEE Trans. Biomed. Eng., pp: 38.
15. Grieve, R. and P.A. Parker, 2000. Nonlinear adaptive filtering of stimulus artifact. IEEE Transactions. Biomed. Eng., pp: 47.