# Sleep-Apnea Detection with the Lempel-Ziv Complexity Analysis of the Electrocardiogram and Respiratory Signals

## Lempel-Ziv Komplekslik Metoduyla Ekg ve Solunum Sinyallerinden Uyku Apnesi Teşhisi

**Somay Kübra Şener**

Kocaeli University, Institute of Science and Technology, Biomedical Engineering, Kocaeli, Türkiye

**Emine Doğru Bolat**

Kocaeli University, Faculty of Technology, Biomedical Engineering, Kocaeli, Türkiye

** Corresponding author: somay.sener@gmail.com*

*Geliş Tarihi / Received: 8.12.2022*
*Kabul Tarihi / Accepted: 24.12.2022*

*Araştırma Makalesi/Research Article*
*DOI: 10.5281/zenodo.7474702*

## ÖZET

Uyku apnesi yaygın olarak görülen ve yaşamsal risk oluşturabilen bir hastalıktır. Hastalığın tedavisi kadar teşhisi de oldukça önemlidir. Toplum bilincinin yükselmesi ve hekimler tarafından fark edilme oranının artması ile teşhis edilmiş hasta sayısında dikkat çekici bir artış gözlenmektedir. Uyku apnesi teşhisinde yararlanılan polisomnografi ölçümleri, hasta için rahatsız edici ve birden fazla fizyolojik veri toplanmasını gerektirmektedir. Bu gibi problemler sebebiyle yeni analiz yöntemleri araştırılmaktadır. Lempel-Ziv hızlı ve doğrusal olmayan bir sinyal işleme metodu olduğundan, fizyolojik verilerin işlenmesinde çok uygundur. Lempel-Ziv komplekslik metodu kullanılarak daha az zaman ve daha az veriyle hastalığın teşhis edilmesi hedeflenmektedir. Bu hedef doğrultusunda tedavi sürecinin öne çekilmesi de sağlanmış olacaktır. Physionet.org veri tabanından alınan EKG ve solunum datalarından yararlanılarak hastalık tespit çalışmaları yapılmıştır.

Analizler sonucunda EKG, göğüs solunum (Resp C) ve abdominal solunum (Resp A) verilerinden apneli zaman aralıklarında anlamlı bir fark olduğu gözlemlenmiştir. Bu yöntemle EKG, Resp C ve Resp A için uyku apnesi teşhiş edilebilmektedir.

**Anahtar Kelimeler**: Obstruktif uyku apne sendromu, Lempel-Ziv komplekslik yöntemi, EKG, Respirasyon

## ABSTRACT

Sleep apnea is a common and life-threatening disease. Diagnosis of the disease is as important as its treatment. A remarkable increase is observed in the number of diagnosed patients with the increase in public awareness and the increase in the rate of being noticed by physicians. Polysomnography measurements used in the diagnosis of sleep apnea disturb the patient and require more than one physiological data collection. Due to such problems, new analysis methods are being investigated. Since Lempel-Ziv is a fast and non-linear signal processing method, it is very suitable for processing physiological data. By using the Lempel-Ziv complexity method, it is aimed to diagnose the disease with less time and less data. In line with this goal, the treatment process will also be brought forward. Disease detection studies were carried out by using ECG and respiratory data from the Physionet.org database.

As a result of the analyzes, it was observed that there was a significant difference in the time intervals with apnea from the ECG, chest respiration (Resp C) and abdominal respiration (Resp A) data. With this method, sleep apnea can be diagnosed for EKG, Resp C and Resp A.

**Keywords**: Obstructive sleep apnea syndrome, Lempel-Ziv complexity method, ECG, Respiration

## 1. INTRODUCTION

Sleep-respiratory disorders, or upper respiratory tract sleep disorders; It is classified as simple snoring, upper respiratory tract resistance syndrome, sleep-apnea syndrome and hypopnea. Snoring can be a common symptom of these syndromes, or it can be seen alone (Kurtulmuş, 2007).

Obstructive sleep apnea syndrome, one of the most common sleep disorders, is estimated to affect 38% of the population (Korkalainen, et al., 2020).

Obstructive sleep apnea syndrome (OSAS) is a sleep disorder that causes the need for excessive daytime sleepiness and a decrease in daytime wakefulness (Pitkänen, et al., 2022). It is one of the most prominent symptoms of obstructive sleep apnea syndrome (OSAS). Snoring is caused by the vibration of the soft tissues in the area due to the increased airflow depending on narrowing of the upper airways. Snoring is seen in every OSAS patient, but not every snoring patient can be diagnosed with obstructive sleep apnea syndrome (A.Şahin, 1993). As a result of intermittent cessation of irregular snoring that occurs with recurrent apneas, breathing stops and another syndrome called witnessed apnea occurs. Sleep is frequently interrupted due to recurrent apnea attacks; quality rest cannot be provided, and excessive daytime sleepiness syndrome occurs. This syndrome can be mild or severe, and its degree is related to factors such as the frequency and duration of apnea periods (Aykent & Özdere, 2015).

Sleep apnea syndromes greatly affect people's quality of life (Dvir, et al., 2020). An unhealthy sleep can cause forgetfulness during the day, and this situation leads to a weakening of memory over time. A person who does not trust his memory and has forgetfulness begins to have difficulty in making decisions and choices. Thus, there is a decrease in decision-making ability. Insomnia and inability to fulfill old abilities cause personality and behavioral changes. There may be difficulties in adapting to the environment and depression (Shoib, et al., 2022).

Atypical chest pain is seen during apnea when the continued strong breathing effort puts strain on the rib cage and organs. This strong breathlessness creates the syndrome of suffocation in sleep and causes patients to wake up (Ulukavak Çiftçi, 2012). Since the expected decrease in blood pressure does not occur during sleep, high blood pressure is observed. Over time, this high blood pressure spreads throughout the day, causing hypertension (Diker, et al., 2007). It prepares not only hypertension but also various cardiovascular diseases (Dua, et al., 2022).

OSAS may cause consequences that may endanger both the baby's health and their own health in pregnant individuals (Felder, et al., 2022).

The definitive diagnosis of sleep apnea is made in a sleep laboratory using cardiorespiratory polysomnography (Korkalainen, et al., 2020). This procedure monitors sleep stages, oronasal airflow, chest wall and abdominal wall movements, respiratory effort, and the effect of breathing (Force, 1999). Thus, oxygen saturation requires additional recording of electroencephalography (EEG), electrooculography (EOG), and electromyography (EMG) signals to determine the ECG for heart rate monitoring and crude arrhythmia detection (Lin, et al., 2022).

There are many studies on sleep apnea. In the literature, there are various studies on the detection of sleep apnea according to respiratory parameter (Várady, et al., 2002), sleep sound recording analysis (Kang, et al., 2017), heart sound analysis (Yıldız, 2017), nasal pressure signal (Sériès, 1999), EEG signal (Sezgin & Tagluk, 2011), SPO2 signal (Almazayde, et al., 2012), ECG signal (Quiceno-Manrique, et al., 2009) properties. The main purpose of these studies is to improve the diagnosis and treatment of sleep apnea.

Lempel-Ziv complexity (LZC) has proven to be a powerful measure of complexity in a variety of biomedical applications (Rivolta, et al., 2014). LZC has been obtained from literature studies that it is a viable method for classification of sleep respiratory disorders (Pregowska, et al., 2019), diagnosis of sleep apnea from EEG data (Taran, Bajaj, Sinha, & Polat, 2021), and evaluation of ECG signal quality (Zhang, et al., 2016)

Some of the studies include electrical connections and apparatus that may disturb the patient during measurement. Prolonged measurement processes also cause adverse effects on the patient (Zhuang, et al., 2022). Considering all these parameters, it becomes difficult to get accurate measurements from the patient. There is a need for a system where healthy measurements can be made from the patient with less time and less data.

In this study, sleep apnea diagnosis was made by applying LZC method to ECG and Respiration signals in line with this need. This paper is organized as follows: the programs and data sets used in this study are introduced and detailed in Section 2, the data, Graphics, Tables and findings obtained from the analyzes made in the study are presented in Section 3, finally the results of the study and the conclusion are given in Section 4.

## 2. MATERIALS and METHODS

The Lempel-Ziv complex method was used as the analysis method. After the data was loaded into Matlab, the code written for Lempel-Ziv complexity analysis was applied to the data set. Values obtained as a result of Lempel-Ziv were prepared in Microsoft Excel program and statistical analysis was performed with ANOVA in R Studio environment.

### 2.1. Data Set

For the diagnosis of sleep apnea from ECG and respiration signals with the Lempel-Ziv method, the data of healthy and sleep apnea individuals whose ECG and respiration were measured during sleep were obtained from physionet.org.

The downloaded data set belongs to 8 different people, 3 healthy and 5 diseased. The data set includes ECG, Respiration A (RespA, abdominal respiration), Respiration C (RespC, chest respiration), Respiration N (RespN, nasal respiration), and SPO2 data.

The sampling frequency is 100 Hz, and the sampling interval is 0.01 seconds. Each measurement is 2 hours 46 minutes long. Since it is aimed to diagnose sleep apnea from ECG and respiratory signals with the Lempel-Ziv method, the SPO2 and Resp N measurement value was not used in the analysis.

The dataset was processed using the 2015 version of the Matlab scripting language and the data is in the 'erm.mat' format. From the data, diseased people are a01erm.mat, a02erm.mat, a03erm.mat, a04erm.mat, b01erm.mat, while c01erm.mat, c02erm.mat, c03erm.mat contain the measurement values obtained from healthy individuals. Measurements taken from each person include 5 rows as ECG, RespA, RespC, RespN and SPO2 and 1.000.000 columns as measurement values.

The records of the individuals in the data set used and features such as age, gender, height, weight, apnea minute are detailed in Table 1.

**Table 1.** Dataset taken from Physionet

| Records of patients | Hours (w/apnea) | Apnea index AI | Hypopnea index HI | Apnea-hypopnea index AHI | Age | Gender | height (cm) | weight (kg) |
|---|---|---|---|---|---|---|---|---|
| a01 | 9 | 12,5 | 57,1 | 69,6 | 51 | M | 175 | 102 |
| a02 | 9 | 57,2 | 12,3 | 69,5 | 38 | M | 180 | 120 |
| a03 | 9 | 38,4 | 0,7 | 39,1 | 54 | M | 168 | 80 |
| a04 | 9 | 73,4 | 4 | 77,4 | 52 | M | 173 | 121 |
| b01 | 2 | 0,12 | 0,12 | 0,24 | 44 | F | 170 | 63 |
| c01 | 0 | 0 | 0 | 0 | 31 | M | 184 | 74 |
| c02 | 0 | 0 | 0 | 0 | 37 | M | 180 | 83 |
| c03 | 0 | 0 | 0 | 0 | 39 | M | 184 | 65 |

### 2.2. Lempel-Ziv Complexity

Lempel-Ziv complexity (LZC) is a complexity measure used to find the randomness of finite series, and the LZC measure is calculated over symbolic sequences (Akar, et al., 2015).

After the signal is converted to a finite string of symbols, the LZC measure $c(n)$ must be calculated. For biomedical signal analysis, $x(n)$ signal is typically discrete-time and converted to binary sequence. When compared with the $Td$ threshold value as given in Equation (2), signals in the form of time series are converted into a symbolic sequence in the form of 0-1. This symbolic sequence is given in Equation (1) and denoted by $P$ (Aboy, et al., 2006).

$$P = s(1), s(2), \dots, s(r) \tag{1}$$

$$s(i) = \{ \quad 0, \ x(i) < Td \quad 1, \ otherwise \tag{2}$$

In Equation (2), the median versus outlier values were used as the $Td$ threshold (Nagarajan, 2002). If the amplitude of the signal is greater than $Td$, it is converted to 1, and if it is small, it is converted to 0 (Aboy, et al., 2006). To calculate LZC, the string $P$ is scanned from left to right and the complexity criterion $c(n)$ is increased by one unit when a new string of consecutive characters is encountered (Daniel Ab´asolo, 2006).

A complexity measure independent of the array length must be obtained. Therefore $c(n)$ must be normalized. If the length of the array is n and the number of each different symbol in the symbol set is called α, the upper bound of $c(n)$ becomes as given in Equation (3) (Ziv, 1976.).

$$c(n) < \frac{n}{(n)} \tag{3}$$

Generally, $n$ / $(n)$ is the upper bound of $c(n)$ where the base of the logarithm is α and $c(n)$, $b(n)$ as given in Equation (4) can be normalized with:

$$\lim_{n\to\infty} c(n) = b(n) = \frac{n}{n} = \frac{n}{(n)} \tag{4}$$

$$C(n) = \frac{c(n)}{b(n)} \tag{5}$$

The normalized Lempel-Ziv complexity, *C(n),* given in Equation (5), reflects the proportion of new patterns that emerge with the sequence. Thus, it captures the temporal structure of the sequence (Ziv, 1976.). To eliminate the problem of time series dependence on length, the normalized LZC is calculated as given in Equation (6) (Akar, et al., 2015):

$$LZC = \frac{c(n)}{b(n)} \tag{6}$$

### 2.3. ANOVA

Analysis of variance is used to test hypotheses about whether the difference between the mean of two or more groups is significant. ANOVA (ANalyis Of VAriance), a single-factor analysis of variance, is used to determine whether there is a significant difference between the means of 3 or more groups-(Ergün & Aktaş, 2009). Among the hypotheses for this purpose, $H_0$ means that there is no difference between the means, while $H_A$ indicates that there is a significant difference between at least two means (Yiğit & Gökpınar, 2010). Another name for ANOVA is the F test and it gives the F statistics. F compares the amount of systematic variance in the data with the unsystematic variance.

The test primarily tests the difference of at least one of the groups from the others. If a statistically significant *p* value is obtained as a result of the ANOVA test, in other words, if $p < 0{,}05$, it means that there is a difference between the analyzed groups (Field, 2013).

In order to apply the ANOVA test, the data must have a normal distribution in each group, the variances obtained must be homogeneous, and the individuals within the group must be independent from each other.

One-way ANOVA was used as a statistical analysis method for the detection of sleep apnea from ECG and respiratory signals with the LZC method. If the *p* value is below 0,05, there is no similarity between the patient and healthy data in the examined time interval. This indicates that the patient have apnea during the examined time period.

## 3. SIMULATION RESULTS AND DISCUSSION

ECG and respirations are composed of 1.000.000 columns separately. In order to analyze the data better, it is necessary to divide it into time intervals. By dividing the 1.000.000 long data into 60.000 time intervals, 16 time intervals were obtained. In the Tables and Figures, these intervals are expressed as time 1, time 2, time 3, up to time 16. These times correspond to a period of approximately 10 minutes and 37 seconds.

All ECG and respiratory data for each subject were divided into 16 time intervals. LZC was performed for each person's ECG, RespA, RespC measurement values. After recording the results obtained with the LZC method, the graphs of the standard deviations were created. Statistical analysis was performed with the ANOVA test.

In the ANOVA analysis, if a statistically significant *p* value was obtained between the healthy a01, a02, a03, a04, b01 and patient c01, c02, c03 data ($p < 0{,}05$), it means that there is a significant

difference between the analysis groups. This indicates that the patient had apnea during the examined time period. In ANOVA Tables, each *p* value is shown in white if it is less than 0,05, and in blue if it is larger.

### 3.1. ECG Statistical Findings

LZC was applied to all ECG data. The obtained values were recorded by paying attention to the time intervals of LZC values. The standard deviation (std.) of the LZC values of the patient and healthy data for each time interval was taken. The graph comparing these standard deviations is given in Figure 1.

The values of the standard deviations are given on the vertical axis and the time intervals (1 time interval=10 minutes 37 seconds) on the horizontal axis in the graph in Figure 1. The blue columns give the ECG standard deviation of the patients, and the red columns are ECG standard deviation of the healthy subjects.

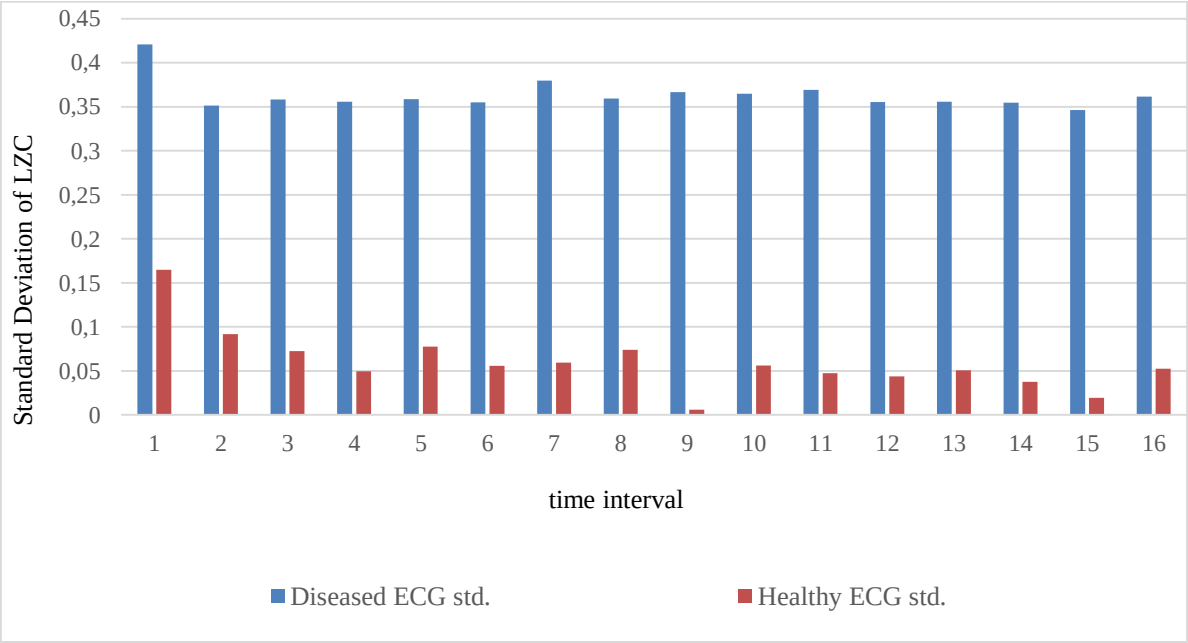


**Figure 1.** Graph of standard deviation obtained from ECG data with normalized LZC

When the standard deviations obtained using the ECG data are examined, it appears to be a difference between sick individuals and healthy individuals at all time intervals. The standard deviation value obtained as a result of the study conducted with sick individuals is higher than the standard deviation value obtained as a result of the study conducted with healthy individuals.

When Figure 1 is examined, a greater difference is observed between the standard deviation of LZC values obtained from healthy data at time 9 and time 15 and the standard deviation of LZC values obtained from diseased data compared to other time intervals.

In time 1, the difference between the standard deviation of LZC values obtained from healthy data and the standard deviation of LZC values obtained from diseased data is at least. ANOVA analysis *p* values applied to LZC values obtained from ECG data in Figure 1 are given in Table 2.

The reason for the observable difference in the time 9 and time 15 intervals in Figure 1 can be examined from Table 2. The significant difference between the standard deviations at time 9 and time 15 may be associated with apnea intervals.

**Table 2.** ANOVA analysis *p* values applied to LZC values obtained from ECG data

| | a01ecg | a02ecg | a03ecg | a04ecg | b01ecg |
|---|---|---|---|---|---|
| time1 | 0,61 | 0,386 | 0,331 | 0,307 | 0,659 |
| time2 | 0,326 | 0,852 | 0,647 | 0,568 | 0,329 |
| time3 | 0,612 | 0,508 | 0,762 | 0,558 | 0,469 |
| time4 | 0,829 | 0,328 | 0,718 | 0,714 | 0,873 |
| time5 | 0,845 | 0,365 | 0,937 | 0,677 | 0,86 |
| time6 | 0,598 | 0,264 | 0,72 | 0,33 | 0,368 |
| time7 | 0,66 | 0,364 | 0,439 | 0,256 | 0,852 |
| time8 | 0,757 | 0,495 | 0,728 | 0,252 | 0,545 |
| time9 | 0,912 | 0,01 | 0,0463 | 0,00314 | 0,0083 |
| time10 | 0,951 | 0,356 | 0,879 | 0,293 | 0,78 |
| time11 | 0,814 | 0,275 | 0,609 | 0,175 | 0,84 |
| time12 | 0,375 | 0,217 | 0,709 | 0,107 | 0,55 |
| time13 | 0,43 | 0,272 | 0,732 | 0,154 | 0,75 |
| time14 | 0,569 | 0,515 | 0,862 | 0,165 | 0,361 |
| time15 | 0,12 | 0,23 | 0,216 | 0,0367 | 0,145 |
| time16 | 0,499 | 0,652 | 0,997 | 0,175 | 0,79 |

### 3.2. Resp A Statistical Findings

LZC was applied to Resp A data. The obtained values were recorded by paying attention to the time intervals of LZC values. The standard deviation of the LZC values of the patient and healthy data for each time interval was taken among themselves. The graph comparing these standard deviations is given in Figure 2.

The values of the standard deviations are given on the vertical axis and the time intervals (1 time interval=10 minutes 37 seconds) on the horizontal axis in Figure 2. The black columns give the Resp A standard deviation of the patients, and the yellow columns are the Resp A standard deviation of the healthy subjects.

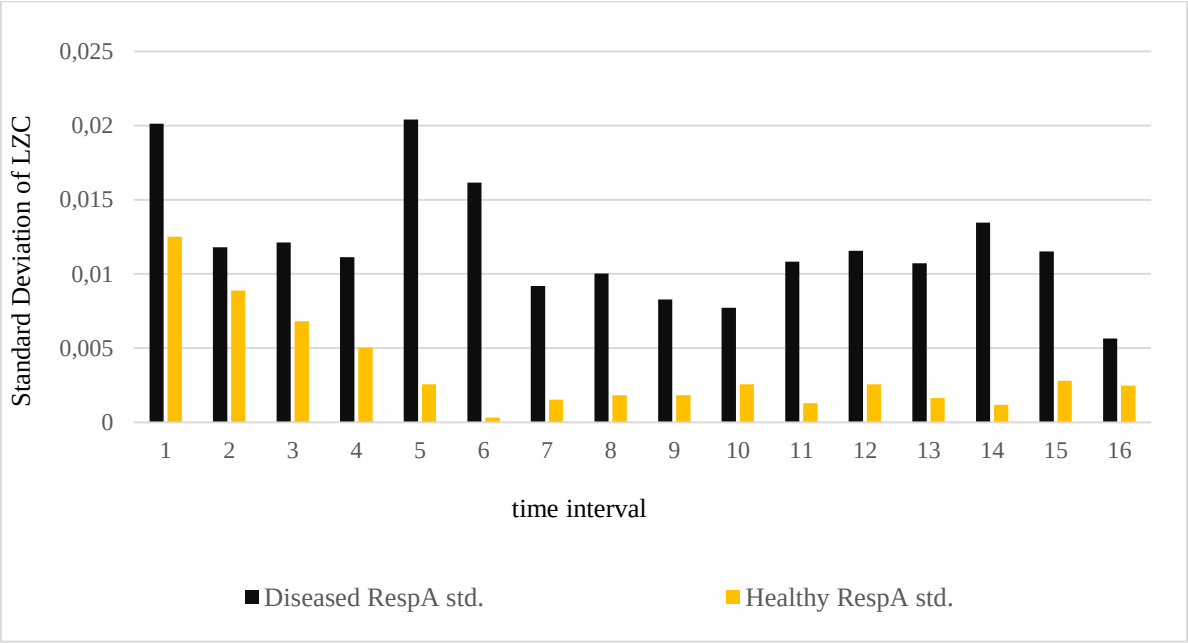


**Figure 2.** Graphs of the mean and standard deviation of the value obtained from the LZC and Resp A data

When the standard deviations obtained using Resp A data are examined, it is seen that there is a difference between sick individuals and healthy individuals at all time intervals. The standard deviation value obtained as a result of the study conducted with sick individuals is higher than the standard deviation value obtained as a result of the study conducted with healthy individuals.

The difference between the standard deviation values of patients and healthy individuals from time 5 to time 16 is much higher. The *p* values obtained from the ANOVA statistical analysis of these time intervals are given in Table 3 detailly.

When Table 3 is examined, it is seen that *p* values for Resp A are generally less than 0,05 from time 5 to time 16. This means that individuals generally have sleep apnea.

In time 1, time 2, time 3, time 4 and time 16, it is observed that the difference between the standard deviation value obtained from the study with sick individuals and the standard deviation value obtained from the study with healthy individuals is less. When the *p* values of these time periods in Table 3 are examined, it is seen that they are greater than 0,05. As a result, time 1, time 2, time 3, time 4 and time 16 for Resp A mean that no patient has sleep apnea. In addition, patient b01 has not apnea at all time intervals

**Table 3.** *p* values obtained from Resp A data as a result of ANOVA analysis

| | **a01RespA** | **a02RespA** | **a03RespA** | **a04RespA** | **b01RespA** |
|---|---|---|---|---|---|
| time1 | 0,456 | 0,384 | 0,591 | 0,456 | 0,0649 |
| time2 | 0,249 | 0,441 | 0,406 | 0,848 | 0,746 |
| time3 | 0,112 | 0,218 | 0,492 | 0,709 | 0,891 |
| time4 | 0,0638 | 0,186 | 0,559 | 0,66 | 0,913 |
| time5 | 0,00562 | 0,0289 | 0,123 | 0,863 | 0,814 |
| time6 | 0,000157 | 0,00112 | 0,00235 | 0,27 | 0,27 |
| time7 | 0,0172 | 0,00902 | 0,723 | 0,102 | 0,943 |

| | a01RespA | a02RespA | a03RespA | a04RespA | b01RespA |
|---|---|---|---|---|---|
| time8 | 0,0457 | 0,01 | 0,767 | 0,0232 | 0,681 |
| time9 | 0,326 | 0,0216 | 0,238 | 0,0537 | 0,336 |
| time10 | 0,83 | 0,0396 | 0,333 | 0,966 | 0,765 |
| time11 | 0,00415 | 0,0402 | 0,932 | 0,0895 | 0,403 |
| time12 | 0,016 | 0,107 | 0,278 | 0,328 | 0,864 |
| time13 | 0,0102 | 0,0126 | 0,401 | 0,718 | 0,529 |
| time14 | 0,00461 | 0,0264 | 0,0154 | 0,0652 | 0,268 |
| time15 | 0,0195 | 0,184 | 0,375 | 0,815 | 0,953 |
| time16 | 0,0598 | 0,125 | 0,652 | 0,256 | 0,894 |

### 3.3. Resp C Statistical Findings

LZC was applied to Resp C data. The obtained values were recorded by paying attention to the time intervals of LZC values. The standard deviation of the LZC values of the patient and healthy data for each time interval was taken among themselves. The graph comparing these standard deviations is given in Figure 3.

The values of the standard deviations are given on the vertical axis in the graph in Figure 3 and the time intervals (1 time interval=10 minutes 37 seconds) are given on the horizontal axis. The green columns give the Resp C standard deviation of the patients, the purple columns are the Resp C standard deviation of the healthy subjects.

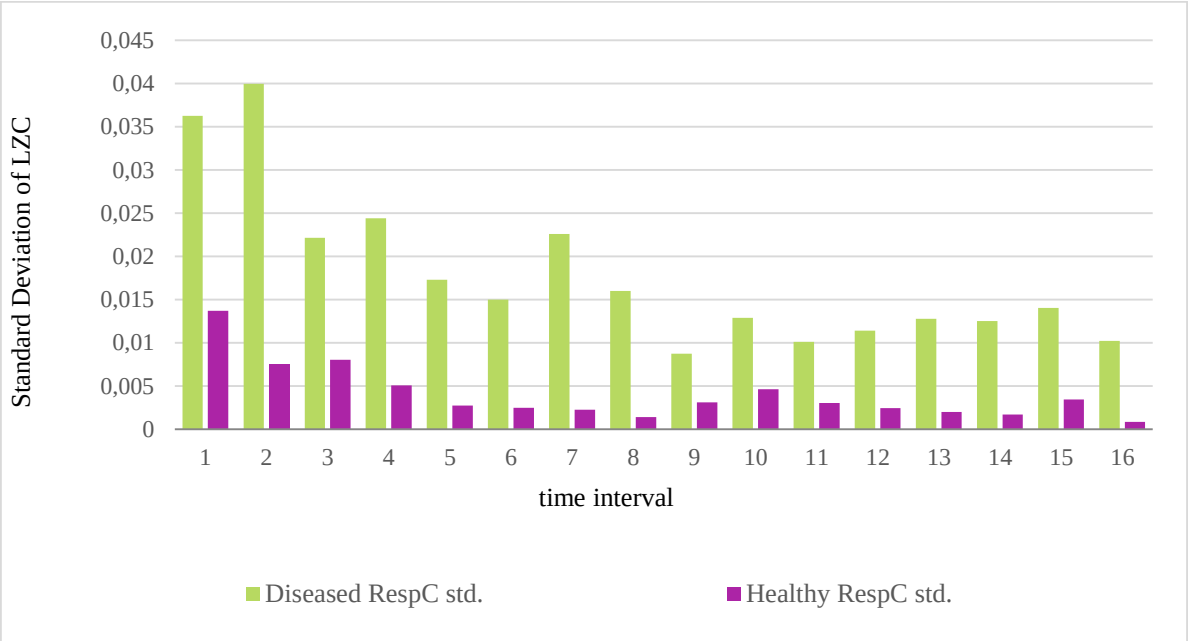


**Figure 3.** Plots of mean and standard deviation from Resp C data with LZC

When the standard deviations obtained using the Resp C data are examined, it is seen that there is a difference between sick individuals and healthy individuals at all time intervals.

The standard deviation value obtained as a result of the study conducted with sick individuals is higher than the standard deviation value obtained as a result of the study conducted with healthy

individuals. The difference between the standard deviation values of patients and healthy individuals from time 4 to time 8 and time 14 is much higher.

The *p* values obtained from the ANOVA statistical analysis of these time intervals are given in Table 4 detailly. When Table 4 is examined, it is seen that has sleep apnea at time 6, which is between time 4 and time 8 for Resp C.

In addition, it is seen that patient a01 has apnea at all time intervals. It is seen that patient a03 has apnea in time 14 and patient b01 has not apnea at all time intervals.

**Table 4.** *p* values obtained from Resp C data as a result of ANOVA analysis

| | **a01RespC** | **a02RespC** | **a03RespC** | **a04RespC** | **b01RespC** |
|---|---|---|---|---|---|
| time1 | 0,0285 | 0,25 | 0,694 | 0,403 | 0,881 |
| time2 | 0,0157 | 0,102 | 0,68 | 0,98 | 0,801 |
| time3 | 0,0346 | 0,143 | 0,365 | 0,822 | 0,91 |
| time4 | 0,0148 | 0,559 | 0,372 | 0,477 | 0,827 |
| time5 | 0,0102 | 0,0905 | 0,0943 | 0,781 | 0,604 |
| time6 | 0,000273 | 0,00158 | 0,002 | 0,00248 | 0,529 |
| time7 | 0,00166 | 0,0793 | 0,271 | 0,971 | 0,52 |
| time8 | 0,00507 | 0,1 | 0,183 | 0,585 | 0,952 |
| time9 | 0,0193 | 0,403 | 0,123 | 0,274 | 0,642 |
| time10 | 0,0149 | 0,379 | 0,205 | 0,347 | 0,966 |
| time11 | 0,00654 | 0,0712 | 0,144 | 0,459 | 0,195 |
| time12 | 0,0228 | 0,0621 | 0,143 | 0,932 | 0,721 |
| time13 | 0,00716 | 0,238 | 0,0848 | 0,0848 | 0,387 |
| time14 | 0,00471 | 0,0669 | 0,026 | 0,0764 | 0,0831 |
| time15 | 0,015 | 0,145 | 0,112 | 0,28 | 0,86 |
| time16 | 0,0157 | 0,0746 | 0,309 | 0,609 | 0,843 |

## 4. CONCLUSION

In this study, Lempel-Ziv complexity method was applied to ECG, Resp A, Resp C data obtained from patients and healthy individuals. After applying the ANOVA statistical analysis to the values obtained from the LZC method, it was aimed to obtain a diagnosis of sleep apnea from the ECG, Resp A, Resp C data. When the result obtained from the ANOVA analysis is examined, the Lempel-Ziv complexity method from the Resp A and Resp C data, especially in patients with high number of apneas, can be diagnosed with sleep apnea in more time intervals.

From the ECG data, the diagnosis of sleep apnea with the Lempel-Ziv complexity method could only be made in two different time intervals. It has been found that deep sleep is more intense, especially in the first time intervals of sleep, and there is a decrease in LZK values. The aim of the study was carried out for ECG, Resp A and Resp C data.

## 5. REFERENCES

A. F. Quiceno-Manrique, J. B.-H.-G.-B.-D. (2009). Detection of obstructive sleep apnea in ECG recordings using time-frequency distributions and dynamic features. *2009 Annual International Conference of the IEEE Engineering in Medicine and Biology Society*, 5559-5562.

A.Şahin. (1993). *Obstrüktif Uyku Apne Sendromu.* Türkiye Akciğer Hastalıkları Vakfı Yayınları.

Aboy, M., Hornero, R., Abásolo, D., & Álvarez, D. (2006). Interpretation of the Lempel-Ziv Complexity Measure in the Context of Biomedical Signal Analysis. *IEEE Transactions on Biomedical Engineering, 53*(11), 2282-2288.

Agnieszka Pregowska, K. P. (2019). Using Lempel-Ziv complexity as effective classification tool of the sleep-related breathing disorders. *Computer Methods and Programs in Biomedicine*.

Akar, S. A., Kara, S., Agambayev, S., & Bilgiç, V. (2015). Major Depresyonlu Hastaların EEG Sinyallerinin Kaotik Özniteliklerle İncelenmesi. *Tıp Teknolojileri Ulusal Kongresi.* Muğla.

Aykent, F., & Özdere, E. (2015). Horlama ve Obstruktif Uyku Apnesi Tedavisinde Oral Aparey. *Atatürk Üniv. Diş Hek. Fak. Derg.*, 123-128.

Daniel Ab´asolo, R. H. (2006). Analysis of EEG background activity in Alzheimer's disease patients with Lempel–Ziv complexity and central tendency measure. *Medical Engineering & Physics*(28), 315–322.

Diker, E., Çiftçi, B., Bayram, H., Bayram, A. N., & Güven, F. S. (2007). Obstrüktif Uyku Apne Sendromu Şiddeti ile Hipertansiyon Arasındaki İlişki. *Anadolu Kardiyol Dergisi, 7*, 378-82.

Dua, A., Huang, Z., Hu, M., Zhao, Z., Zhao, Q., Jin, Q., . . . Liu, Z. (2022). The comorbidity burden and disease phenotype in pre-capillary pulmonary hypertension: The contributing role of obstructive sleep apnea. *Sleep Medicine*.

Dvir, H., T, B. L., S, K., A, K., S, M., J, T., & H, K. (2020). Central Sleep Apnea Alters Neuronal Excitability and Increases the Randomness in Sleep-Wake Transitions. *IEEE Transactions on Biomedical Engineering*, 3185-3194.

Ergün, G., & Aktaş, S. (2009). ANOVA Modellerinde Kareler Toplamı Yöntemlerinin Karşılaştırılması. *Kafkas Universitesi Veterinerlik Fakültesi Dergisi, 3*(15), 481-484,.

Felder, J. N., Baer, R. J., Rand, L., Ryckman, K. K., Jelliffe-Pawlowski, L., & Prather, A. A. (2022). Adverse infant outcomes among women with sleep apnea or insomnia during pregnancy: A retrospective cohort study. *Sleep Health*.

Field, A. (2013). *Discovering Statistics Using Spss.* İngiltere: SAGE.

Force, A. A. (1999). Sleep-Related Brecommendations for Syndrome Definition and Measurement Techniques in Clinical Research. *Sleep-Related Breathing Disorders in Adults*.

Kang, B., Dang, X., & Wei, R. (2017). Snoring and apnea detection based on hybrid neural networks. *2017 International Conference on Orange Technologies (ICOT)*, 57-60.

Korkalainen, H., T, L., J, A., S, N., S, K., A, L., . . . J, T. (2020). Accurate Deep Learning-Based Sleep Staging in a Clinical Population With Suspected Obstructive Sleep Apnea. *IEEE Journal of Biomedical and Health Informatics*, 2073-2081.

Kurtulmuş, H. (2007). Obstrüktif Uyku Apnesi ve Horlamanın Tedavisinde Mandibular.

L. Almazaydeh, M. F. (2012). A Neural Network System for Detection of Obstructive Sleep Apnea Through SpO2 Signal Features. *International Journal of Advanced Computer Science and Applications*, 7-11.

Lin, X., Cheng, H., Lu, Y., Luo, H., Li, H., Qian, Y., . . . Wang, M. (2022). Contactless sleep apnea detection in snoring signals using hybrid deep neural networks targeted for embedded hardware platform with real-time applications. *Biomedical Signal Processing and Control*, 103765.

M. W. Rivolta, M. M. (2014). Effects of the series length on Lempel-Ziv Complexity during sleep. *2014 36th Annual International Conference of the IEEE Engineering in Medicine and Biology Society*, 6.

Pitkänen, H., Leppanen, B., S, T. K., A, K., S, M., J, T., & H, K. (2022). Gamma Power of Electroencephalogram Arousal Is Modulated by Respiratory Event Type and Severity in Obstructive Sleep Apnea. *IEEE Transactions on Biomedical Engineering*, 1417-1423.

Sériès, F. (1999). Nasal pressure recording in the diagnosis of sleep apnoea hypopnpea syndrome. *Thorax*, 506-510.

Sezgin, N., & Tagluk, M. (2011). A new approach for estimation of obstructive sleep apnea syndrome. *Expert Systems with Applications*, 5346-5351.

Shoib, S., Ulla, I., Nagendrappa, S., Taseer, A. R., Berardis, D. D., Singh, M., & Asghar, M. S. (2022). Prevalence of mental illness in patients with obstructive sleep apnea-A cross-sectional study from Kashmir, India. *Annals of Medicine and Surgery*, 104056.

Taran, S., Bajaj, V., Sinha, G., & Polat, K. (2021). Detection of sleep apnea events using electroencephalogram signals. *Applied Acoustics*.

Ulukavak Çiftçi, T. (2012). Obstrüktif Uyku Apne Sendromu Tanı ve Tedavi Uzlaşı Raporu. *Türk Toraks Derneği*.

Várady, P., Micsik, T., Benedek, S., & Benyó, Z. (2002). A Novel Method for the Detection of Apnea and Hypopnea Events in Respiration Signals. *IEEE Transactions on Biomedical Engineering*, 936-942.

Yiğit, E., & Gökpınar, F. (2010). A Simulation Study on Tests for One Way ANOVA UNDER THE Unequal Varience Assumption. *Communications, Series A1:Mathematics and Statistics, 59*(2), 15-34.

Yıldız, M. (2017). Kalp Seslerinden Uyku Apnesi Tespit Edilebilir mi? *Türk Uyku Tıbbı Dergisi*, 16-21.

Zhang, Y., Wei, S., Maria, C. D., & Liu, C. (2016). Using Lempel–Ziv Complexity to Assess ECG Signal Quality. *J Med Biol Eng*, 625–634.

Zhuang, Z., Wang, F., Yang, X., Zhang, L., Fu, C.-H., Xu, J., . . . Hong, H. (2022). Accurate contactless sleep apnea detection framework with signal processing and machine learning methods. *Methods*, 167-178.

Ziv, A. L. (1976.). On The Complexity of Finite Sequences. *IEEE Transactions on Information Theory, IT-22* (1), 75–81.