The Role of Sports Participation in Hemispheric Dominance: Assessment by Electrodermal Activity Signals

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Abstract: *This study aims at evaluating hemispheric differences between active sportsmen (n=17) and sedentary control subjects (n=21) using Electrodermal Activity (EDA), which is a physiologic measure of emotional sweating. Following the denoising of the acquired EDA records, feature extraction functions were utilized for each record to generate a feature vector, containing 14 parameters per record. Statistical significances of the differences and similarities between feature vectors were determined by unpaired t-test (p<0.05 and p>0.95). Findings from this study show that the agreement of hemispheric dominance test with hand preference is significantly lower for active sportsmen in comparison to control group. This implies that participation in sport activity may play a facilitative role in a more equally weighted development of both hemispheres by somewhat decreasing the hemispheric lateralization.*
Keywords: *signal processing; feature extraction; statistical comparison; denoising methods, electro dermal activity.*

1. Introduction

Electrodermal Activity (EDA) is defined by the electrical activity that is stemming from the electrochemical interactions between sweat glands and, epidermal and dermal layers of the skin.

Electrodes positioning on the certain locations of the skin surface can measure this activity [1,2].

EDA is a physiologic measure for the assessment of the sympathetic activity. Therefore, this technique has found widespread applications in the clinical neurophysiology and psychophysiology.

In most cases, EDA signals are not used solely. Instead, they are commonly utilized as a supporting parameter for polygraph tests. Nevertheless, EDA records have been evaluated in the investigation of diseases such as hemispheric asymmetry, anxiety, depression and schizophrenia [3]. For example, Bakker et al. (2011) have classified parameters according to their effects on the dynamic stress levels in daily life by applying median filtering and symbolic assembly methods [4].

Several other studies have focused on combined assessment of physiological signals together with EDA [5]. Furthermore, EDA have been taken into account along with electrocardiogram (ECG) and electromyogram (EMG) records for the real-time stress level monitoring during driving [6].

Note that EDA terms a general notion to describe all electrical activity occurring on the skin level. These activities comprise active and passive electrical properties of the skin and its secondary structures.

There are two common techniques in the evaluation of skins electrical properties, known as endosomatic and exosomatic methods. The exosomatic method can either use a direct current (DC) or alternating current (AC) through a circuit consisting of a galvanometer, electric battery and human body to measure changes in EDA; however DC currents are used more often than AC currents. In contrast the second method, the endosomatic method, uses a human body and galvanometer circuit to measure changes in resting electromotive force, or voltage of the skin [7-13].

In the present study, we hypothesized that sport participation reduces hemispheric lateralization. The aim of the study was to test this hypothesis by employing exosomatic technique.

2. Methods
2.1. Subjects and Data Recording

In this study, data recording and experimental procedures were approved by the Ethics Committee of Clinical Sciences at Erciyes Univesity. All data recordings were carried out at Brain Dynamics Laboratory, Physiology Department, Medical School, Erciyes University.

Among the 38 healthy individuals (age: 20±0.4, mean±SD) who agreed to participate, 17 were sportsmen (8 right-handed and 9 left-handed) and the remaining were sedentary control subjects (11 right-handed and 10 left-handed).

Sportsmen's expertisement branches which are especially needs team coordination just as football (n=6), basketball (n=4) and volley (n=7).

EDA records were acquired using MP30 (Biopac Systems Inc., USA) via electrodes placed on the palmar regions of the distal phalanxes of the thumb and index fingers of both hands, with a sampling frequency of 200HZ is seen Fig. 1.
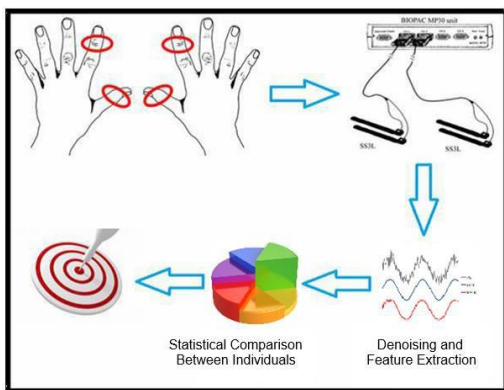

Figure 1. Schematic flow-chart of the data acquisition and processing steps. Electrode positions are indicated by circles on the fingers.

Signal processing, denoising and feature extraction operations were carried out in Erciyes University Biomedical Engineering Department.

2.2. Phasic and Tonic EDA Records

In the present study, resting state (tonic) EDA signals were recorded during 120 seconds, whereas phasic EDA signals were recorded during the Raven Progressive Matrices (RSPM) protocol, which requires subjects to answer 20 questions. Prior to signal recording, hemispheric dominance and hand preference tests were applied per subject.

In addition, SPO2 and ECG wristband (W/Me, Phyode Inc., USA) was monitored to ensure that subjects were not under the influence of hormonal, emotional, physiological and environmental effects. This wristband is responsive against the physiological changes occurring in response to subjects' mood. If any signs of internal or external excitatory factors were detected, subjects were given enough time before appropriate conditions for data recording were reached.

2.3. Determination of Hemispheric Dominance and Hand Preference

Human brain is "cross-wired" so that the left hemisphere controls the right handed side of the body and the right hemisphere controls the left handed side of the body.

Hand preference has been commonly taken as a basis for the determination of hemispheric dominance for many years. Recent reports also provide support for the relationship between handedness and hemispheric dominance.

In the present study, cerebral dominance was determined according to the subjects' score on the Annett Hand Preference Questionnaire and Hemispheric Dominance Test. [14]. Results from these tests are further compared with the RSPM procedure which is a measure of general cognitive abilities and can also be used in the determination of hemispheric dominance. Findings from these test were compared with the verbal declaration of hand preference made by participants.

2.3.1. Annett Hand Preference Questionnaire

Hand preference is related with hemispheric dominance. Therefore, we utilized Annett Hand Preference Test to compare our results.

This test directs 13 questions to determine handedness of an individual. Assessment is based on the choice of hand preference for different daily activities such as brushing teeth, using spoon and other handtools, opening jar, striking a match etc.

If score falls between 13-17 points, subject is considered as right handed. Whereas, if it is between 18-32 points, individual is ambidextral. Aby scores above 32 indicates left handedness [14].

2.3.2. Hemispheric Dominance Test

Although Annet's test is a commonly preferred method for hand preference determination, this evaluation is based solely on the script. To strengthen this evaluation, we also applied RSPM, in which the hand preference is determined using visual test items.

2.3.3. Raven's Progressive Matrices

Raven's Progressive Matrices method dates back to past in the assessment of general cognitive abilities. However, it can also be employed to determine hemispheric dominance.

This test includes 20 visual test items. For each test item, the subject is asked to identify the missing element that completes a certain pattern. Fig.2 shows a sample question from RSPM test.
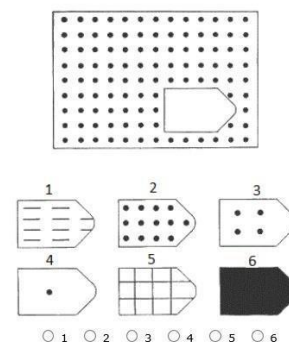

Figure 2. A sample question from RSPM procedure

2.4. Signal Denoising

Biopotential signals attain low frequency components. For example, EDA signal has a characteristic signal frequency within a range of 0.0167 to 0.25 Hz. Therefore, it is highly affected by line frequency noise interference [15].

Based on the comparison of signal denoising performance measures by Aladag et al. (2015), Singular Spectrum Analysis (SSA) was qualified as a substantially efficient method for the noise removal of EDA signals thanks to its high decomposition sensitivity. Therefore, this technique was utilized to eliminate power-line interference from the noisy-raw EDA signals are seen above section of Fig. 3.
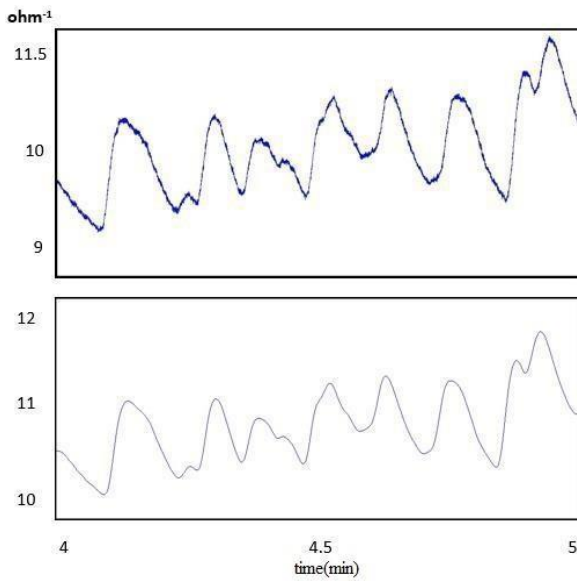

Figure 3. Original EDA signal from a representative subject (upper panel) and the same signal after denoising with SSA (lower panel).

2.5. Feature Extraction

Parameter identification is the first step to create a feature vector that enables between-groups comparisons for detecting significant differences. Essential statistical measures such as average, median, standard deviation, variance, maximum, minimum, range, mode values, entrophy, skewness, kurtosis, peaks of the EDA signal can be incorporated into feature vector as parameters.

In the present study, measures for uncertainty such as entropy, skewness and kurtosis are also included in the feature vector along with essential statistical measures. Furthermore, mean signal power and root mean square (RMS) are added into feature vector as additional signal characterization metrics. Feature vector generation method applied in this study has been described in detail elsewhere [16]. And feature extraction function was applied phasic and tonic records, after the signal denoising with SSA.

3. Determination of Feature Vector Identification Way

Parameter identification is an essential step to determine statistical differences or similarities between individuals. Therefore, we have chosen parameters with utmost attention to provide a sufficient separation power for statistical significance.

In the present study, three different methods were employed on the denoised signals to determine statistical differences (p<0.05) and similarities (p>0.95). These techniques are detailed within this section.

3.1. Application of SSA Followed by Feature Extraction Function

The Singular Spectrum Analysis (SSA) technique is a powerful technique of time series analysis, incorporating the elements of classical time series analysis, multivariate statistics, multivariate geometry, dynamical systems and signal processing [17].

The aim of SSA is to decompose original time series into the sum of a small number of independent and interpretable components such as slowly varying trends, oscillatory components and random noise. Decomposition of signal into its principal values is carried out with respect to the selected window length (Fig4).
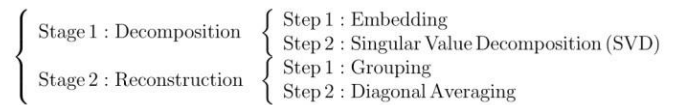

Figure 4. A short description of the SSA technique (for more information see [18])

After several trials, a window length of 7 was considered suitable to obtain an acceptable signal. Following this, subsignals were acquired, which were denoted as "R" in Fig. 5. Feature extraction function was applied to R2+R3 as seen Fig 6, R4+R7 and other combinations are also applied.

A "p value" lower than 0,05 indicates statistical significance, whereas "p value" higher than 0,95 implies similarity. Application of SSA did not reveal any statistical significance or similarity.
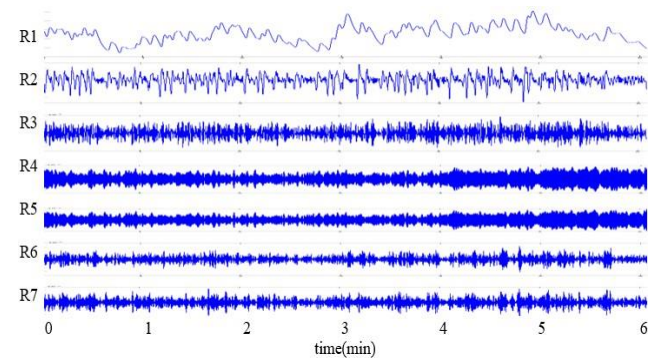

Figure 5. SSA decomposition with a window length of 7 and demonstration of components.
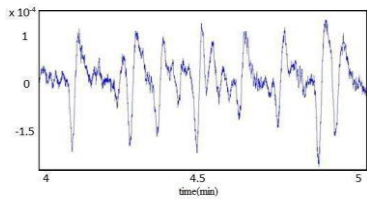
Figure 6. SSA applied for the R2 an R3 summation

3.2. Standalone Employment of Feature Extraction

Using SSA method only, feature extraction function was applied on denoised signal. However, no statistical meaning was observed among the participants with this approach.

3.3. Application of DWT Followed by Feature Extraction Function

Discrete wavelet transforms (DWTs), analyze signals and images into finer octave bands progressively. This multiresolution analysis enables the detection of the patterns that are not visible in the raw data. This method can also be used to reconstruct signals (1–D) and image (2–D) approximations that contains desired features only, and to compare the distribution of energy in signals across frequency bands [19]. In the present study, we applied 10th Degree Haar Filtering DWT to the denoised signals (Fig. 7). This transform is calculated using the equation 1.

When DWT is applied to a certain sampled function s(t), this function becomes decomposed as the addition of a set of signals, namely wavelet signals: An approximation of a signal at a certain decomposition level n (a_n) plus n detail signals (d_j with j varying from 1 to n). The mathematical expression characterizing this process is given by equation 1, where $(\alpha_i)^n$, $(\beta_i)^j$, are the scaling and wavelet coefficients, $\varphi^n(t)$, $\psi^j(t)$ are the scaling function at level n and wavelet function at level j, respectively, and n is the decomposition level [20-22].

$$s(t) = \sum_i \alpha_i^n \cdot \varphi_i^n(t) + \sum_{j=1}^n \sum_i \beta_i^j \cdot \psi_i^j(t) = a_n + d_n + \dots + d_1 \quad (1)$$
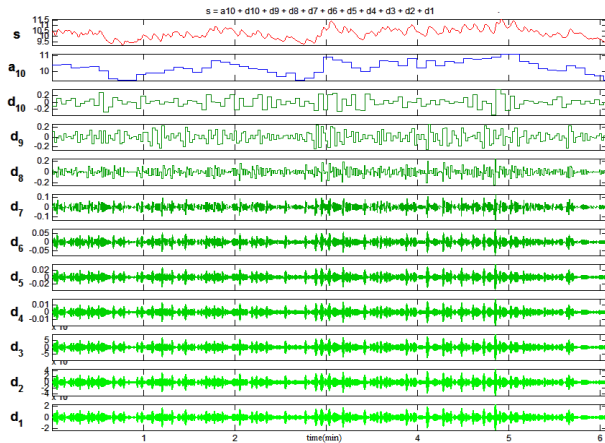

Figure 7. 10th degree Haar Filtering DWT

Next, we applied feature extraction function to reconstructed signal from 10th degree DWT's subsignals (Fig. 8).
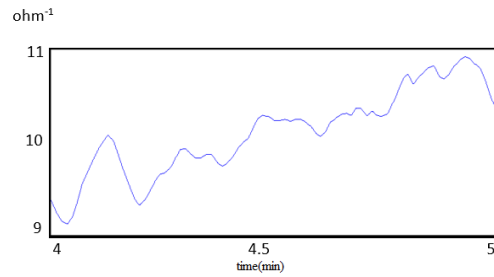

Figure 8. Reconstructed signal from 10th degree DWT's subsignals (a10+d9+d8+d1)

We found statistical differences and similarities using this method. Findings from this method explained in the results section.

4. Results
4.1. Annett Hand Preference Questionnaire Result

Test results from the control group revealed that among the sedentary participants who declared right-handedness, 18,2% were left handed. Ratio of the subjects whose hand preference was rejected by the tests was 10% for left handedness in the sedentary group.

In sportsmen the ratio of the rejection were higher. Among these participants who declared right-handedness only 37,5% was scored as right handed in tests, whereas 62,5% was characterized as ambidextral. Similarly, ratio of the subjects who are characterized as left handed and those as ambidextral were 33,3% and 66,7% respectively.
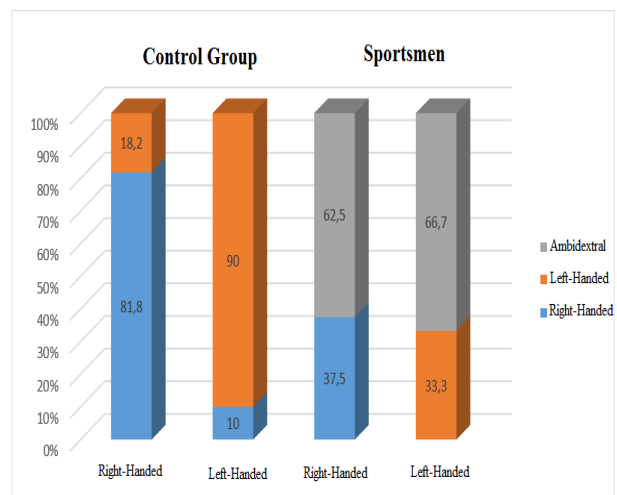

Figure 9. Annett hand preference questionnaire results

4.2. Hemispheric Dominance Test Result

Hemispheric dominance test results showed that 80% of right-handed individuals use left hemisphere, whereas 90,9% of left-handed individuals use right hemisphere (Fig. 10).

In sportsmen, 21,4% of right-handed individuals appeared to use their left hemisphere, whereas 7,1% them use right hemisphere and 71,5% use both hemispheres. On the other hand, 14,2% of left-handed individuals appeared to use right hemisphere, whereas 7,1% use left hemisphere and 78,7% use both hemispheres (Fig. 9).

Note that such less emphasized hemispheric lateralization of sportsmen constitutes a support for the hypothesis. However, a statistical confirmation is required for its acceptance.

Due to the involvement of stimulation, EDA values from phasic records were higher than those obtained from tonic records.

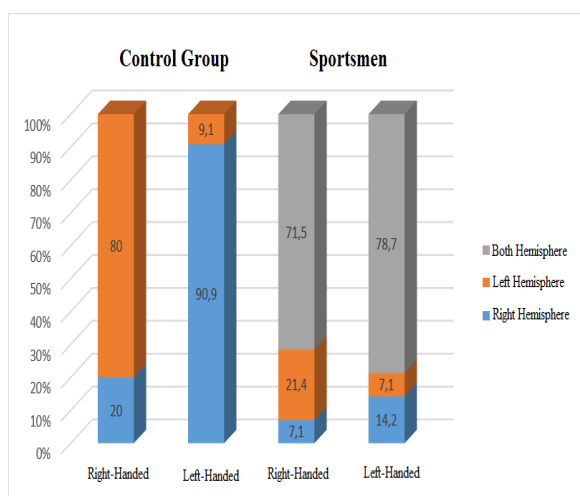Statistical significance of phasic records was equal to that of tonic records.

Figure 10. Hemispheric dominance test results

5. Conclusions

Effect of sports participation on hemispheric dominance was evaluated in the present study.

EDA records were denoised using signal processing methods to extract reliable information. Next feature extraction functions were applied on denoised EDA signal for to create feature vectors for comparison. 14 parameters were incorporated into this vector with regard to their statistical significance.

In accordance with the previous findings from literature [2], our findings show that hemispheric difference is more emphasized in sedentary subjects in comparison to sportsmen.

Handedness indicated by Annett and hemispheric dominance tests were in good compliance with the hand preference of the sedentary subjects in their daily lives. However, such compliance was less prominent for sportsmen. This implies that sportsmen follow a more balanced strategy for hemispheric recruitment.

The evaluation of this compliance was based on the statistical significances ($p<0.05$) of the differences or similarities ($p>0.95$) by applying unpaired t-test between feature vectors those are obtained using EDA signals.

According to Table 1, sedentaries left hand entropy is different than their right hand entropy. However, for sportmen, left hand entropy equaled to the right hand entropy, indicating a difference between sedentary subjects and sportsmen.

According to Table 2, right hand significance value of left handed sedentary subjects is different from that of left handed sportmen's for Kurtosis, indicating a difference between sedentary subjects and sportsmen.

Significant differences between sportsmen and sedentary subjects were indicated by entrophy, skewness and kurtosis calculations in Table 3 for those subject shown in Table 2.

Findings from this study accept our hypothesis, suggesting that the agreement of hemispheric dominance test with hand preference is significantly lower for active sportsmen in comparison to control group.

This implies that participation in sport activity may play a facilitative role in a more equally weighted development of both hemispheres by decreasing the hemispheric lateralization.

Table 1. Comparison of intra-group significance values

Feature	Right Hand and Left Hand Comparison of Right Handed Sedentery	Right Hand and Left Hand Comparison of Left Handed Sedentery	Right Hand and Left Hand Comparison of Right Handed Sportmen	Right Hand and Left Hand Comparison of Left Handed Sportmen
Entrophy	0,83	0,69	1,00	1,00

Table 2. Comparison of sportmen and sedentary subjects with identical hand preferences.

Feature	Right Hand Comparison of Right Handed Sedentery and Sportmen	Left Hand Comparison of Right Handed Sedentery and Sportmen	Right Hand Comparison of Left Handed Sedentery and Sportmen	Left Hand Comparison of Left Handed Sedentery and Sportmen
Kurtosis	0,38	0,23	0,05	0,13

Table 3. Comparison of sportmen and sedentary subjects with difference hand preferences.

Feature	Left Hand Comparison of Right Handed and Left Handed Sportmen	Right Hand Comparison of Right Handed and Left Handed Sportmen	Left Hand Comparison of Right Handed and Left Handed Sedentery	Right Hand Comparison of Right Handed and Left Handed Sedentery
Entrophy	0,70	0,70	0,05	0,05
Skewness	0,04	0,04	0,87	0,16
Kurtosis	0,23	0,28	0,05	0,05

6. Acknowledgements

7. References

[1] Bouscein W. Electrodermal Activity. Newyork, Plenum Pres. 1992, 1-372.
[2] Dolu N, Özbek H, Determination of the Hemispheric Difference at Attention Level in Sportsman, Erciyes University, Kayseri, 2009

[3] Dolu N, Yüksek A, Sizer A, Alay M. Arousal and continuous attention during Ramadan intermittent fasting. J Basic Clin Physiol Pharmacol. 2007;18(4):315-22.

[4] Bakker J., sensor data, ICDMW '11 Proceedings of the 2011 IEEE 11th International Conference on Data Mining Workshops.

[5] Begum S., Ahmed MU., Funk P., Xiong N., and Schéele B.V, (2009), Case-Based Decision Support System for Individual Stress Diagnosis Using Fuzzy Similarity Matching, The Journal of Computational Intelligence (CI), vol 25, nr 3, p180-195.

[6] Rigas G., Goletsis Y., and Fotiadis DI., Real-Time Driver's Stress Event Detection, IEEE Transactions on Intelligent Transportation Systems 2012; 13:221-234.

[7] Stefan Schmidt and Harald Walach, (2000), Electro Dermal Activity (EDA) Research – State of the art measurement and techniques for Parapsychological purposes.

[8] Boucsein W. Electrodermal Activity. New York: Plenum Press. 1992.

[9] www.stanfordchildrens.org, "What is a superficial SDYstdegree burn?", Standford's Children Health Lucile Packard Children's Hospital, Standford

[10] Ethan Leng, Mihir Mongia, Charles Park, Tiffany Varughese, Andrew Wu, SMART Belt: A Low-cost Seizure Detection Device, Rice University

[11] Geddes LA, Baker LE. Principles of Applied Biomedical Instrumentation, 3rd ed. New York: John Wiley and Sons.1989.

[12] Qiao ZG, Morkrid L, Grimnes S. Three-electrode Method to Study Event-related Responses in Skin Electrical Potential, Admittance and Blood Flow. Med Biol Eng Comput 1987;25: 567-72.

[13] Stern RM, Ray WJ, Davis CM. Psychophysiological Recording. New York: Oxford: Oxford Universty Press. 1980: 196-210.

[14] Uslu, R. (1996). Neurological Soft Signs In Children With Psychiatric Disorders. Child Psychiatry Thesis. Department of Child Psychiatry, Ankara University.

[15] Aladağ S., Güven A., Özbek H., Dolu N., "A Comparison of Denoising Methods for Electrodermal Activity Signals", Tıp Teknolojileri Kongresi 2015, MUĞLA, TURKEY, 15-18 Ekim 2015, ss.213-216

[16] Aladağ S., Güven A., Dolu N., Özbek H., (2016). "Measuring Electrodermal Activity To Determining Sympathetic Activity In Sportsman And Feature Extraction With Signal Processing Methods", Tıp Teknolojileri Kongresi, TIPTEKNO, ANTALYA, TURKEY, 27-29 Ekim 2016, ss.98-101

[17] Hassani H., "Singular Spectrum Analysis: Methodology and Comparison", Journal of Data Science 5(2007), 239-257

[18] Golyandina, N., Nekrutkin, V., and Zhigljavsky, A. (2001). Analysis of Time Series Structure: SSA and related techniques, Chapman & Hall/CRC, New York - London.

[19] Chaovalit P., Gangopadhyay A., "Discrete Wavelet Transform-Based Time Series Analysis and Mining",ACM Computing Surveys, Vol. 43, No. 2, Article 6, Publication date: January 2011.

[20] Burrus, C.S.; Gopinath, R.A.; Guo, H.: "Introduction to Wavelets and Wavelets Transforms. A Primer." Prentice Hall, 1997.

[21] Mallat, S.: "A Wavelet Tour of Signal Processing, Third Edition". Academic Press, dec. 2008.

[22] Chui, C.K.: "Wavelets: A Mathematical Tool for Signal Analysis", SIAM, 1997.

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