

Identification of Drug-addicted People using Short Length of Voice Signal through Haar and Symlet Wavelet Transform

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ABSTRACT

Recognizing and classifying signals is one of the most significant tasks nowadays. For an uncountable number of purposes, classification, pattern recognition, data pre-processing, and prediction science are used worldwide. In this work, our objective is to understand, analyze, visualize, recognize, and identify drug-addicted and non-addicted people by using their short length of voice signals through Haar and Symlet (Sym2) wavelet transform. Here, we used signals of speech at a considerable length to achieve our goal and provide opportunities for the law-and-order enforcing authority and the people who are interested in this area. We visualize each signal and analyze them using different wavelet transform to understand the similarities and dissimilarities between the voice signals. After wavelet transform, we calculate the PSNR and SNR values of the voice signals using MATLAB wavelet toolbox. To the PSNR and SNR values of the voice signals and try to make the similarities and dissimilarities between the voice signals. From the values we can make a decision to identifying a Drug-addicted people.

Keywords: Drug-addicted people detection, wavelet transform, power spectrum, signal to noise ratio (SNR), peak signal to noise ratio (PSNR)

INTRODUCTION

Now a days, drugs are a vibrant issue for the whole world. Drug addiction is an illness that affects a person. Any legal or illicit substance might cause a people to become fascinated with it. Certain drugs can lead to addiction in certain people. When an individual continuing to take the substance despite the harm it produces, addiction develops gradually. Alcohol, and marijuana are two of the most often abused narcotics in today's society. According to the Journal of Family Medicine and Primary Care, 2019 [10] alcohol consumption was responsible for 50% of deaths from liver cirrhosis, 30% of deaths from oral and pharyngeal cancers, 22% of deaths from interpersonal violence, 22% of deaths from suicide, 15% of deaths from traffic injuries, 12% of deaths from tuberculosis, and 12% of deaths from liver cancer worldwide. According to the WHO, there are 2 billion alcoholics, 1.3 billion smokers, and 185 million illegal drug users in the globe [7]. Currently, 80 percent of tobacco users live in low- and middle-income countries (LMICs) [6], and by 2030, LMICs are expected to account for 80 percent of tobacco-related fatalities [9]. Smoking and alcohol usage are responsible for 20% of tuberculosis (TB) cases globally, in India accounting for 27% of the world's TB patients in 2017 [1]. In Australia, about 6,000 individuals die each year from alcohol-related disorders, with "drunk and drive" instances accounting for 30% of fatal automobile accidents [8]. The largest incidence of alcohol use disorder (7.5%) is found in Europe, whereas the lowest is found in the East Mediterranean Regions, which include Afghanistan, Bahrain, and Egypt [10]. Drug misuse is increasingly rampant everywhere: in the home, on the streets, at work, in parks, slums, marketplaces, and even in rural and urban educational institutions. This issue has a significant impact on almost every aspect of society [8].

To identification of Drug-addicted people is very essential in many aspect. There are many types of test system are available in the world such as Urine drug tests, DOT drug tests, Hair drug tests, Alcohol tests [2] etc. For developing and under developing countries addicted people is a major issue. Most of the country Dope tests is using for identifying drug addicted people. All the testing process are time consuming and costly. In our research we are trying to identify the addicted people fast and foremost. We assumed that if an individual continue to take drug it affected on his voice. In our research we used voice signal to identifying drug addicted people.

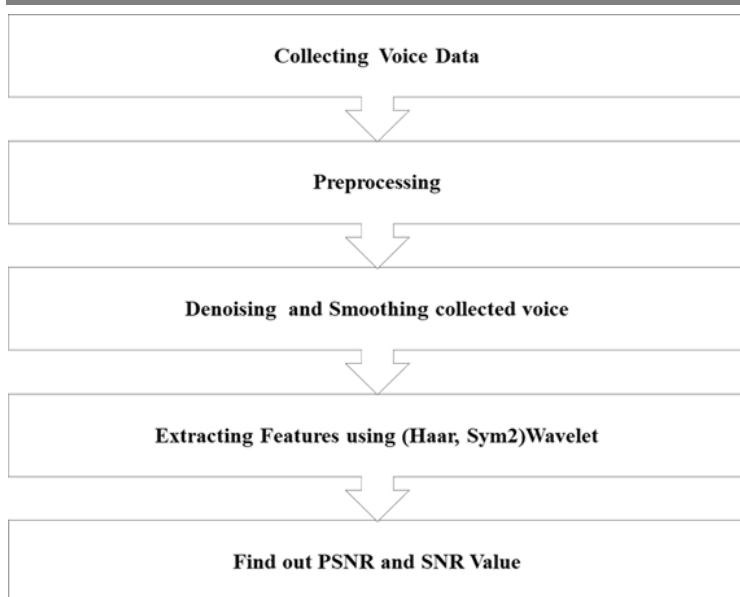
In this work only on two different types of drugs, which are alcohol and marijuana. Many governments all over the world permit alcohol and marijuana consumption with limitations. If anyone takes over the limit, then it is a high risk for health and also breaks down the government rules. Then it's considered an offense. For numerous grown-ups, drinking small quantities of alcohol doesn't affect serious health problems. Women who drink no further than 1 drink a day (and not further than 7 drinks per week) and men who drink no further than 2 drinks a day (and not further than 14 drinks per week) are at low threat for developing problems with alcohol use [5]. Grown-ups 21 or aged can fairly retain up to 28.5 grams of marijuana, as well as over to 8 grams of cannabis concentrate. However, the answer is yes, if you're wondering if you can fairly grow marijuana in California. They can have up to six live marijuana shops. Grown-ups between the periods of 18 and 20 times old can fairly buy and retain up to 8 ounces of marijuana and 12 live shops if they have a medical marijuana license attained through a croaker's recommendation [4].

Wavelets are mathematical functions that divide data into multiple frequency components and analyze each component with a resolution equal to its scale. A wavelet transform is a representation of a function using wavelets [12]. A wavelet is a mathematical function that separates a continuous-time signal or function into discrete scale components in more technical terms. A frequency range is commonly allocated to each scale component. Then, at a resolution that corresponds to its scale, each scale component may be studied. The wavelet will resonate if the unknown signal contains information of a same frequency, similar to how a tuning fork physically resonates with sound waves of the same frequency. The concept of resonance is used in many practical applications of wavelet theory. The use of wavelet methods for processing one-dimensional and two-dimensional data is highlighted in contemporary wavelet signal processing research. In 1-D wavelet signal processing, acoustic, voice, music, and electrical transient signals are common. Noise reduction, signature identification, target detection, signal and picture compression, and interference suppression are all part of 2-D wavelet signal processing [3].

METHODOLOGY

We collect voice samples from publicly available sources, specifically YouTube videos, where users have voluntarily shared their content online. Consequently, the data were gathered from public domain material without direct interaction or intervention with the individuals. For this research, we are using the voices of those people who have taken over the legal limit of alcohol, marijuana, or both more than 25 years. To respect privacy and confidentiality, all voice samples were anonymized by using only short segments of speech without any personal identifiers or sensitive information. This approach ensured that individual identities remain protected throughout the research.

The individual people's voice data is collected from YouTube and converted to audio mp3 format. We take 16 non-addicted people's voices and 16 addicted people's voices. We take only five seconds of each voice's speech. Then we process the raw data using denoising and smoothing the collected voice data, we transform it through Haar and Sym2 wavelet. Haar wavelet is effectively captured abrupt changes and also discontinuities in signals that are generally expected in drug addicted people voices. Its orthogonality and compact mechanism for fast processing makes it practical for real world applications [11]. Sym2 wavelet capture subtle variations in voice patterns by using its symmetry and frequency localization with minimal phase distortion [13]. We analyze the power spectrum of the transformation. Then calculate the PSNR and SNR values using MATLAB toolbox. The summary of the methodology in block diagram:



To statistically validate the differences observed in PSNR and SNR values between the addicted and non-addicted peoples, we applied hypothesis testing. Initially, we conducted the Shapiro-Wilk test [14] to assess the normality of the data and the PSNR and SNR distributions followed a near normal distribution ($p > 0.05$), we used the independent sample t-test to compare the people means.

RESULT AND DISCUSSION

The result discussion part we divide it into two parts:

a) Using power spectrum graph, b) Using PSNR and SNR values.

Using power spectrum graph

Power spectrum graph of addicted people's voice:

Haar Wavelet

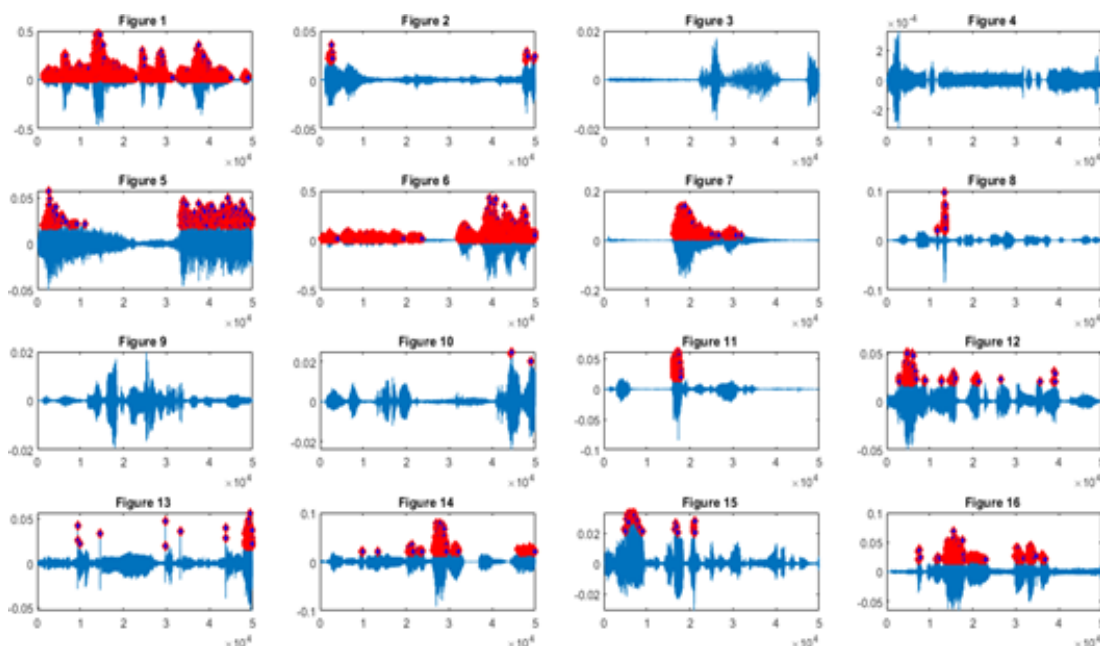


Fig-1: Power spectrum graph using Haar wavelet at level 2. In this graph, the power distribution exhibits narrow and sharp peaks, indicating a concentration of signal energy within a limited frequency band. These

sharp peaks suggest the presence of abrupt changes and discontinuities in the voice signals of addicted people. The power spectrum is notably asymmetric, reflecting non-uniform energy distribution across frequencies. This asymmetry and the localization of power indicate irregularities in the vocal patterns that can be attributed to the physiological and neurological effects of addiction. The Haar wavelet's ability to effectively capture such sudden changes makes it particularly suitable for analyzing addicted voices.

Sym2 Wavelet:

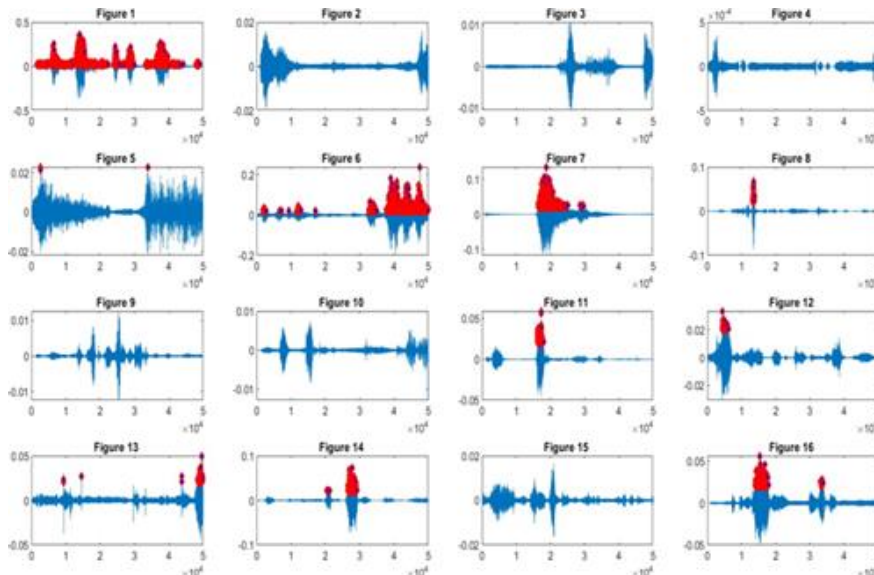


Fig-2: Power spectrum graph using sym2 wavelet at level 2. Sym2 power spectrum displays smoother and more symmetric peaks, although it still retains evidence of irregular vocal characteristics. The energy remains concentrated within a localized frequency range but is broader than that observed with Haar. The Sym2 wavelet's symmetry and minimal phase distortion allow it to capture more subtle variations in the voice signal, highlighting nuanced changes associated with addiction.

Power spectrum graph of non-addicted people's voice:

Haar Wavelet:

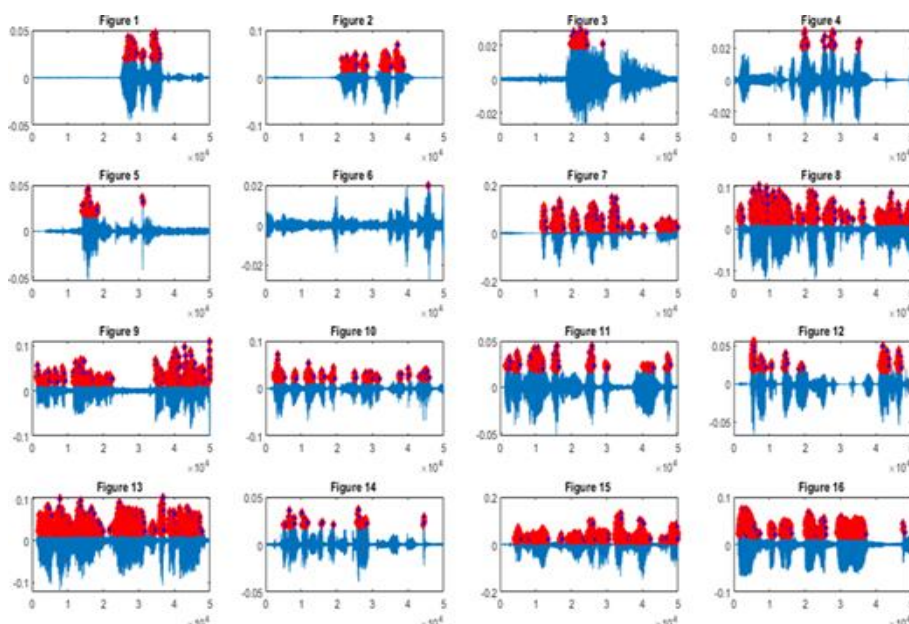


Fig-3: Power spectrum graph using Haar wavelet at level 2. The signal energy is distributed more evenly across a broader frequency range, reflecting a stable and consistent voice pattern. Additionally, the peaks are

denser and exhibit a higher point density, indicative of healthy voice signals without abrupt distortions or irregularities. This more uniform distribution underscores the absence of sudden changes in the voice signals of non-addicted individuals

Sym2 Wavelet:

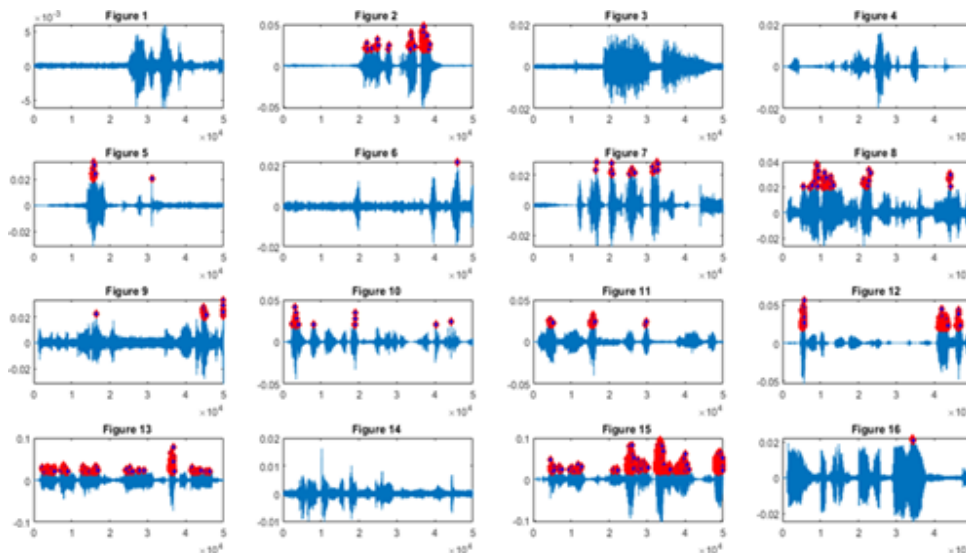


Fig-4: Power spectrum graph using sym2 wavelet at level 2. The graph reveals a smooth and symmetric power distribution, with broad frequency bands similar to the Haar wavelet results but emphasizing subtle frequency components with less distortion. The even energy spread and dense peak formation signify stable and regular vocal characteristics typical of non-addicted individuals.

From Fig.1-4, x-axis and y-axis are represent respectively frequency (Hz) and power spectrum (dB). For the same frequency of both cases, we see that non-addicted people's power spectrum has a symmetric limit corresponding to each other, but addicted people's power spectrum has no symmetric limit corresponding to each other. For addicted people, the width of the frequency is relatively small at the point where the highest peak points (which is denoted as the red color) of the coefficient are found, but for non-addicted people, the frequency is much wider and the maximum peak point density is much higher. In comparing Haar and sym2 wavelet, Haar wavelet is given better result.

The comparative analysis of the power spectrum graphs reveals marked differences between addicted and non-addicted voices. Addicted voices display asymmetric, narrow, and sharp peaks reflecting irregularities and abrupt changes, particularly well captured by the Haar wavelet. In contrast, non-addicted voices show symmetric, broader, and denser peaks that correspond to healthy and stable vocal patterns. The Haar wavelet's strength lies in detecting sudden discontinuities, while the Sym2 wavelet highlights smooth and subtle variations. These distinct spectral signatures reinforce the viability of wavelet-based power spectrum analysis as an effective approach for distinguishing drug-addicted voices from non-addicted ones using short speech segments.

Use of Calculating Peak Signal to Noise Ratio (PSNR) and Signal to Noise Ratio (SNR) values

Table

Name of Wavelet	Group	PSNR Value	SNR Value
Haar	Addicted	36.60–37.10	25.20–26.30
	Non-addicted	34.70–35.20	21.40–22.30
Sym2	Addicted	34.50–35.90	22.30–23.70
	Non-addicted	32.25–33.90	19.10–20.80

From the Table, in case of PSNR values by using Sym2 wavelet are lower than Haar wavelet for non-addicted people. So, for identification of addicted people by using PSNR values it is better to use Sym2 wavelet than Haar wavelet. In case of SNR values by using Haar wavelet are higher than Sym2 wavelet for non-addicted people. So, for identification of addicted people by using SNR values it is better to use Haar wavelet than Sym2 wavelet. To ensure that the differences in PSNR and SNR values between the addicted and non-addicted peoples, we conducted a series of statistical tests. Subsequently, independent t-tests were used to compare the mean PSNR and SNR values:

PSNR (Haar wavelet): $t = 39.097$, $p < 0.001$; PSNR (Sym2 wavelet): $t = 15.505$, $p < 0.001$; SNR (Haar wavelet): $t = 38.043$, $p < 0.001$; SNR (Sym2 wavelet): $t = 21.661$, $p < 0.001$. The p-values less than 0.001 across all tests indicate that the observed differences are statistically significant. The Shapiro-Wilk normality test confirmed that all groups approximately followed a normal distribution.

CONCLUSION

Nowadays, identifying drug-addicted people by the dope test is a very expensive and time-consuming process. Our proposed method allows fast and foremost identification of addicted people compared to any other technique. Moreover, when comparing Haar and Sym2 wavelets, the Haar wavelet gives better results. However, this research has some limitations: it only worked with male voices, used voices from 16 drug-addicted and 16 non-addicted people, requires people to speak under normal circumstances, and voices must be in English. For future work, we plan to include female voices and non-English speakers and expand our dataset by adding more voices from drug-addicted and non-addicted people. Most addiction tests today are slow, expensive, and require taking samples from the body. Our method only needs a few seconds of a person's voice and uses special wavelet analysis (Haar and Sym2) to quickly and easily detect addiction. Unlike other studies, we look closely at subtle changes in the voice and back it up with strong statistics. We plan to do a more detailed comparison with other methods in the future.

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REFERENCES

1. Beena Elizabeth Thomas, K. T. 2019. Smoking, alcohol use disorder and tuberculosis treatment outcomes: A dual comorbidity burden that cannot be PLOS ONE, 14(7), 1-12. Retrieved from <https://doi.org/10.1371/journal.pone.0220507>.
2. Health Street. 2022. Drug Tests. Retrieved from Health Street: <https://dki.health-net/D4/V1?pkw=drug%20testing>.
3. Islam, R. 2011. Wavelets, its Application and Technique in signal and image. Global Journals Inc.(USA),11(4).Retrieved from, March+2011, Volume-11(Issue+4)
4. Lessem, &. 2020. What's the Maximum Amount of Marijuana a Person. Retrieved from LESSEMNEWSTAT&TOOSON,LLP: <https://www.lnlegal.com/blog/2020/february/whats-the-maximum-amount-of-marijuana-a-person-c/>
5. Limit Alcohol. 2022. National Center for Health Promotion and Disease Prevention. Retrieved from UnitedStatesDepartmentofVeteransAffairs: https://www.prevention.va.gov/Healthy_Living/Limit_Alcohol.asp
6. Maxwell Oluwole Akanbi, A. 2018. The efficacy of smoking cessation interventions in low and middle-income countries: a systematic review and meta-analysis. *Addiction*, 114, 620–635. doi:10.1111/add.14518.
7. Ming Li, M. B. 2010. New insights into the genetics of addiction. *Nat Rev Genet*. Author manuscript, 10(4), : 225–231. USA: NIH Public Access. doi:10.1038/nrg2536.

8. Mohiuddin, A. K. 2019. Drug Addiction in Bangladesh: “A Consequence of Social Demoralization Rather Than Individual Flaws”. M. Nasirullah Memorial Trust, 2:10, pp. 1-11. Retrieved from <https://escipub.com/international-journal-of-addiction-research-and-therapy/>
9. Samuel Asare, S. 2019. Effects of Prices on Youth Cigarette Smoking and Tobacco Use Initiation in Ghana and Nigeria. *Int. J. Environ. Res. Public Health*, 16, 1-14. doi:10.3390/ijerph16173114.
10. V. M. Anantha Eashwar, S. G. 2019. Pattern of alcohol consumption and its associated morbidity among alcohol consumers in an urban area of Tamil Nadu. *Family Medicine and Primary Care*, 8(6), 2029-2035. doi:10.4103/jfmprc.jfmprc_226_19.
11. Subramani, P., Sahu, R., & Verma, S. (2006). Feature selection using Haar wavelet power spectrum. *Bmc Bioinformatics*, 7, 1-11.
12. Sk, M. S. I., & Alam, M. G. R. (2024). Unveiling personality traits through Bangla speech using Morlet wavelet transformation and BiG. *Natural Language Processing Journal*, 9, 100113.
13. Li, Z., Jiang, X., & Pang, Y. (2019). Evaluation of face recognition techniques based on Symlet 2 wavelet and support vector machine. In *Security, Privacy, and Anonymity in Computation, Communication, and Storage: SpaCCS 2019 International Workshops, Atlanta, GA, USA, July 14–17, 2019, Proceedings 12* (pp. 228-239). Springer International Publishing.
14. Hanusz, Z., Tarasinska, J., & Zielinski, W. (2016). Shapiro–Wilk test with known mean. *REVSTAT-statistical Journal*, 14(1), 89-100.