

Single-Period Single-Frequency (SPSF) Visualization of an EEG's Striatal Beat Frequency

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Abstract— Motivated by the neuroscience concept of striatal beat frequency a new method is presented that takes an electroencephalogram of brain-wave activity and searches for spectral components using a sliding bank of windows consisting of individual single-period single-frequency sinusoids. This new approach is now practical due to the presence of high performance computing architectures. And is a departure from legacy time-frequency spectrogram approaches which use one sliding window of constant size to calculate all frequency components simultaneously. The standard time-frequency approach relies on a Fourier Transform which, in a strict sense, assumes if a frequency component is said to be present in a window of time then that component must be uniform, continuous, and fully periodic across the entire window; at best the time-frequency approach can only characterize spectral content. The proposed single-period single-frequency search method is more tangible in identifying the existence, in time, of a frequency component due to its self-imposed constraint of using a bank of windows consisting of single period sinusoids, the length of each being a function of frequency and sampling rate. The result of this approach is a rendering of the on-off nature of the conceptualized striatal beat frequency components through a visualization of a matrix of correlation coefficients, where the rows are individual frequencies, (presented up to 1000 Hz in this paper), and where the columns indicate the position of each detected striatal beat frequency window of time.

Index Terms—Single-Period Single-Frequency (SPSF), neuroscience, striatal beat frequency, (non) Fourier Transform, (non) wavelet, (simple) correlation coefficient

I. INTRODUCTION

This paper is an extension of the poster that was presented at the AIPR 2019 workshop held at the Cosmos Club in Washington, DC. We presented, and defended, a method that utilizes the (seemingly) simple correlation coefficient calculation to exploit the presence of cortical neurons firing in an oscillatory manner, known as striatal beat frequency (SBF) [1][2], within a time domain recording of an electroencephalogram (EEG).

This paper asks the question, “Why are we stuck on the Fourier Transform?”, when it comes to analyzing electroencephalogram or electrocardiogram or other time invariant signals. We would not argue that for many applications the Discrete Fourier Transform (DFT) does indeed give a good estimate of frequency content within a time domain signal, but there are certainly many real-world applications where the output from a DFT is limited [3], or maybe more to the point,

it is in fact, at times misleading, in what it purports to describe. To be precise in our argument, whereas the DFT is generally described as a transform that decomposes a discrete and finite function of time into a set of (orthogonal) frequency components indigenous to the signal, we prefer to look at the DFT, from a subtly different point of view, that being, as a way to rewrite a time domain function, one that may not have any (sinusoidal) frequency components at all, in terms of a bank of orthogonal frequency components. For instance, we can rewrite a discrete set of points making up a line (segment) in terms of frequency components, but why? And then, there is the (well known, but usually pushed to the side) fact that a DFT is only reliable, in its display of frequency component content in a time domain signal which, contains exact periods of each frequency component (recognized in the display of the spectrum) throughout the entire clip (or window) of discretely sampled points.

The concerns stated above are similar to concerns found in recent publications that demonstrate approaches using either improved Fourier Transform or Wavelet methods to improve EEG analysis [3][4][5]. Yet, these recent approaches still rely on a “one-window-for-all” approach, be it time domain or wavelet based.

To differentiate our approach from the approaches mentioned above, ours is one that leverages, the concept of, and a simplistic model for, striatal beat frequency (SBF). Our approach uses the correlation coefficient calculation in a very time consuming and very tedious point by point, frequency by frequency, search for evidence of short term SBFs. Our sampling rate was set to $F_s=19,200$ samples/second and the highest SBF (frequency component) searched for was limited to 1000 Hz; an order magnitude less than the Nyquist limit of 9.6 KHz.

It is a calculation only recently made practical with the advent of high performance computers because our approach demands a set of individual windows, each comprising of a single-period of a single-frequency (SPSF) sinusoid, shifting in time. In stark contrast to the DFT and Wavelet approaches, the SPSF approach is extremely computationally intensive but offers the advantageous trade-off in being able to reliably pinpoint the start/stops of an SBF at frequencies up to 1000 Hz.

We close the introduction by including a comment from a report that was cited in a recent Master's Thesis [6] whose subject area centered on Augmented Cognition. The comment came from a 2010 report by M. L. Cummings [7] where (Missy) states "Without critical advances in EEG and other neurologic and physiologic technologies, the AugCog effort cannot make significant progress or be operationalized."

To that end, we submit our approach as being half-way there as we believe it pushes back against the limitations of the Heisenberg Uncertainty Principle in order to gain the upper hand in capturing a gain in SNR (signal-to-noise-ratio) while relaxing the very difficult to achieve hardware restrictions. As this paper proceeds we note that the figures shown throughout this paper are taken from our patent pending USPTO application [9].

II. A SINUSOID AND ITS LIMITED FOURIER TRANSFORM

This section shows a very simple example of how a Fourier Transform is limited in its portrayal of frequency content of a time domain signal. Figure 1 contains four time domain plots with their corresponding frequency domain plots. The example uses a 10 Hz frequency component that is sampled at $F_s=1000$ samples per second so that one period of this waveform consists of 100 points. This waveform can be found in plot A. The spectrum of A is given in plot D where, at a spectral resolution of 10 Hz/div (1000 F_s /100 samples) there is only one indication of frequency content; that being the contrived 10 Hz wave; perfect. It should be "textbook clear" that except for the multiples of 10 Hz, any other pure sinusoidal waveform would show a spectrum spread out among the frequency divisions, e.g. 100 points sampling of a 15 Hz waveform would necessarily result in indications given at the 10 and 20 Hz divisions (and beyond) since at this F_s the waveform cannot end on the period.

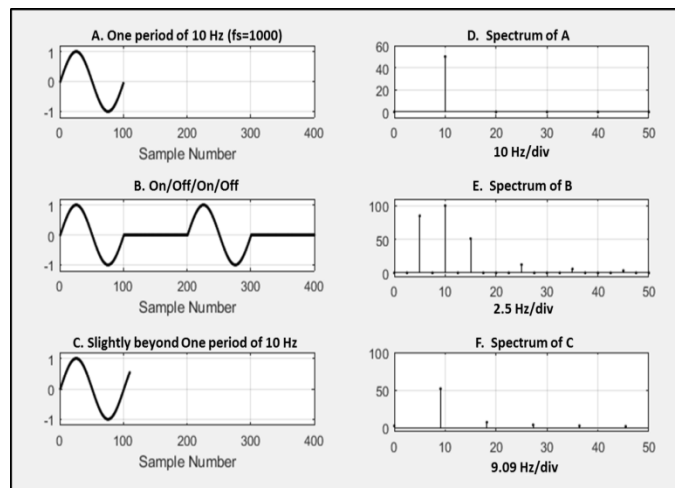


Fig. 1. A B, C are time domain plots. D, E, F are corresponding spectrums. D indicates that A consists solely of a periodic 10 Hz wave which can be Verified in A. E indicates that there are frequency components of 5, 10, 15, 25, and 35 Hz which is not visually apparent in B. F shows that there is a strong component at 9.09 Hz (along with multiples of 9.09) which is an artifact of sampling resolution and the fact that C is an extension of A.

In plot B we have formed a signal comprised of the 100 pt. 10 Hz wave followed by an "off" period of 100 points only to be followed with a copy of the wave and off period for a total of 400 pts., which yields a resolution of 2.5 Hz/div. Plot E is the spectrum of B and it indicates many frequencies besides the 10 Hz wave; a consequence of the fact the FT expects continuous sinusoids across the window of samples.

Finally, in plot C we took the same 10 Hz wave from plot A but extended the sampled window to 110 pts which now changes the frequency resolution to $F_s/110 = 9.09$ Hz/div, thus leading to the indication of multiples of 9.09 Hz components in the spectrum shown in plot F. This distortion is similar to the distortion described above with the 15 Hz wave. What we are seeing is the imposing destructive nature of the Heisenberg Uncertainty Principle when we are not in control of sampling rate, window size, frequency content, and frequency duration.

III. MOVING ON TO AN EEG AND A BASIC SPECTROGRAM

Centered our poster around five seconds of an electroencephalogram (EEG) sampled at 19200 samples/sec. The EEG, shown in Fig. 2, was taken at the Guger Technology (G-Tec) shop located on the Rensselaer Polytechnic Institute campus. An electrode was placed at the E14 position (256 node set-up) on this author's forehead.

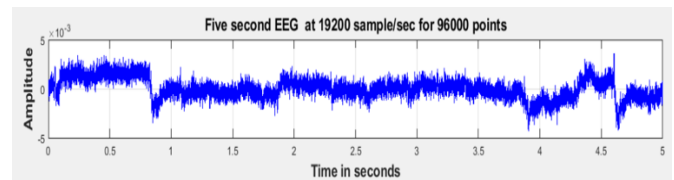


Fig. 2. Five second EEG from electrode placed at E14, with sampling rate $F_s=19,200$ samples/sec.

Figure 3 shows a spectrogram of the EEG where we invoked a window size of 19,200 pts with 90% overlap with a frequency axis spanning to 1000 Hz. The area below the 100 Hz mark does not indicate any outstanding neural activity across the 40 (one-at-time) windows.

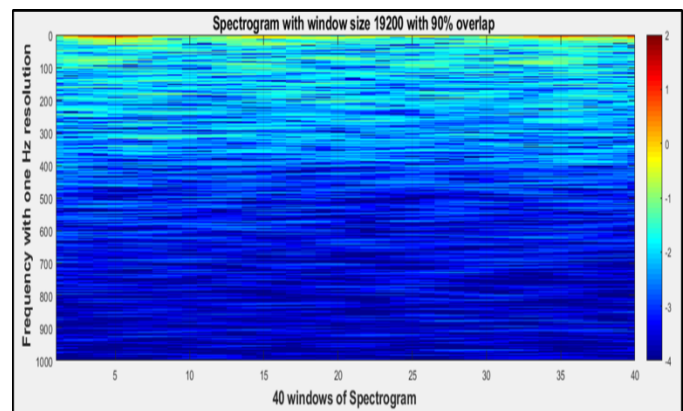


Fig. 3. Spectrogram of author's five second EEG taken at electrode E14. Frequencies are shown up 1000 Hz. There are 40 windows of 1 second duration, with 90% overlap, being analyzed.

Figure 4 is a zoom-in of Figure 3, spanning to 40 Hz, the usual span of frequencies shown in the literature over the past 50+ years. We will note that the previously cited papers, [3] [4][5], have demonstrated better techniques which would undoubtedly bring out visually appealing features in comparison to our (naively) generated spectrogram, yet their approach is still a generalized approach, by which we mean, their spectrogram (or wavelet) is based on a window in which for all practical purposes is not built around periodic sinusoidal waveforms; while ours is. Figure 4 is a depiction of the (generalized) DFT approach and it should be visually apparent that there is a smearing effect across consecutive windows in time.

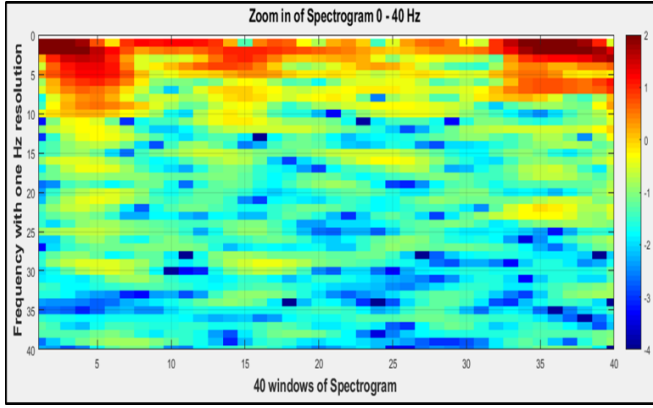


Fig. 4. Zoom-in of Fig. 3 from 0-40 Hz showing the smearing effect of the overlapping consecutive windows.

IV. THE SPSF BASIS FOR MODELING STRIATAL BEATS

The basis for our SPSF approach is a (somewhat bold) departure from the workhorse DFT, it is simple in that it calculates a correlation coefficient, and it is realistic in that we are only expecting a small number of contiguous oscillations when an SBF is detected. Figures 5 and 6 will briefly describe our approach in two parts. Figure 5 shows (52) as a continuous 10 Hz waveform sampled at $F_s=1000$ samples/sec. We apply a 100 point 10 Hz SPSF (53) at the center point sample number of 100 and take the correlation coefficient, in which case we calculate a -1; an indication of 180 degrees out of phase between the SPSF and the piece taken from (52). The -1 is registered in the bottom matrix at row number 10 and column number. As (53) is slid to the right one point at a time (we show some waveforms along the way) towards (57) we see that (55), indicated by the dashes is separated by 10 points, is in-phase with a piece of (52) and thus a +1 is recorded in the matrix in the bottom of Figure 5 at row 10, column 150. Other stopping points for this 10 SPSF would register correlation coefficients between these two extremes along the corresponding column entries for this 10 Hz row.

Figure 6 shows the case where a set of SPSFs at varying frequencies ((62) is a 1 Hz SPSF sampled at $F_s=19,200$, and (63), (64) are 2 and 3 SPSFs correspondingly) are correlated to a piece of EEG (61). The SPSFs centered on the same center

point indicated by (65). In this case the set of corresponding calculated correlation coefficients are recorded as entries in the column of the matrix shown at the bottom of Figure 6.

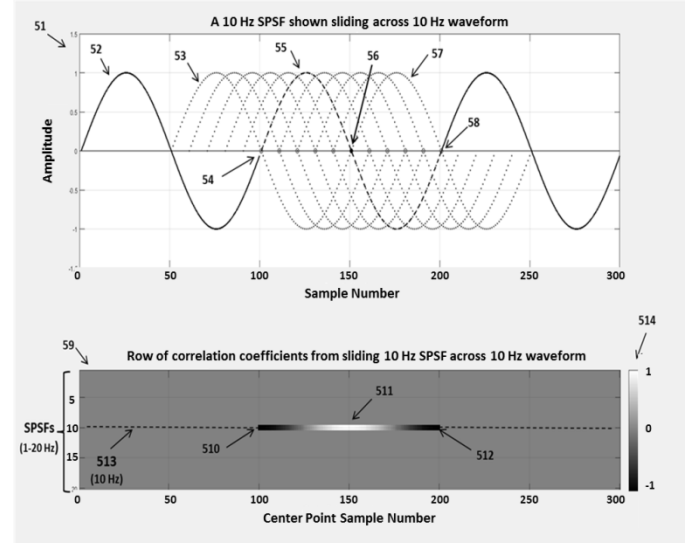


Fig. 5. A set of 10 Hz SPSFs passing through a 10 waveform with correlation coefficients being recorded in row 10 at column entries corresponding the centered location of the sliding SPSF.

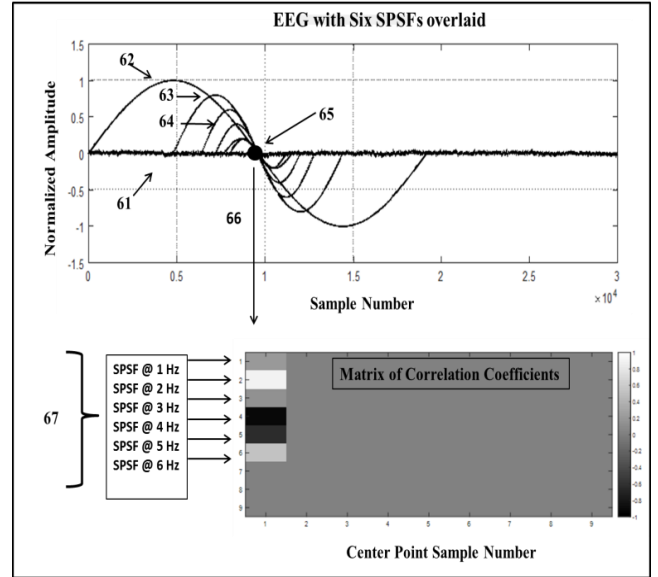


Fig. 6. A set of SPSFs formed as integral multiples of 1 Hz, are placed across the same central point where their individual correlation coefficients with respect to the EEG (61) are recorded as column entries in the correlation matrix.

We would like to note here, as we did in our patent application, that a colleague from the AFRL Information Directorate suggested the centralizing of sample number for the purpose of keeping a consistent base of time referencing. We now move on to the results section to examine how well our proposed method exploits SBFs.

V. EXPLOITING THE TRANSIENT PRESENCE OF SPSF IN EEG (AND NON-PRESENCE OF SPSF WITH DETACHED ELECTRODE)

Figures 7-9 show the results of our SPSF method using the EEG collected at electrode E14. Figure 10 is added to show the results of our SPSF method using the raw noise collected from that same probe when laid out on the table. The results are straight forward; we have a matrix where entries are correlation coefficients between the EEG (or raw noise) and the basis of SPSFs; we apply a threshold to show correlations above 0.75 and below -0.75, and we zoom in to show the short transient detection of SPSFs.

We sampled the EEG at $F_s=19,200$ samples/sec for a total of 30 seconds and picked a 5 second interval to serve as the center points, see Figure 2. (Note we included $\frac{1}{2}$ second of EEG on each side for our calculations); thus we have 96,000 center point columns. We applied SPSFs starting at 1 Hz and increase by 1 Hz intervals up to 1000 Hz; thus we have 1000 SPSF rows.

Figure 7 shows a 1000×9600 dimensional matrix where each entry is a correlation coefficient determined by the process shown in Figures 5 and 6 for a total of 9.6 million calculations. Each entry ranges from -1 to +1.

Figure 8 is the result of setting any entry in the matrix between ± 0.75 to zero. We now see a sparse set of streaks among the many entries set to zero. We need to point out that there are many streaks that cannot be seen due to resolution of the monitor. Although this figure shows possible indications of SPSFs being present it is the next figure, a zoom-in look that shows the method may be viable in defending our apparent exploiting presence of SPSFs.

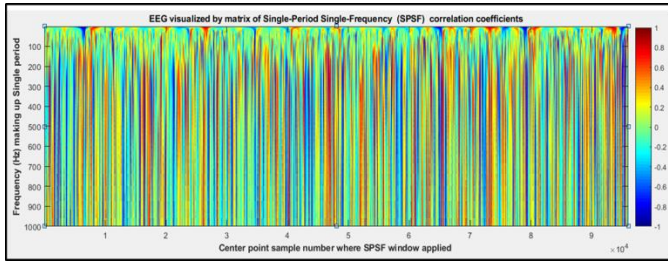


Fig. 7. Shows the 1000×96000 matrix of correlation coefficients collected from the SPSF process.

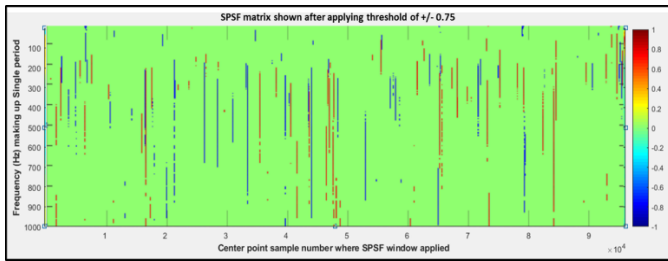


Fig. 8. Show the result of thresholding Fig. 7 at ± 0.75 .

Figure 9 (top plot) shows a 26 msec zoom-in of the EEG from Figure 2 and the corresponding 500 contiguous columns (center point samples 70,001 to 70,500) of the correlation ma-

trix (bottom plot) from Figure 8. The streaks in red depict highly positive correlation coefficients close to +1 while the streaks in blue depict highly negative correlation coefficients close to -1. A black arrow has been placed in the matrix to point out an encircled patch of correlation coefficients nearest to +1 and approximately centered on the 300 Hz SPSF. In the EEG plot we have added what a discretely sampled 300 Hz SPSF would look like at center point sample number 143. The thresholding of the matrix makes it visually clear that there is a transient nature of an approximate 300 Hz SPSF lasting about 2 oscillations between center points 100 and 225 followed by another set of possibly 3 oscillations lasting between 250 and 375. Thus we have shown possible evidence of start/stops of SBFs.

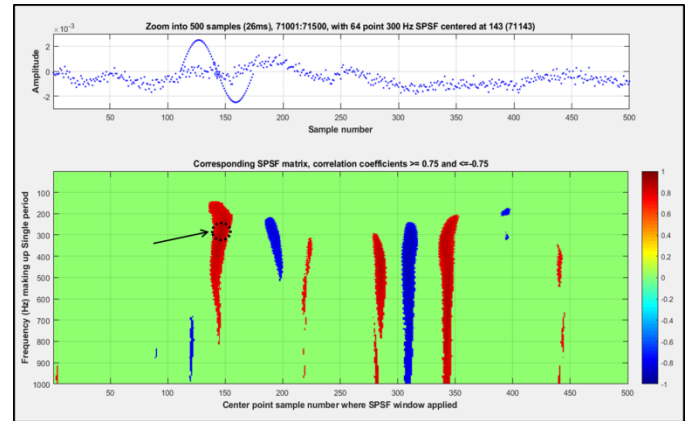


Fig. 9. A zoom-in of Figure 8 to show the easily detected evidence of the in-phase/opposite-phase transient nature of SBFs, in this case, mainly centered at (approximately) 300 Hz.

Figure 10 is presented as a sanity check. The EEG probe was left on the table and 10 seconds of raw noise was recorded. A $\frac{1}{2}$ second window is shown in the top plot. The middle plot is the corresponding SPSF generated correlation coefficient matrix before applying a threshold. This plot appears similar to Fig. 7. However, the bottom plot shows that after applying the same ± 0.75 threshold to the matrix there is no evidence of any SPSF present; it is in fact a matrix of zeros.

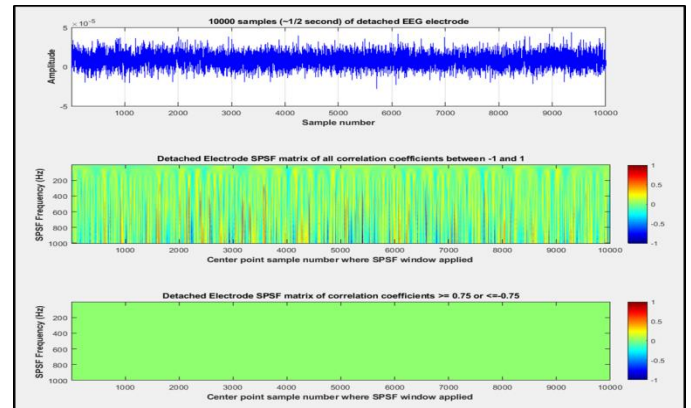


Fig. 10. Shows that there is no evidence of SPSFs when our method is applied to the raw noise collected by the electrode placed on the table.

VI. CONCLUSIONS OF A NOT SO TIMELY EXECUTION

SPSF matrix shown in Figure 7 was formed by taking a 5 second clip of (this author's) EEG and producing 9.6 million correlation coefficient calculations using several (notoriously slow) FOR LOOPS on an Asus Notebook B53F Series computer with an Intel i5 CPU @ 2.67 GHz processor; it took six hours to complete in contrast to the 40 window Spectrogram shown in Figure 3 which took a mere 0.012 seconds to complete; so there is a trade-off in 'timely execution'. Of course, there are signal processing matrix multiplication tricks available to mitigate the use of the FOR LOOPS and greatly reduce the SPSF matrix execution time; it just wasn't a concern to do so since we simply pushed the start button in the morning and went off to our day jobs. What was of concern to us was to obtain a high resolution, if not near perfect, indicator of the beginning and end of (striatal beat frequency) oscillations at frequencies up to 1,000 Hz. And, we point to the evidence of achieving such a viable indicator, not so much with respect to the series of Figures 7, 8, and 9 which lead to what we have referred to as patches of highly correlated events of SBF presence, but rather, we believe the strongest piece of evidence that this SPSF approach has merit is found in Figure 1,0 where the time domain signal collected from the detached electrode laying openly on the table by the G-Tec machine under the observation of the Engineer operating the machine, showed no sign of SBF presence, and thus strongly indicating that the patches of SBF that are shown in Figures 7, 8, and 9 were not artifacts of ambient noise.

We end this section with a notable observation: although there is activity shown in the frequency band 0-100Hz in Figure 7, after applying the threshold restriction of ± 0.75 , all evidence of activity disappears in Figure 9.

VII. NEXT STEPS

The next step to take is to combine the (real) SPSF-based EEG method presented in this paper with our method that converts (an artificial) feed-forward neural network into a faster bi-directional neural network, (presented at AIPR 2017 and granted status of USPTO Patent in 2019) [10][11], with the overall goal, in mind, to form a Joint Proximity Association Template (JPAT) for a human-computer interface.

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