Effect of yoga on pulse rate variability measured from a venous pressure waveform

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Abstract— The benefits of yoga have been studied in different fields, from chronic health conditions to mental disorders, showing that it can help to improve the overall health. In particular, it has been proven that yoga also improves the autonomic function. Heart rate variability (HRV) at rest is commonly used as a non-invasive measure of autonomic regulation of heart rate. Alternatively, pulse rate variability (PRV) has been proposed as a surrogate of HRV. VoluMetrix has developed a novel technology that captures venous waveforms via sensors on the volar aspect of the wrist, called NIVAband. This study aims to assess the effect of yoga in the autonomic nervous system by analyzing the PRV obtained from the NIVA signal. Temporal (statistics of the normal-to-normal intervals), spectral (power in low and high frequency bands) and nonlinear (lagged Poincaré Plot analysis) parameters are analyzed before and after a yoga session in 20 healthy volunteers. The PRV analysis shows an increase in parameters related to parasympathetic activity and overall variability, and a decrease in parameters related to sympathetic activity and mean heart rate. These results support the beneficial effect of yoga in autonomic nervous system, increasing the parasympathetic activity.

I. INTRODUCTION

Several studies have taken advantage of the peripheral venous line in hospitalized patients, used primarily to allow fluids and medications to be given directly into the circulatory system, to derive patients' hemodynamic information.

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For example, continuous monitoring of intravascular volume status permitted to detect early Stage 1 hemorrhage, while other physiological parameters such as heart rate, SpO2 or mean arterial pressure did not show any differences [1]. Also, peripheral venous signal is able to not only give the volume status of the patient, but also additional information such as the respiratory rate and pulse rate [2].

This capability to offer valuable additional information raises the interest of obtaining this signal in a non-invasive way that will allow a continuous monitoring in daily life. VoluMetrix is developing a new technology to capture venous waveforms non-invasively via sensors on the volar aspect of the wrist, called NIVAband. They propose Non-Invasive Venous waveform Analysis (NIVA) to obtain information on volume status, heart rate, and respiratory rate. In a previous work, we validated the ability of NIVAband to provide a measure of autonomic nervous system (ANS) via pulse rate variability (PRV) analysis [3]. Results showed that high frequency power was significantly higher in PRV analysis from NIVA than in heart rate variability (HRV) from ECG, suggesting that the NIVA signal may enhance measurement of parasympathetic activity.

Some authors have studied the effect of yoga on the autonomic function via HRV analysis, showing an increase in parasympathetic activity [4], [5]. In this work, we want to study the effect of yoga on PRV measured with the NIVAband. We will obtain both temporal and spectral PRV parameters before and after a yoga session in 20 volunteers. In addition, we propose the Lagged Poincaré Plot (LPP) for nonlinear analysis of PRV series. Significant differences were already found in Poincaré Plot parameters, when they were used together with time and frequency analyses of heart rate variability, to study autonomic regulation in yogic and control groups of subjects [5]. Moreover, LPP has been been proven to be reliable for ultra-short time HRV analysis [6]. This is important since NIVA signal is very sensitive to movement and other interferences, making it difficult to have clean pulse rate series long enough for spectral analysis.

II. MATERIALS AND METHODS

A. Experimental Protocol and Acquisition Set-up

Twenty healthy subjects agreed to participate in the study (written informed consent was obtained from each subject). The study was performed in accordance with the Vanderbilt University Medical Center and the University of Alabama-Birmingham Institutional Review Boards. There were 5 men and 15 women with an age range of (27-79, mean 52,

median 56). The subjects reclined in savasana position with the head and lower extremities supported with blankets. Venous waveform signals were collected for 5-6 minutes, before (pre-yoga) and after (post-yoga) a 2 hour "awareness yoga" session, which is a slow restorative type of relaxation yoga. Venous waveforms were collected using a piezoelectric sensor (Mu rata, Nagaokakyo, Japan), placed on the volar aspect of the wrist overlying the venous plexus, secured with Coban elastic wrap (3M, Minneapolis, MN). The sensor was interfaced with a prototype NIVA device (which contains an amplifier, microcontroller, and flash memory, VoluMetrix, Nashville, TN). The data was transferred to a computer as .txt files using a USB cable and analyzed as described below.

B. Preprocessing and Pulse Detections

The NIVA signal is first low-pass filtered with a cut-off frequency of 5 Hz to remove high frequency noise. Frequencies below 0.3 Hz are also removed using a high-pass filter to remove low oscillations such as the baseline wander. Pulse detection is based on [7]: first, a linear-phase FIR low-pass-differentiator (LPD) filter is applied to accentuate the upslopes of the pulses; and then an adaptive threshold is applied to detect the peaks in the LPD filtered signal, which represents the points with maximum slope in the NIVA signal. These k-th pulse detections are denoted as n_k.

From n_k, the pulse interval series are obtained as $d(k) = n_k - n_{k-1}$. Five recordings (two in pre-yoga and three in post-yoga) had to be discarded due to low quality signal and poor pulse detections: more than 80% of the pulse intervals in these recordings were considered not normal, i. e., the difference between that pulse interval and the previous one was higher than 150 ms [8]. Therefore, only 15 out of 20 subjects were included for further analysis.

Pulses in NIVA signal are sometimes masked by noise, yielding erroneous or missed pulse detections, which result in outlier (or anomalous) pulse intervals. These outliers are identifed, based on the algorithm in [9], and removed, obtaining the normal-to-normal (NN) intervals [10]. Figure 1 shows an example of pulses detection with an incidence and its correction (upper panel), which also reflects in the NN interval series (lower panel).

C. Pulse Rate Variability Parameters

Temporal Domain: For temporal domain analysis, PRV parameters are derived from the NN intervals [10]. Three parameters were considered: the standard deviation of the pulse intervals ($SDNN$), the square root of the mean squared differences of successive pulse intervals ($RMSSD$) and the mean pulse interval time ($\overline{NN}$).

Frequency Domain: For frequency domain analysis, PRV parameters are derived from the modulating signal $m(n)$, which is assumed to have information about ANS activity, and is computed and described below. The instantaneous pulse rate signal, $d_{PR}(n)$, is derived from $d(k)$, following a method based on the time-varying integral pulse frequency modulation (TVIPFM) model, and resampled at 4 Hz. This signal is high-pass filtered to remove the mean heart rate
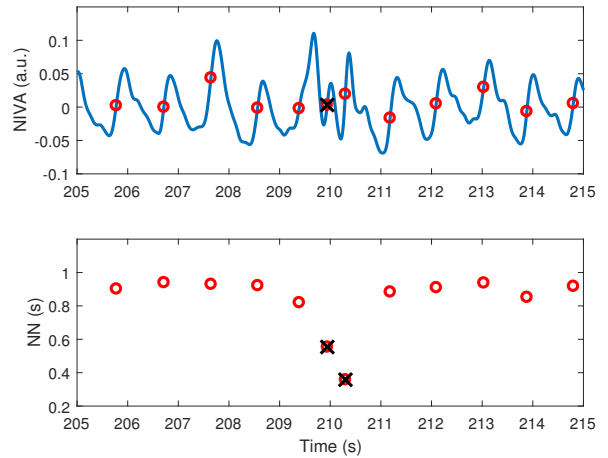

Fig. 1. Example of the NIVA signal (upper panel) with pulse detections (red circles) including an incidence (black cross). Corresponding pulse interval series (lower panel) with outlier intervals removed.

tendency $d_{PRM}(n)$ (very low frequency components) and corrected to obtain the pulse rate modulating signal $m(n)$: $m(n) = (d_{PR}(n) - d_{PRM}(n))/d_{PRM}(n)$ [11], [9].

Although the method in [9] takes into account the possible presence of ectopic beats, false or missed detections, if there are too many outliers following each other, the gap is too long and the estimated $m(n)$ can introduce artificial oscillations. Therefore, we do not take into account these gaps if they are longer than 3 seconds. In order to have a reliable frequency domain analysis, we only considered segments no shorter than 90 seconds without gaps longer than 3 seconds. Only 9 subjects had both pre- and post-yoga recordings suitable for frequency domain analysis.

The power spectral density (PSD) of $m(n)$ is computed using the Welch periodogram, with 60 s windows 10 s overlapped. The powers in the LF and HF bands are computed integrating the power spectrum in the corresponding bands: P_{LF} from 0.04 to 0.15 Hz, and P_{HF} from 0.15 to 0.4 Hz. The normalized LF power is obtained as $P_{LFn} = P_{LF}/(P_{LF} + P_{HF})$.

Lagged Poincaré Plot: The Poincaré Plot is a graphical representation of interbeat dynamics, inspired by the return map theory to describe the phase space trajectories [12]. In the standard version, the Poincaré Plot is a scatterplot where each pulse interval $d(k)$ is plotted against the immediately previous pulse interval $d(k-1)$. In the lagged Poincaré Plot (LPP) technique, a lag l is introduced and scatterplots are made by the points with coordinates $d(k)$ and $d(k - l)$. Previous studies investigated a range of lag values equals to $1 \le l \le 10$.

The most used quantitative approach to describe the shape of LPP is the ellipse fitting technique [13]. Following this methodology, the LPP is turned 45° clockwise and the two standard deviations of the points around the vertical ($SD1$) and horizontal ($SD2$) axes are computed. $SD1$ is a measure of the short-term variability of pulse interval series, whereas $SD2$ describes long-term dynamics. In this study

we investigated the two standard deviations, $SD1$ and $SD2$, together with their ratio $SD12 = SD1/SD2$.

We computed the values of $SD1$, $SD2$, and $SD12$ in 50% overlapped windows lasting 35 sec, both in pre-yoga and post-yoga NN intervals. The standard range $1 \leq l \leq 10$ for the lag value was considered in the LPP analyses. The reliability of LPP parameters calculated using the ellipse fitting technique in 35 sec windows was already investigated in our previous studies, through synthetic and real data [6], [14].

Considering each LPP parameter ($SD1$, $SD2$, and $SD12$) and each lag l, we calculated the median values among the 35 sec windows, in the pre-yoga session and in the post-yoga session. For each subject, we obtained two median values of each LPP parameter and each lag corresponding to pre-yoga and post-yoga, respectively.

D. Statistical analysis

A paired Wilcoxon non-parametric statistical test was applied to all PRV parameters to study the differences between pre- and post-yoga sessions. Analysis of temporal ($SDNN$, $RMSSD$, $\overline{NN}$) and LLP parameters ($SD1$, $SD2$, $SD12$, for each lag) included 15 subjects, while analysis of spectral parameters (P_{LFn} and P_{HF}) included 9 subjects. The difference is considered to be significantly different from zero when p < 0.05.

III. RESULTS

Figure 2 shows an example of the NN interval series for pre- and post-yoga sessions, as well as their corresponding PSD. An overall increase in power is observed after the yoga session.
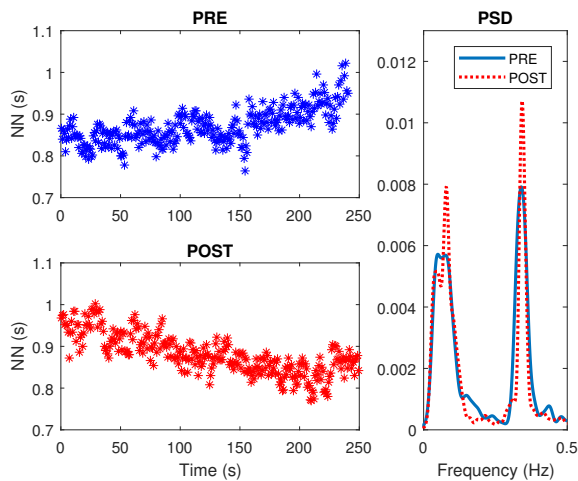

Fig. 2. Example of NN interval series for pre- and post-yoga sessions (left panels) and their corresponding power spectral densities (right panel).

Temporal PRV parameters are shown in Figure 3: there is an increase in $\overline{NN}$ (which translates to a decrease in the mean heart rate), $SDNN$ and $RMSSD$, but it is only statistically significant in $SDNN$. Spectral PRV parameters are shown in Figure 4: there is a decrease in P_{LFn} and an

increase in P_{HF}, but both are not significant. The only LPP parameter which was found to be statistically different was the ratio $SD12$ (lags 5 and 7), shown in Figure 4: there is a significative increase after yoga.
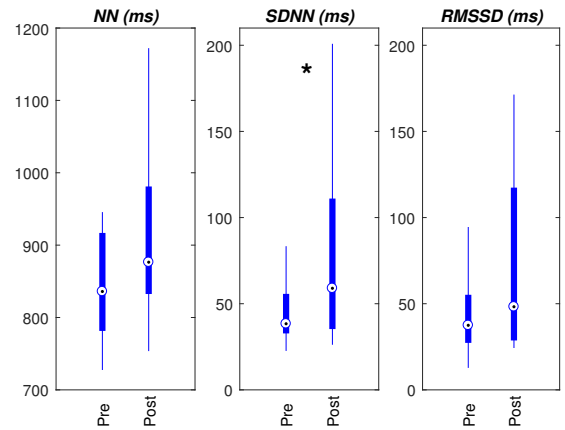

Fig. 3. Temporal PRV parameters in pre- and post-yoga recordings. * denotes significant differences (p<0.05).

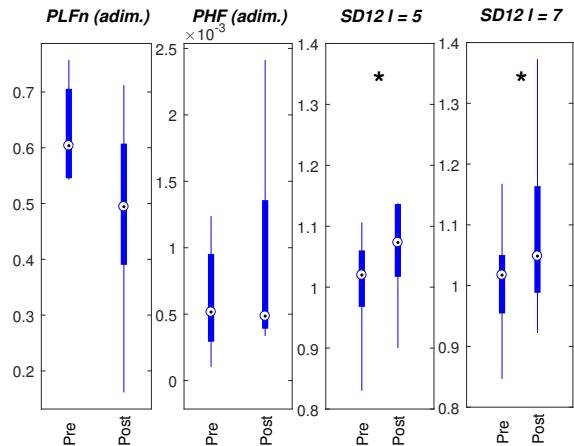

Fig. 4. Spectral and LLP ($SD12$, lags 5 and 7) PRV parameters in pre- and post-yoga recordings. * denotes significant differences (p<0.05).

IV. DISCUSSION AND CONCLUSION

Several works have studied the role of yoga in the overall health and a healthy lifestyle [15], [4], [5]. Also, yoga has been proposed in severe mental illnesses: it was found a reduction in general psychopathology ratings and an improvement in cognition and functioning in schizophrenic patients, and a significant benefit in reducing the severity of depressive symptoms [16]. In those studies which focus on the autonomic function, they found an increase in parasympathetic activity, a decrease in sympathetic activity and an overall increase heart rate variability [4].

Our results agree with those found in the literature. While most temporal and spectral parameters did not show

significative differences, possibly due to the small size of data, they indeed followed the same tendencies than in other studies. We found an increase in $\overline{NN}$ (a decrease in mean heart rate) which was also observed in previous works. In most recordings, we found a tendency similar than the example shown in Figure 2: in pre-yoga, the heart rate decreases over time as the yoga session approaches, while in post-yoga the heart rate increases over time. The increase in $SDNN$ is related with an overall increase of total variability, while the increase in $RMSSD$ is related to an increased parasympathetic activity [10].

Spectral parameters also show similar results. There is a decrease in LF power (in normalized units), an increase in HF power and a decrease in the LF/HF ratio, which translates to an increase in parasympathetic activity and a decrease in both sympathetic activity and sympathovagal tone. Figure 2 also shows an increase in both LF and HF power, which may be related to the increased parasympathetic activity affecting both bands. Taking advantage of the capability of the NIVAband to estimate the respiratory rate [3], we found that it was located within the classic HF band (0.15 to 0.4 Hz) for all recordings, and no statistical differences were found in P_{HF} when centering the HF band around respiratory rate compared to using the classic HF band. The main limitation for spectral analysis is that NIVA signal is very sensitive to movement artifacts, and only in 9 subjects we could find segments longer than 90 s with no outliers in the pulse interval series. We also repeated the statistical test for temporal parameters with only these 9 subjects, and the tendencies were the same, with $SDNN$ being non significative this time.

To overcome this limitation, we used other nonlinear parameters which can be computed in very short time windows, such as Lagged Poincaré Plot. Several previous studies reported the correlation between lagged $SD1$ and HF power, revealing its strong ability to detect increase in vagal modulation [17]. According to recent literature, $SD12$ parameter relates to the nonlinear component of heartbeat dynamics (especially for $l = 5$, 6) and an increase of sympathetic activity was found to decrease its value [18]. Therefore, the increase in $SD12$ found in this work suggests a decrease in sympathetic activity. We also repeated this analysis using the whole recordings instead of the 35 s windows, and we found similar statistical differences in $SD12$ with lags 4 and 5.

In summary, we have shown that the NIVAband is able to detect changes in autonomic function after a yoga session. Similar to other heart rate variability studies, we have found that yoga increases parasympathetic activity and decreases the sympathovagal balance and the mean heart rate. There is also an overall increase in the total variability. To overcome the limitations found in the NIVA signal, which make difficult to analyze PRV parameters in the frequency domain, we used temporal and non linear parameters, finding similar results than with spectral parameters. Future studies will focus on investigating the NIVA's potential enhancement of parasympathetic activity measurement compared to other PPG devices.

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