Deep Quasi-Periodic Priors: Signal Separation in Wearable Systems with Limited Data

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***Abstract*—Quasi-periodic signal separation poses a significant challenge in wearable systems with limited data, particularly when the measured signal, influenced by multiple physiological sources, is under-represented. Addressing this issue, we introduce Deep Quasi-Periodic Priors (DQPP), a signal separation method for non-stationary, single-detector, quasi-periodic signals using an isolated input data. This approach incorporates masking and in-painting of the time-frequency spectrogram, while integrating prior harmonic and temporal patterns within the deep neural network structure. Moreover, a pattern alignment unit transforms the input signal's time-frequency patterns to closely align with the deep harmonic neural structure. The efficacy of DQPP is demonstrated in non-invasive fetal oxygen monitoring, using both synthetic and *in vivo* data, underscoring its applicability and potential in wearable technology.**

***Index Terms*—Signal Separation, Wearable Systems, Deep Prior Learning, Quasi-Periodic**

I. Introduction

Wearable systems have gained considerable attention in recent years for their potential to improve health and quality of life. However, their advancement faces challenges, particularly in scenarios where sensor data is obscured by quasi-periodic, non-stationary interferences. This problem is prevalent in applications like tissue oximetry or blood glucose monitoring, where the desired signals are often overshadowed by other physiological activities such as heart rate, respiration, and Mayer waves. The effectiveness of these devices, in absence of extensive high-quality data, depends on the successful separation of relevant signals from interference with limited data.

To address this, we have developed a novel methodology called Deep Quasi-Periodic Priors (DQPP). This technique is designed for the separation of quasi-periodic, non-stationary signals using a singular mono-detector signal. To apply DQPP effectively, it is assumed that the fundamental frequencies of these signals are known, either through additional sensing methods or by analyzing the mixed signals. This approach aims to enhance the reliability and functionality of wearable devices in challenging scenarios.

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II. Proposed Methodology

DQPP is an iterative method for separating non-stationary quasi-periodic signals with limited data. Each round isolates a selected target signal from the mix by masking non-target signals and in-painting overlaps and crossovers with the target. The deep harmonic neural network, designed for effective in-painting with just one isolated single-detector input signal, acts as an implicit prior, inspired by the *Deep Image Prior* technique [1]. This prior setup comprises two complementary components: a signal pattern aligner and the Spectrally Accurate Light U-Net (SpAc LU-Net). The pattern aligner resamples the signal, unwarping the target into a strictly-periodic pattern and reshaping its fundamental frequency to a constant 1Hz. This allows for the temporal neighborhood of harmonic convolutions to be achieved through simple dilation. In the frequency domain, the convolutional neighborhood over the spectrum is defined by integral multiples of each frequency bin. Moreover, SpAc LU-Net consistently preserves the harmonic structure by eliminating any max-pooling in frequency, ensuring a stable deep prior setup. The in-painted spectrogram amplitudes, combined with the original phase information, pass through an inverse short-time Fourier transform to extract the separated, pattern-aligned target signal. This signal, once resampled and rewarped to its original fundamental frequency, is the final separated target. After each round, the separated source is subtracted from the mixed signal, with the residual used for further signal separation in subsequent rounds.

III. Experimental Results

A. Signal Separation Results: Synthesized Data

We have created a tool for generating synthesized quasi-periodic timeseries, characterized by the desired input function per period, time duration per period list, and amplitude per period list. We have also generated 5 distinct synthesized mixed quasi-periodic signals with sampling frequency of 100 for Transabdominal Fetal Oximetry (TFO) application. Each mixed signal has 2-3 sources for respiration, maternal pulsation, and fetal pulsation. The respiration PPG shape is extracted from real sheep experiment after filtering out other dynamics. The pulsation PPG shape is randomly extracted from MIMIC-IV dataset [6].

Metrics: We present Signal to Distortion Ratio (SDR) and Mean Squared Error (MSE) for each separated source from the five input mixed signals. For averaging MSE values, we

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TABLE I: Performance comparison of various signal separation methods applied on synthesized mixed signals 1-5. Best performance per source separation is highlighted.

		EMD [2]		VMD [3]		NMF [4]		REPET [5]		REPET-Ext. [5]		Spect. Masking		DQPP	
		SDR(db)	MSE	SDR(db)	MSE	SDR(db)	MSE	SDR(db)	MSE	SDR(db)	MSE	SDR(db)	MSE	SDR(db)	MSE
Syn. MSig1	source1	-1.38	7.4e-4	7.32	1.5e-4	-9.03	8.9e-4	4.68	2.0e-4	9.91	1.0e-4	12.31	6.4e-5	**21.63**	**7.4e-6**
	source2	-6.17	1.3e-4	3.17	1.1e-4	-7.53	1.3e-4	-0.77	6.4e-05	-10.82	1.1e-4	6.44	3.3e-5	**15.51**	**4.1e-6**
Syn. MSig2	source1	-6.36	9.1e-4	3.14	7.1e-4	-4.58	7.8e-4	0.09	4.8e-4	4.82	3.4e-4	4.51	3.5e-4	**9.29**	**1.1e-4**
	source2	-21.75	7.2e-4	-21.06	7.0e-4	-4.98	6.4e-4	-1.25	4.5e-4	-6.2	4.4e-4	1.16	5.6e-4	**9.02**	**9.2e-5**
Syn. MSig3	source1	5.65	5.3e-3	7.24	3.9e-3	-8.79	2.2e-2	6.59	3.3e-3	14.36	8.1e-4	**26.95**	**5.7e-5**	21.18	2.1e-4
	source2	0.07	2.6e-4	-0.15	1.8e-4	-0.18	8.3e-4	-0.04	2.7e-4	-1.63	2.1e-4	-17.3	9.9e-3	**6.96**	**4.0e-5**
Syn. MSig4	source1	5.2	1.1e-2	15.16	1.5e-3	-4.95	3.6e-2	3.83	9.9e-3	18.19	7.8e-4	23.81	2.2e-4	**28.86**	**6.9e-5**
	source2	0.36	9.5e-4	0.76	8.7e-4	-2.63	1.0e-3	-0.11	9.3e-4	-4.29	6.0e-4	4.03	3.8e-4	**14.25**	**3.7e-5**
	source3	-13.79	4.0e-4	-19.95	4.0e-4	-5.59	4.6e-4	-15.76	3.9e-4	-7.26	3.2e-4	8.9	5.3e-5	**14.7**	**3.3e-5**
Syn. MSig5	source1	2.11	1.6e-2	15.53	1.1e-3	-4.31	2.6e-2	1.26	1.1e-2	18.81	5.2e-4	19.26	4.2e-4	**23.97**	**1.4e-4**
	source2	-5.27	7.4e-4	1.02	7.0e-4	-5.64	7.2e-4	-0.05	7.3e-4	-4.42	4.3e-4	1.27	5.5e-4	**14.48**	**2.6e-5**
	source3	-18.59	1.2e-4	3.01	1.1e-4	-10.47	1.2e-4	-11.59	1.2e-4	-7.82	1.0e-4	6.82	2.7e-5	**15.06**	**5.1e-6**
	Average	0.10	9.5e-4	8.69	5.0e-4	-4.84	1.4e-3	1.49	6.7e-4	11.86	3.2e-4	18.56	2.1e-4	**20.88**	**3.6e-5**

employ geometric averaging, whereas for SDR averaging, we use arithmetic averaging in their original linear scale.

We compare against six previous signal separation methods, which accommodate single-detector signal separation, EMD [2], VMD [3], NMF [4], REPET and REPET-Extended [5], and spectral masking. The comparison results is presented in Table I. These results are all calculated on band-pass filtered mixed signals (MSig) between $[0Hz, 12Hz]$.

Discussion: DQPP delivers approximately 26% $(2.3db)$ SDR improvement and 80% MSE enhancement on average when contrasted with the best previous signal separation algorithms. Evaluating the signal separation performance for sources with less than $\times 0.1$ amplitude of the dominant source (mixed signal 3 source 2, mixed signal 4 source 3, and mixed signal 5 source 3), the DQPP method exhibits $7.2db$ average SDR enhancement and 92% average MSE improvement compared to the best preceding method.

B. Signal Separation Results: In Vivo *SpO2 Estimation*

We study the performance of our approach on fetal SpO2 estimation in an *in vivo* dataset of TFO from two pregnant ewes. The data consists of 40 minutes of continuous mixed PPG signals at $740nm$ and $850nm$ wavelengths gatherd from pregnant ewe's abdomen and ground-truth fetal blood oxygen saturation readings, i.e. SaO2, measured from blood-draws with the time distance of 2.5, 5, and 10 minutes [7]. Since the ground-truth fetal PPG signal is not accessible, we report the correlation of SpO2 estimation with measured SaO2 readings when the fetal signal is separated using spectral masking and DQPP method.

Discussion: Fig. 1 presents the SpO2 estimation for both sheep, when the separated fetal signal is obtained through spectral masking (similar to [7]) and DQPP. Our method improves the correlation from 0.24 to 0.81 and from 0.44 to 0.92 in sheep 1 and sheep 2, respectively (80.5% average error improvement from ideal correlation of 1).

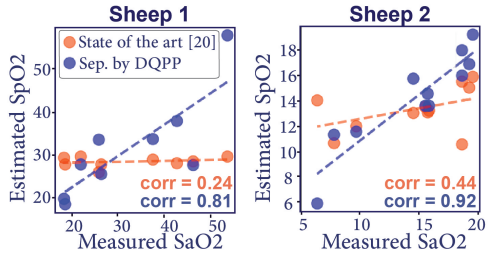

Fig. 1: Comparison of fetal signal separation and SpO2 estimation using DQPP and the state of the art [7].

IV. Conclusion

Limitations in dataset capacity and quantity, present in many quasi-periodic signal separation applications in wearable systems, have hindered their success despite their significant potential. Deep prior methods can enhance learning performance with limited data. We showcase our deep prior signal separation method in the TFO application, using both synthesized and *in vivo* data, with significant improvement compared to the state of the art.

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