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Progressive Dynamic Time Warping for Noninvasive Blood Pressure Estimation

Abstract: Arterial blood pressure is one of the most important cardiovascular parameters. Yet, current-generation devices for continuous, noninvasive acquisition are few, expensive and bulky. Novel signal processing applied to easily acquired unimodal signals can alleviate this issue, reducing size, cost and expanding the use of such devices to ambulatory, everyday settings. The features of pulse waves acquired by photo- or impedance-plethysmography can be used to estimate the underlying blood pressure. We present a progressive dynamic time warping algorithm, which implicitly parametrizes the morphological changes in these waves. This warping method is universally applicable to most pulse wave shapes, as it is largely independent of fiducial point detection or explicit parametrization. The algorithm performance is validated in a feature selection and regression framework against a continuous, noninvasive Finapres NOVA monitor, regarding systolic, mean and diastolic pressures during a light physical strain test protocol on four clinically healthy subjects (age18-33, one female). The obtained mean error is 2.13 mmHg, the mean absolute error is 5.4 mmHg and the standard deviation is 5.6 mmHg. These results improve on our previous work on dynamic time warping. Using single-sensor, peripherally acquired pulse waves, progressive dynamic time warping can thus improve the flexibility of noninvasive, continuous blood pressure estimation.

Keywords: progressive dynamic time warping, arterial blood pressure, impedance, photo plethysmography, non-invasive, continuous, unobtrusive, DTW, PPG, IPG.

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1 Introduction

1.1 Motivation

The monitoring of cardiovascular parameters is an important part of modern healthcare, with arterial blood pressure (ABP) being one of the most prominent ones. However, reliably acquiring it in a continuous and unobtrusive manner is still not a fully met goal. Gold standard methods like arterial catheterization are very accurate but are restricted to high-acuity supervised settings due to their highly invasive nature. Noninvasive methods, of which volume clamping is the most readily available, are held back by an inconvenient recording setup, or/and by low accuracy in real world conditions. Furthermore, they require dedicated, custom hardware, incurring large supplementary costs. Instead, it would be preferable to use an already available, ubiquitous and cheap sensor, placed at a single, convenient location. Pulse wave analysis (PWA) methods rely on such unimodal, localized plethysmographic signals to infer the underlying blood pressure and other parameters (e.g. arterial stiffness) [1][2]. They can be fed with photoplethysmographic (PPG) or impedance plethysmographic (IPG) waveforms.

At the time of writing, blood pressure measurement is still performed with an obtrusive apparatus, which greatly restricts its adoption for ambulatory applications, as well as for some special stationary settings, e.g., sleep monitoring [3]. Classic ABP measurements rely on noninvasive intermittent sphygmomanometers, while in high-acuity settings continuous invasive arterial catheterization is employed. Some devices claim to both continuously and noninvasively estimate ABP to various degrees of accuracy [4]. Disregarding performance figures, these systems are very expensive and still require either complicated and bulky opto-mechanical loops, or multiple, body-spanning heterogeneous sensors. Cost and size reduction of devices is enabled by new and robust signal processing methods. Algorithms based on fiducial point detection or pulse decomposition analysis (PDA) have been proposed, yet they still face problems such as flat slopes and noisy signals for fiducial point identification or physiological plausibility parametrization bounds for PDA [2][5].

We propose progressive dynamic time warping (PDTW) as an alternative processing of plethysmographic waveforms, which does not rely on identifying fiducial points or performing PDA. Consequently, it is easily implemented, robust and flexible in location and modality of the acquisition by being applicable to all types of pulse wave signals.

1.2 Warping Considerations

The pulse wave is primarily shaped by blood pressure, vascular geometry, tonus and cardiac output [1][2], making a physiological interpretation of pulse wave morphology very complex. One physically well-motivated fact, however, is the wave propagation speed depending on the pressure in a medium: the higher the pressure, the quicker the speed. The pulse wave can be described as an overlay of reflections of the incipient systolic pulse at the heart [1]. Since these reflections occur at different locations along the arterial tree, the resulting overlay is dependent on their propagation speed from origin to measurement location – the shifts are thus a function of ABP.

Dynamic time warping (DTW) is widely used in voice processing [6]. It describes the warping of waveforms with similar features into one another, and is therefore a means of quantizing the temporal expression of signal features. In the actual case of pulse waves, it implicitly quantifies the change in position of systolic and diastolic peaks, dicrotic notches and other wave expressions, similarly to PDA. If consecutive waves are similar, the warping approach can accommodate any Dawber class, without explicit information thereof. Amid other cardiovascular factors, the shift of these wave constituents is strongly related to blood pressure [1]. One issue of DTW is sensitivity to amplitude mismatches, usually demanding complex regional or affine DTW implementations.

Our observations show that, when human subjects are presented similar pulse waves, they are good at matching and warping them, even those overlaid by disturbances. One mechanism of this error rejection is based on first identifying the underlying main, rough shape and matching it between the two, adding detail progressively afterwards with decreasing weight. Consequently, this newly developed PDTW method is inspired by analyzing and breaking down this approach.

2 Methods

2.1 Experimental Setup and Hardware

Four clinically healthy subjects (age 18-33, one female) were included in the study. The base posture is sitting upright on a chair with backrest. The measurement protocol totals 15 minutes, and is composed of the following segments: 180 s baseline, 20 s Valsalva maneuver, 100 s rest, 60 s unpaced, slow, deep breathing, 60 s rest, 30 s squeeze with right hand, 150 s rest, 20 s isometric squat, 100 s rest and 180 s return to baseline. This effects gradual increases, decreases, as well as transients in ABP, in the ranges of 81-182 mmHg systolic, and 53-124 mmHg diastolic.

The Einthoven II lead of the electrocardiogram (ECG) was recorded across the thorax, PPG on the right index finger, IPG on the inner side of the left elbow, along the arteria brachialis, with 20 cm electrode separation. The blood pressure reference was measured on the left arm.

ECG, PPG and IPG were acquired by a custom-built hardware platform, part of our robust body sensor network (rBSN). ECG is single channel with an active driven right leg. PPG is reflective, green monochromatic. IPG is tetrapolar, current driven with 100 µA at 20 or 80 kHz, and demodulated on-board. All signals are sampled at 500 Hz with 16 bits of resolution. The reference ABP is derived beat-to-beat from a Finapres NOVA noninvasive blood pressure (NIBP) measuring device. The arm cuff calibration on the left arm is performed once at the beginning of the measurement, and the NIBP measurement cuff is placed on the left index finger.

2.2 Processing and Performance

In our previous work, we already have investigated simple and derivative dynamic time warping (DDTW), and have shown it to be a viable path toward blood pressure estimation [8]. However, the warping method itself needed improvement, which is presented in this current paper. Furthermore, a regression framework for estimating blood pressure is introduced. The (pre-) processing is very similar to the one described in previous work [7][8], so only the main differences will be elaborated here.

At the start of each measurement, a calibration to the NIBP's ABP_{ref} is performed. By averaging 10 pulses, a reference waveform X_{ref} is constructed at this blood pressure. Each of the following pulse waves $X(i)$ is broken down into five distinct, non-overlapping frequency bands $B_k, k \in [0.05\text{-}1,1\text{-}3,3\text{-}10,10\text{-}25,25\text{-}50]\,Hz$. To simplify, only the distinction between two and not five frequency bands will be exemplified here, $k \in [LF, HF]$. First, the low-frequency LF band is warped between $X_{LF}(i)$ and $X_{ref,LF}$, yielding a warp path $W_{LF}(i)$. Then, the warp path $W_{LF}(i)$ is applied to the full frequency band $FF = LF + HF$ of $X(i)$, yielding $X_{WLF}(i)$. Finally, $X_{WLF}(i)$ is warped to the full bandwidth reference $X_{ref,FF}$, resulting in a new warp path $W_{HF}(i)$, which also

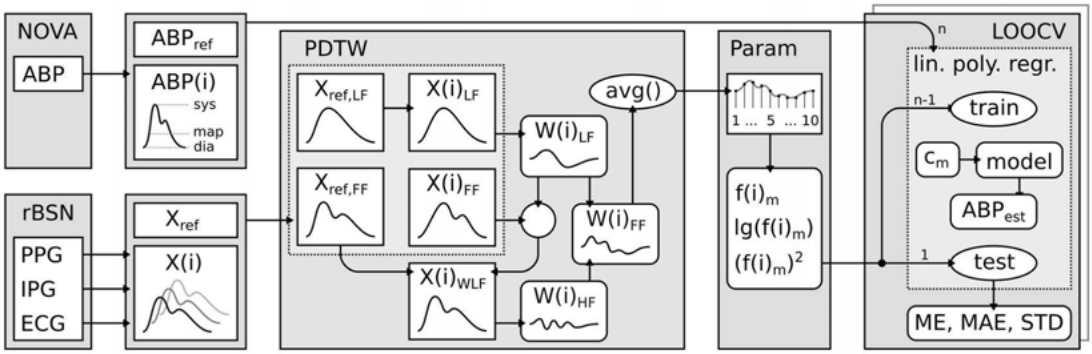

Figure 1: Flowchart of the signal processing. Data from the Finapres NOVA and the rBSN are recorded. PDTW generates warp paths W(i) from IPG and PPG pulses, which are parametrized to f(i) and fed with ABP to the LOOCV framework, performing the regression.

includes the high-frequency components. Overlaying $W_{LF}(i)$ and $W_{HF}(i)$, we obtain the warp path $W_{FF}(i)$, describing the full progressive warp of $X(i)$ to X_{ref}.

Compared to the previous algorithm, a supplementary warping constraint is implemented. The maximum absolute time shift allowed in each frequency band is bound by the lowest passband frequency $|\Delta t_{max}| \leq 1/2f_{p,min}$. This prevents phase shifts greater than 180° of the base frequency.

The deviation of the warping path $W_{FF}(i)$ from the ideal 45° diagonal (i.e. perfect match) is computed and averaged over 10 heartbeats using gliding rectangular windowing with 80% overlap, returning $W_{FF,avg}(i)$. This reduces the impact of noise and glitches, making the processing more robust at the cost of bandwidth. The warp path is parametrized by sampling it equidistantly at $m = 10$ points. These 10 warp amplitudes are the features $f_m(i)$ used as inputs for the regression model.

A simple linear polynomial regression model is chosen for estimating systolic, mean and diastolic ABP. The features are squared $\left(f_{sqr,m}(i) = f_m^2(i)\right)$ and logarithmized $\left(f_{log,m}(i) = \log\left(f_m(i)\right)\right)$, and are fed together with the original $f_m(i)$ into the regression model weighted with the coefficients c_m. The first resulting prediction value $ABP_{est,1}$ is calibrated to the reference ABP_{ref}. All following predictions $ABP_{est,*}$ are adjusted without any metadata input.

Leave one out cross validation (LOOCV) is used in the validation framework for the $n = 4$ subjects. Least mean squares (LMS) regression is performed in order to find the optimal coefficients c_m for the features. Since the regression is point-to-point, no causality is considered between the sample points. All i samples of the $n - 1$ subjects are concatenated into a learning model with $j = i \cdot (n - 1)$ samples, which is validated on the data of the left-out subject.

The mean error (ME), mean absolute error (MAE) and standard deviation of the error (STD) are computed for each of the remainder of ABP value pairs. The average error is calculated for each feature across all LOOCV sets.

3 Results

The ABP estimation results fall roughly within, or slightly below, the same category as a sphygmomanometer's standardized 5±8 mmHg (cf. Table 1). These values, however, should be looked at critically, since they are derived from only four datasets. PPG seems to return insignificantly better estimations than IPG for the most part. In contrast, PDTW outperforms both DTW and DDTW (concatenated under the "DTW" label) by as much as a 41% in some cases, but minimally by 19%. Compared with the previously introduced spectral parametrization [7], the best results are similar, ranking slightly lower at 5.4±5.6 mmHg vs. 4.6±5.3 mmHg. Mean (MAP) and diastolic (DIA) ABP estimation show better results than the systolic (SYS) in all scenarios.

PDTW performs as expected and is more robust and consistent than DTW in virtually all circumstances (cf. Figure 2). Features at the beginning of the warp path (i.e. at the location of the pulse upslope) seem to be used more often and with bigger coefficients in the models. Performance is strongly dataset-dependent. Because of the small sample size, no further patterns in this distribution can be asserted with confidence.

		SYS		***MAP***		***DIA***	
		PDTW	*DTW*	***PDTW***	*DTW*	***PDTW***	*DTW*
PPG	*ME*	**4.62**	7.37	**2.13**	3.55	**1.23**	1.98
	MAE	**7.52**	9.15	**5.44**	8.22	**5.47**	9.05
	STD	**8.85**	9.37	**5.63**	6.12	**5.39**	6.34
IPG	*ME*	**5.19**	4.85	**3.49**	4.85	**1.79**	2.83
	MAE	**7.83**	10.48	**5.87**	7.9	**6.64**	7.31
	STD	**8.85**	11.34	**5.84**	9.03	**6.88**	10.33

Table 1: ABP performance measures of PDTW vs. DTW over all probands. DTW includes DDTW, best value of both was picked.

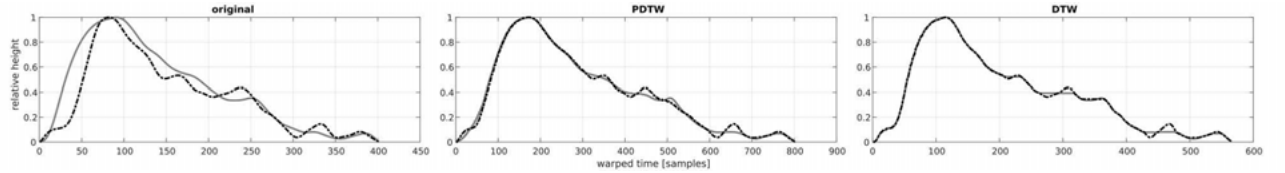

Figure 2: Comparison of DTW and PDTW. PDTW creates no large warping singularities and better preserves the original shape.

4 Discussion

IPG and PPG show similar performance characteristics, confirming previous research about their interchangeability. This enables either a flexible choice of which method to employ in specific settings, or simultaneous use of both in a hybrid setup. The performance is acceptable, considering the linear regression model in use.

The results validate the progressive warping method for parametrizing pulse wave features, showing that it performs better than the original DTW and DDTW [8]. Whether it also is better at warping has not been specifically investigated, yet the results suggest it does. However, as long as the frequency components are dispersion-free, the progressive warping method converges on warp paths capable of directly mapping the two original, full frequency waveforms $X(i)$ and X_{ref} onto each other. The best warping is achieved as the width of each frequency band approaches zero ($\Delta B_k \to 0$). The PDTW steps then return the equivalent of the signal phase spectrum. This explains the similar results to our previous work on spectral parametrization of pulse waves, where the phase information proved to be very predictive of ABP [7].

One major drawback is the small number of subjects included to date in the trial, as the obtained results and drawn conclusions are possibly not representative of the general population. Though the approach is validated in principle, further measurements are indeed being performed. Furthermore, benchmarking our estimation against a non-gold-standard (the Finapres) remains questionable.

5 Conclusion

The current paper presents an unobtrusive, continuous ABP estimation method based on PDTW. It implicitly quantizes morphological changes in the plethysmogram without fiducial point detection. This allows the interchangeable use of single, peripherally acquired PPG and IPG pulse waves for flexible and unobtrusive measurements. The obtained results, albeit on a small sample set of 4 probands, place it performance-wise above the simple DTW processing, and slightly below the spectral decomposition outlined in previous work [7][8]. The best result of 5.4±5.6 mmHg is comparable to the ISO 810601-2 norm for automated sphygmomanometers (5±8 mmHg), validating it as a proof of concept. However, a larger sample size should be aimed for in follow-up studies.

Author Statement

The author state no funding involved. Authors state no conflict of interest. Informed consent has been obtained from all individuals included in this study. The research related to human use complies with all the relevant national regulations, institutional policies and was performed in accordance with the tenets of the Helsinki Declaration, and has been approved by the authors' institutional review board or equivalent committee.

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