Proceedings of the 9th International Conference on Information Technology and Applications in Biomedicine, ITAB 2009, Larnaca, Cyprus, 5-7 November 2009

On Enhancing Cardiac Pulse Measurements Through Thermal Imaging

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***Abstract*— This paper presents methodological advances on pulse measurement through thermal imaging of the face - a modality that recovers thermo-physiological function. Two previous methods that capitalized on heat transfer effects along and across the vessel during pulse propagation have been brought together in a fusion scheme. In addition, the quality of the extracted physiological signals has improved thanks to sophisticated tracking and noise reduction algorithms. Finally, parameter optimization has fine-tuned harmonic analysis of the signals, thus, strengthening the measurement accuracy. Comparative experiments that were conducted on a dataset of 12 subjects highlighted the virtues of the new methodology versus the legacy ones. Specifically, the new method reduced the instantaneous measurement error from 10.5% to 7.8%, while it improved mean accuracy from 88.6% to 95.3%. This advancement brings clinical applications of the technology within sight.**

***Index Terms*—** *Pulse Recovery, Tracking, Thermal Imaging*.

I. Introduction

The arterial pulse is produced by the rise and fall in blood pressure as the heart goes into systole and diastole. Clinically this is observed by palpation of the radial artery. Traditionally, Electrocardiography (ECG) is utilized for measuring the arterial pulse [7]. Other commonly used devices that extract the cardiac frequency are piezoelectric [1], photoplethysmography [9] or Doppler Ultrasound [5].

The main disadvantage of all the aforementioned traditional methods to measuring the arterial pulse is that they are based on active sensing. Thus, their accuracy is highly dependent on subjects' cooperation due to sensor and natural noise. With the higher accuracy of present day thermal imaging systems (TIS) and increased computational ability of modern computers, the limitations of earlier systems can be overcome.

Passive sensing through thermal imaging (TI) has only a few years history in the monitoring of human vital signs, which include heart and breathing rate, blood pressure and superficial perfusion. Recently, Chekmenev et al. [3] developed a TIS to measure the arterial pulse. Good performance results were reported on a dataset of eight subjects. However, a major drawback of the method is that the authors do not address the issue of tracking the Region of Interest (ROI). Thus, this method is impractical and cannot guarantee high quality data as well as high performance results. Moreover, an extensive sensitivity and statistical analysis would be needed so that this method can be considered as an integrated solution to the problem of cardiac pulse recovery.

Garbey et al. utilized FFT-based signal analysis to measure the cardiac pulse in the vicinity of the major superficial temporal vessels [6]. This is performed by employing a computer vision methodology that is based on passive sensing and is built to accurately measure the effect of the arterial pulse propagation in a contract-free non-intrusive manner. The dominant heart rate frequency was estimated by averaging the power spectra of each pixel in the preselected segment of the superficial vessel. Two methods were adopted: *Along* (ALM) [6] and *Across* (ACM) [11]. In ALM a thermal imprint along the center line of a large Superficial Temporal Vessel (STV) is selected, while in the case of ACM the imprint is selected at 90 degrees across the direction of the target vessel within the ROI.

There are a number of limitations with the above work which we address in this paper. The authors in [6] and [11] employed a static parameter set for both ALM and ACM models. Furthermore, both models were confounded by the presence of tracking errors. Neither model utilized a noise cleaning algorithm. Finally, the performance presented for both models was not evaluated by statistical significance tests.

In this paper, we solve all the above limitations and report substantial improvements in the design and methodology of our TIS that recovers the cardiac pulse. In our design strategy, both ALM and ACM methods have been brought together in a fusion scheme. In

This research was supported in part by the National Science Foundation under Grant G089270 and by the start-up funds of Dr. I. Pavlidis of the Computer Science Department at the University of Houston. The views expressed by the authors do not necessarily reflect the views of the funding agencies.

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addition, the quality of the extracted physiological signals has improved thanks to our new tracking and noise reduction algorithms. After parameter optimization, a fine-tuned harmonic analysis which improves measurement accuracy, we investigate two alternative tracking optimization approaches. These are the *S*ingle Tracking Approach (SITA), where only one tracker is used, and the *A*utomatic Tracking Approach (AUTA), that is again one tracker but enhanced with a micro-tracking capability. This investigation reveals which model and which motion tracking methodology can offer a better trade-off between performance and computational complexity. The measurement ROI where we applied our methodology is the superficial temporal vessel located at the forehead. The computed pulse is compared against a "ground-truth" measurement provided by an ADInstruments piezoelectric device [10]. The system has been evaluated via a set of experiments using the best quality thermal video clips of twelve subjects in our dataset.

The rest of the paper is organized as follows. Section II describes our pulse recovery system in detail. In Section III, we discuss our experiments. In Section IV we present the results of the system optimization. Finally, conclusions are presented in Section V.

II. Pulse Measurement System

Our pulse measurement system is a fusion scheme that involves the *Selection of Region of Interest (ROI)*; *Motion Tracking*; *Registration of the Vessel Imprint*; *Noise Cleaning* and finally the *Statistical Analysis* (see *Fig. 1 (a)*).

In this study we focus on the superficial temporal vessel that is always exposed in the side forehead region. The system employs two tracking algorithms, SITA and AUTA, to compensate for motion and provide consistent ROI measurements over time. SITA, a coalitional tracking algorithm [4] with no micro-tracking capabilities (see *Fig. 1 (b)*). Alternatively, AUTA is a novel micro-tracking algorithm (AUTA) which is an enhanced version of SITA (see *Fig. 1 (c)*). AUTA measurement ROI is localized at each point in time through a segmentation algorithm that operates in a smaller area around the temporal vessel. This segmentation fine-tunes the localization of the vessel's thermal imprint, stopping the propagation of error from the top tracker (see top row of *Fig. 1 (c)*). The segmentation process involves the following steps: (1) Perform top-hat segmentation within the inner ROI to differentiate the vessels from the surrounding tissue [2]. The vessels' thermal imprints are usually at a gradient from the remaining region, due to convection from the flow of hot arterial blood; (2) Thin the blood vessel network down to one pixel thickness [2]; (3) Find the largest vessel in case there are more than one within the inner region; (4) Find the best fit for the points of the largest vessel through linear regression.

After selecting the ROI for tracking in the first frame, the operator can select a thermal imprint along the center line of the temporal vessel or at 90 degrees across it (see *Fig. 1*). The algorithm expands symmetrically into an elongated rectangle that the tracker follows for the duration of the measurement. Finally, ALM or ACM is applied to the rectangle respectively.

To achieve sensor and natural noise reduction we employ tracking, filtering and normalization techniques [6], [11]. In this paper noise reduction is further improved by a two stage algorithm that discards problematic frames as a result of bad tracking. First we are using the coalitional tracking method to compute in each frame the *average template matching score* (a number in [0, 1]) of all the trackers in the winning coalition. This score rewards trackers that maintain consistent imaging content [4]. The decision to include the current frame to the pulse measurement estimation process is based on a 70% score. Then we ignore frames where frequency spikes are noticed. Frequency spikes are triggered by low estimation of the camera's frame rate, which in turn affects the estimation of the pulse dominant frequency. Ultimately, this error propagates to the conversion of this frequency (Hz) to the reported pulse rate (in *beats per minute*-BPM).

In the final step of our system we apply a Fourier-based method on the tracked ROI of the temporal vessel and extract the dominant pulse frequency [6], [11].

III. Experimental Setup

A high-quality TI system has been designed for data collection that can obtain highly accurate measurements. The centerpiece of the system is a MWIR camera with 50-mm lens [8]. We operate at a standoff distance of 6 feet. The camera is capable of capturing 30 fps in a full spatial resolution of 640×480 pixels. We tested our approach on 12 subjects (6 male/female) with ages in the range of 24-55 years old. Note also that for our experiments we are using a Windows Vista 32-bit system, with 3GB RAM, and Intel Core Duo CPU T7500 at 2.2GHz.

IV. System Optimization

The optimization framework of the pulse recovery system in terms of performance and computational cost is quite complex. Global optimization requires an exhaustive evaluation of an uncountable number of

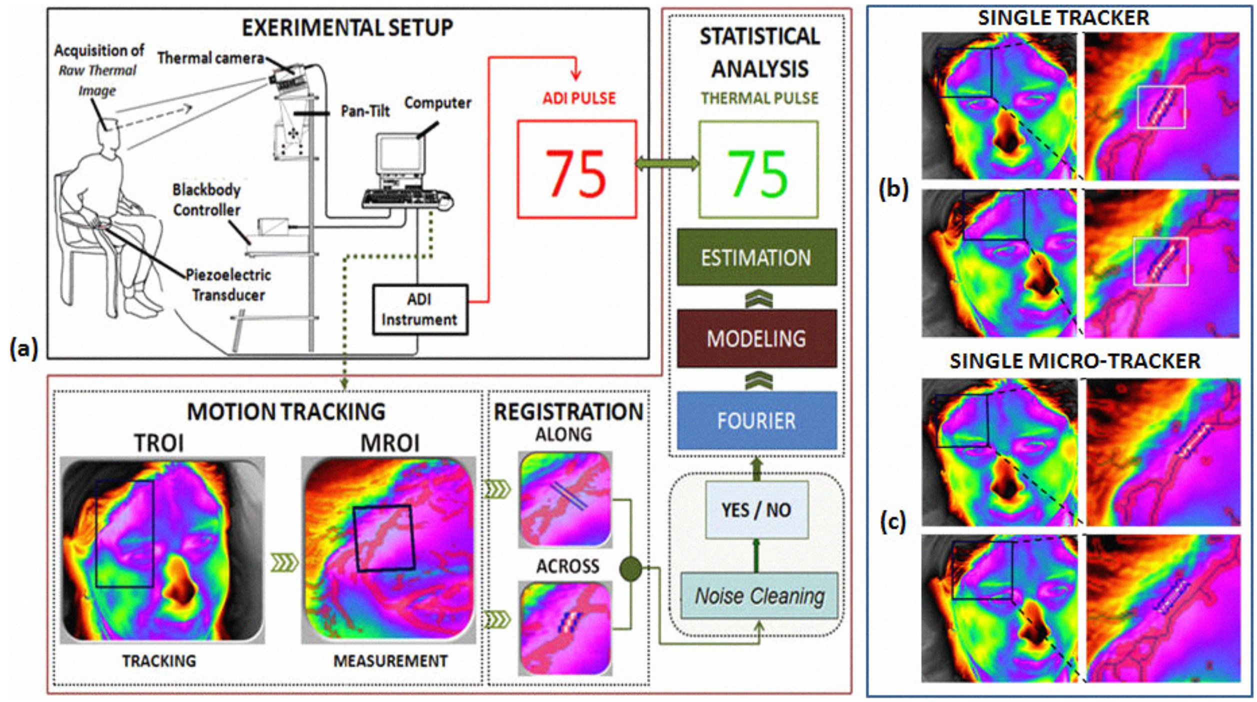

Fig. 1. (a) Our new pulse measurement methodology. The TI measurements are compared against a 'ground-truth standard' provided through a high-quality contact sensing device from ADInstruments [10]. Note that overall methodology is enhanced: the *ALM* and *ACM* models have been optimized, *Motion Tracking* has become automatic and the *Noise Cleaning* step has been developed to improve the tracker's performance. (b) Example of Single Tracker performance. (c) Example of Single Micro-Tracker performance. (b, c) *Left column*: We can see the thermal snapshots of a subject at time t = 0 and t = 5 sec for each tracker, and having as a target the temporal area. (b, c) *Right column*: Blow-ups of the ROI at the same times.

values for all system parameters. Hence, in practice only partial optimization is feasible with many parameters taking default values after an efficient parameter selection process.

In this paper our optimization process features an efficient parameter selection (i.e., the length/width of the thermal imprint, operational pulse range, and time window of the history data - previous frames) for both the ALM and ACM models. Then we combine parameter selection with noise cleaning, and we finally investigate which of the two models can pair with what motion tracking algorithm to offer a better trade-off between performance and computational complexity. The main combinations investigated are SITA and AUTA with either measurement model. These tracking optimization approaches are compared with the baseline pulse measurement methods reported in [6], [11].

To evaluate system performance we employ three criteria: (1) the cumulative sums (CUSUM) between the instantaneous pulse measurements and their corresponding ground-truth ones ($E^i_{cum} = \frac{1}{T}\sum_{t=1}^{T}\frac{|S^i_T(t)-S^i_G(t)|}{S^i_G(t)}$); (2) the *normalized mean pulse difference* (NMPD) which is based on the *complement of the normalized absolute difference* (CNAD) of the mean pulse against the mean ground-truth measurements over the whole thermal clip ($NMPD = 1 - \frac{|\overline{S}_T-\overline{S}_G|}{\overline{S}_G}$); (3) the Wilcoxon signed-rank test, a non-parametric statistical hypothesis test comparing the ground truth to the TI measurements of the optimized models. It is used as an alternative to the paired Student's t-test since the pulse measurements cannot be assumed to be normally distributed.

In *Table I* we can compare (horizontally) the performance of the baseline system with the system after using the optimum parameter sets per model (OPT). We can also compare (vertically) the optimized system before and after applying our improved noise cleaning algorithm. We can see that parameter optimization and noise cleaning improve the overall system performance.

In the final step we select the optimum parameter set per model, apply the noise cleaning algorithm, and then we investigate which motion tracking methodology we should follow to achieve maximum performance with the minimum computational cost. In *Table II* we can see the benefits of optimization when comparing the baseline and SITA approaches where only a single tracker

TABLE I

PERFORMANCE RESULTS BEFORE (BASELINE) AND AFTER (OPT) AN EFFICIENT PARAMETER SELECTION AND THE USE OF THE NOISE CLEANING ALGORITHM. NOTE THAT WE ACHIEVED AN OPTIMIZED PARAMETER SET PER SUBJECT. HOWEVER, DUE TO SPACE HERE WE PRESENT ONLY THE AVERAGE PERFORMANCE RESULTS FOR ALL SUBJECTS. NC=NOISE CLEANING.

MODEL	NC	BASELINE		OPTIMIZATION	
		CUSUM	NMPD	CUSUM	NMPD
ALONG	No	10.54	88.63	7.78	97.26
	Yes	-	-	6.89	97.57
ACROSS	No	10.14	94.56	8.15	98.50
	Yes	-	-	6.88	98.55

was used before and after parameter optimization while also using the noise cleaning algorithm. We can also see that the micro-tracking approach (AUTA) further improves system performance.

The Wilcoxon test fails to reject the hypothesis (H=0) of zero median for the difference between GT and AUTA samples in 6/8 out of 12 subjects for the ALM/ACM (mean P-value=0.39/0.36) model respectively. In SITA the test either rejects the hypothesis (H=1) for all subjects for the ALM, and for the ACM it accepts (H=0) it in only 3/12 subjects (mean P-value=0.09). In the baseline case H=1 for both models and for all subjects.

TABLE II

FINAL PERFORMANCE RESULTS WHEN USING THE BASELINE SYSTEM AND ALL OUR MOTION TRACKING APPROACHES AFTER OPTIMIZATION. THE MEAN VALUES AND STANDARD DEVIATION FOR ALL SUBJECTS ARE PRESENTED AFTER RUNNING EACH EXPERIMENT 10 TIMES PER SUBJECT. ALM/ACM=ALONG/ACROSS, ME=MEAN ERROR (%), MA=MEAN ACCURACY (%).

CRITERIA	MODEL		BASELINE	SITA	AUTA
CUSUM	ALONG	ME	10.56	8.11	7.82
	ACROSS	ME	10.14	9.84	9.35
NMPD	ALONG	MA	88.63	95.24	95.32
	ACROSS	MA	94.56	95.23	95.04

Finally, in terms of response time and when employing our ALM model, we manage to improve our baseline system by 21%/16% when compared to optimized SITA/AUTA approaches. When employing our ACM model the response time was dramatically improved by 74%/73% when compared to optimized SITA/AUTA approaches. Although we still cannot process all frames in real time, we managed to go from processing 1/77 frames (baseline system), up to 1/1.67 frames specifically in the case of employing the ALM model with the optimized AUTA tracking approach.

V. CONCLUSIONS

In this paper we report substantial improvements in the design and methodology of a baseline pulse recovery thermal imaging system. The experimental results demonstrate that the overall improvement of the performance is due to choosing better parameters as well as due to the noise reduction scheme. Noise cleaning in particular improves system performance up to 15.6%. We have identified that AUTA is the preferable tracking approach in terms of performance, statistical significance, and response time.

The conclusions of this work were drawn in the context of our database. For future work we plan to include an improved tracking approach, and perform a new data collection process where a minimum of 30 subjects will participate. A new camera with a better spatial resolution and a new protocol will be used that has been designed so that motion noise is minimized. We believe that our advanced research work will find great applications in the areas where the monitoring of heart rate through a passive sensing system is needed and in the cases where motion artifacts and poor subject cooperation are considered a serious problem.

REFERENCES

[1] K. Aminian, X. Thouvenin, P. Robert, J. Seydoux, and L. Girardier. A piezoelectric belt for cardiac pulse and respiration measurements on small mammals. *IEEE Engineering in Medicine & Biology Society*, pages 2663–2664, 1992.

[2] P. Buddharaju, I. Pavlidis, P. Tsiamyrtzis, and M. Bazakos. Physiology-based face recognition in the thermal infrared spectrum. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 29(4):613–626, April 2007.

[3] S. Chekmenev, A. Farag, and E. Essock. Thermal imaging of the superficial temporal artery: An arterial pulse recovery model. *CVPR*, pages 1–6, 2007.

[4] J. Dowdall, I. Pavlidis, and P. Tsiamyrtzis. Coalitional tracking. *Computer Vision and Image Understanding*, 106(2-3):205–219, 2007.

[5] D. H. Evans and W. N. McDicken. Doppler ultrasound: Physics, instrumentation and signal processing (second edition). *Chichester: Wiley*, 2000.

[6] M. Garbey, N. Sun, A. Merla, and I. Pavlidis. Contact-free measurement of cardiac pulse based on the analysis of thermal imagery. *IEEE Trans. Biomed. Eng.*, 54(8):1418 – 1426, August 2007.

[7] A. C. Guyton. Textbook of medical physiology. *8th ed. Philadelphia, PA: Saunders, Unit 3, ch. 11*, 1991.

[8] I. S. Inc. Available: http://www.indigosystems.com. *Goleta, California [Online]*.

[9] S. Loukogeorgakis, R. Dawson, N. Phillips, C. Martyn, and S. Greenwald. Validation of a device to measure arterial pulse wave velocity by a photoplethysmographic method. *Physiol. Meas.*, 23:581–596, 2002.

[10] PowerLab. Adinstruments owner's manual. *Castle Hill, NSW, Australia, ADInstruments Pty Ltd.*, 2004.

[11] N. Sun, I. Pavlidis, M. Garbey, and J. Fei. Harvesting the thermal cardiac pulse signal. *MICCAI 2006, Lecture Notes in Computer Science, Springer*, 4191:569–576, 2006.