rPPG BASED HEART RATE ESTIMATION USING DEEP LEARNING

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PROBLEM DESCRIPTION

- With every heartbeat, there are changes in the light and hence color reflected from our skin caused by the cardiac cycle.
- We cannot see these changes with our eyes, but we can analyze the intensity of these colors with image processing techniques.
- By processing these color changes, we can estimate the heart rate from facial videos.

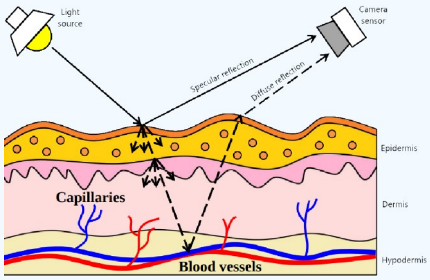


Figure 1: Skin reflection model illustration [1]

DATASETS

PURE
Pulse Rate Detection Dataset - PURE [2] data set consists of 10 people (8 male, 2 female) that were recorded 60 videos in 6 different setups.

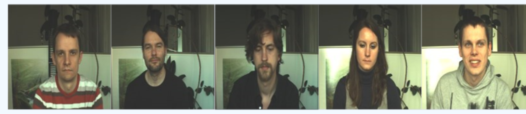


Figure 2: A few examples from PURE [2]

UBFC
There are 42 videos in UBFC dataset. Each people about 1m away from the camera. 30fps with a resolution of 640x480.

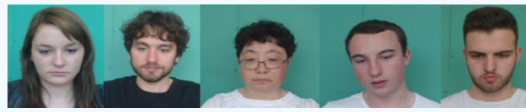


Figure 3: A few examples from UBFC [3]

METHODS

Traditional Methods

As traditional methods, we used iPhys library methods:

- ***CHROM DEHAN [7]***
- ***ICA POH [8]***
- ***GREEN VERCRUYSSE [9]***
- ***POS WANG [10]***

- Viola-Jones [4] face detection
- skin detection and remove non-skin pixels
- The pixels in the ROI are spatially averaged, the process repeated for each video frame detected.
- The result of this process is then used to obtain the rPPG signal.

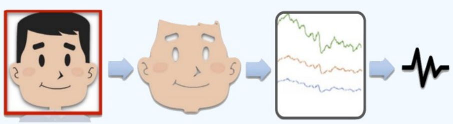


Figure 4: Obtained rPPG signal from ROI [5]

Deep Learning Based Methods

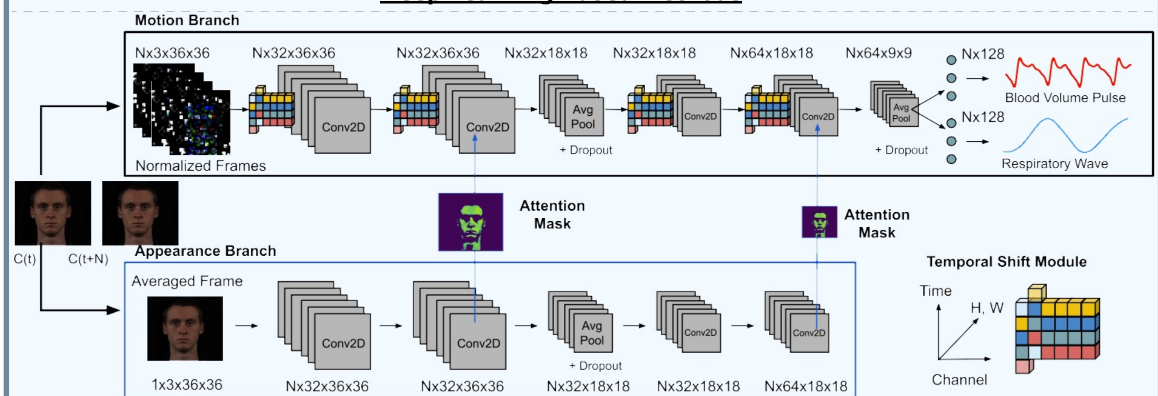


Figure 5: Multi-task temporal shift convolutional attention network for camera-based physiological measurement [6]

- Power spectrum density with a hamming window to the BVP signal from the MTTS-CAN model
- Masking process for 1 and 4 frequency ranges for the signal
- Estimate the heart rate by multiplying the frequency at the maximum point of this signal by 60
- RMSE calculations with the ground truth values of the results
- Improvement in the results by applying SNR to the signal which obtained as a result of power spectrum density

RESULTS

Video from UBFC	Traditional Methods				Deep Learning Based Method
	CHROM DEHAN	ICA POH	GREEN VERKRUYSSE	POS WANG	MTTS-CAN with SNR f~ 0,167
13.avi	10,4263	10,6027	12,358	10,6355	30,172
14.avi	16,284	22,6972	27,8859	24,4553	7,907
17.avi	18,4104	16,5873	12,84	17,787	2,207
31.avi	8,7691	8,6861	21,5627	1,1123	1,740
37.avi	6,0574	6,0336	27,3165	6,0389	3,579
40.avi	7,7885	7,821	16,7349	7,8318	0,854
42.avi	17,4668	16,6722	24,4086	45,6642	18,347
43.avi	2,824	2,8962	41,8808	3,2266	4,237
Average RMSE	**14,5**	**16**	**27,2**	**20,6**	**11,421**

Table 2: RMSE values of sample videos from UBFC obtained with traditional methods and deep learning based method

UBFC			PURE		
Video	**MTTS-CAN without SNR**	**MTTS-CAN with SNR f~ 0.167**	**Video**	**MTTS-CAN without SNR**	**MTTS-CAN with SNR f~ 0.167**
5.avi	2,197	2,072	**01-03**	1,908	1,908
8.avi	22,985	2,431	**03-03**	3,615	1,772
10.avi	14,309	9,299	**03-05**	0.830	17,894
12.avi	1,755	1,738	**03-06**	4,942	1,553
16.avi	1,887	1,958	**04-03**	4,035	3,325
31.avi	1,946	1,740	**04-04**	12,682	7,193
34.avi	1,782	1,356	**04-06**	5,616	5,048
35.avi	7,674	4,990	**06-02**	56,048	49,427
37.avi	8,254	3,579	**07-01**	1,814	1,848
44.avi	6,277	6,081	**07-03**	4,046	3,763
46.avi	2,179	1,982	**10-03**	5,343	5,426
48.avi	16,655	4,764	**10-06**	1,173	1,165
Average RMSE	**15,052**	**11,421**	**Average RMSE**	**8,449**	**17,322**

Table 1:Examples of RMSE values from processing videos in UBFC and PURE with and without SNR with MTTS-CAN

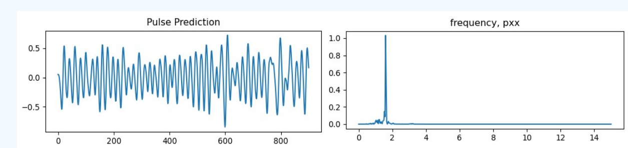


Figure 6: BVP signal and Power Spectrum Density (PSD) of 16.avi from UBFC

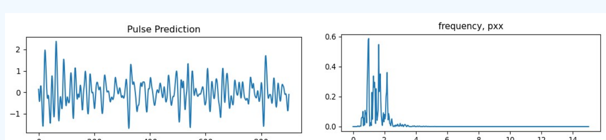
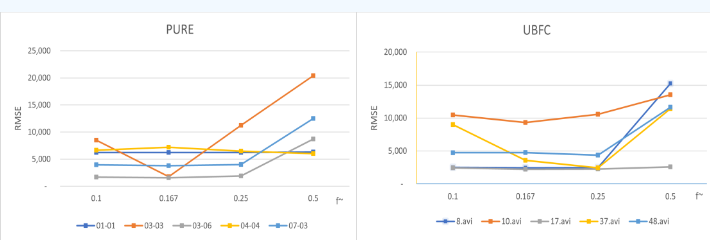


Figure 7: BVP signal and Power Spectrum Density (PSD) of 06-02 from PURE



Graph 1: RMSE values obtained by calculating some videos from UBFC and PURE with different f~ values of BVP signals from MTTS-CAN

CONCLUSION

As a result of this study, we have seen that deep learning based methods generally give more accurate and faster results than traditional methods. When we used SNR while calculating the heart rate according to the BVP signal formed as a result of deep learning based methods, we observed a significant improvement in some results.

REFERENCES

[1] W. Wang, A. C. den Brinker, S. Stuijk, and G. de Haan, "Algorithmic principles of remote ppg" , IEEE 2016

[2] Stricker, R., Müller, S., Gross, H.-M. "Non-contact Video -based Pulse Rate Measurement on a Mobile Service Robot" , IEEE 2014

[3] S. Bobbia, R. Macwan, Y. Benezeth, A. Mansouri, J. Dubois, (2017), Unsupervised skin issue segmentation for remote photoplethysmography, Pattern Recognition Letters

[4] Paul Viola and Michael Jones (2001), Robust Real-time Object Detection, International Journal of Computer Vision

[5] Fouad, R. M., Osama A. Omer, Abdul-Magid M. Ali, and Moustafa H. Aly. "Refining ROI selection for real-time remote photoplethysmography using adaptive skin detection." 2019

[6] Xin Liu, Josh Fromm, Shwetak Patel, Daniel McDuff "Multi-Task Temporal Shift Attention Networks for On-Device Contactless Vitals Measurement." 2020

[7] De Haan, G., & Jeanne, V. (2013). Robust pulse rate from chrominance-based rPPG.

[8] Poh, M. Z., McDuff, D. J., & Picard, R. W. (2010) Non-contact, automated cardiac pulse measurements using video imaging and blind source separation.

[9] Vercruysse, W., Svasand, L. O., & Nelson, J. S. (2008). Remote plethysmographic imaging using ambient light.

[10] W. Wang, A. C. den Brinker, S. Stuijk, and G. de Haan, "Algorithmic principles of remote ppg," IEEE 2016