Convolutional Neural Network for ECG-based Virtual Pathology Stethoscope Tracking in Patient Heart Auscultation

Haben Yhdego[1] Nahom Kidane[1] Sahil Aggarwal[2] Andrew Cross[2]
Frederick Mckenzie[1] Michel A Audette[1]

[1]Old Dominion University (ODU)
[2]Eastern Virginia Medical School(EVMS)

IEEE International Conference on Bioinformatics and Biomedicine:
2nd Workshop in Artificial Intelligence Techniques for Biomedicine and Healthcare
November 18, 2019

Objective

Hybrid Simulations: Tracked Virtual Pathology Stethoscopes (VPS)

- a simulation-based solution that train students to perform cardiac examinations by listening to abnormal heart sounds in otherwise healthy standardized patients (patient actors).

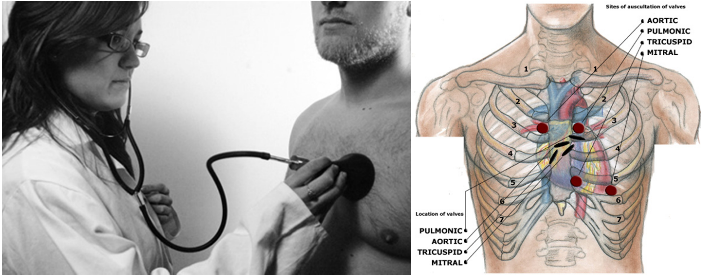


Figure 1: Points of Cardiac Auscultation [1]

Outline

Cardiac Auscultation (CA)

- The auditory detection of heart sounds to diagnose abnormalities, a crucial skill that is both efficient and cost-effective in medical practice.
- CA requires a consistent approach to site detection.
  - The areas of auscultation are generally correlated with the cardiac valves.

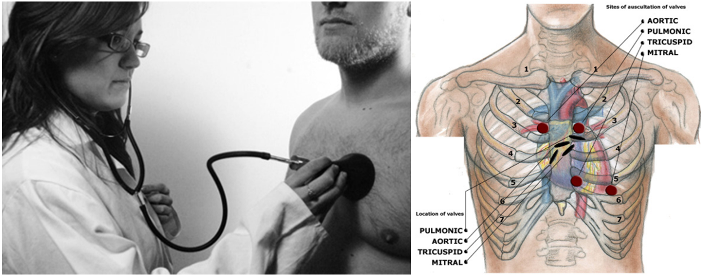


Figure 2: Points of Cardiac Auscultation [1]

Current level of CA proficiency

- Several surveys [1] [2] [3], have highlighted a rapid decline in this time-honored skill.
- Many new physicians and trainees have difficulty performing basic cardiac examinations on their patients.

Obstacles encountered in CA Training:

1. lack of patient access due to short hospital stay.
2. shortage of training time & experienced auscultation teachers.
3. reliance on competing & more expensive technologies.

Simulation Based Auscultation Training

Medical simulators

- Provides a safe and controlled environment for repetitive practice.
- Immediate training opportunities. (No need to wait for a suitable real patient)
- Allow easy access to a wide variety of clinical scenarios.

Figure 3: Harvey cardiology patient simulator [1] and PAT Pediatric Auscultation Trainer [3]

Simulation Based Auscultation Training

Medical simulators

- Provides a safe and controlled environment for repetitive practice.
- Immediate training opportunities. (No need to wait for a suitable real patient)
- Allow easy access to a wide variety of clinical scenarios.

Limitations

- Limited number of speakers and require precise stethoscope placement
- mechanical noise from manikin's internal hardware
- Inanimate objects

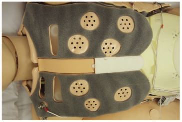


Figure 4: SimMan 3G manikin [1]

Simulation Based Auscultation Training

Standardized Patients (patient actors)

- Individuals trained to portray a patient with a specific condition in a realistic, standardized and repeatable way.
  - document learner performance,
  - provide feedback on both clinical and interpersonal skills and
  - realistically represent patient satisfaction.

Simulation Based Auscultation Training

Standardized Patients (patient actors)

- Individuals trained to portray a patient with a specific condition in a realistic, standardized and repeatable way.
  - document learner performance,
  - provide feedback on both clinical and interpersonal skills and
  - realistically represent patient satisfaction.

Limitation

- Range of symptoms and syndromes they can physically portray is limited.

Related Works

Hybrid Simulations: Virtual Pathology Stethoscopes (VPS)

- The student hears the abnormal sound instead of the SP's when he/she performs cardiac auscultation.
- There are currently two methods of activating the VPS:
  - Instructor/SP triggered VPS
  - Tracked VPS

Figure 5: Ventriloscope stethoscope [4]

Related Works

Hybrid Simulations: Virtual Pathology Stethoscopes (VPS)

- The student hears the abnormal sound instead of the SP's when he/she performs cardiac auscultation.
- There are currently two methods of activating the VPS:
  - Instructor/SP triggered VPS
  - Tracked VPS

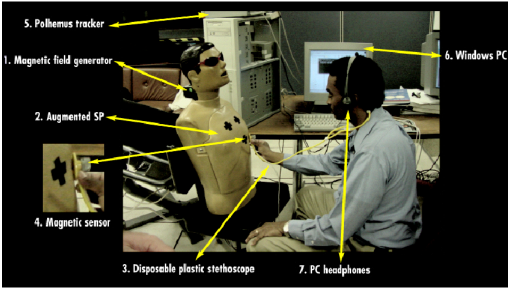


Figure 6: Magnetic based Tracked VPS [5]

Related Works

Hybrid Simulations: Virtual Pathology Stethoscopes (VPS)

- The student hears the abnormal sound instead of the SP's when he/she performs cardiac auscultation.
- There are currently two methods of activating the VPS:
  - Instructor/SP triggered VPS
  - Tracked VPS

Limitation

- It requires additional SP training.
- The transmitter requires a direct line of sight for signaling.
- Magnetic Tracking system is expensive; Sensor is sophisticated.

Proposed System

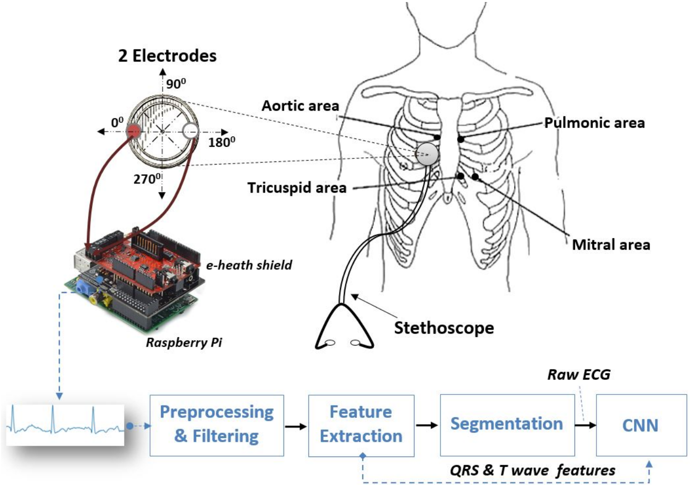


Figure 7: Stethoscope apparatus and proposed system.(top-right) The four primary cardiac auscultation sites that the algorithm can detect. (top-left) Two direct-contact electrodes fixed on a standard stethoscope head to record ECG signals. (bottom) The setup was attached to an e-health sensor connected to a RaspberryPi computer to run the ECG signal acquisition program.

Data Acquisition and Preprocessing

Standardized Patients

- 10 healthy individuals (8 males and 2 female)
  - Exclusion criteria include the presence of a pacemaker,a history of chronic or hypertension.
  - All patients signed consent forms and data was anonymized.

Preprocessing

- e-health sensor shield [6] + Raspberry Pi
  - 10 second ECG at a sampling rate of 1KHz
  - Noises and artifacts from breathing, body movements, and power line interference were filtered using low pass and high pass filters.

Data Acquisition and Preprocessing

Acquisition Procedure

- 160 ten-second ECG recordings
  - 4 auscultation area (Aortic, Pulmonic, Mitral, and Tricuspid)
  - 4 orientations/auscultation area,
  - 5 runs/orientations, and
  - 2 postures (seated and supine)

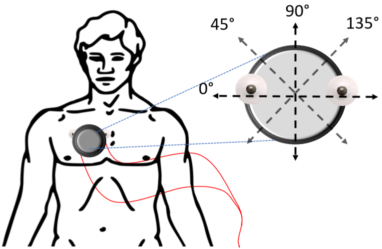


Figure 8: Data Collection

Segmentation and Hand-crafted features

Hand-crafted features

- Amplitude and interval feature vector (size = 14)
  - Pan-Tompkins algorithm [7]: to identify the Q, R, and S peaks.
  - Wave segmentation method [8]: to find the T wave peak.

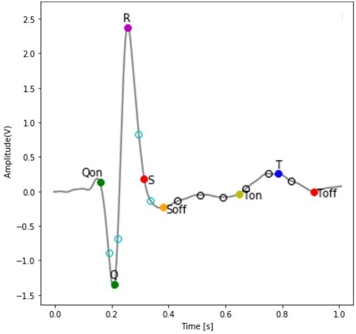
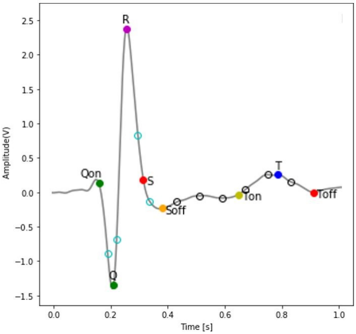


Figure 9: Amplitude and interval features are extracted from onset, peak, and offset of QRS and T waves.

Segmentation and Hand-crafted features

Segmentation

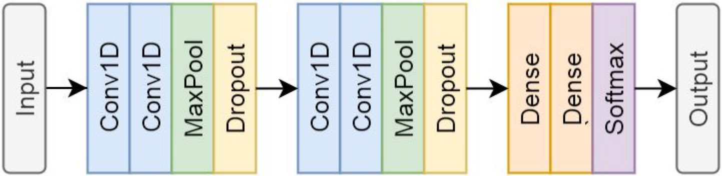
- Using the RR interval, we segmented the raw signal into 1 second window centered on each R-peak.
- The signal was downsampled to 200Hz (200 samples)



Convolution Neural Network Model

1D CNN Model

- The CNN is trained to output a class prediction for every beat.
  - 2 hidden CNN layers and 2 fully-connected layers
  - 128 parallel feature maps and Kernal size of 5
- The total training dataset is divide into 80% training and 20%testing.



Experimental Results

Table 1: Comparison of the CNN model with the previous work

Classifier	Features	Accuracy	Precision	Recall	F1
Random Forest [9]	QRS + T waves	0.84	0.82	0.83	0.83
CNN (current method)	QRS + T waves	0.89	0.85	0.87	0.86

Experimental Results(Cont'd)

Table 2: Model performance for different SP postures

Raw ECG Data[a]	Average Model Performance(%)			
	Accuracy	Precision	Recall	F1
Seated	86.1	86.0	86.0	86.2
Supine	92.0	92.0	92.0	92.0
Combined	90.0	90.0	90.0	90.0

[a] 1 sec row data segmented between each RR interval.

Experimental Results(Cont'd)

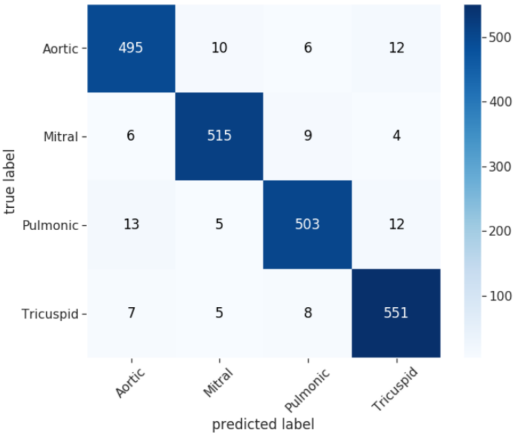


Figure 11: Confusion Matrix

Conclusion

- We investigated the accuracy and validity of a CNN based virtual pathology stethoscope tracking system.
- The preliminary analysis done on 10 subjects, showed promising performance gain over our previous system.
- However, testing on additional subjects as well as different postures is required to determine the reliability of the system.

References

[1] J. J. Ward and B. A. Wattier, "Technology for enhancing chest auscultation in clinical simulation," *Respiratory care*, vol. 56, no. 6, pp. 834–845, 2011.

[2] j. M. Vukanovic-Criley, "Competency in cardiac examination skills in medical students, trainees, physicians, and faculty: A multicenter study," *Archives of Internal Medicine*, 2016.

[3] D. B. Wayne, J. Butter, E. R. Cohen, and W. C. McGaghie, "Setting defensible standards for cardiac auscultation skills in medical students," 2009.

[4] A. Verma, H. Bhatt, P. Booton, and R. Kneebone, "The ventriloscope® as an innovative tool for assessing clinical examination skills: appraisal of a novel method of simulating auscultatory findings," *Medical teacher*, vol. 33, no. 7, pp. e388–e396, 2011.

[5] F. D. McKenzie, H. M. Garcia, R. J. Castelino, T. W. Hubbard, J. A. Ullian, and G. A. Gliva, "Augmented standardized patients now virtually a reality," in *Third IEEE and ACM International Symposium on Mixed and Augmented Reality*, pp. 270–271, IEEE, 2004.

[6] C. Hacks, "e-health sensor platform v2. 0 for arduino and raspberry pi [biometric/medical applications]," *Recuperado el*, vol. 24, 2014.

[7] J. Pan and W. J. Tompkins, "A real-time qrs detection algorithm," *IEEE Trans. Biomed. Eng*, vol. 32, no. 3, pp. 230–236, 1985.

[8] A. Espiritu-Santo-Rincon and C. Carbajal-Fernandez, "Ecg feature extraction via waveform segmentation," in *2010 7th International Conference on Electrical Engineering Computing Science and Automatic Control*, pp. 250–255, IEEE, 2010.

[9] E. M. L. T. H. A. Cross, N. Kidane and F. McKenzie, "Board 322-research abstract validation of an ecg-based stethoscope tracking technology (submission# 1247)," vol. 8, no. 6, pp. 528-825, 2013.

Thank You! Questions ?