"DZAM": A Software Based System For Assessing Foot Perfusion From Doppler Signals: How Does It Work & Advantages

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Things aren’t always what they seem….

OUR HYPOTHESIS:
Subjectivity of doppler interpretation can be reduced by acquisition and meaningful processing of relevant data

Background & Significance:
• Continuous Wave ("handheld") Doppler devices are used everywhere (ICU, PACU, floor) by variety of medical professionals, BUT…
  • Operator dependent
  • Subjective acquisition interpretation

AND….

Background & Significance:
• Many (?most) users lack training and expertise to correctly interpret what they are hearing
• Worst case scenario = failure to identify impending limb loss

Back to the Future:
• Arterial disease changes the shape of Doppler ultrasound waveforms
• These changes can be described numerically by computer analysis of waveforms

Disclosure(s)
• None
Basic Considerations:

Analysis of Doppler waveforms from the lower limb arteries:
- An area of promise
- Still limited clinical applicability

Doppler used routinely in vascular dx
Handheld devices (cellphones etc) are ubiquitous:
- Multiple apps for capturing, analyzing and identifying sound wavelengths from the surroundings (i.e. Shazam)

A LOT has changed since then….

Methodology:

Sound Acquisition
- Data Enrichment with Numerical Simulations
- Feature Extraction, Machine Learning, and Classification

A Word About Machine Learning:
- Just as experienced humans (vascular surgeons) use sound from a Continuous Wave Doppler Device to make decisions, we can train algorithms to accomplish this task
- Our main goal is to **diagnose peripheral arterial disease** based on the audio signal from a hand-held Doppler device and reduce risk of human error

Machine Learning:
- Why use an algorithm over a human?
  - quantify classification error (healthy vs unhealthy signal)
  - decrease error by augmenting data sets and information
- In essence, this is a “big data” problem that can be treated formally as a learning process. We train, learn, test, deploy, make decisions.

System Components:
- The main components for developing this system are:
  - Gathering of patient data for training a machine learning algorithm
  - Training of algorithm to learn how sound can differentiate between healthy and unhealthy signals
  - Testing on control group different from training set
  - Use of the tested system with new information to classify, communicate with expert, and help in decision process
What is Signal Processing?

- The signal processing technique (Fourier Transform)
- Decomposes a signal into its component frequencies
- This FT shows five well defined frequency components

Clinical Applicability – Benefits:

- We now understand the importance of doppler analysis in PAD
- Still lack STANDARDIZATION AND CONSISTENCY
- Highlights the role for machine learning/interpretation of doppler waveforms

Overview of Application Progression:

- 38 patients
- 5 CWDoppler recordings per patient
- Experts assign binary patient labels: “healthy” = 0, “unhealthy” = 1
Methods:

Research
- Find key pieces of information ("features") from signals

Build model
- Use features to discriminate between healthy and unhealthy signals
- Refit the accuracy by repeating evaluation with new randomized subsets of the same group of patients

Evaluate model performance using standard Machine Learning metrics

Methods:

Model Training
- Used various feature subsets to train Machine Learning (ML) models
- Trained different ML models, including: K-Nearest-Neighbor (KNN), Support Vector Machine (SVM), Linear Discriminant Analysis (LDA), Gradient Boosting, and Naive Bayes

Model Testing
- Performed 10-fold Cross-Validation (CV) on entire data set to generate a Receiver Operating Characteristic (ROC) curve
- Selected optimal classifier using 2 performance metrics:
  - Area Under Curve (AUC) (best: AUC = 1, worst: AUC = 0.5)
  - Percent accuracy (best: accuracy = 100%, worst: accuracy = 50%)

Results:

Cross-Validation ROC curves for 7 Features

<table>
<thead>
<tr>
<th>Metric</th>
<th>AUC</th>
<th>Accuracy</th>
</tr>
</thead>
<tbody>
<tr>
<td>Performance</td>
<td>AUC = 0.90</td>
<td>Accuracy = 92%</td>
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Best Features
- Mean frequency, Peak frequency (high), Power, Total Harmonic Distortion, RI, SDR

2 Important Limitations:
- Only 38 patients (model may not be general enough)
- Only used 10-fold cross-validation for performance metrics (not enough data for a test set to be meaningful)

Hot Off the Press….PCA Analysis:

PCA (principal component analysis), a second method of model validation, also showed accurate identification of patients with physiologic vs. pathologic signals

Separation between healthy and unhealthy patients, as evidenced by first 2 principal components of 12-dimensional feature space (97.2% variance explained)

• The selected best features achieved:
  - AUC of 0.9 and accuracy of 92%
Summary:
- Technological advancements in the last decade:
  - have opened previously inaccessible areas of research for their integration in everyday clinical practice

Summary:
- Preliminary data on a small number of patients:
  - DZAM can be utilized to evaluate lower extremity perfusion with high accuracy
  - Potential to eliminate errors from pulse exams and Doppler signals in a huge array of clinical settings
- Continue to accrue patients and refine technology
- Create widely accessible interface (app)

Thank you!