Heart Failure Assessment Using Multiparameter Polar Representations and Deep Learning*

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Abstract—Heart failure refers to the inability of the heart to pump enough amount of blood to the body. Nearly 7 million people die every year because of its complications. Current gold-standard screening techniques through echocardiography do not incorporate information about the circadian rhythm of the heart and clinical information of patients. In this vein, we propose a novel approach to integrate 24-hour heart rate variability (HRV) features and patient profile information in a single multi-parameter and color-coded polar representation. The proposed approach was validated by training a deep learning model from 7,575 generated images to predict heart failure groups, i.e., preserved, mid-range, and reduced left ventricular ejection fraction. The developed model had overall accuracy, sensitivity, and specificity of 93%, 88%, and 95%, respectively. Moreover, it had a high area under the receiver operating characteristics curve (AUROC) of 0.88 and an area under the precision-recalled curve (AUPR) of 0.79. The novel approach proposed in this study suggests a new protocol for assessing cardiovascular diseases to act as a complementary tool to echocardiography as it provides insights on the circadian rhythm of the heart and can be potentially personalized according to patient clinical profile information.

Clinical relevance—Implementing polar representations with deep learning in clinical settings to supplement echocardiography leverages continuous monitoring of the heart’s circadian rhythm and personalized cardiovascular medicine while reducing the burden on medical practitioners.

I. INTRODUCTION

Heart failure is a progressive condition affecting more than 65 million people worldwide and causes around 7 million deaths every year [1]. In HF, the heart becomes incapable of pumping an adequate amount of blood to satisfy the demand of body organs [2]. During the assessment of HF, clinicians designate the stage and risk of further progression using echocardiography, which is the current gold standard, where they look mainly at the left ventricular ejection fraction (LVEF). LVEF provides a central measure for the amount of blood pumped at each contraction, which is equivalent to the stroke volume relative to the amount of blood in the left ventricular chamber by the end of the diastole [3].

Despite how reliable current echocardiography systems are, they still raise concerns in less developed countries due to their high-cost equipment [4]. In addition, echocardiography images do not provide any cardiovascular information relative to the circadian rhythm as it is not continuously screening the heart for a longer duration, i.e., 24-hour screening, and without accounting for patient clinical information during the session [5]. Therefore, one would prefer to develop additional indicators to complement echocardiography and provide a holistic representation of the cardiovascular system of patients.

A potential option would be long-term Holter electrocardiography (ECG), which carries information on heart rate variability (HRV). The latter is considered an essential indicator for the autonomic nervous system (ANS) that includes modulation of the cardiac electrical and physiological rhythms [6], [7]. In the presence of HF, this modulation gets interrupted, making it detectable through analysis of heart rate markers [8]. However, the conventional protocols do not integrate patient profiles that include rich information on the clinical and demographic status of the patient with the attributes extracted from HRV. In addition, there are currently big patient data in multiple forms due to the increase in hospital databases, which increases the burden on medical doctors to analyze all forms at once.

In this paper, we propose a deep learning approach to validate a novel methodology of integrating 24-hour HRV and patient clinical and demographic information in a single color-coded image, which paves the way toward simpler clinical diagnostic protocols for HF or other cardiovascular diseases. The generated image provides a holistic insight into the variations of the cardiac autonomic balance, as reflected by multiple HRV markers, with respect to the circadian rhythm of the heart. Moreover, it incorporates information about patients relative to their clinical profiles that becomes useful while assessing HRV changes over 24 hours; all in a single image, which maximizes the diagnostic value and minimizes the load on physicians.

METHODS

A. Data collection

The data included in this study (n = 303 patients) was collected from two resources; the archives of the Intercity...
Digital Electrocardiography Alliance (IDEAL) study of the University of Rochester Medical Center Telemetric and Holter ECG Warehouse (THEW) [9] and the PRESERVE EF study [10]. The enrolment protocol of the THEW study was conducted following the Declaration of Helsinki and in accordance with Title 45, U.S. Code of Federal Regulations. In contrast, the PRESERVE EF study was approved by the ethics committee at seven participating cardiology departments in Greece and was endorsed by the Hellenic Society of Cardiology, Greece. All patients provided consent before participating in the studies. These patients were then classified following the recommendations of the American Society of Echocardiography and the European Association of Cardiovascular Imaging (ASE/EACVI) [11], [12] as preserved EF (>55%), mid-range EF (between 55% and 50%), and reduced EF (<50%). Thus, the dataset consisted of 129 patients in preserved EF, 92 in mid-range EF, and 82 in reduced EF. Patients’ clinical information were age, sex, body mass index (BMI), smoking, diabetes, hypertension, angina pectoris (AP), ventricular tachycardia (VT), myocardial infarction (MI), angiotensin-converting enzyme (ACE) inhibitors, antiarrhythmics, and diuretics. Patient information and statistical analysis (one-way ANOVA) were performed on several variables and provided in Table I.

### B. Heart rate variability (HRV)

HRV data were extracted from the 24-hour ECG recording of each patient on an hourly basis. The R-peak detection was performed using the Pan-Tompkins algorithm. The extracted data was fixed to start from hour 12 AM by applying the Cosinor analysis approach [13], [14]. Features were extracted from the adjusted HRV data for each hour (Fig. 1a), including time and frequency domains, non-linear, and fragmentation features [14], [15].

### Table I

**PATIENT CHARACTERISTICS AND STATISTICAL ANALYSIS**

<table>
<thead>
<tr>
<th>Variables</th>
<th>Overall patients (n = 303)</th>
<th>Heart failure groups</th>
<th>p-value</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Preserved (n = 129)</td>
<td>Mid-range (n = 92)</td>
<td>Reduced (n = 82)</td>
</tr>
<tr>
<td>LVEF, %</td>
<td>55 (46.5-63)</td>
<td>63 (60-70)</td>
<td>52.5 (50-55)</td>
</tr>
<tr>
<td>Age, yrs</td>
<td>58 (50-65)</td>
<td>57 (38-64.5)</td>
<td>58.5 (52-66)</td>
</tr>
<tr>
<td>Male</td>
<td>258 (85.15)</td>
<td>108 (83.72)</td>
<td>76 (82.61)</td>
</tr>
<tr>
<td>BMI, kg/m²</td>
<td>27.28 (24.91-29.41)</td>
<td>27.12 (24.39-28.95)</td>
<td>27.22 (25.35-29.92)</td>
</tr>
<tr>
<td>Diabetes</td>
<td>43 (14.19)</td>
<td>10 (7.55)</td>
<td>13 (14.13)</td>
</tr>
<tr>
<td>Hypertension</td>
<td>154 (50.83)</td>
<td>64 (49.61)</td>
<td>46 (50.00)</td>
</tr>
</tbody>
</table>

All values are represented as median (inter-quartile range) or n (%). Bold p-values show statistically significant differences (p < 0.050) amongst the three groups using the one-way analysis of variance (ANOVA) test. ** Significant difference between Preserved and Mid-range groups; * Significant difference between Preserved and Reduced groups.

### C. Polar Map representation

Each hourly feature value was plotted on a polar map representation, forming a shape of feature variations across the 24-hour cycle (Fig. 1b). The radius of the plot depends on the normalized amplitude of the feature, whereas the angle degree depends on the actual hour. These polar dimensions were then converted to their corresponding Cartesian (x, y) coordinates that can then be mapped into pixel space to form the actual edges of the line plot as an image. The edges are then filled in to form the full feature image. The final feature image is multiplied by a scale factor corresponding to the percentage difference between the feature plot and a full circle, *i.e.*, maximum hourly values.

### D. Color-coding patient information

Patient clinical and demographic information was normalized according to pre-defined color coding rules on a scale...
from 0 to 1. These color-coding rules provide a more visual-friendly representation of each variable. For age, the value was divided by 100, whereas for subjects older than 100 years old, it was set as 1. For sex, a male subject is a colored blue (value: 0.3) and a female subject pink (value: 0.6). For BMI, the value was normalized through a sigmoid function using a pre-calculated mean and standard deviation from the whole subject cohort. For the remaining variables, the color was either dark blue (value: 0.2) or white (value: 1), corresponding to no or yes, respectively.

E. Final image generation

Each color-coded patient information was placed on a circular ring (Fig. 2a) to form a colored circle of multiple rings changing in size from the center to the edges (from 1 to 13 features). Then, each hourly segment (pie-shaped triangle) was masked to extract the corresponding segments from the HRV feature binary image and the color-coded patient information rings (Fig. 2b). The ring segments were scaled by a factor from 0 to 1 to be the same size as the HRV feature segment. Upon multiplying both segments to fill in the HRV binary segment by the color-coded information, all pie-shaped segments were stacked and smoothed to form the final uniquely shaped image.

F. Deep learning validation

We validated the proposed polar maps by training a deep learning model (Fig. 3) on inferring the corresponding category for heart failure from these images. A leave-one-subject-out (LOSO) cross-validation scheme was followed to provide a prediction for each patient after training with 7,575 images. The model uses cross-channel two-dimensional (2D) convolutions and depth-wise convolutions. All parameters were optimized based on the iterative hyperparameter optimization approach with a learning rate of 0.001 and regularization of 0.001 in the adaptive moment estimation (ADAM) optimiser.

RESULTS AND DISCUSSION

The performance of the trained model is provided in Table II. The model had overall discrimination accuracy of 93% with an area under the receiver operating characteristics curve (AUROC) of 0.88 and an area under the precision-recall curve (AUPR) of 0.79. This performance varies slightly between the three heart failure groups, with the reduced EF group having the highest sensitivity of 95% while mid-range EF has the highest specificity of 96%. The preserved EF group had the best performance across all metrics, including the precision (92%) and F1-score (92%). The normalized Matthews correlation coefficient (NMCC) was 93%, 92%, and 94% for preserved EF, mid-range EF, and reduced EF, respectively.

After proper validation through deep learning, the generated color images can potentially reduce the stress on cardiologists when they diagnose heart failure. It integrates multiple parameters’ (ECG, HRV, and patient profiles) in a single source of data; a 2D-colored image. Therefore, the
simplicity of the proposed approach could pave the way for new protocols in the clinical assessment of diseases. Moreover, by integrating 24-hour data in a simple image, the analysis of the circadian rhythm and ANS modulation can be done easier while making conclusions relative to the current patient’s clinical and demographic status. This could make the assessment more personalized to fit the patient according to his disease progression or medications procedures.

CONCLUSIONS

A novel method for generating multi-parameter and color-coded images was provided to integrate information from ECG, HRV, and patient profiles in a single source. The reliability of the approach was validated through a high-performance deep learning model to infer heart failure groups. The current approach could be a complementary tool for echocardiography to provide additional insights into the heart’s circadian rhythm relative to ANS modulation and patient clinical and demographic status.

REFERENCES

[9] University of Rochester Medical Center, “Telemetric and Holter ECG Warehouse,”