2021 43rd Annual International Conference of the
IEEE Engineering in Medicine & Biology Society (EMBC)
Oct 31 - Nov 4, 2021. Virtual Conference

Star-ECG: Visualization of Electrocardiograms for Arrhythmia and Heart Rate Variability

Po-Ya Hsu,[1*] Po-Han Hsu,[1] Hsin-Li Liu,[2] Chi-Te Lin,[2] Hung-Tao Chou,[3] Yu-Fang Tseng[2] & Tsung-Han Lee[1]

***Abstract*— Conventional electrocardiograms (ECG) are displayed in one dimension. Reading one-dimensional ECG waveform becomes challenging when one wants to visualize the heart rate variability with naked eye. Some ECG visualization techniques have been proposed. However, they rely on domain knowledge to comprehend the heart rate variability. To improve the readability for patients and non-experts, we introduce Star-ECG, a novel ECG visualization approach. Such approach projects ECG waveforms onto a two-dimensional plane in a circular form. We demonstrate that Star-ECG offers not only easily deciphered visualization of cardiac abnormalities and heart rate variability, but also the application of state-of-the-art arrhythmia classification with integrated deep neural networks. We also report positive user feedback from both experts and non-experts that Star-ECG can provide readable and helpful information to monitor cardiac activities.**

***Clinical relevance* — A powerful and easy-to-read ECG visualization tool can critically improve healthcare environment and raise awareness of abnormal cardiovascular functioning.**

I. INTRODUCTION

Cardiovascular diseases are the leading cause of global death due to its high prevalence and associated high mortality [1], [2]. Given its severity, real time monitoring and early diagnosis of abnormal cardiac activities are critical in clinical practice. In this end, electrocardiogram (ECG) has become a popular arrhythmia diagnostic tool, as ECG is non-invasive and easily accessible. ECG is a recording of the electrical activity of the heart [3]. Each cardiac cycle is identified by the periodic characteristic points. It is widely known that variations of the ECG signal are associated with changes in cardiac dynamics. Most of the time, ECG is examined through simple visual inspection of the one-dimensional (1D) temporal ECG waveform [4].

However, abundant information remains hidden to human observation in 1D ECG, especially to people without the domain knowledge. To effectively improve the healthcare environment, easy-to-read ECG is highly required. It is reasonable that arrhythmia patients are eager to learn how to read their abnormal heart rhythms. More importantly, once the patients can read the abnormality in their cardiac activities, they can make effective conversations with the cardiologists and improve health outcomes throughout the treatment [5]. In addition to arrhythmia patients, people around the globe can also benefit from a user-friendly ECG reading tool to monitor their cardiovascular health. A different ECG visualization method is desired since 1D ECG waveform is difficult for general public to interpret.

In an effort to improve ECG rhythm readability, we present a novel ECG visualization technique along with an integrated convolutional neural network (CNN) arrhythmia classifier. We proposed Star-ECG, a novel ECG visualization tool that generates a star-like image and reflects the ECG waveform in a circular form. Such visualization enhances the readability of heart rate (HR) and heart rate variability (HRV) without the requirement of heavy computation. Moreover, we integrate deep learning into Star-ECG to classify arrhythmia, and we demonstrate that Star-ECG achieves satisfying classification performance with experts' approval.

II. METHODS

A. Experimental Design

To ease the reading of ECG for people without expertise, we aim at designing an intuitive ECG visualization method. Such method is expected to meet below the five requirements:

- **Easy-to-read visualization:** The designed visualization should deliver ECG information in a fashion that relies on no expertise, which enables the users to learn how to visualize the new ECG in a short time.
- **Fast heartbeat regularity identification:** The visualization approach should make the users feel comfortable on determining the regularity of ECG heartbeats.
- **Straightforward heart rate computation:** The visualization strategy should allow the users to easily compute the HR without any additional computing resources such as a calculator or a computer.
- **Simple heart rate variability computation:** The visualization technique should ease the users' burden on figuring out the HRV.
- **Accurate arrhythmia classification:** The visualization tool should include an accurate automated arrhythmia classification program.

This work was not supported by any organization.

[1]Po-Ya Hsu, Po-Han Hsu and Tsung-Han Lee are with the Department of Computer Science & Engineering, University of California, San Diego, The USA

[2] Hsin-Li Liu, Yu-Fang Tseng, and Chi-Te Lin are with the Department of Nursing, Central Taiwan University of Science and Technology, Taiwan

[3]Hung-Tao Chou is with the Division of Cardiovascular Surgery, Department of Surgery, Lin Shin Hospital, Taiwan

[*]Po-Ya Hsu is the corresponding author p8hsu@eng.ucsd.edu

B. Star-ECG Generation

To fulfill the design requirements, we propose **Star-ECG**, a visualization technique that represents ECG like a ninja star and incorporates arrhythmia classification into the system. We elaborate on the design of Star-ECG by first explaining the transformation from 1D ECG to Star-ECG, introducing the visual features of Star-ECG, then describing the integrated arrhythmia classification function, and last demonstrating how to read Star-ECG.

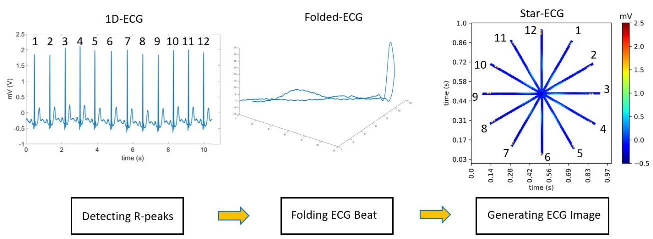

Fig. 1: Demonstration of the Star-ECG generation technique. First, we detect R-peaks in the ECG data, which are the peaks labeled with Arabic numbers on the top. Next, we fold each ECG beat into two halves as illustrated. Last, we run our Algorithm 1 to generate the Star-ECG image. We label the sequence of heartbeats with Arabic numbers 1-12 on both the 1D-ECG signal and Star-ECG. The sequential order on Star-ECG is the same as the Arabic numbers on a clock.

C. Intuitive Visualization Design

To generate the intuitive Star-ECG visualization, we devise a procedure containing three steps as illustrated in Fig. 1 to transform traditional 1D ECG into Star-ECG.

- **Step 1:** Detecting ECG Heartbeats;
- **Step 2:** Folding ECG Heartbeats;
- **Step 3:** Rotating ECG Heartbeats.

The primary step is to identify all the heartbeats in 1D ECG, and as displayed in Fig. 1, each recognized heartbeat is labeled with an Arabic number above. To accomplish this task, we run the famous Pan-Tompkins algorithm to recognize the highest voltage peak in each heartbeat [6], which is known as the *R-peak* in conventional ECG. The Pan-Tompkins algorithm is one of the state-of-the-art real-time ECG R-peaks detection techniques, and it possesses the advantages of high R-peaks detection sensitivity and fast computation time [7].

In the second step, we fold each ECG heartbeat into two halves. To perform this task, we first compute the positions of the two endpoints in each heartbeat. For searching the endpoints of one heartbeat, we need three consecutive R-peaks positions, with the middle one being the heartbeat that we want to fold. Subsequently, we acquire the two endpoints by computing the midpoints of the positions of each two consecutive R-peaks. Once we have the two endpoints, we fold the ECG heartbeat into two equal halves. To explain the folding process, let's denote the timing positions of the two midpoints as M_1, M_2, the original ECG data as $D(t)$, and the folded ECG data as $F(x,y)$. Our ECG heartbeat folding then follows the mathematical expressions:

$$F(1:\lfloor\frac{M_1+M_2}{2}\rfloor - M_1 + 1, 2) = D(M_1 : \lfloor\frac{M_1+M_2}{2}\rfloor),$$
$$F(1:M_2 - \lfloor\frac{M_1+M_2}{2}\rfloor, 1) = D(M_2 : -1 : \lfloor\frac{M_1+M_2}{2}\rfloor + 1).$$

We project the 1D ECG onto a 2D matrix with the first half ECG directly assigned to the first row and the second half mapped reversely to the second row of the matrix.

Finally, we rotate the folded ECG heartbeats to produce Star-ECG. Given N number of folded ECG heartbeats, we project them onto an image in a circular form with equally split angle. To be more specific, we demonstrate the rotation in the following algorithm 1: The inputs to Algorithm 1 are

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Algorithm 1: Star-ECG Image Generation

Input: Folded ECG Data $\{F_1, F_2, ..., F_N\}$, Starting Angle θ, Sampling Rate f_s
Output: Star-ECG Image Im
$Im = zero(f_s+1, f_s+1)$ // Create an image of zeros;
for $i = 1:N$ **do**
  $C = Coordinate(F_i)$;
  $rx = C(x) \times \cos(-2\pi \times (i-1)/N + \theta)$;
  $ry = C(y) \times \sin(-2\pi \times (i-1)/N + \theta)$;
  $Im[rx+f_s, ry+f_s] = F_i$;
end

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the folded ECG matrices along with a specified starting angle θ and sampling rate f_s; the output is a two-dimensional Star-ECG image Im representing N ECG heartbeats. The algorithm consists of a for loop, and in each iteration, it projects data matrix F onto image Im with an increase in the angle of rotation by $2\pi/N$ rad. In Fig. 1, we illustrate an example of 12 heartbeats case.

Read a Clock: Star-ECG displays 12 ECG heartbeats in a clockwise fashion as illustrated in Fig. 1. When designing the number of ECG heartbeats to display in Star-ECG, we consult both experts in cardiology and visualization. Experts in cardiology suggested the range of ECG heartbeat number being 10 to 15. Experts in visualization recommended to present 12 ECG heartbeats clockwise because then reading Star-ECG is like reading a clock. Based on the advice from the experts, we decide to exhibit 12 consecutive ECG heartbeats clockwise on Star-ECG. Moreover, to align with the clock reading, we set the starting angle θ as $\pi/3$, so the first heartbeat on Star-ECG is consistent with number *1* on the clock. Star-ECG is anticipated to provide intuitive perception since reading the Star-ECG is analogous to reading a clock.

Color-coded ECG Voltage: Star-ECG colors the voltage with a Jet colormap to enhance the image readability for the users. While painting Star-ECG, we also consult the experts in cardiology for the range of voltages to plot. The experts suggested a range from -0.5 to 2.5 milli-volts (mVs). Therefore, we took the advice and set Jet colormap to span from -0.5 mV to 2.5 mV. We map the lowest voltage to color dark blue and the highest voltage to color dark red. Moreover, to intensify the contrast of R-peaks to other parts in ECG waveforms, we assign white color to the background. We depict an example of the contrast in the rightmost plot in Fig. 1. The R-peak regions are short and in red-orange color compared to the long and blue-colored low voltage segments.

D. Heart Rate Features

To enhance visualizing heart rate related information, we add three features to Star-ECG. The first feature assists on determining the regularity of heartbeats. The second feature accelerates the speed of HR computation. The third feature speeds up the calculation of HRV. We will discuss each feature in the following paragraphs.

View Heartbeat Regularity: As depicted in Fig. 2, we use light purple colored circles to aid visualizing the heartbeat regularity. The origin of this circle lies in the center of Star-ECG, and the diameter is equal to the HR of the 1D ECG. To derive the HR, we discussed with the expert on the HR computation. The expert recommended computing the HR of 20 consecutive ECG heartbeats using the following algorithm: The inputs to this algorithm are 20

Algorithm 2: Star-ECG Heart Rate Computation

Input: 20 Consecutive R-peaks Positions $\{R_1, R_2, ..., R_{20}\}$, Sampling Rate f_s
Output: Star-ECG Heart Rate HR
$DR = []$ // Create an empty array ;
for $i = 2:20$ **do**
  $DR[i-1] = R_i - R_{i-1}$;
end
$HR_1 = mean(DR[1:9])$ // R-R intervals 1 - 10;
$HR_2 = mean(DR[6:14])$ // R-R intervals 6 - 15;
$HR_3 = mean(DR[11:19])$ // R-R intervals 11 - 20;
$HR = (HR_1 + HR_2 + HR_3)/(3f_s)$

R-peaks positions and the sampling rate f_s; the output of Algorithm 2 is the computed HR. According to the expert, the more accurate HR computation should be the average of the heart rates of the overlapping heartbeats; therefore, we adopt this computation strategy in Star-ECG. For the 12 ECG heartbeats on Star-ECG, they are the middle 12 ECG beats of the 20 consecutive heartbeats.

View Heart Rate: We utilize the horizontal and vertical ticks as the scale of the HR. To derive the HR from Star-ECG, the users only have to refer the diameter of the circle to either the horizontal or vertical ticks for the answer. Since Star-ECG is pictured as a squared image of one-second side length, we leverage the usage of the ticks by stretching the scale from 0 to 1 for both horizontal and vertical axes (Fig. 2).

View Heart Rate Variability: To disclose the HRV on Star-ECG, we portray two additional circles on top of the HR circle as displayed in Fig. 2. We first compute the HRV with the standard deviation R-R interval (SDRR) metric defined in the study written by Shaffer and Ginsberg [8], and following the HRV computation, we illustrate two circles on Star-ECG with both origins at the center and diameters of $HR - HRV$ and $HR + HRV$, respectively. As a result, we arrive at the Star-ECG shown in Fig. 2.

E. Integration of Arrhythmia Classification

To meet the last design requirement, we leverage the CNN model to carry out the arrhythmia classification mission. We choose one of the state-of-the-art CNN models, ResNet-18, to train the arrhythmia classifier [9]. We classify the arrhythmias into 12 types: normal rhythm (N), 2° heart block (BII), pre-excitation (PREX), supraventricular tachyarrhythmia (SVTA), atrial flutter (AFL), atrial fibrillation (AFIB), paced rhythm (P), ventricular bigeminy (B), ventricular trigeminy (T), idioventricular rhythm (IVR), ventricular tachycardia (VT), and ventricular flutter (VFL). Succeedingly, we place the CNN classification result at the title position of Star-ECG as exhibited in Fig. 2.

F. Visualizing Star-ECG

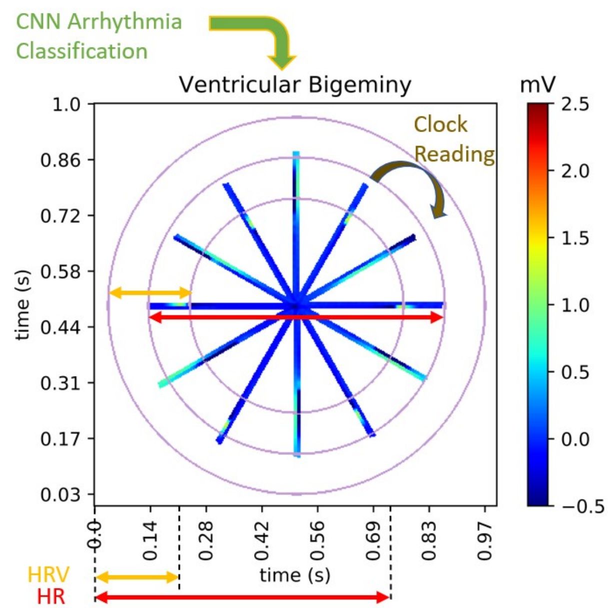


Fig. 2: Guide of reading Star-ECG. Reading Star-ECG is analogous to reading a clock: the first ECG is near the bottom of the brown curved arrow, and the following ECGs are read clockwise. The voltages of ECG can be read on the right colorbar. The HR is readable from the middle purple circle and the scale on the tick, and we use red-colored double-side arrows and the text *HR* to clarify. The HRV is comprehensible from the inner and outer purple circles and the scale on the tick. We use yellow-colored double-side arrows and the text *HRV* to demonstrate the HRV. The CNN arrhythmia classifier is integrated, and the classification result is displayed in the title.

Star-ECG aims at encouraging non-experts and arrhythmia patients to easily visualize and monitor their ECG data. Learning to read Star-ECG is expected to be simple and requires no domain knowledge. A complete Star-ECG should contain a ninja star-like color-coded ECG with a color bar, three purple-colored circles, scale on the ticks, and the arrhythmia classification result displayed as text in the title. Below we describe the reading instructions of Star-ECG with the help of Fig. 2 as guidance:

How To Read Heartbeat Regularity: Reading Star-ECG is similar to reading a clock, and the users can perceive the heartbeat regularity through observing the lengths and colors of the star blades. Regular ECG heartbeats have nearly equal lengths and the same color distribution of star blades, and the users should visualize that all star blades' endpoints are close to the middle circle. Conversely, irregular ECG heartbeats possess variant lengths or differentiated colors among the star blades, and their endpoints are far away from the middle circle. We provide an example of regular versus irregular ECG heartbeats in Figures 3b and 4b.

How To Read Heart Rate: The users can straightly compute the HR on Star-ECG. To arrive at the HR, the users should first measure the diameter of the middle circle and succeedingly refer its length to the scale labeled on the ticks. The approach is analogous to calculating the distance from the start point to the destination on a map.

How To Read Heart Rate Variability: To obtain the HRV, the users can refer the distance between the inner circle and the outer circle to the scale on the ticks. The method is very similar to obtaining the HR on Star-ECG.

How To Read Arrhythmia Type: The users can read the arrhythmia type classified by the CNN model in the title of Star-ECG. In addition, the users can perceive the existence of arrhythmia through observing the patterns of the star blades. According to the cardiology experts, arrhythmia can be abnormal HR, abnormal waveform, or abnormal intervals of some characteristic points in ECG. Thus, the users can perceive the arrhythmia by visualizing the consistency of the colors, the lengths, and the positions of R-peaks in the 12 star blades. A healthy user should observe 12 consistent star blades in length, color, and fiducial points' position. While for users having abnormal cardiac activities, they will cognize the inconsistent patterns across the 12 star blades. We present the examples of normal and arrhythmia Star-ECG in Figures 3b and 4b.

G. Participants and Dataset

We recruited 13 volunteers in our study with the approved consent form. All the volunteers did not have color vision deficiency. Ten volunteers do not have any cardiology expertise, while three volunteers do. They are aged 22 - 62 (mean: 38) and from different technical backgrounds. All the participants conducted the experiments through visualizing the data on the screen.

We used the MIT-DB dataset to run on Star-ECG. MIT-DB dataset is a popular publicly available arrhythmia dataset and has been employed in over thousands of studies relevant to cardiac abnormalities [10], [11].

H. Tasks

We designed four tasks for the participants to complete. In all the four tasks, the participants were asked to complete with both traditional 1D-ECG and Star-ECG. The four tasks were:

- **T1:** Identify Heartbeat Regularity
- **T2:** Compute Heart Rate
- **T3:** Compute Heart Rate; Variability
- **T4:** Classify Arrhythmia Type.

For tasks T1-T3, every volunteer was invited to accomplish. For task T4, only the experts were invited to participate since it requires the domain knowledge.

I. Procedure

The study started with a brief tutorial to the participants about reading 1D-ECG and Star-ECG. We showed the participants how regular and irregular heartbeats looked on 1D-ECG and Star-ECG. Moreover, we demonstrated how to compute the HR and HRV with 1D-ECG and Star-ECG to the participants. Next, we asked the participants to complete the four tasks and timed the completion time. For tasks T1-T3, we asked the participants to carry out the tasks with the cases illustrated in Figures 3 and 4. For task T4, we had the experts classify the 12 arrhythmia types as displayed in the supplementary files. After the participants finished the tasks, we conducted an interview with each participant to collect their feedback. In the interview, we asked the participants about their choice between the two visualization tools to perform the given tasks. Besides, the participants were encouraged to provide reasons over their choices and criticisms on Star-ECG.

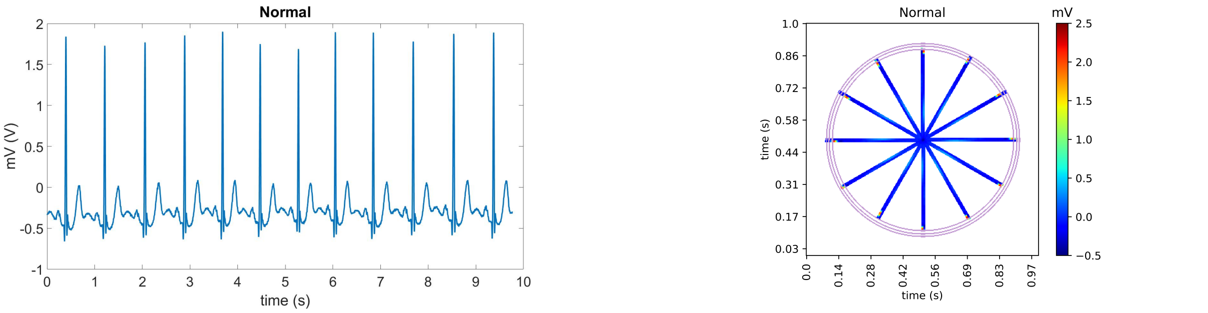
Concerning the quantitative performance of the CNN model, we followed exactly the same data segmentation setting in Yildirim et al.'s work [12] except that they used the 1D-ECG and we trained the CNN with Star-ECG images.

III. Results of Visualization Tasks

We present the results in the order of the numbering of the tasks. In each task, we will first exhibit the time of completion and next the categorized feedback from our participants.

T1 Time of Completion: All the participants successfully identified the regular and irregular ECG patterns on 1D-ECG and Star-ECG. The participants spent an average time of 12 seconds (SD = 3.4) to complete T1 using Star-ECG and 31 seconds (SD = 5.2) using 1D-ECG. Based on the results, visualizing heartbeats regularity on Star-ECG is 2.58x faster than on 1D-ECG.

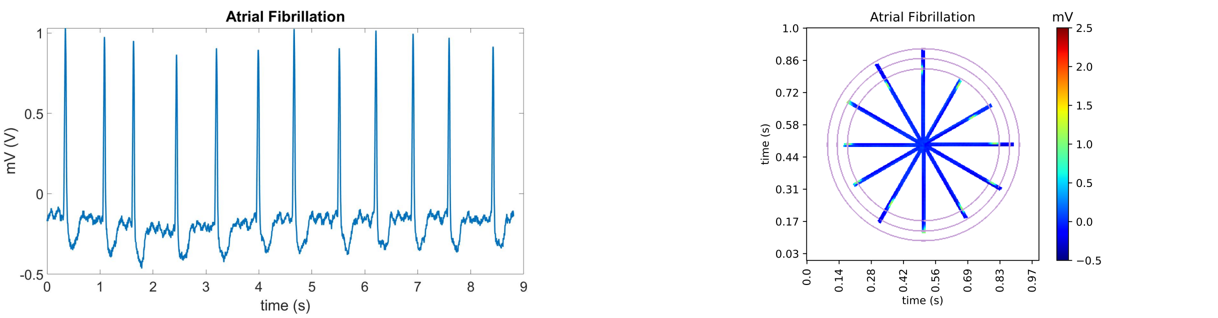
T1 Interview Feedback: As exhibited in Table I, we received positive feedback on Star-ECG from most participants (80%) and neutral responses from all three experts. The participants voting for Star-ECG enjoyed the ease of visualizing 12 ECG heartbeat lengths. Participant N3 said " *I like the idea of an auxiliary circle plus the ninja star blades. I can quickly notice the irregular heartbeats on a circular plot but not the 1D wave."* Participant N6 said " *I like the color-coded ECG because I have difficulty interpreting*



(a) 1D Normal ECG

(b) Normal heartbeats on Star-ECG with the HRV circles

Fig. 3: Exhibition of normal's 1D-ECG (left) and Star-ECG (right) used in the interview.



(a) 1D Abnormal ECG

(b) Abnormal heartbeats on Star-ECG with the HRV circles

Fig. 4: Exhibition of arrhythmia's 1D-ECG (left) and Star-ECG (right) used in the interview.

TABLE I: Results of the tasks. The users choose their preferences between Star-ECG and 1D-ECG to complete the tasks. X stands for the scenario that the participants can observe regularity easily on both Star-ECG and 1D-ECG.

ID	Heartbeat Regularity Observation	Heart Rate Computation	Heart Rate Variability Computation
E1	X	Star-ECG	Star-ECG
E2	X	Star-ECG	Star-ECG
E3	X	Star-ECG	Star-ECG
N1	Star-ECG	Star-ECG	Star-ECG
N2	X	Star-ECG	Star-ECG
N3	Star-ECG	Star-ECG	Star-ECG
N4	Star-ECG	Star-ECG	Star-ECG
N5	Star-ECG	Star-ECG	Star-ECG
N6	Star-ECG	Star-ECG	Star-ECG
N7	Star-ECG	Star-ECG	Star-ECG
N8	X	Star-ECG	Star-ECG
N9	Star-ECG	Star-ECG	Star-ECG
N10	Star-ECG	Star-ECG	Star-ECG

*the ups and downs on a one-dimension ECG. The colors definitely enhance the readability of ECG."*As for the experts and two non-experts, they mentioned that they encountered no difficulties visualizing ECG regularity on both 1D-ECG and Star-ECG.

T2 Time of Completion: All the participants successfully figured out the HR on Star-ECG, but not on 1D-ECG. Participants N9 and N10 did not complete T2 on 1D-ECG. We considered all the successful cases and found out that the participants spent an average time of 6 seconds (SD = 2.2) to complete T2 using Star-ECG and 454 seconds (SD = 63) using 1D-ECG. Based on the results, computing the HR is 75.7x faster on Star-ECG than on 1D-ECG.

T2 Interview Feedback: We received 100% positive feedback on Star-ECG from our participants upon finishing task T2 as listed on Table I. We summarized the interview talks from all the participants and concluded with the mainly two supportive reasons:

1) Ease of use: Users of Star-ECG can directly compute the HR instead of tracing the whole 1D-ECG, which takes several minutes to complete. Every recruited participant agreed with it.
2) Transferable skill: Users can apply their knowledge on computing the distance on the map to calculating the HR on Star-ECG. Participants N2, N4, N5, N7, N9 approved such transferable knowledge. Participant N7 reported *"Star-ECG is really interesting! I didn't realize we can measure time distance in this way as we do on Google Map until now!"*

For the two non-experts who were unable to complete T2 on 1D-ECG, they complained that 1D-ECG required complicated computations that they could not afford.

T3 Time of Completion: All the participants successfully figured out the HRV on Star-ECG, but not on 1D-ECG. Only the experts and participants N2, N8 complete T3 on 1D-ECG; the rest of the participants did not arrive at the HRV with 1D-ECG. We considered all the successful cases and found out that the participants spent an average time of 8 seconds (SD = 4.3) to complete T3 using Star-ECG and 632 seconds (SD = 101) using 1D-ECG. Based on the results, computing the HR is 79x faster on Star-ECG than on 1D-ECG.

T3 Interview Feedback: We also received 100% positive feedback on Star-ECG (Table I). More importantly, all the experts endorsed the HRV visualization on Star-ECG. Expert E1 said, *"The straightforward HRV visualization is great. I am willing to use it to monitor the patients' health status."* Expert E2 mentioned, *"The HRV idea is good. I hope you keep doing the great work."*Expert E3 stated, *"The HRV is doable, really really exciting! It can bridge the communication gap between the patients and us."* For other participants without the expertise, they mentioned the concept of HRV was difficult to comprehend and that the computation loading was even heavier than computing the HR on 1D-ECG. Therefore, they would favor Star-ECG over 1D-ECG for task T3.

A. Results of Arrhythmia Classification T4

We present the CNN classification result and the feedback from the experts on task T4.

Quantitative Results: We showcase the competitiveness of the Star-ECG CNN model in Table II. Star-ECG outperforms the state-of-the-art 1D-ECG CNN model with an overall accuracy of 92.6%. Moreover, Star-ECG beats 1D-ECG in the sensitivity of some of the classes: normal rhythm, supraventricular tachyarrhythmia, ventricular bigeminy, ventricular trigeminy, and ventricular flutter.

Validation with Experts: We interviewed with the experts about their opinions on arrhythmia classification and received helpful feedback. Every expert liked the CNN model of Star-ECG, especially the sufficiently high classification accuracy. However, the experts were concerned about reading arrhythmia directly through Star-ECG visualization. According to expert E1, *"I like the way combining CNN together with Star-ECG. It helps me to make accurate arrhythmia diagnosis. However, if I were to classify arrhythmia through reading the star blades only, I would still go with 1D-ECG."* Expert E2 said, *"CNN is great, but I would suggest visualizing multiple ECG-leads on Star-ECG instead of a single lead for arrhythmia decision. It is easy to visualize specific types of arrhythmia on Star-ECG, such as ventricular bigeminy and trigeminy, but not those relative to abnormal P-wave segments."* Expert E3 mentioned, *"I would still choose 1D-ECG because some detailed waveform information is not obvious to read on Star-ECG. Nevertheless, I would recommend showing Star-ECG to the patients instead of 1D-ECG for basic understanding of cardiac abnormalities."* In summary, the experts believed that Star-ECG would be a good visualization tool for non-experts, and CNN was a brilliant idea. Nevertheless, the experts would like to view additional physiology information on Star-ECG in order to have confidence on making precise arrhythmia diagnosis.

IV. Discussion

Based on the results, Star-ECG has showcased its effectiveness over conventional 1D-ECG in visualizing heartbeat regularity, heart rate, and heart rate variability, especially for people without the cardiology expertise. Furthermore, the integrated CNN model enhances the functionality of Star-ECG.

Visualization Tasks: Star-ECG succeeded in providing easy visualization in terms of the heartbeat regularity, heart rate, and its variability. For the heartbeat regularity, the circular star-blades, auxiliary circle, and color-coded ECG were pointed out to be helpful in the judgment. With respect to HR and HRV, Star-ECG was favored due to its readability. What's more significant, the experts approved the HRV visualization and are willing to put into clinical practice.

Arrhythmia Classification: The integration of CNN model won positive feedback from the experts, and the developed CNN model has achieved state-of-the-art performance. Although some detailed physiology information is difficult to read due to its simplicity, Star-ECG is recommended by the experts to provide the fundamental learning of arrhythmia to users without the domain knowledge. We found the good classification performance reasonable since CNN models have been shown to perform excellent in recognizing the patterns of ECG images [13], [14].

Limitations: Based on the collected feedback from both experts and non-experts, we have discovered certain limitations of the current Star-ECG:

- **Demand for detailed physiology:** Star-ECG provides friendly visualization of certain features due to its simplicity, but such simplicity hinders the detailed physiology information from display. In addition, one of the experts mentioned that visualizing multiple ECG leads could strengthen the confidence in arrhythmia diagnosis.
- **Constraints on the user's activity:** The experts pointed out that Star-ECG might not function as expected if the users are performing extreme physical exercise. Therefore, to manage such scenario, Star-ECG should integrate advanced ECG signal processing technology.

V. Conclusion and Future Work

In this paper, we present Star-ECG, a novel ECG visualization tool. We describe the procedure to transform a traditional one-dimensional ECG into Star-ECG and showcase the effectiveness of Star-ECG in visualizing the heartbeat regularity, heart rate, and heart rate variability. Besides the innovative visualization, we also integrate deep learning technology and deliver a state-of-the-art arrhythmia classifier. Moreover, we receive positive feedback on Star-ECG visualization from both the experts and people without the medical expertise.

In our future work, we aim at addressing the limitations of the current Star-ECG. We plan to add more physiological features into a new version of Star-ECG. Furthermore, we intend to investigate the visualization techniques for multiple ECG leads.

VI. Acknowledgments

We would like to express our sincere gratefulness to expert Yi-Ting Yang and all the other volunteers.

TABLE II: Arrhythmia classification performance of the state-of-the-art work and this study. Rhythm types are abbreviated as described in Section II arrhythmia classification part.

Method	Sensitivity (%)												Accuracy (%)
	N	BII	PREX	SVTA	AFL	AFIB	P	B	T	IVR	VT	VFL	
1D-ECG [12]	94.4	**100**	**100**	50	**100**	**94.4**	**100**	66.7	0	**100**	**50**	**100**	89.4
Star-ECG [Ours]	**95.0**	88.2	42.9	**100**	41.2	86.1	98.1	**86.2**	**66.7**	0	33.3	**100**	**92.6**

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