Electrocardiogram Collection, Pattern Recognition, and Classification Sensor System Supporting a Mobile Cardiovascular Disease Detection Aid

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***Abstract*— Current mobile monitoring solutions do not offer the ability to recognize cardiac problems without human interpretation. A combination of electrocardiogram (ECG) detection and classification software running on a mobile cardiovascular disease detection sensor is proposed to replace the need for human interpretation. The ECG is filtered using the Wavelet Transform; the ECG wave points detected using a modified version of the Pan Tompkins rule set and the cardiac rhythm is classified using an N-ary tree. The wireless mobile application is designed on a custom printed circuit board (PCB). Testing results show autonomous classifications are possible using a three lead ECG system while the patient is at rest. The proposed solution serves as a stepping stone towards a fully reliable patient disease management teaching tool with the potential to serve as an aid to the cardiovascular healthcare industry.**

Keywords-embedded ECG sensor; real-time algorithm; ECG classification.

I. INTRODUCTION

According to the Centers for Disease Control and Prevention (CDC) Division of Vital Statistics, 24.2% of total deaths in 2010 were directly related to heart diseases [1]. Preliminary 2011 data shows this lethal disease continues to be the number one leading cause of death for 596,339 Americans [2].

Studies have shown as heart failure (HF) symptom severity increased, patient symptom uncertainty levels decreased [3] correlating with previous studies suggesting HF patients delay seeking timely treatment for symptoms [4]. Dedicated nurse staffed care facilities have helped decrease levels of patient symptom uncertainty [5], but a real-time mobile monitoring and motivational solution is desired [6].

Advancements in science and technology have made it feasible to continuously shrink signal processing systems aiding in the development of wearable biometric monitoring equipment and replacing systems that rendered the user with limited mobility. Mobile monitoring systems [7]-[11] are not new, but systems that monitor and interact with users in ways that improve health management are evolving [6][12].

The Electrocardiogram (ECG) subsystem is described as an important part of the overall cardiac wellness system's ability to aid patients in learning to recognize disease specific symptoms and understand the effect on their health [12]. The purpose of this paper is to describe the development of a mobile cardiovascular disease detection sensor that combines wavelet transformation filtering processes with a modified version of the Pan Tompkins detection rule set and using an N-ary tree for classification of ECG arrhythmias. Research using these three methods has been performed before [13]-[21], but nothing combining all three methods applied to ECG arrhythmia detection and classification in support of a mobile cardiovascular disease detection aid has been.

In Section 2, this paper will discuss ECG raw data collection, waveform extraction, waveform classification and describe the testing process the system underwent. Section 3 will discuss the testing results. A conclusion and recommendation for future work will be presented in Section 4.

II. MATERIALS AND METHODS

The ECG subsystem can be broken down into three serial processes (see Figure 1); collection, extraction, and classification. Each process feeds into the next resulting in a heart health classification. Each process is briefly described below.

Figure 1. ECG subsystem process representation.

A. ECG Raw Data Collection

An ECG is the measured electrical activity representing the heart's conduction system typically recorded on a 1 by 1 millimetre (mm) gridded paper representing 40 milliseconds (ms) by 0.1 millivolts (mV). This paper's ECG sensor was designed using a three lead chest only concept since abnormalities of interest are detected using 3 leads. Abnormalities of interest include normal sinus rhythm, atrial arrhythmias (bradycardia, tachycardia, flutter), conduction abnormalities (1st degree AV block, 2nd degree AV block, 3rd degree AV block), and ventricular abnormalities (premature complex, tachycardia, fibrillation).

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The differential voltage between two silver chloride (AgCl) electrodes placed on the right and left side of the chest is measured with reference to body ground, amplified by a gain of 1000, and fed to an analogue to digital converter (ADC) on board an Atmel 32-bit UC3 microcontroller (MCU). The Atmel UC3 MCU uses a 12-bit analogue comparator sampling the ECG at 250Hz with a reference at 60% of the supply voltage. Sampling at 250 Hz, creates 1 sample every 0.004 seconds. Using a 12-bit ADC with an analogue circuit gain of 1000 creates 100 ADC units for every 1 mm or 0.1 mV of ECG signal strength prior to amplification.

B. ECG Waveform Extraction

An ECG waveform is described by its principally important points (PIPs) (see Figure 2). In basic terms, the PIPs are the onset, offset, and peak height of the P wave, T wave, U wave and QRS complex. In total there are twelve PIPs. From these PIPs an ECG's P wave, T wave, U wave, QRS complex, PR Interval, Atrial Rate, Ventricular Rate, and Rhythm can be calculated. With the PIPs known an ECG waveform can begin to be classified.

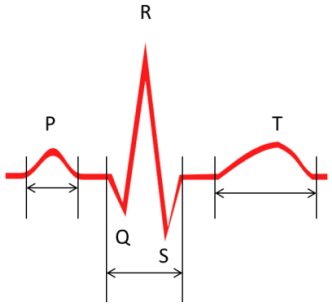

Figure 2. ECG waveform showing principally important point with widths calculated in seconds and heights calculated in millimetres.

To extract the PIPs, the ECG signal is passed through a bank of filters equivalent to the Dyadic Quadratic Spline Wavelet Transform focusing on the time frequency analysis of the signal. Using the dyadic wavelet allows for faster computations on an ECG signal to extract characteristic points by distinguishing between the sharp variations translated into local maxima and minima on different filter scales.

The wavelet transform (WT) equivalent filter described by Li [16] was derived using the work of Mallat [22]. Li derived the WT as a series of high-pass and low-pass filters, used to deduce the equivalent filter as an antisymmetric FIR digital filter with generalized linear phase.

To sync the output of the filters and avoid busy wait loops, an individual delay was added to each filter through the use of the translation property of the Fourier Transform. This caused an overall unified filter bank delay of 62 milliseconds and produced the signal output shown in Figure 3.

The Wavelet Transform equivalent filter has the ability to separate the different characteristic points of an ECG onto various scales, allowing use of individual filter outputs to find each waveform's peak, onset and offset.

The amplitude-frequency response of the WT filters (see Figure 4) shows the first five filters in the bank, used to cover the frequency spectrum of an ECG signal sampled at 250 Hz.

To find the QRS complex, originally all five filters were used as discussed by Bahoura [17]. Preliminary testing indicated that filters 2^1 through 2^3 are the minimum needed. A QRS complex peak is found by locating the zero crossing of a set of modulus maximum peaks with different polarities on the output of the first three filters simultaneously [18][19][20].

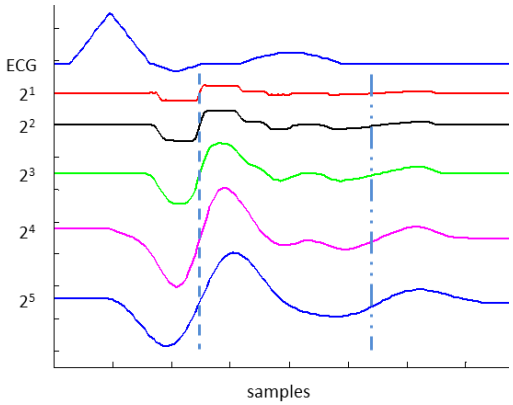

Figure 3. Equivalent WT filter bank output. ECG signal is top line and filter bank out are bottom 5 signals. Dashed line corresponds to QRS complex peak. Dash double dot corresponds to P, T, or U wave peak.

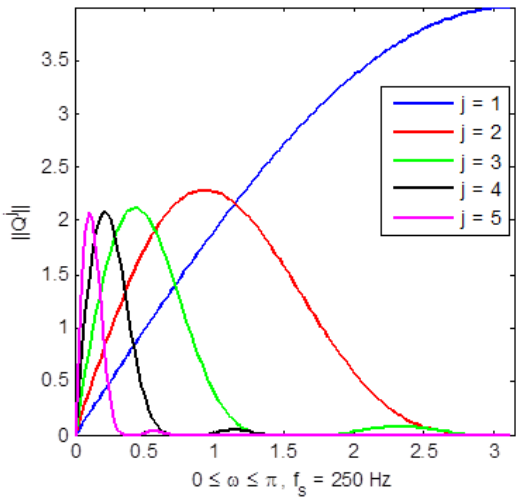

Figure 4. WT filter bank amplitude frequency response.

Once a possible QRS peak is found, all other QRS detections are ignored for a period of 200 milliseconds. An autonomous thresholding technique [23] is employed to find the local minima and maxima peaks on each filter output, allowing the detection algorithm to adjust to a patient's ECG signal strength. The idea behind the technique was to capture as much of the possible QRS complexes without

low noise with the first threshold and then apply a second threshold to capture missing lower amplitude QRS complexes due to the initialization process. If no QRS complex is found within a 4 second interval, the thresholds are reset [23].

After the QRS peak is found, filter 2^2 is used to find the onset and offset pair using the location of the local minima onset and maxima offset respectively. From preliminary testing using the MIT-BIH databases [24], it was noticed the Q and S waves periodically appear on the filter 2^2 output, so the onset was shifted to the beginning of a second modulus peak found immediately before the first with opposite polarity and the same with the offset, looking at the end of a second modulus peak found immediately after the original offset. Once the QRS complex onset, offset, peak and peak polarity data points are found (see Figure 5), these PIPs are passed to a post-detection scheme to prepare for the classification stage.

Current methods to find P, T, and U waves require first locating the QRS complex and then traversing the ECG signal forwards and backwards in time. The problem with this solution is it's not real-time and does not take into consideration arrhythmias that do not always include a QRS complex for each P and T wave in the ECG, such as Atrial Fibrillation.

Instead, 'blips' which are possible P, T, U waves or just noise, are detected and then categorized in the post-detection scheme. This allows QRS complexes and P, T, U waves to be detected in parallel similar to Bahoura [17]. Preliminary testing proved 2^3 through 2^5 are the only filters required to find blip waves. A blip peak is found by locating the zero crossing of a set of modulus maximum peaks with different polarities on the output of either 2^3 and 2^4 or 2^4 and 2^5 filters, but not necessarily all three filters simultaneously.

Once a possible blip peak is found, the location is saved for 100 ms before reporting to ensure the blip wave is valid and not a QRS complex or noise. If the blip wave is found to be a QRS complex, the information for the wave is transferred to the QRS complex detection to be categorized as such. Again, a thresholding technique is used to find the local minima and maxima peaks on each filter output, except lower than the thresholds used by the QRS. The thresholds adjust to P/T wave amplitudes based upon a pre-calculated ratio between P/T waves and QRS complexes and are re-adjusted every time a new QRS complex is detected.

After the blip peak is found, filter 2^4 is used to find the onset and offset simply because a blip wave will always show on filter 2^4. The onset/offset pair is found using the location of the local minima onset and maxima offset respectively on filter 2^4 similar to QRS onset/offset detection.

In post-detection, a detected blip is run through a set of test and checks to verify its validity based upon the last detected blip and QRS complex before it is categorized as a P, T, or U wave.

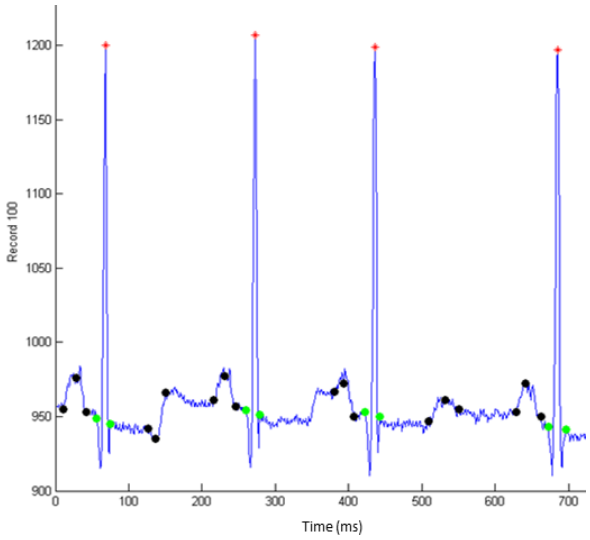

Figure 5. Detected QRS complex (green dots, red stars) and blip waves (black dots) on record 100 from MIT-BIH Arrhythmia database.

This nine point rule set for the test and check is used to construct a finite state machine running on the MCU.

1. Upon start-up, if a blip is detected first, then it is immediately categorized as a P wave and saved in the 'ekgWaveHistory' buffer.
2. Upon start-up, if a QRS complex is detected first, then it is immediately saved in the 'ekgWaveHistory' buffer.
3. A detected blip is invalid and discarded if its onset and/or offset overlap that of the previously detected blip or QRS complex.
4. A detected valid blip is a T wave if its peak is located within 50-75% of the current ventricular heart rate from the offset of the last detected QRS complex and if no other T wave has been detected as of that moment.
5. A detected valid blip is a U wave if its peak is located within 50-75% of the current ventricular heart rate from the offset of the last detected QRS complex, if a T wave has already been detected, and no other U wave has been detected as of that moment.
6. A detected valid blip is a P wave if its peak is located outside 50-75% of the current ventricular heart rate from the offset of the last detected QRS complex or if within that time frame, then it will be a P wave if a T wave and U wave has already been found.
7. A detected QRS complex is always considered valid.
8. A detected QRS complex can invalidate the last detected blip if that blip overlaps the QRS complex in any way.
9. A detected QRS complex can re-categorize a detected P, T, U wave as a T wave that came after the newly detected QRS complex if the last detected blip does not overlap the QRS complex AND comes after the newly detected QRS complex.

Upon type validation, each wave is saved in an ECG buffer by its type, onset, offset, peak and polarity. When the buffer contains one QRS or two P waves, the saved

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waveform is sent to classification the next time a third valid P wave is detected or after a second QRS complex has arrived.

The maximum QRS complex detection delay is 462 ms before a QRS complex is detected to when it happened and similarly is 362 ms for a P/T wave detection. This corresponds to 129 beats per minute (bpm) and 165 bpm for a QRS complex detection and P/T wave detection respectively before a lag is seen after each wave occurs. These delays can be attributed to a standard 62 ms filter delay, 200 ms QRS blanking window, 100 ms blip blanking window, and a 200 ms future value collection window.

C. ECG Waveform Classification

Classification is done similar to how a physician classifies an ECG. First the rates are examined, followed by the rhythm, intervals and wave morphology. When a new waveform is detected it's appended to the end of a three waveform historic buffer, shown in Figure 6.

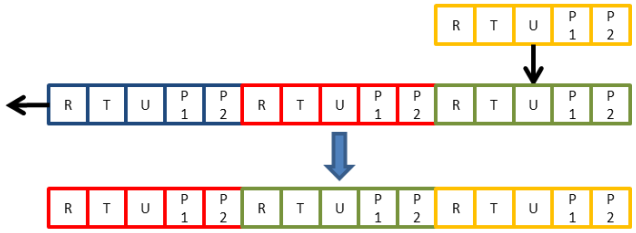

Figure 6. Historic ECG buffer.

The ECG rates are calculated by measuring the lapsed time between each QRS (ventricular) or P (atrial) wave in milliseconds and then dividing that number into sixty thousand milliseconds or equivalently 1 minute to obtain a value in beats per minute (bpm).

The waveform buffer passes through each branch of an N-ary tree (see Figure 7), first eliminating all rhythms that do not correlate. The tree uses cardiac rhythms and classifications along with normal ECG characteristics from best evidence practice literature to determine a waveform's classification.

If there is at least one P wave in the buffer and all available P waves are upright (see Figure 7, branch 00000), then the waveform falls into a Normal Sinus Rhythm (NSR), Atrial Arrhythmia, Conduction Abnormality, Premature Ventricular Contraction (PVC), or Asystole. In this group for a waveform to be considered NSR it must have is a 1:1 P wave QRS complex ratio with normal morphology, PR interval, and ventricular rate.

If there is at least one P wave in the buffer, all available P waves have a negative polarity, are followed by a normal QRS complex with a short PR interval, and all available T waves have normal morphology (see Figure 7, branch 00001), then the waveform could either be Supraventricular Tachycardia (SVT) or a Junctional Rhythm. In this case, the ventricular rate would be used to differentiate between the two.

If there are no P waves available in the buffer (see Figure 7, branch 00010), then the waveform could be classified as a Ventricular Arrhythmia, Atrial Fibrillation, or SVT. In this group, the morphology of the QRS complex and ventricular rate are used to determine which arrhythmia is present.

By default, if the waveform is unclassifiable, then it is most likely abnormal or if an underlying sinus rhythm is present, but the waveform cannot be classified in the given tree, it is classified as an Abnormal Sinus Rhythm.

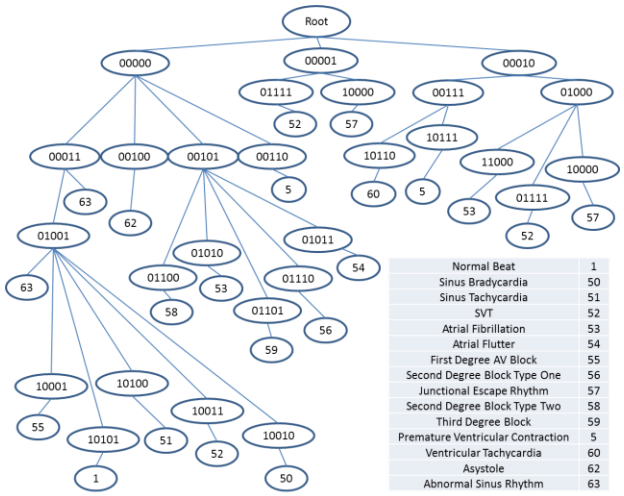

Figure 7. Classification N-ary tree.

The delay between when the heart beats and when that beat waveform is classified by the ECG subsystem is equivalent to one heartbeat. The way the N-ary tree is built takes into account the length of the history buffer in which the algorithm analyses an entire ECG waveform three beats in length at a time. Therefore an NSR classification will only occur when there are three normal heart beats in a row.

D. ECG Sensor System Testing

Testing took place in two stages, the first known canned events followed by live system testing. For the known canned events, ECG signals from the MIT-BIH Arrhythmia and Normal Sinus Rhythm databases [24] were resampled at a frequency of 250 hertz and fed through the algorithm. The results were recorded, reconstructed and analysed using MATLAB.

Only ten minutes of each ECG was used starting at 20 seconds into the signal with results categorized into five areas, positive abnormal classification (PC), positive unknown classification (PU), positive normal classification (PN), negative or missed abnormal classifications (NC), and negative or missed normal classifications (NU). The classifications were cross checked with the annotations included with each signal. If the abnormal annotation matched the abnormal classification, then the result was categorized as a positive abnormal classification. If they

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didn't match, but the abnormality was not looked for and the classification wasn't normal, then the result was a positive unknown classification. If neither case, then the result was a negative abnormal classification. In the normal case if the annotation and classification agreed on normal, then the result was a positive normal classification. If the annotation said normal and the classification said anything other than normal, then the result was a negative normal classification.

The ECG records picked from the MIT-BIH Arrhythmia database reflected the classifications the software was attempting to identify. With the exception of records 100, 101, and 222, each record contained PVCs mixed in with various other arrhythmias and normal sinus rhythms. Arrhythmias included Atrial Premature beats, Bundle Branch Blocks, Junctional Premature Beats, Ventricular Tachycardia, Ventricular Flutter, Atrial Fibrillation, Atrial Flutter, and Second Degree Blocks. How well the algorithms could classify normal sinus rhythms mixed with abnormalities and Paced Beats was of interest.

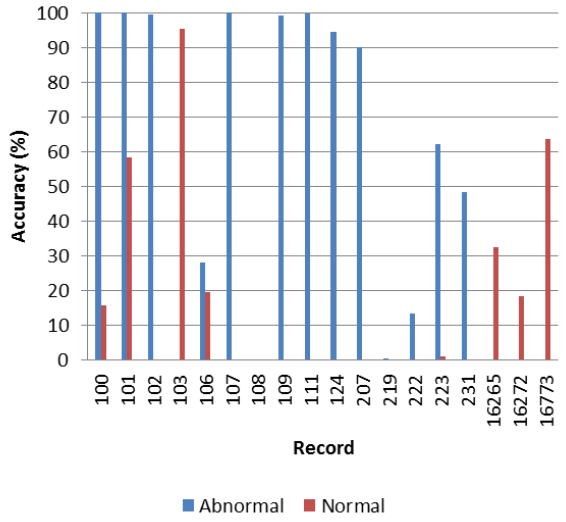

Figure 8. Known canned event testing results. Records 1xx and 2xx are from the MIT-BIH Arrhythmia database. Records 16xxx are from the MIT-BIH Normal Sinus Rhythm database.

In general, the algorithm was able to distinguish between a normal ECG and an arrhythmia (see Figure 8). An analysis of the results showed not one arrhythmia classified as normal, though some were classified as unknown abnormal. Normal classification results shows room for improvement. Majority if not all of the reasons why a given normal rhythm was not classified as such are due to invalid P and T wave detections and increased heart rate from movement.

The results from known canned events testing were collected and analysed and are depicted in Figure 8. To verify the accuracy of the normal sinus rhythm, records from the MIT-BIH Normal Sinus Rhythm database were also run (see Figure 8). Each of those signals mixed with additional noise originating from movement such as running or jogging.

For live system testing and implementation, the ECG algorithms were compiled using the Atmel Studio IDE and uploaded to a custom designed printed circuit board (see Figure 9), running an Atmel 32-bit UC3 microcontroller.

Figure 9. ECG subsystem printed circuit board.

The crucial point of live testing was to ensure the ECG signal collected by the algorithm was the same signal measured and not skewed by the algorithm run time. Using a 2 channel oscilloscope, measurements were initiated during system initialization, when a classification is not found or found using a 16MHz clock source for the MCU. The relative accuracy of the classification process was also studied using a healthy normal ECG by illuminating a series of LEDs corresponding to various classifications.

III. TESTING RESULTS AND DISCUSSION

In some instances, a normal ECG was classified as PVC or could not be identified. This was mainly due to high frequency noise such as in records 108 and 222 or falsely identified and/or unidentified P waves due to wave morphology and P wave proximity to QRS complexes such as in record 222. In other instances a normal ECG would be classified as an Abnormal Sinus Rhythm or Sinus Tachycardia. An Abnormal Sinus Rhythm came about because wave morphology did not fit textbook normal such as in records 100, 101, 103, 106, 223, 16265, 16272, and 16773. Altering the default normal setting in the algorithm would fit this very well. Sinus Tachycardia came about because of an altered heart rate with normal morphology. In a doctor's office, if the patient was running, this would be considered normal, which was the case with records 16265 and 16773.

PVCs in records 106 and 109 were classified as Unknown Arrhythmias because of incorrect QRS polarity detections. In the case of records 109 and 219, PVCs were classified as Unknown Arrhythmias because P waves and underlying sinus rhythm was not detected, both required for a PVC classification. In record 124, the QRS complexes were too wide for this algorithm to be able to detect them and classify the waveform as PVC, but instead classified it as an Unknown Arrhythmia.

The fibrillatory waves' amplitude was too low to detect an atrial rate in records 219 and 222 in order to classify them as Atrial Fibrillation. In record 222, the P waves were

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back to back causing incorrect polarity detections to classify the record as Atrial Flutter.

While testing a live healthy and normal ECG signal, the classification was normal for the majority of the test while the user was at rest. The algorithm proved to be resilient to small amounts of movement and noise, but failed as expected when the user began to jog calling for a need to supress invalid classifications with the addition of an accelerometer and front end smoothing filter.

IV. CONCLUSION AND FUTURE WORK

Overall a new method of autonomously measuring, detecting, and classifying ECG arrhythmias for use in a mobile cardiovascular disease detection sensor system was introduced through combining the Wavelet Transform filtering method with a modified Pan Tompkins detection method and classifying with an N-ary Tree. The main algorithm modifications needed to continue this work would be in the P and T wave detection method and adding an algorithm training method to learn a user's normal sinus rhythm wave morphology.

The training system would include the same detection scheme used throughout the system, but instead of classifying detected sequences, would examine the frequency of the morphology of each P wave, PR interval and QRS complex to determine a proper normal setting within the classification system. Training would be done in the presence of a professional to ensure that a normal ECG is actually occurring rather than an abnormal ECG.

The ECG subsystem would also benefit from a user movement indicator to inform the algorithm that the user is engaged in activity that raises the ventricular heart rate. This battles false classifications of Sinus Tachycardia during a Normal Sinus Rhythm. Movement artifact removal would also be taken care of outside the subsystem by the main monitoring system using motion sensors for scaling.

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