Gender Differentiation Through the Use of Wavelet Decomposition on the T Wave

Gregor Altvater

December 19, 2000

Abstract

This project was performed to be able to answer qualitative questions about the feasibility of utilizing the discrete wavelet transform (DWT) to analyze the T wave in human ECGs. It was shown that by analyzing higher detail components of the DWT, a separation between male and female waveforms could be found.

1 Introduction

Since its conception, the wavelet transform has become extremely prevalent in ECG processing. There are a multitude of applications for the DWT, ranging from simple ECG fiduciary point detection [2] to more complicated arrhythmia detection [1, 5] and classification, with denoising and compression [6] in the middle. However, little attention has been focused on its use in gender specific applications.

It has been long known that women have much longer durations of repolarization than men. Merri quantified these Q-T interval differences in [4] showing statistical significance ($p < 0.0001$) for longer Q-T duration in women. This result may help to shed some light onto an explanation for long Q-T syndrome. In this syndrome, the Q-T interval (see Figure 1 for parts of the ECG waveform) becomes sufficiently long so that atrial depolarization can occur before complete ventricular repolarization. Illustrated in Figure 2 is the layout of the cardiac chambers and a brief sketch of electrical conduction. An overlap of the P and T waves can cause the heart to be thrown into dangerously irregular rhythms, such as ventricular tachycardia or ventricular fibrillation.

Further, it has been shown that there is a significant difference in the slope of repolarization between the genders [7]. Mainly, Yang has shown that the early stages of repolarization, the ascending T wave slope is almost 300% larger in men, than in women. However, even with this preliminary work, the T wave has been a much neglected region of focus in the ECG community. Further analysis of the nature of gender differences in ventricular repolarization is warranted.

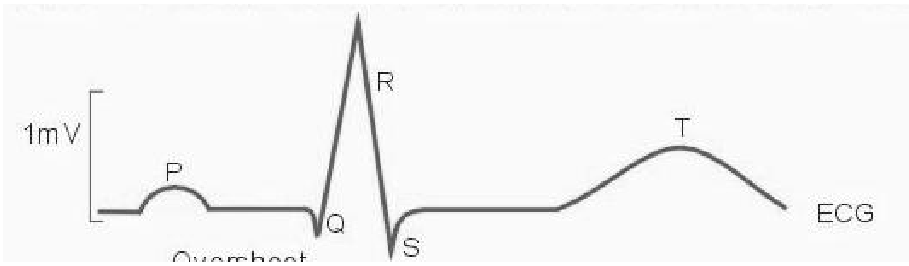

Figure 1: *Normal sinus rhythm beat. The P wave corresponds to atrial depolarization, QRS complex is the ventricular depolarization, and the T wave is the ventricular repolarization.*

2 Methods

ECG data was acquired from 635 patients whose ECGs were recorded through a routine hospital procedure by GE Marquette Medical Systems. Patients with irregular rhythms or a history of heart disease were excluded (82 patients). This left 553 patients (426 male, 127 female) for the study. For this paper, it should be noted that all the results reported were obtained from only 60 of those patients (20 for each heart rate category). A full set of 12 surface ECG leads were recorded at 250 Hz and digitized with 12 bits. Six of these leads (I, II, III, aVr, aVl, aVf) are bipolar leads, which measure electrical activity in the frontal plane. The other six leads (V_1 – V_6) are unipolar precardial leads that measure activity in the horizontal plane. Refer to Figure 3 for a detailed view of the lead configurations.

For each patient, the window width for one ideal sinus rhythm (SR) beat (Figure 1) was selected to be 1.2 seconds (300 samples). From these SR passages, the T wave segment was isolated. This was done by pinpointing the J point (the point at the end of the S wave), which indicates the onset of the T wave. From this point, 448 milliseconds (112 samples) of passage were utilized. Taller people tend to have larger heart muscles, creating larger surface electric potentials, hence an adjustment was made for patient height. This normalization was accomplished by dividing each ECG value by height$^{2.7}$.

The ECG was then converted to the vectorcardiogram (VCG). The VCG is composed of three spatial vectors (X, Y, Z measured from the center of a person's chest), that indicate the direction of electrical activity of the heart. In [3] it is shown that the inverse dower matrix approach is the best method for VCG calculation. So, the VCG was calculated in the following fashion:

$$\mathbf{VCG}_{X,Y,Z} = \mathbf{Dower} \times \mathbf{ECG}_{I,II,V1\text{-}V6} \tag{1}$$

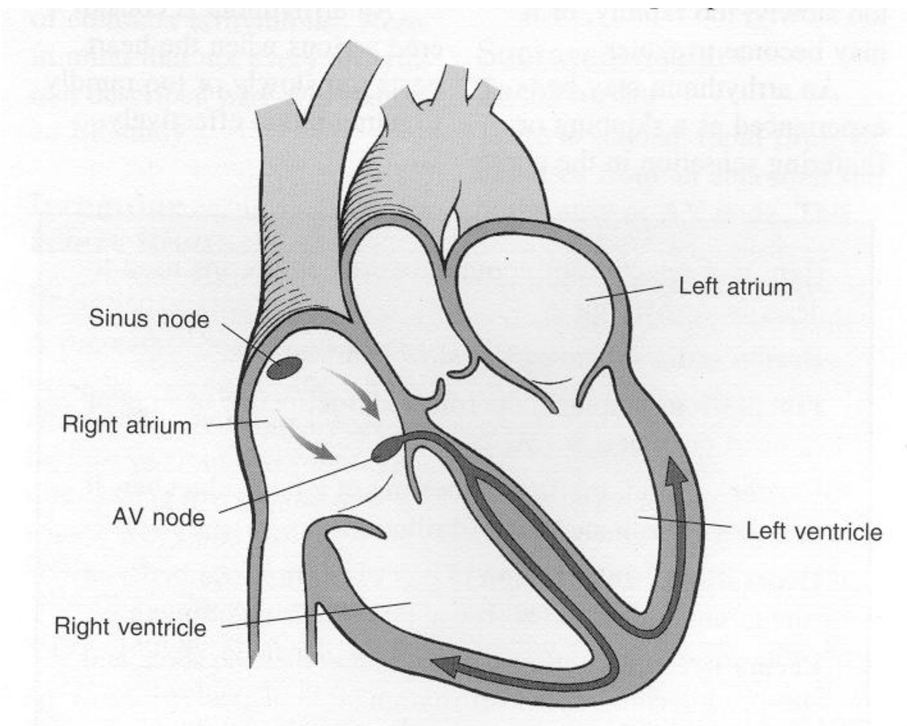

Figure 2: *The chambers and electrical conduction patterns of the heart. The electrical conduction is indicated by the arrows.*

where,

$$\mathbf{ECG}_{I,II,\,V1\text{-}V6} := \begin{pmatrix} I \\ II \\ V_1 \\ V_2 \\ V_3 \\ V_4 \\ V_5 \\ V_6 \end{pmatrix} \tag{2}$$

and,

$$\mathbf{Dower} := \left(\begin{array}{c|c|c|c|c|c|c|c} -0.172 & -0.074 & 0.122 & 0.231 & 0.239 & 0.194 & 0.156 & -0.01 \\ 0.057 & -0.019 & -0.106 & -0.022 & 0.041 & 0.048 & -0.227 & 0.887 \\ -0.229 & -0.31 & -0.246 & -0.063 & 0.055 & 0.108 & 0.022 & 0.102 \end{array}\right) \tag{3}$$

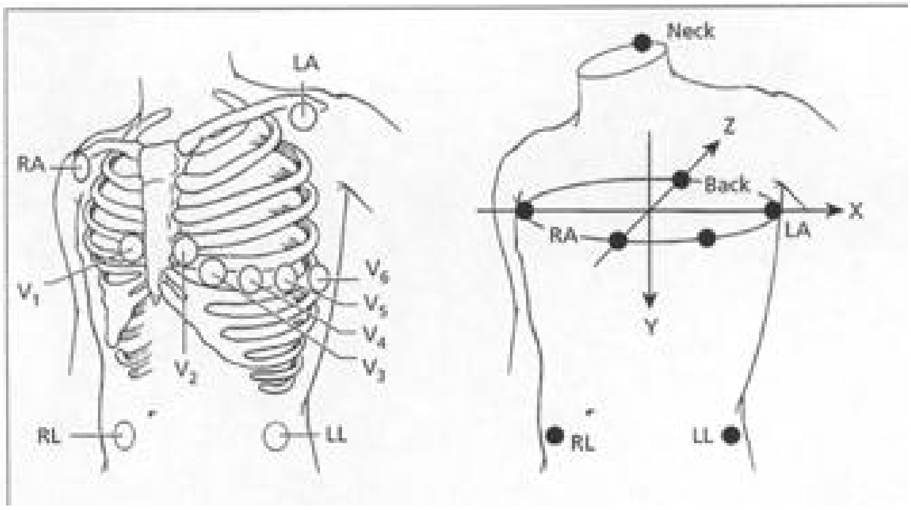

Figure 3: *Surface lead placements. V_1 - V_6 can be clearly seen. Lead I is the voltage between RA and LA, II is between RA and LL, and III is between LA and LL.*

The magnitude of the composite vector is calculated via

$$VCG_{comp} = \sqrt{VCG_X^2 + VCG_Y^2 + VCG_Z^2} \tag{4}$$

.

Patients were then separated into three categories, each with 10 male and 10 female patients: Group 60 consisted of patients with a resting heart rate of 60 beats per minute (BPM), Group 70 of patients with heart rate 70 BPM, and Group 80 of patients with heart rate 80 BPM. This was done because ECG waveform amplitudes are dependent on heart rate. Segregation of the population would allow us to eliminate this dependence.

All operations were performed on the magnitude of the VCG composite vector given in equation 4. The DWT of each patient's VCG_{comp} was taken and all the detail components for each group of men and women were averaged. To view the Matlab code, see Appendix B. Using this process, I analyzed the VCG_{comp} waveforms doing a 3 level DWT decomposition using various Daubechies wavelets and Coiflets.

3 Results

In Figure 4 we can see the DWT using the Coiflet3 wavelet. By observing the detail coefficients, mainly the finer components d_1 and d_2, a difference between the men and women becomes evident. The female d_1 and d_2 components fluctuates a lot, whereas the male component seems somewhat more stable.

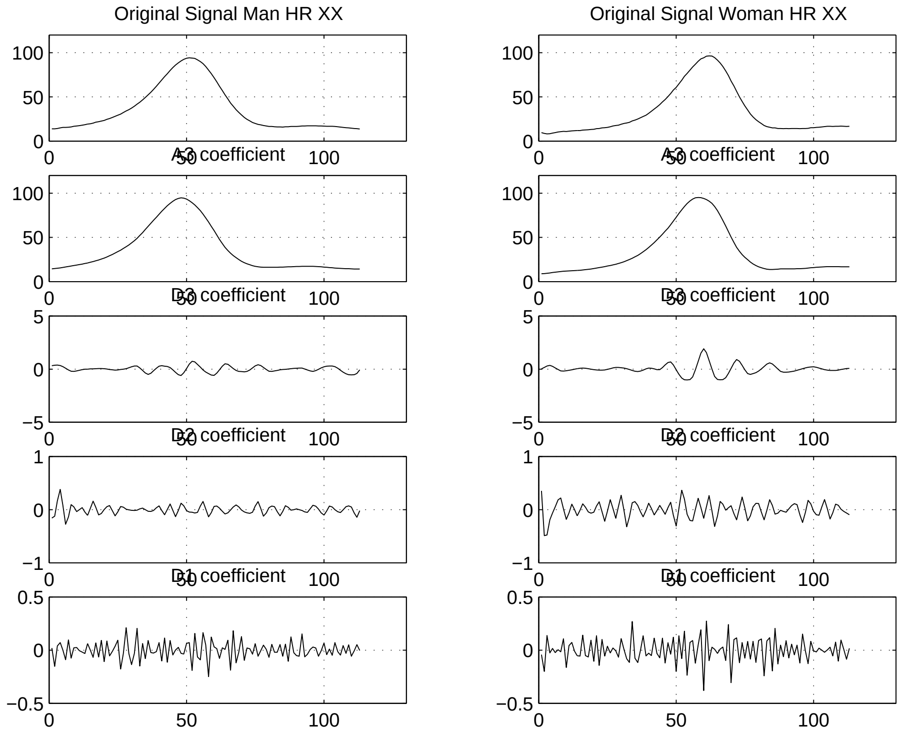

Figure 4: *Coif3 DWT of the male (left column) and female (right column) T wave for group 60. Each column, from top to bottom: Signal,* a_3*,*d_3*,* d_2*, and* d_1 *components.*

A similar relationship was found in groups 70 and 80 as shown in Figure 5 and Figure 6.

Next I used the Daubechies3 wavelet and was able to observe the same sort of behavior, with a slight discrepancy in group 80. These results are shown in Appendix A. Finally, I undertook to analyze waveforms with Coiflet2 and Daubechies2 wavelets. Both of these wavelets are lower order, which makes them less smooth and more compact than the Coiflet3 and Daubechies3. These wavelets do not seem to yield such a clear metric that would allow for an easier differentiate between the genders. As can be seen in Figure 7 the finer detail coefficients look very similar.

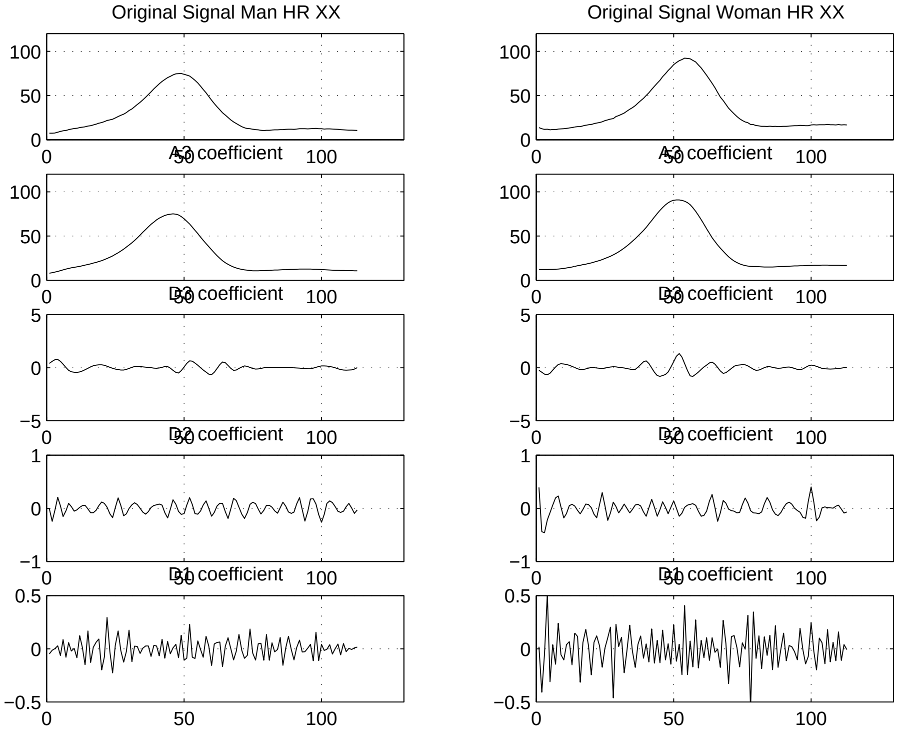

Figure 5: *Coif3 DWT of the male (left column) and female (right column) T wave for group 70. Each column, from top to bottom: Signal,* a_3,d_3, d_2, *and* d_1 *components.*

4 Discussion

As far as I can tell, almost all of this is new work, so no true comparison can be made to existing findings. When I began, I did not believe that there would be any discernible difference in the decomposition components between the genders. However, I was mildly surprised to find there is.

I was expecting to observe more detail coefficient differences in the late (descending) sections of the T wave. The rationale behind this can be explained by the significantly larger and faster descent of the wave in men. Hence I would have assumed to see more of the finer detail coefficient concentrations in these regions. The detail concentrations, however, seem spread throughout the spectrum.

From Figures 8 and 9 it can be seen that the argument of a discernible difference between gender in heart rates 60 and 70 is valid. However, a point can be made against HR 80. For HR 80 all the components look very similar. I attribute a lot of this to the small sample population selected (10 females and 10 males). I did run the same algorithm on the entire population (553

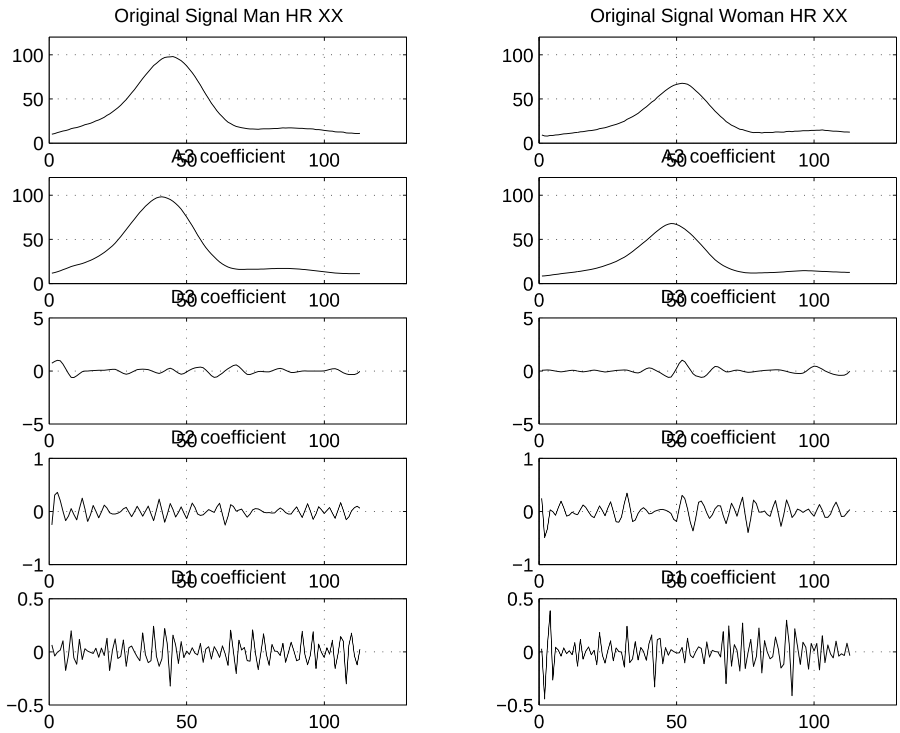

Figure 6: *Coif3 DWT of the male (left column) and female (right column) T wave for group 80. Each column, from top to bottom: Signal,* a_3*,*d_3*,* d_2*, and* d_1 *components.*

patients) and the difference in detail coefficients became clear. Group 80 detail coefficients d_1 and d_2 exhibited the same gender difference as is observable in groups 60 and 70.

Some suggestions may be made that a lot of the differences that are being picked up in the fine detail components may be attributable to noise. It should be stated that the signals were pre-filtered, and the distinct detail coefficient relationships that are observable for every group of patients and across wavelet families would be incredibly unlikely to be dismissable as noise.

5 Conclusion and Limitations

The detail coefficients of the DWT can be used to indicate gender differences when analyzing the T wave. However, more work will have to be done to quantify these differences and establish a distinct correlation between some of the coefficients. Perhaps through the use of other scaling functions and wavelets, this relationship can be perspicuously segregated. Lastly, it would be nice to

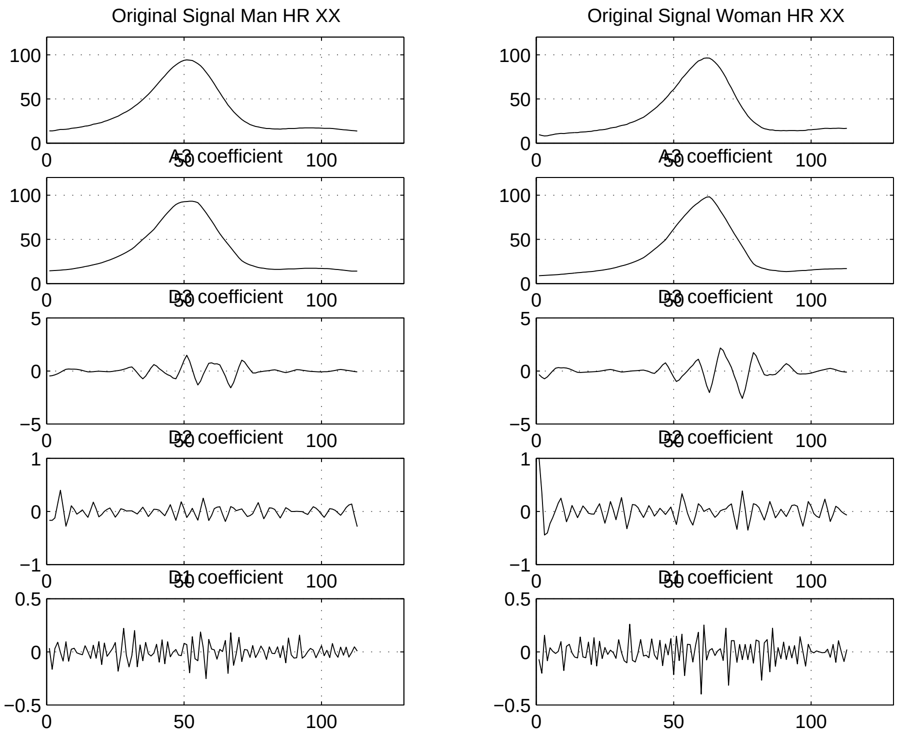

Figure 7: *Coif2 DWT of the male (left column) and female (right column) T wave for group 60. Each column, from top to bottom: Signal,* a_3*,*d_3*,* d_2*, and* d_1 *components.*

take a closer look at longer scaling functions and wavelets, such as db8 or coif8. I believe that these wavelets would yield even more discriminative power.

Acknowledgements

I would like to thank Dr. Michael Lehmann, from the University of Michigan Medical Center, Department of Cardiology for allowing me to use some of his ECG data.

6 Appendix A

Daubechies3 plots follow in Figures 8–10.

7 Appendix B

%%

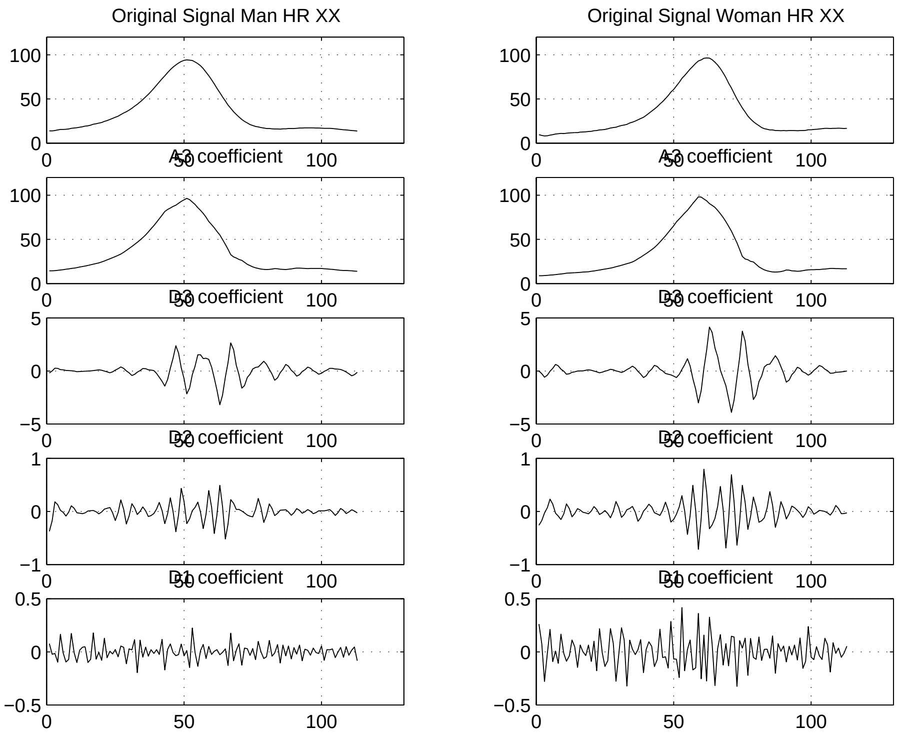

Figure 8: *db3 DWT of the male (left column) and female (right column) T wave for group 60. Each column, from top to bottom: Signal,* a_3,d_3, d_2, *and* d_1 *components.*

```
% Now we are doing the difference in men and women
% T-wave wavelet project
clear all
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
% This does the DWT decomposition on all men, HR 60, HR70, HR80
load maindata
% Mask for sorting through all patient files
masks = [1361,1371,1381];
wavelet = 'coif2';
%Levels of decomposition
level = 3;

for j = 1:3

package1 = isolate(masks(1,j),ecgvalues,vcg_xyz_height);
package1 = package1(:,:,1:10);
```

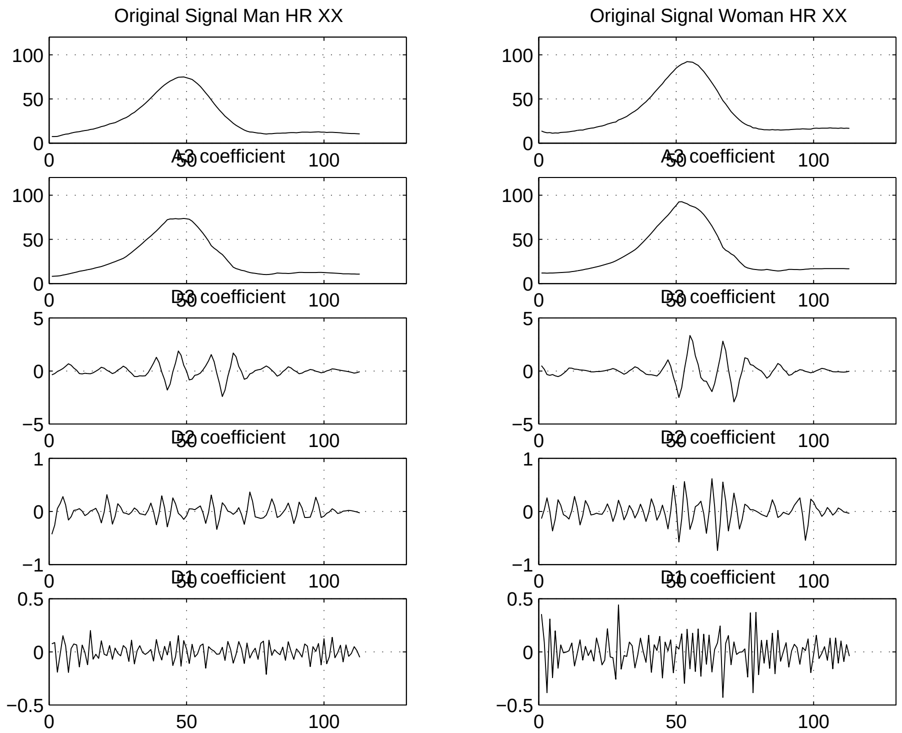

Figure 9: *db3 DWT of the male (left column) and female (right column) T wave for group 70. Each column, from top to bottom: Signal,* a_3*,*d_3*,* d_2*, and* d_1 *components.*

```
if(j==1)
    men60_mean = calculate(package1);
elseif (j == 2)
        men70_mean = calculate(package1);
  else
          men80_mean = calculate(package1);
  end % if

for i = 1:size(package1,3)
    [j,i]
    % this is the individual patient to have the DWT done on them
    tmen = package1(:,1,i);
ltmen = length(tmen);

% Doing the wavelet deconstruction of a male T-wave
[c_men, l_men] = wavedec(tmen,level,wavelet);
```

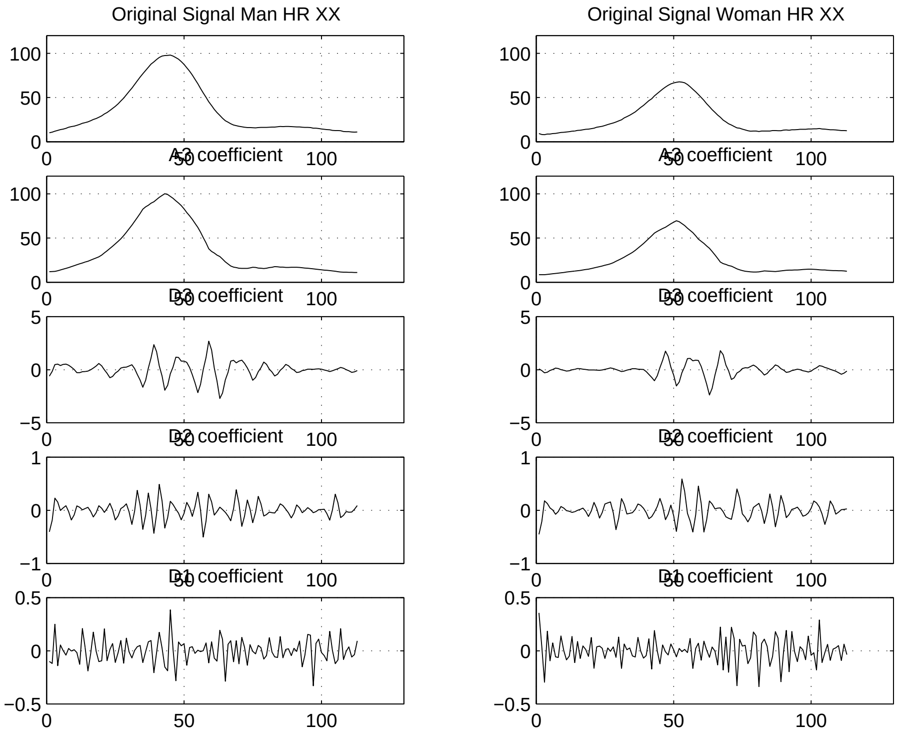

Figure 10: *db3 DWT of the male (left column) and female (right column) T wave for group 80. Each column, from top to bottom: Signal,* a_3*,*d_3*,* d_2*, and* d_1 *components.*

```
% Extracting the detail components, where c_man1 is the coarsest
% and c_man3 is the finest
[d_men1,d_men2,d_men3] = detcoef(c_men,l_men,[1 2 3]);

% Extracting the approximation coefficient
a_men3 = appcoef(c_men,l_men,wavelet,level);

% Little test of upcoeff on the side
% Which works, but the d3 coefficient does not correspond to the one I get from
% looking at it in wavemenu. Further, the error between the synthesized signal
% a3+d3+d2+d1 and the signal tmen is too large

d1 = upcoef('d',d_men1,wavelet,1,ltmen);
d2 = upcoef('d',d_men2,wavelet,2,ltmen);
d3 = upcoef('d',d_men3,wavelet,3,ltmen);
a3 = upcoef('a',a_men3,wavelet,3,ltmen);
```

```
if(j==1)
dwtcoef_men60(:,1:4,i) = [d1,d2,d3,a3];
elseif (j == 2)
      dwtcoef_men70(:,1:4,i) = [d1,d2,d3,a3];
  else
      dwtcoef_men80(:,1:4,i) = [d1,d2,d3,a3];
  end % if
end % for i
end % for j

% Now I'll calculate the mean values on each group for each component
dwtcoeff_men60_mean = mean(dwtcoef_men60,3);
dwtcoeff_men70_mean = mean(dwtcoef_men70,3);
dwtcoeff_men80_mean = mean(dwtcoef_men80,3);

%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
% Now, let's take a look at the women at all heart rates
masks = [1360,1370,1380];

for j = 1 : 3

package1 = isolate(masks(1,j),ecgvalues,vcg_xyz_height);
package1 = package1(:,:,1:10);

if(j==1)
    women60_mean = calculate(package1);
elseif (j == 2)
        women70_mean = calculate(package1);
  else
          women80_mean = calculate(package1);
  end % if

for i = 1:size(package1,3)
    [j,i]
    twomen = package1(:,1,i);

ltwomen = length(twomen);
[c_women, l_women] = wavedec(twomen,level,wavelet);
[d_women1,d_women2,d_women3] = detcoef(c_women,l_women,[1 2 3]);

a_women3 = appcoef(c_women,l_women,wavelet,level);

clear a3 d1 d2 d3

d1 = upcoef('d',d_women1,wavelet,1,ltwomen);
d2 = upcoef('d',d_women2,wavelet,2,ltwomen);
```

```
d3 = upcoef('d',d_women3,wavelet,3,ltwomen);
a3 = upcoef('a',a_women3,wavelet,3,ltwomen);

if(j==1)
dwtcoef_women60(:,1:4,i) = [d1,d2,d3,a3];
elseif (j == 2)
      dwtcoef_women70(:,1:4,i) = [d1,d2,d3,a3];
  else
      dwtcoef_women80(:,1:4,i) = [d1,d2,d3,a3];
  end % if
end % for i
end % for j

dwtcoeff_women60_mean = mean(dwtcoef_women60,3);
dwtcoeff_women70_mean = mean(dwtcoef_women70,3);
dwtcoeff_women80_mean = mean(dwtcoef_women80,3);

%This plots the mean values
project_plot(men60_mean,dwtcoeff_men60_mean,women60_mean,dwtcoeff_women60_mean);
project_plot(men70_mean,dwtcoeff_men70_mean,women70_mean,dwtcoeff_women70_mean);
project_plot(men80_mean,dwtcoeff_men80_mean,women80_mean,dwtcoeff_women80_mean);
```

References

[1] P. Addison, J Watson, G Clegg, and et al. Evaluating arrhythmias in ECG signals using wavelet transforms. *IEEE EMB Mag*, 19, 2000.

[2] V. Di Virgilio, C. Francalancia, S. Lino, and et al. ECG fiducial points detection through wavelet transform. *Conf Proc IEEE EMBS, 1995*, 2:1051–1052, 1995.

[3] L. Edenbrandt, O. Pahlm, and et al. Vectorcardiogram synthesized from a 12-lead ECG: Superiority of the inverse dower matrix. *J Electrocariol*, 21:361–367, 1988.

[4] M. Merri, J. Benhorin, M. Alberti, and et al. Electrocardiographic quantitation of ventricular repolarization. *Circulation*, 80:1301–1307, 1989.

[5] J. Millet-Roig, J.J. Lopez-Soriano, A. Mocholi, and et al. Study of frequency and time domain parameters extracted by means of wavelet transform applied to ECG to distinguish between VF and other arrhythmias. *IEEE Comp in Cardio*, 25:17–20, 1998.

[6] R.V.S. Sastry, K. Rajgopal, and et al. ECG compression using wavelet transforms. *Conf Proc IEEE EMBS, 1996*, pages 2/52–2/53, 1995.

[7] H. Yang, P Elko, B. Fromm, and et al. Maximal ascending and descending slopes of the T wave in men and women. *J Electrocariol*, 30:267–276, 1997.