Thoracic Biometrics – Investigations of the Human Heartbeat as a Biometric: Heart Sounds, Electrocardiogram, and Vibrometry

Final Report

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Section 1. Introduction

One of the most fundamental activities we humans perform on a regular basis is human recognition.

Suppose we are interested in finding someone in a very large room. Let's call this person our target. From afar, we might first observe the gates and the builds of the people in the room and compare what we observe to the gate and build of the target that we have stored in our memory from a previous encounter with the target. When we find someone that we believe has a similar gate and build as our target we begin to walk toward that candidate. As we get closer we are able to observe his hair and skin color. We find the hair and skin colors of the candidate matches to some degree the hair and skin color that we remember about the target, so we continue to walk toward the candidate. As we approach the candidate, the details of the candidate's facial features are observed. We observe the shape of his nose, eyes, and note the contours of his jawline and cheekbones. As we process this information we match what we observe to the facial features of the target that we have in our memory. Since the match gives us confidence that we are approaching the correct person, we proceed. When we have reached the target we extend our hand and greet the target. As he reciprocates we hear his voice and are confident that we have found the man we have been looking for.

All of these human traits we unconsciously observe and compare (gait, build, hair color, skin color, facial features and voice) are called biometric traits. Biometric traits can be behavioral, as in a person's gait, or can be biological such as a person's hair color. Using biometric traits to identify an individual is called biometric recognition.

The process of human biometric recognition, that we are able to perform almost instantaneously, can be described by two functions: modeling and matching. First, when we observe someone, we filter the information we receive from our senses

and save only the most useful information as a model of the individual – an abstraction of the person we are observing. As the observation time increases our brains automatically adjust and enhance the models we have created. When we seek to recognize an individual we recall the model for the target individual from our memory and compare that model against the model of a candidate we are observing. The matching process is sophisticated, as we are able to compare models that were constructed at different times, under different circumstances and in different environments. The matching process returns to us a confidence level for a match and when a match with a suitable confidence level is performed we call this recognition.

Since the advent of the computer, the Intelligence Community and others have sought to automate the biometric recognition process using the above traits as well as others. Today, biometrics authentication systems using biological traits such as fingerprints, iris images and facial images are employed as a means for identity management in government and commercial applications. But despite their widespread use and strong performance, many challenges remain as outlined in The National Biometrics Challenge by National Science and Technology Council.

Often these systems require cooperation by the individual who is to be identified. Other applications however require the identity of a target to be ascertained without the target knowing he is being observed. Systems that provide this functionality are called non-cooperative biometric recognition systems and often utilize sensors that collect biometric characteristics and traits at a significant distance from the target.

One class of non-cooperative biometric systems is crowd surveillance systems. These systems currently use facial images collected by high definition cameras to identify and track individuals in crowds. Since facial recognition systems are ineffective when the target uses a disguise, some have proposed utilizing other biometric traits that are more difficult to disguise.

In this work we discuss one such biometric traits, the carotid pulse. The carotid pulse is a mechanical signal produced by the heart and measured on the neck of the subject by using laser Doppler vibrometry. In addition, we will discuss our investigation into using the electrocardiogram (ECG), the electrical signal produced by the heart, as a biometric trait. These signals as well as other signals that originate in the thoracic cavity are called thoracic biometric traits.

The outline of this report is as follows. In Section 2, we introduce the three thoracic signals produced by the heart that we investigated in this study and in Section 3 we describe the project outcomes of this study and give an overview of our results. In S4 we provide a survey of the research on using these thoracic signals as a biometric. In Section 5 we discuss the human subject experiment we performed to collect thoracic signals for our analysis including the adverse events that occurred during the experiment. In Section 6 we provide a description of the modeling and

matching algorithms utilized in our automated biometric recognition system and in Section 7 we discuss our test results. We conclude this report by acknowledging those who have made this work possible and provide a bibliography of works on thoracic biometrics.

Section 2. Thoracic Signals

The biometric traits that we investigate in this study are produced by the heart and include the electrocardiogram, the phonocardiogram and the carotid pulse. In this section we describe each of these signals and describe their physiological manifestation.

The electrocardiogram (ECG) is a trace of the measurement of the difference in the electrical potential between two electrodes placed on the human body. Changes in the electrical potential are caused by the electrical depolarization and repolarization of the heart. The electrical activity originates as action potentials in the sinoatrial (SA) node and is propagated throughout the atria via cell-to-cell conduction. As this wave of action potentials depolarizes the atrial muscle the cardiomyocytes in the atrium contract, forcing blood into the ventricles. The wave of action potentials is slowed by the atrioventricular node allowing for the complete depolarization and contraction of the atrium. The impulse then enters the base of the ventricles at the Bundle of His which conducts the impulse at a high velocity causing rapid depolarization and contraction of the ventricular myocytes. This is followed by atrial and ventricular repolarization. Different lead placements produce different ECG traces.

The phonocardiogram (PCG) is a trace of the measured mechanical waves (vibrations) in the thoracic region caused by the closing of the valves of the heart. There are two primary sounds produced by the heart. The first, referred to as S1 and having a duration of approximately 150 milliseconds is believed to be the reverberation within the blood produced when the mitral and tricuspid valves close. The second primary sound, referred to as S2 and approximately 120 milliseconds in duration, is produced upon the closure of the aortic and pulmonary valves. Auscultation for S1 is best when performed near the left fourth intercostal space and auscultation for S2 is best performed near the left second intercostal space.

The movement of the skin over an artery or vein (a pulse) is a mechanical signal produced when the valves of the heart close, generating oscillating waves of pressure that are propagated through the arterial system. The pulse over the left carotid artery on the neck is often measured due to its high energy level and its proximity to the heart. The velocity of the pulse can be measured and recorded using a laser Doppler vibrometer. The velocity signal contains two main peaks we call the left peak and the right peak. The left and right peaks correspond, respectively, to the time periods in which the left ventricle starts and then finishes ejecting blood into the aorta (systole). As the right peak marks the end of the systole it is beginning of when the heart refills with blood (diastole).

Section 3. Project Outcomes and Results

The project goals have undergone a number of changes since the initial project approval. On September 27, 2011 our project sponsor requested modifications to two of the original outcomes and added a third outcome. These modifications were 1) Do not collect traditional biometric data (face, iris, and fingerprint), 2) Do not investigate multimodal algorithms, and 3) add a new outcome to investigate relationship between the different thoracic modalities. In addition, after an internal review, on January 16, 2013, the CIA Grants Office instructed us to cease collecting data on human subjects. Below is a list of the project outcomes and a summary of our results.

1. Outcome: A publically released dataset of thoracic biometrics (heart sound, ECG, LDV) of 300 subjects, two visits each.

   Results: The protocol was first approved by the Clarkson University (CU) Institutional Review Board (IRB) on August 23, 2010. R. Eric McGregor was brought into the project as IC Fellow on July 9, 2011. By January 2012 the collection room was set up, the recording software had been written and the equipment to record the phonocardiogram (PCG), electrocardiogram (ECG) and carotid pulse (CP) were ready for use. Final changes to the protocol were submitted to the CU IRB on February 2, 2012. After multiple modifications, approval of the protocol was granted by the CU IRB on July 18, 2012. We received approval from CIA HSRP on August 1, 2012. We began the first round of data collection in September 2012. We were able to collect one session of data from 36 subjects prior to suspending the collection on September 10, 2012 in order to review the protocol in light of two adverse events. Modifications to the protocol to address the adverse events were approved by the CU IRB on November 29, 2012. On January 16, 2013 the CIA Grants Office instructed us to cease collecting data on human subjects. The data that was collected may available for research use from CU following a signed Joint Multi-modal Biometric Dataset Release Agreement.

2. Outcome: An assessment of universality and uniqueness.

   Results: Clearly thoracic signals are universal to all living human beings. Regarding uniqueness, we were able to show that there is information in the ECG signal that is persistent throughout a session and that is unique to each subject. Performing intra-session testing on 24 subjects using 60 randomly chosen training heart beats from trial 1 and 30 randomly chosen testing heart bests from trial 2 we were able to correctly identify the test subject 100% of the time. The same results were found when training on trial 5 data and testing on trial 6 data. Match rates fell as the difference between the training average heart rate and the testing average heart rate increases.

Similar results were found when matching 30 random heart beats from CP data from trial 1 against models constructed with 60 random heart beats from CP data from the same trial. Here match rates also decreased when matching test data against training data with different average heart rates. See Section 7 for complete details.

3. Outcome: An assessment of additional characteristics: collectability, acceptability, ease of use, and spoof-ability.

   Results: In general, thoracic signals are easily collected, given ample time to position sensors, in a controlled environment. The subjects that participated in our study were comfortable with the collection procedure and were intrigued with the notion of using thoracic signals as a biometric identifier. The sensors used differ in their ease of use. Below we discuss the collectability, acceptability and ease of use for each modality. Our study did not analyze the potential for spoofing of thoracic signals.

   Of the three signals recorded in the study, PCG was the easiest to collect and was less prone to noise than ECG and CP. PCG was collected using a digital stethoscope held against the chest using an elastic band. Slight subject movement did not appear to impact the recording, however speech and coughing did. Subjects did not appear uncomfortable with the placement of the stethoscope over their second intercostal space.

   ECG was more difficult to collect due to the sensor type used, sensor placement, subject movement, and electromagnetic interference (EMI). We chose to have subjects affix electrodes to their person in a Type II configuration behind a privacy screen to ensure subject comfort. Often subjects would not follow directions and would have to re-affix the electrodes in the correct locations. This took between 5-10 minutes. This method appeared to be acceptable to the subjects. Muscle movement causes noise in the signal. Though most subjects were able to refrain from movement while recordings were being made, two subjects had significant noise in their signals due to their inability to remain still during the recordings. Another source of noise in the signals was EMI from the florescent lights, a motor in the HVAC unit next to the original collection room and DC power. Actions were taken to reduce or eliminate these distortions to the signals.

   The CP signals were recorded by targeting a laser Doppler vibrometer (LDV) at the left carotid artery on the subject's neck. Subjects were asked to tilt their head back against a headrest to reduce neck movement while the signals were being recorded. Due to the design of the headrest, this produced discomfort for a number of subjects, possibly causing dizziness and fainting during an adverse event. After review, the headrest was redesigned

and modified. It was difficult to find the carotid artery on a number of subjects, especially for overweight subjects, resulting in less than ideal CP recorded signals for these subjects. Ease of use was reduced by the fact that the laser source distance had to be measured and kept near an optimal distance.

4. Outcome: Algorithms for biometric recognition using heart sound, ECG, and LDV

   Results: We have produced a biometric software system named "Thoracic Identification System" that can model individuals using their thoracic signals and classify subjects using training and testing datasets. Modeling is accomplished using spectral information in the signals as features and classification can be performed using either a support vector machine (SVM) or statistical method. The algorithms are based on algorithms found in [29,37]. Please see Section 6 for a complete description of the algorithm and Section 7 for results.

5. Outcome: Algorithms to investigate relationship between thoracic modalities

   Results: Included in our system is the capability to classify one modality given training data in a second modality. This heterogeneous classification allows us to train our classifier using ECG data and then test the models using LDV data. Our method is based on the heterogeneous matching of face images presented in [56]. Due to the lack of data, we were not able to ascertain if there is a relationship between the different modalities. See Section 6 for a discussion of the algorithm incorporated in our software and in Section 7 you will find further comments on our test results.

Section 4. Survey of Thoracic Biometric Recognition

Several research groups have documented the use of heart sounds, electrocardiogram and carotid pulse signals as biometric traits. The first of which was written by Biel, et.al., in their 2001 paper [6] titled "ECG Analysis: A New Approach in Human Identification". In 2006, PCG was proposed [44] as a biometric identifier at a workshop and a year later the first paper [45] on the use of PCG as a biometric was published. In 2008, the first paper [37] investigating the use of the carotid pulse signal as a biometric trait was published. Following these initial papers, dozens of other works have been published that have extended these works and explored other thoracic signals. Below we provide a brief survey of the some of the work in thoracic biometrics.

Electrocardiogram

The biomedical field has found many applications for the classification of ECG signals [1-5]. However it was Beil et.al. who in [6] first considered using information from the ECG trace for biometric identification. Following [6], many research groups have tried different feature sets and used different classification systems toward the same end [7-34]. A survey of thoracic biometrics from 2001to 2010 using ECG can be found in [35].

Many of the first approaches used beat segmentation and fiducial point detection to find landmarks in the signals. In these approaches, features were calculated by measuring geometric properties of the ECG trace between fiducial points.

In [6] the authors modeled individuals using fiducial measurements included the amplitude of the signal at distinct fiducial points, the length of time between fiducial points, and the slope of the wave between fiducial points. The authors tested numerous feature sets consisting of between 7 and 360 features and concluded that only 21 features using a single lead or 30 features using 12 leads were needed to achieve 98% accuracy in identification of 20 subjects.

In [10] the authors showed that fiducial measurements are persistent across different anxiety states. In their study they tested 29 individuals with 12 returning for second sessions. In each session subjects performed seven two-minute tasks where each task was designed to produce a different state of anxiety. They were able to achieve a 97% recognition rate for heart beats with the same anxiety state as the training model and 98% recognition for heart beats with different anxiety states than the training model.

Wübbeler et.al., in [16], showed that fiducial measurements are "to a great extent […] stable even during several years and, moreover, with changing heart rates." In their study they collected data from 74 Caucasian subjects (40 male, 34 female). Most subjects' ECG was recorded at least twice and the average time between recordings was 500 days. Their method produced a 3% equal error rate (EER).

Non-fiducial approaches have also been suggested. In [14] the authors used an autocorrelation of ECG data segments to capture the repetitive nature of the signal while avoiding the issues of beat segmentation. Features were then obtained from the discrete cosine transformation of the autocorrelation signal and classification was conducted using Gaussian log likelihood estimates. Using data from 14 healthy subjects they reported a False Reject Rate (FRR) of $2*10^{-4}$ and a False Accept Rate (FAR) of 0.02. In a follow-up work [17], the authors report perfect recognition with 26 subjects.

Though most studies showed near perfect recognition rates, most studies had less than 30 subjects. Two studies that had larger data sets were [15], who had 502 subjects, and [29] who had 269 subjects. In these studies the recognition rates were 97.4% and 76.9% respectively.

In [15] the authors used interval measurements between fiducial point as features and performed intra-session testing, partitioning each signal into training data and test data. PCA is used for dimensionality reduction and a statistical scoring method based on Bayes' Theorem was used for classification. Their method produced a 97.45 identification rate.

In [29] the authors collected data from 269 subjects, three session each, over a seven month period. Feature sets were obtained using spectral analysis. Results from intra-session and inter-session tests. The best result, 76.9% rank-1 recognition, was obtained when training data was selected from two sessions and test data was selected from a third.

Carotid Pulse

A research groups at the forefront of biometric identification research using the carotid pulse is led by Joseph A. O'Sullivan and John W. Rohrbaugh at Washington University and Washington University Medical School in St. Louis, respectively. Between 2007 and 2010, the Washington University group published 5 papers [37, 39-42] on biometrics applications using the carotid pulse. These papers differ in the experimental variables incorporated into the study, number of subjects tested, the features used to model individuals, and the classification methods used.

The first paper [37] showed that when modeling subjects with a resting heart rate with sessions separated by a period of 1-3 months a 7.6% EER, using 30 training pulses and testing with 12 pulses per subject, could be achieved on a sizable dataset of 191 subjects. The data was collected by pointing a 633 nm laser Doppler vibrometer (LDV) at a piece of reflective tape placed on the subject's left carotid artery. The laser was positioned at a distance of approximately 1 meter from the subjects. Modeling was achieved by using a prolate spheroidal time frequency decomposition of the signal and classification was used using a scoring function and threshold.

In [39] the authors investigated the effects of changes in heart rate on performance. In this smaller experiment they collected one session of data from 21 healthy subjects. In these sessions, subjects were asked to exercise then rest eight times. Exercise was performed on a bicycle, pedaling until their heart reached 55% of their age adjusted maximum heart rate. They reported 100% recognition rates when training on average baseline pulse signals and testing average pulse signals collected after all exercise in the study. Also notable in this study is the fact that when testing with averaged elevated heart rate signals the recognition rate fell to 61.9% but when testing with averaged signals collected between exercise periods the recognition rate was 90.5%.

Chen et.al., in [42] improved their algorithm in [37] and showed a 6.3% EER can be achieved with information fusion of data within sessions and information fusion of data from multiple session. The data set consisted of data from 285 subjects, 3

sessions each, each session collected 1-6 months apart. Training models utilized 150 pulse signals and 4 pulses signals were found needed for testing.

Phonocardiogram

In 2006 the use of phonocardiograms as a biometric trait was first proposed [44] at the Second International Workshop on Multimodal User Authentication. Other papers followed [45-54]. In 2011, Beritelli and Spadaccini published a notable paper [55] on past works and future directions for PCG as a biometric.

Though based on a small dataset of only seven subjects collected over two months, the authors showed that biometric identification can be performed – particularly using cepstral analysis for feature selection and Guassian mixture models (GMM) for classification. In [46] the same authors continued their work, this time with a dataset containing 1000 heart sounds from 10 subjects collected over two months. In this work they reported a 96% match accuracy rate.

In [45] the authors identified S1 and S2 as the more informative sounds produced by the heart. They also identified the pulmonary region, aka the second intercostal space left of the sternum, as the ideal location for auscultation. The study used data, from 20 individuals, found in the medical Cardiosource database. They showed that by segmenting the recordings and using frequency decomposition for their feature space, their matching algorithms can achieve a FAR of 2.2% with a FRR of 5%.

The authors Beritelli and Spadicci have been pioneers in this field[47-50]. In their 2010 work [50], using the open source ALIZE/SpkDet software for feature extraction and GMM for classification they were able to establish an EER of 15.53% on a dataset of 147 individuals.

Section 5. The Human Subject Testing Experiment

In order for us to evaluate thoracic signals as a biometric we designed and executed a human subject experiment protocol to collect thoracic signals from Clarkson University students, faculty and staff. The protocol was approved by the Clarkson University Institutional Review Board and the Central Intelligence Agency Human Subject Review Panel.

As described in our proposal, our goal was initially to collect electrocardiogram, carotid pulse, and phonocardiogram signals from 300 subjects, with two sessions for each subject. Due to internal mission requirement changes after we began our experiment we were asked by our sponsor to cease data collection. We were therefore only able to collect data from 36 subjects, one session each.

In this section we discuss the human subject experiment we performed to collect ECG, PCG and carotid pulse signals. We discuss the sensors that were used, the data

that was collected, the experiment setup and the method for collecting the data and the adverse events that occurred during our experiment.

Hardware

To collect ECG signals we employed a Psylab Bio Amplifier and stand-alone monitor (SAM). The typical electrical signal on an ECG lead wire is ±300 microvolts. The Phsylab Bio Amplifier amplifies this original signal to *±5* volts. The amplified signal is then input into the SAM unit where it can be band pass filtered. We chose to band pass filter the signal to between 0.3 Hz. and 500 Hz. This removed some noise associated with breathing but kept the frequency domain as narrow as possible without loosing important information in the signal.

We utilized a Thinklabs ds32a digital stethoscope to record the sounds of the heart. The stethoscope typically outputs an electrical signal of approximately ±1/2 volts. No hardware filters are used on this signal.

We used a Polytec IVS-400 laser Doppler vibrometer to read the carotid pulse signal. The laser was set to read up to 20 mm/s. We also configured the laser to utilize its internal 5 kHz low pass filter. The analog signal output by the laser was ±4 volts (5mm/V).

The three analog sensors were connected to a Measurement Computing 2404-10 data acquisition device (DAQ). This DAQ digitizes the three analog signals within a ±10 volt range synchronously using 24 bit resolution.

The DAQ was connected to the USB port of a laptop and the laptop was connected to a battery power supply to reduce electromagnetic interference (EMI). The digitized data was captured and saved to common tab delineated text files by data acquisition software that was developed in house by our team using LabView.

Data Collected

The ECG, PCG and carotid pulse signals that we collected were collected in a controlled environment. Three sets of ECG, PCG and carotid pulse recordings were collected to provide heart rate variability in the data. Within each of the three sets, four recordings were made which provide variability in the focal point of the vibrometer's laser beam and the width of the laser beam. Thus, for each subject, three signals were recorded 12 times producing individual 36 recordings.

Heart rate variability within the data provides opportunity to determine if these thoracic signals are persistent over changes in heart rate and variability in laser beam focal point and width provides opportunity to determine if slight misalignment of the laser beam or insufficient focus of the laser beam impacts biometric performance. The differences in the recordings are described below.

The first set of recordings was collected while the subject had their normal heart rate and was collected immediately after the sensors were placed and targeted on the subject. We refer to these recordings as *baseline* recordings. We attempted to reduce potential subject anxiety by initiating friendly personal conversations with the subjects and by maintaining a clean and orderly collection room. Each recording in this set is two minutes in duration.

The second set of recording is refereed to as *elevated* data and was collected after the baseline data was recorded. These recordings were collected after the subjected pedaled a recumbent bicycle until their heart rate reached 65% of their maximum heart rate. The maximum heart rate (*HRmax*) was calculated based on their age using the following formula:

$$HRmax = 205.8 - (0.685 \cdot age)$$

Eq. 1

Each of the elevated recordings has a duration of one minute.

The third set of recordings, referred to as *rested* data, was collected after the elevated data was collected. Following the elevated data collection, the subject was asked to sit still for approximately five minutes to allow their heart rate to decrease. Each recording in this set was for one minute.

For each of the baseline, elevated and rested sets of recordings, four recordings were made. For each of the four recordings, the ECG and PCG equipment was unchanged but changes in the vibrometer's laser beam focal point and width were made. For the first recording the vibrometer was aimed at the subjects carotid artery and the laser beam was focused as sharp as possible. For the second recording the vibrometer was aimed one inch to the right of the carotid artery and the laser beam was again focused as sharp as possible. For the third recording the vibrometer was aimed back on the carotid artery and the laser beam was intentionally blurred by focusing the beam as tight as possible, then turning the lens 90 degrees clockwise. For the fourth recording the vibrometer was aimed one inch to the right of the carotid artery and the laser beam was again intentionally blurred as in the third recording.

Experiment Setup

Prior to each data collection, the subject informed about the study and was asked to read and sign a consent form. If the subject agreed to continue, a unique random subject number was affixed to the consent form that was used throughout the study to identify the individual. The subject was also entered into the demographics database and asked to provide the following information: gender, date of birth, ethnicity, native dialect, comfortable dialect and eye color.

Following the collection of the demographic information, the subject was prepared for the data collection. First, the subject was instructed on how to attach electrodes and lead wires to themselves in a Lead II configuration and asked to do so behind a privacy screen. Lead II configuration specifies electrodes on the right shoulder (negative lead), on the left lower abdomen (positive lead) and on the right lower abdomen (ground). The subject was then asked to sit on a recumbent bicycle. After the subject was seated, the collector attached the lead wires to a Psylab Bio amplifier that was connected to the SAM unit. The SAM unit was attached to the DAQ.

Next, the subject was asked to wrap a 3-inch elastic band around their chest and then insert the diaphragm of a Thinklabs ds32a digital stethoscope under the elastic strap and over the pulmonary valve region of the subject. This region corresponds to the second intercostal space on the left side of the subject's sternum. A cable was then attached to the control panel of the stethoscope and connected to the DAQ.

To ensure the laser was targeted consistently throughout the experiment, two ½-inch in diameter circles were drawn on the subject's neck as targets using a washable marker. The first circle was drawn directly over the carotid artery approximately one inch below the subject's jaw and the second was drawn one inch to the right of the first circle. The laser Doppler vibrometer was then adjusted so that the vibrometer was approximately 92.4 cm (a peak performance distance for the vibrometer) from the target and the laser beam was perpendicular to the subject's carotid artery.

Data Collection Method

After the subject was prepared for data collection, the collector described the differences between the 12 recordings. Using a monitor that was positioned in front of them which displayed their three analog thoracic signals in real time, they were asked to move and speak in order to observe the distortions in the signals. They were asked to remain still, place their feet on the ground, place their arms to their sides, rest their head against the headrest, and to not speak when recordings were being made. They were also informed that they were free to move and speak when the software was not recording.

To reduce EMI, the lights in the room were turned off and the bicycle was unplugged from the wall.

Following the instructions, the subject was asked to remain still and the first four baseline recordings were made. Next the elevated recordings were made. Prior to the fifth, sixth, seventh and eighth recordings, the subject was asked to pedal a recumbent bicycle until their heart rate reached their target heart rate. While pedaling they were given bottled water and were monitored by the collector. Once the subject reached their target heart rate, the recordings were made. Following the

four elevated recordings, the subject was asked to rest for approximately five minutes to allow their heart rate to decrease. Following this rest period, the rested recordings were made.

After the recordings were made, the sensors were removed from the subject and the subject was informed about the second session.

Adverse Events

While conducting our experiment two adverse events occurred. On September 07, 2012, we reported to the Clarkson University Institutional Review Board (IRB) that a subject came to the study on September 04, 2012 immediately after she performed a high stress one-hour work out. While she was sitting for a baseline recording she felt light headed. She went to the bathroom and came back and she said she was fine and wanted to continue the study. Since too much time had elapsed and another subject was to arrive at the top of the next hour, the collector asked her to reschedule.

The second adverse event occurred on September 10, 2012 and was reported to the Clarkson University IRB on the same day. We reported that after exercising to increase her heart rate and sitting still through a 60 second recording (trial 8), the subject complained of feeling dizzy. The subject was assisted off the bicycle to a chair where she rested for 2-3 minutes. After stating she was well and was ready to continue, she continued the study. She completed the trials requiring an elevated heart rate, then rested approximately 5 minutes and began the rested heart rate trials. Approximately 10 minutes after the first dizzy spell, during the recording of trial 9, the subject briefly lost consciousness while sitting on the bicycle and caught herself from falling. The subject sat in the chair again, then after resting approximately 5 minutes, began walking around and insisted she was fine and could continue the study. She then sat down on the bicycle and the collector attached the sensors and began trial 10. A few seconds later, she again lost consciousness, this time, falling off the bicycle and cutting her nose on the corner of the desk adjacent to the bicycle. While unconscious, the collector checked the subjects pulse and breathing. The subject gained consciousness a few seconds later. The collector assisted her to a chair where he helped clean the cut on her nose with an alcohol wipe. A few minutes later she was escorted to her office.

On September 10, 2012, the Clarkson Institutional Review Board instructed us to halt the experiment while they investigated the incidents. Leslie Russek, a member of the Clarkson University IRB, conducted an audit of the protocol and issued her final report on October 25, 2012. Dr. Russek concluded in her report that "Cervical extension appears to be a risk. The most likely reason for this would be positional internal carotid compromise, though vestibular dysfunction could also lead to dizziness." We modified the headrest so the subject would not need to tilt their head back while the recordings were taken and made other changes to the protocol. On November 9, 2012, the Clarkson University IRB approved the protocol.

On September 14, 2012 we informed our project manager of the two adverse events. On October 5, 2012 a teleconference was held with CIA and Clarkson University represented and on October 24, 2012, CIA representatives visited Clarkson University to investigate the incident and discuss modifications to the protocol. On January 16, 2013 we received instructions from CIA to permanently shut down the experiment.

Section 6. Modeling and Matching Algorithms

In order to determine the biometric capabilities of the thoracic signals, our team developed Matlab software named Thoracic Identification System. The software is based on the homogeneous algorithm described in [29] and on the heterogeneous matching strategy presented in [56].

The homogenous algorithm first isolates heartbeats from the recordings and then using a sliding short-time Fourier transform constructs a spectrogram for each heartbeat. The spectrogram is a matrix containing floating-point numbers, each representing the power of the signal over a window of time and a range of frequencies. Each cell in the matrix is referred to as a bin. A predetermined number of bins are chosen as identifying features based on how well they remain constant over time for the individual and how well they differentiate the individual from the rest of the population. Once the feature sets are calculated, classification is performed. The system has two classification capabilities, a support vector machine (SVM) and a probabilistic classifier similar to the classifier described in the above paper.

The heterogeneous algorithm attempts to match a subject when training data in one modality is available but testing data is only available in a second modality. The approach we have implemented works when a subset of the subjects in the training set, called the *kernel*, has the following property: for every subject i in the kernel, the k most similar subjects to i in the kernel when matching ECG signals are the same k most similar subjects to i in the kernel when matching LDV signals. When a kernel exists, if we have test data, say LDV, for a subject s', we can find the k most similar subject to s' matching against the kernel's LDV data. We can then check the ECG data set to see if anyone has the same k similar subjects. If so, then we can presume the identity of the individual.

Below we give a detailed description of our software and a more detailed description of the algorithms it uses.

Graphical User Interface

Our software, written in MatLab, has a graphical user interface with four components: the menu system, the variable editor panel, the action bar, and the Plot Panel.

The menu system allows the user to select a set of variables that are displayed in the variable editor panel. With a set of variables displayed, the user can see the current value for the variables and modify them. The different sets of variables available are Modeling Options, Input-Output Settings, Training and Testing Set Selection, ECG Preprocessing Options, ECG Feature Set Options, LDV Preprocessing Options, LDV Feature Set Options, and Plot Settings.

After the user is satisfied with the variable settings in the menus, using the buttons on the action bar, the user may calculate training features and calculate testing features. Once the training and testing features have been calculated the user may select the classify button to run the classifier. The action bar also includes a button to exit the software. When the user chooses an action, the software displays plots in the plot panel for each step in the algorithm (if turned on in the Plot Settings menu).

Modeling Options

As described above our software can perform homogeneous or heterogeneous classification. The Modeling Options menu allows the user to select which classification mode to perform. In addition, the user can select which classifier to use: the SVM or the probabilistic classifier. If using the SVM, other SVM tuning parameters can also be set.

Training and Testing Set Selection

If given a set of pairs (x_i, y_i) where $x_i$is a subject identifier and $y_i$is a feature set for x_i , the biometric classification problem seeks to determine the subject identifier for a given feature set y'. In order to evaluate a system that solves the biometric classification problem, we often partition the data we have into two sets: training data and testing data.

Our software allows the user to select which of the 36 recordings in our data set to use for training and which to use for testing. Given data from two sessions, the software will allow the user to select which of the 72 potential recordings to use as training and testing. The software user may select multiple recording to train and test with. The default setting uses the first ECG recording for both testing and training.

Given our dataset, intra-session homogeneous classification can be performed, for example, by training the system with data from the 1st, 5th, and 9th ECG recordings and then test the system with data from the 12th ECG recordings. Intra-session heterogeneous classification on the other hand can be performed, for example, by training the system with data from the all the ECG recordings and test with data from say the elevated LDV recordings (recordings 5,6,7, and 8). Although we have not implemented multimodal algorithms in our software at this time, the training

and testing set selection menu currently allow training and testing with signal from multiple modalities.

Preprocessing

Our software allows the user to toggle on or off a number of preprocessing steps and choose the number of samples/sec to process.

All of the thoracic signals were sampled at 10k samples/sec. This provides an abundance of data points many of which are unnecessary for our purposes. Our software allows the user to decimate the signal to a lower sample rate. The default setting is 10k samples/sec.

In addition, the user may toggle on/off a high pass filter for the individual signals, remove dropouts in the LDV signal and convert the native LDV velocity signal to measure displacement.

Feature Selection

Our software allows the user to configure a number of variables in the feature selection algorithm. These are shown below in **bold** typeface.

The first step in feature selection is beat segmentation. To identify individual beats in the ECG and LDV signals we use a modified version of the publicly available (www.librow.com) ECG beat identification software written by Sergey Chernenko. This software identifies the main peaks within the signal, corresponding to the R-peak in the ECG signal and the dominant peak in the LDV signal. Once the peaks are identified we segment the signal taking a **number of samples before the peak** and a **number of samples after the peak**. We then select a **number of beats** and discard the others. The beats are automatically chosen **consecutively** or **randomly**.

Once the segments are chosen we generate spectrograms for each of the segments based on the **window step**, **window length**, and **window type** (Hamming or Hanning).

Recalling that each bin in a spectrogram is associated with a particular time window and range of frequencies, after the spectrograms have been calculated, we generate a nominal model, $\hat{\theta}_0(l) = (\mu_{0l}, \sigma_{0l}^2)$, where μ_{0l} is the mean of bin *l* over all spectrograms of all subjects and σ_{0l}^2 is the variance of bin *l* using all spectrograms of all subjects.

Similarly, using just the spectrograms for subject *i*, we calculate a mean spectrogram (μ_{il}) and a variance matrix (σ_{il}^2) for subject *i*. These are called the maximum likelihood (ML) estimates, $\theta_i(l) = (\mu_{il}, \sigma_{il}^2)$, where *i* is the subject and *l* is the bin.

Next, we calculate a new matrix (SRE matrix) for each subject containing symmetric relative entropy (SRE) scores for each bin. These scores are based on the nominal model and the ML estimates. The symmetric relative entropy score for bin *l* of subject *i* is defined as

$$d\left(\hat{\theta}_i(l), \hat{\theta}_0(l)\right) = \frac{\sigma_{il}^2 + (\mu_{il} - \mu_{0l})^2}{2\sigma_{0l}^2} + \frac{\sigma_{0l}^2 + (\mu_{il} - \mu_{0l})^2}{2\sigma_{il}^2} - 1$$

Eq. 2

After the SRE matrix has been calculated, for dimensionality reduction, a reduced SRE matrix is computed by saving the bin values in a predefined number of bins and zero the other bins. The reduced SRE matrix is used as the subject's feature set in homogeneous classification. Let us define $sel(i, l) = 1$ if bin *l* of subject *i* is non-zero, otherwise $sel(i, l) = 0$.

Homogeneous Classification

Once training and testing sets are selected and features sets are calculated for the subjects in the training and testing sets, the homogeneous classification algorithms can be run. We have two types of classifiers for homogeneous classification in our software system.

The first classifier, a support vector machine (SVM), is publicly available and called libsvm. Libsvm was created by Chih-Chung Chang and Chih-Jen Lin and is available at www.csie.ntu.edu.tw/~cjlin/libsvm. This classifier creates a model (training) with an array of subject identifiers and feature set pairs and a pair of SVM options. The options, a **kernel parameter** and a **penalty parameter**, are configurable in the Model Options menu. Once a model has been created, the software can predict the subject identifiers for an array of feature sets. The predicted identifiers are compared to the actual identifiers and accuracy statistics are displayed in the plot panel.

The second classifier is a probabilistic classifier. Here, for each test heartbeat we calculate a log-likelihood score, Λ_i for each subject *i* defined by

$$\Lambda_i = \sum_{l=1}^{L} \log\left[\frac{p_i\left(Y(l)|\hat{\theta}_i(l)\right)}{p_0\left(Y(l)|\hat{\theta}_0(l)\right)}\right] sel(i, l)$$

Eq. 3

where *L* is the number of bin and $Y(l)$ is the value of bin *l* of the test heartbeat. The predicted identifier is the identifier belonging to the subject with the highest log-likelihood score.

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As with the SVM, the predicted identifiers are compared to the actual identifiers and accuracy statistics are displayed in the plot panel.

Heterogeneous Classification

In our heterogeneous classification implementation there are three stages: kernel identification, training the classifier and testing the classifier. Note that similarity scores of spectrograms, not the spectrograms themselves, are used as feature sets in kernel identification, modeling and classification.

In order to establish a kernel, we first calculate reduced SRE matrices as described above for the ECG and LDV recordings in the training set. Then, for each subject, we use the probabilistic scoring method from Eq. 2 to create a similarity matrix comparing the subjects' ECG reduced SRE matrix with all the other training ECG reduced SRE matrices. We select a predefined number of highest scores and zero out the others to generate an ECG reduced similarity score matrix. We follow this same procedure for the LDV training data to obtain LDV reduced similarity score matrices.

In order for us to establish a kernel, for each individual in the kernel, each subject should be identifiable by similarity scores for one modality, when testing is performed in a second modality. To check which subjects have this property our software run the SVM classifier using the ECG reduced similarity scores as the training data and the LDV reduced similarity scores as the test data. Subjects that have this property are identified as kernel members.

Given a kernel of appropriate size, the software creates a model for recordings in one modality and tests recordings in a second modality. When given a dataset containing ECG and LDV signals for a subject not in the kernel we produce two feature sets. The first is a ECG reduced similarity score matrix calculated using the ECG reduced SRE matrices of the kernel members. The second is a LDV reduced similarity score matrix calculated using the LDV reduced SRE matrices of the kernel members.

The training model is constructed using the ECG reduced similarity score matrices of the test subjects and the ECG reduced similarity score matrices of the kernel members. The classifier then tries to classify the LDV reduced similarity score matrices.

Section 7. Test Results

Tuning the system to find the best values for the system variables is important to maximize performance. Consider the results in Figure 1 obtained when using a set of 120 random training heartbeats per subject from the first recordings to test 60 random test heartbeats per subjects from varying recordings.

Recordings Used For Training	Number Of Training Beats Per Subject	Recordings Used For Testing	Number Of Testing Beats Per Subject	True Match Rate
1	120	1	60	100
1	120	2	60	100
1	120	3	60	94.29
1	120	4	60	94.12
1	120	5	60	42.86
1	120	6	60	42.86
1	120	7	60	45.71
1	120	8	60	45.71
1	120	9	60	67.65
1	120	10	60	68.57
1	120	11	60	65.71
1	120	12	60	64.71

Figure 1

With these settings, system performance drops significantly when the difference between the average heart rate of the training samples and average heart rate of the test samples increases. The greatest difference is found when the test heartbeats come from the elevated recordings (5,6,7,8).

It is not necessary to train the model with 120 heartbeats per subject. When testing a set of 30 random heartbeats per subject from the 4th recording on a varying number of training heartbeats from the first recording, performance is best (Figure 2) when training on only 12 heartbeats. Similar results are found in Figure 3 when training on a varying number of training heartbeats from recording #10, with 15 training heartbeats per subject being optimal.

Recordings Used For Training	Number Of Training Beats Per Subject	Recordings Used For Testing	Number Of Testing Beats Per Subject	True Match Rate
1	60	4	30	94.12
1	40	4	30	94.12
1	30	4	30	94.12
1	20	4	30	94.12
1	16	4	30	94.12
1	15	4	30	94.12
1	14	4	30	97.06
1	13	4	30	97.06
1	12	4	30	100
1	11	4	30	97.06
1	10	4	30	94.12
1	5	4	30	85.29

Figure 2

Recordings Used For Training	Number Of Training Beats Per Subject	Recordings Used For Testing	Number Of Testing Beats Per Subject	True Match Rate
1	60	10	30	68.57
1	40	10	30	62.86
1	30	10	30	65.71
1	20	10	30	65.71
1	16	10	30	65.71
1	15	10	30	71.43
1	14	10	30	68.57
1	13	10	30	65.71
1	12	10	30	68.57
1	10	10	30	68.57
1	5	10	30	68.57

Figure 3

Training the system on 12 random heartbeats per subject from the first recording and testing 30 random heartbeats from varying recordings (Figure 4) show sustained or slightly elevated performance for 11 of the 12 recordings when compared to training on 120 random heartbeats per subject (Figure 1).

Recordings Used For Training	Number Of Training Beats Per Subject	Recordings Used For Testing	Number Of Testing Beats Per Subject	True Match Rate
1	12	1	30	100
1	12	2	30	100
1	12	3	30	94.29
1	12	4	30	94.12
1	12	5	30	42.86
1	12	6	30	42.86
1	12	7	30	45.71
1	12	8	30	45.71
1	12	9	30	67.65
1	12	10	30	68.57
1	12	11	30	65.71
1	12	12	30	64.71

Figure 4

Figure 5 shows results of testing varying number of test heartbeats on a model made with 12 heartbeats from the first recoding for each subject.

Recordings Used For Training	Number Of Training Beats Per Subject	Recordings Used For Testing	Number Of Testing Beats Per Subject	True Match Rate
1	12	4	30	97.06
1	12	4	20	97.06
1	12	4	15	97.06
1	12	4	13	97.06
1	12	4	12	97.06
1	12	4	10	97.06
1	12	4	8	97.06
1	12	4	7	97.06
1	12	4	6	94.12
1	12	4	5	94.12

Figure 5

Recordings Used For Training	Number Of Training Beats Per Subject	Recordings Used For Testing	Number Of Testing Beats Per Subject	True Match Rate
1	12	1	7	100
1	12	2	7	100
1	12	3	7	91.43
1	12	4	7	97.06
1	12	5	7	45.71
1	12	6	7	48.57
1	12	7	7	48.57
1	12	8	7	40
1	12	9	7	73.53
1	12	10	7	82.86
1	12	11	7	82.86
1	12	12	7	73.53

Figure 6

Recordings Used For Training	Number Of Training Beats Per Subject	Recordings Used For Testing	Number Of Testing Beats Per Subject	Number Of Features	True Match Rate
1	12	10	7	60	65.71
1	12	10	7	30	65.71

1	12	10	7	27	68.57
1	12	10	7	24	65.71
1	12	10	7	21	65.71
1	12	10	7	19	62.86
1	12	10	7	18	62.86
1	12	10	7	17	62.86
1	12	10	7	15	57.14

Figure 7

Recordings Used For Training	Number Of Training Beats Per Subject	Recordings Used For Testing	Number Of Testing Beats Per Subject	Maximum Frequency	True Match Rate
1	12	10	7	250	65.71
1	12	10	7	220	65.71
1	12	10	7	190	65.71
1	12	10	7	160	65.71
1	12	10	7	130	60
1	12	10	7	100	57.14
1	12	10	7	70	65.71
1	12	10	7	60	65.71
1	12	10	7	40	62.86

12 random training heart beats per recording, 7 random testing heartbeats, 27 features, and maximum frequency of 60 Hz.

Recordings Used For Training	Number Of Training Beats Per Recording	Recordings Used For Testing	Number Of Testing Beats Per Subject	True Match Rate
1,2,3,4	12	1	7	100
1,2,3,4	12	2	7	100
1,2,3,4	12	3	7	97.14
1,2,3,4	12	4	7	100
1,2,3,4	12	5	7	40
1,2,3,4	12	6	7	40
1,2,3,4	12	7	7	42.86
1,2,3,4	12	8	7	42.86
1,2,3,4	12	9	7	79.4
1,2,3,4	12	10	7	82.86
1,2,3,4	12	11	7	77.14
1,2,3,4	12	12	7	79.41

Recordings Used For Training	Number Of Training Beats Per Recording	Recordings Used For Testing	Number Of Testing Beats Per Subject	Identification Rate
1,5,9	12	1	7	94.26
1,5,9	12	2	7	100
1,5,9	12	3	7	100
1,5,9	12	4	7	100
1,5,9	12	5	7	94.29
1,5,9	12	6	7	82.86
1,5,9	12	7	7	80
1,5,9	12	8	7	80
1,5,9	12	9	7	94.12
1,5,9	12	10	7	97.14
1,5,9	12	11	7	94.29
1,5,9	12	12	7	94.12

In our heterogeneous testing, based on current data, we were unable to establish a kernel of sufficient size. Our analysis showed only 2 subjects with similar score arrays. This does not necessary preclude this method from being a viable approach for we only have data from 32 subjects to test.

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