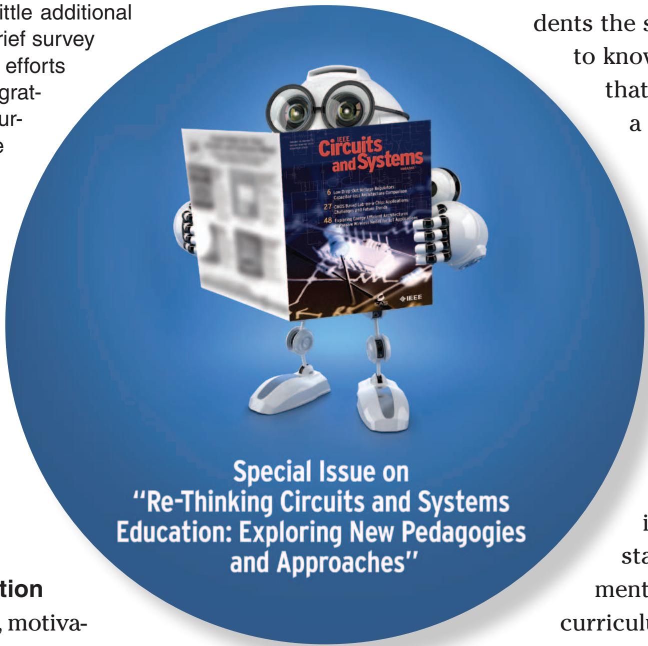
Vertical Integration of Biometrics Across the Curriculum: Case Study of Speaker, Face and Iris Recognition

Ravi P. Ramachandran, Kevin D. Dahm, Robert M. Nickel, Richard J. Kozick, Sachin S. Shetty, Liang Hong, Steven H. Chin, Robi Polikar, and Ying Tang

Abstract

Vertical integration is a powerful curricular tool that allows students to better appreciate the interconnections among the concepts acquired and learned in different courses. It can be used to bring a modern topic at all levels of the undergraduate curriculum with little additional resources. This paper gives a brief survey of various vertical integration efforts and describes one effort at integrating biometrics throughout the curriculum. The focus is on three senior level projects (speaker, face and iris recognition) that not only rely on vertical integration but also reinforce design, software skills and knowledge of STEM concepts. The freshman through junior levels are also described. The assessment results show that students acquire specific learning outcomes and perceive the value of vertical integration.



I. Introduction and Motivation

The theme, importance, motivation and curricular need for vertical integration is best expressed as part of a keynote address given by Dr. Joseph Bordogna at a National Science Foundation (NSF) conference [1], "Most curricula require students to learn in unconnected pieces—separate courses whose relationship to each other and to the engineering process are not explained until late in a baccalaureate education, if ever. Further, an engineering education is usually described in terms of a curriculum designed to present to students the set of topics engineers need to know, leading to the conclusion that an engineering education is a collection of courses. The content of the courses may be valuable, but this view of engineering education appears to ignore the need for connections and for integration—which should be at the core of an engineering education". Vertical integration refers to a series of laboratory exercises in a given topical area that start as well-structured experiments at the lower levels of the curriculum and proceed as increasingly complex open-ended design projects at the upper levels of the curriculum. An experiment in an upper level course builds upon a previous experiment performed in a lower level course. The topical area is biometrics [2] which is the science of recognizing and authenticating people using their physiological and/or behavioral traits.

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In this paper, the concentration is on the description of three senior level projects in biometrics (speaker, face and iris recognition) that rely on vertical integration, design, software skills and knowledge of STEM (Science, Technology, Engineering, and Math) concepts. An explanation of how this is achieved (freshman to junior levels) in leading up to the three projects is explained and assessment results are given for the speaker and face recognition projects.

Vertical integration of a curricular topic is a widely used educational tool and concept. It is usually implemented by (1) offering a full-fledged and specialized undergraduate program in a particular area, (2) a handful of elective courses within an Electrical and Computer Engineering (ECE) program and/or (3) exposing the student to the topic and skills required throughout the curriculum. A full-fledged program provides the most complete treatment of course and project work dedicated to a given area and is usually tied to a strong research laboratory. For example, the number of undergraduate biomedical engineering programs is expanding. Other innovative programs include:

1) University of Colorado at Colorado Springs: An undergraduate program, known as the Bachelor of Innovation (BI), started in Fall 2007 [3] and is jointly supported by the College of Engineering and Applied Science and the College of Business. The program defines common cores that include entrepreneurship, technical education, international business and policy issues and creative communication [3]. The BI in computer security includes courses in biometrics, bioinformatics, computer network security and cryptography that are related to biometrics.
2) West Virginia University: A Bachelor of Science in Biometric Systems is offered along with dual degrees in Biometrics/Computer Engineering and Biometrics/Electrical Engineering [4]. The Biometric Systems degree is a 133 credit program that includes fundamentals of mathematics, engineering science, computer science, forensics, electrical engineering and computer engineering. The objective is for students to understand the design, operation and application of biometric systems along with the social and policy issues.
3) Oregon Institute of Technology: In 2005, a new Bachelors of Science in Renewable Energy Systems program was started [5]. The aim is to prepare graduates for careers in the various fields associated with renewable energy.

Offering one (or a handful) of elective courses in a given area is a common practice at many institutions. For example, the U.S. Naval Academy has a Biometrics Research Laboratory with an aim to enhance undergraduate biometric education [4], [6] where a senior undergraduate elective course on Biometric Signal Processing is offered that integrates lecture and laboratory experiences.

Starting a new program requires enormous resources that are beyond reach for most institutions even during the best of economic times. Electives and seminar courses are indispensable tools that provide students an overview of specific topics within an area like biometrics. However, delivering a novel content through such means has its inherent limitations, including, but not limited to: (1) very few (typically one) electives/seminar courses are offered in any given area, (2) since only a limited amount of material can be covered in a single course, either depth or breadth (or both) must be sacrificed; and (3) students who have not been exposed to the topical area previously may feel hesitant in electing such a course. This motivates the use of vertical integration throughout the curriculum and establishes a bridge between configuring a new program and offering a few electives. Moreover, it provides a viable approach to many institutions with limited resources which cannot duplicate the effort of creating a new degree program in biometrics or any other area. The curricular success of using vertical integration at different institutions with little additional resources is a further motivating factor. In fact, many of the laboratory and curricular exercises at the freshman through junior levels can be made to be part of the existing courses in the curriculum. Only new senior level courses need to be configured. Examples include:

1) Iowa State University: A new set of three courses on embedded computer systems design are configured

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and developed such that their content is both overlapping and complementary. In addition, a coordinated set of learning outcomes further unify the courses [7].

2) James Madison University: A six course undergraduate design sequence is developed that spans sophomore through senior years and focuses on sustainability in four contexts: environmental, socio-cultural, economic, and technical [8].
3) Louvain School of Engineering: A three year integration of laboratory exercises in analog circuits has shown to improve student learning. Students also become increasingly aware that there exists a curricular flow in which previous knowledge is used to gain and build new knowledge [9]. The experiments start from Kirchoff's laws to the building of an audio amplifier for an MP3 player [9].
4) Temple University: The traditionally disparate threads of microelectronics and digital logic are unified [10]. There is a coupling between the electronics and digital logic course sequences with lecture materials and laboratory assignments that emphasize the target architecture and the reconfigurable environment of System-On-Chip design [10].
5) Wichita State University: The Industrial and Manufacturing Engineering Department formed a partnership with six industries. The aim was to use virtual reality models of factories for teaching aircraft manufacturing [11]. The virtual reality models used case studies in many courses over four years of the curriculum to achieve vertical integration.
6) Linkoping University, Sweden: In medical education, both horizontal integration (among different courses taken in parallel) and vertical integration (between the science and clinical aspects of the curriculum) have been configured [12], [13]. This has resulted in improved student learning.
7) University of Southern Maine: Vertical integration of concepts in thermodynamics, fluid mechanics and heat transfer is stimulated by a variety of laboratory exercises [14].
8) Rowan University: Vertical integration of experiments in the areas of biomedical engineering [15], [16], system-on-chip design (digital, analog and signal processing projects) [17], [18] and green engineering [18] have been successfully implemented.
9) Union College: A biometrics senior level elective and a general education sophomore level course in biometrics technology have been introduced and assessed [19]–[21].

II. Biometric Systems Overview

A general overview of biometric systems is given in this section. A more detailed treatment can be found in [2], [22]–[24]. There are two types of biometric systems. Biometric identification (BID) systems identify a person as being one among a set of candidate persons in a database. Biometric verification (BV) systems accept or reject the claimed identity of a person. Biometrics is primarily a signal processing and pattern recognition problem involving three distinct phases: (1) feature extraction, (2) training (enrollment) and (3) validation (identification or verification).

The objective of feature extraction is to create a compact representation of the signal (like a face image or speech waveform) that has sufficient variability to discriminate among different individuals while showing little variation to changes in the environmental factors (robustness). For example, the features used in a speaker recognition system should be sensitive enough to variations in different speakers voices, but be robust and invariant to changes in the same speakers voice due to background noise. Hence, even when the speech is corrupted by noise, the resulting extracted feature should not vary within the speech of a given speaker. Similarly, features used in a face recognition system should be robust to illumination effects, occlusion and pose variation. During training, the feature vectors form a model for each enrolled person. Examples of models include a vector quantizer codebook [25], a Gaussian mixture model [23]–[26] and a neural network [27]–[29].

In the validation phase, the test signal is again converted to a set of feature vectors. The feature vectors are compared to the model formed during training to generate a score for that model. For biometric identification (BID) systems, the model (among all enrolled models) that yields the best score serves to identify

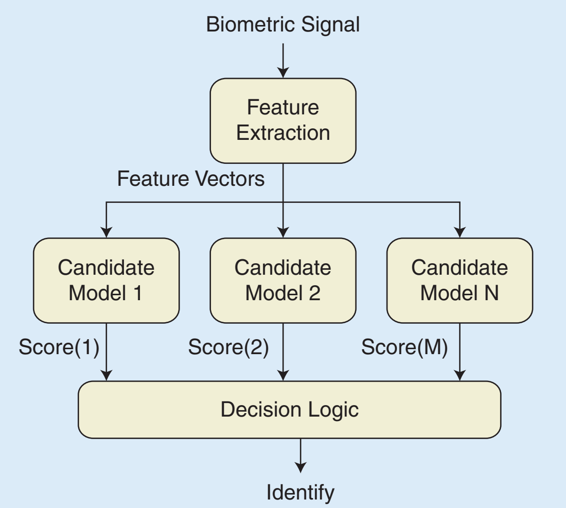

Figure 1. Biometric identification system.

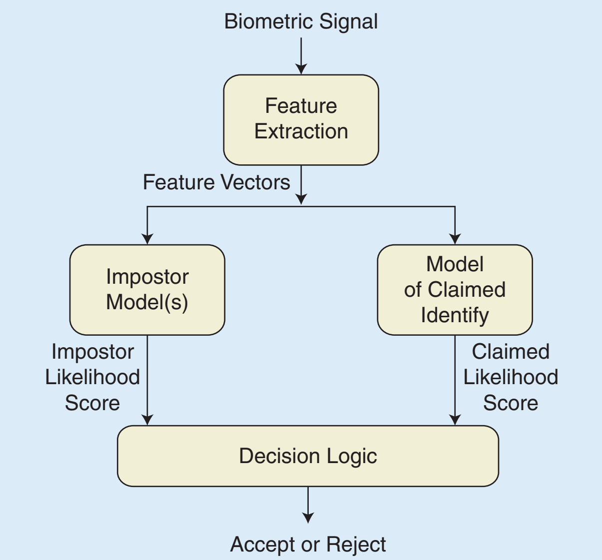

Figure 2. Biometric verification system

the individual. This is depicted in Figure 1. The performance measure is the identification success rate (ISR) which is the number of test samples that lead to correct identification of the individual divided by the total number of test samples.

In biometric verification (BV), the feature vectors are compared to the model of the claimed identity of the person and to an impostor model to generate a likelihood score for each model. These two scores are subtracted and compared with a threshold to render a decision of acceptance or rejection. This is depicted in Figure 2. Two types of errors can result. A false accept (FA) is when an impostor is accepted and a false reject (FR) is when an individual with appropriate credentials is incorrectly rejected. The FA rate is the number of times an impostor is accepted divided by the total number of impostor trials. The FR rate is the number of times a genuine individual is rejected divided by the total number of genuine person trials. Varying the threshold varies the FA and FR rates. A receiver operating characteristic (ROC) is a plot of the FA rate versus the FR rate for varying thresholds. The point on the ROC when the FA rate is the same as the FR rate is known as the equal error rate (EER).

There is a great interest in biometrics due to its widespread forensic [30] (corpse identification, crime investigation, parenthood determination), government (border crossing, drivers license) and commercial (physical access control, remote access control especially to secure websites, electronic commerce, use of mobile devices) applications [2]. Biometrics is directly applicable in enhancing global cybersecurity. A cyber attack can be catastrophic in that private medical records can be accessed, much money can be stolen from banks, essential services (like the power grid) can be disrupted, defense systems can be infiltrated and weapons systems can be sabotaged.

Biometrics is also applicable in cognitive radio networks. Due to its capability of dynamic spectrum access, Cognitive Radio (CR) is a promising technology that mitigates the spectrum shortage problem and achieves considerable improvement in spectrum utilization [31]–[33]. Spectrum sensing is one of the key mechanisms of CR and is an active area of research. At the same time, spectrum sensing techniques are vulnerable to adversarial attacks whose primary motivation is to steal spectrum [34]. The security challenges of spectrum sensing can be enhanced using biometrics. Consider the deployment of CR nodes in a wireless local area network (WLAN). The WLAN infrastructure covers a range of tens of meters to hundred meters and is comprised of a base station (BS) and a number of CR nodes (CRNs) ranging from PDAs to laptops equipped with cognitive radios. Spectrum sensing data falsification (SSDF) poses a serious threat to distributed spectrum sensing in CR networks [35], [36]. In an SSDF attack, the attacker emulates the characteristics of the primary signal transmitter as depicted in Fig. 3. An SSDF threat is the transmission of false spectrum sensing data by malicious or unauthorized CRNs to the BS, causing the BS to make a wrong spectrum sensing decision. These SSDF attacks can cause intrusion and jamming in a complex wireless environment used by army personnel, ground vehicles and airborne platforms [37], [38]. Biometric speaker recognition can either permit or deny access to a CR network based on the user's speech. A person seeking access speaks into the microphone of his/her CRN. This speech signal is communicated to the BS. The BS uses a biometric based speaker recognition algorithm to accept or reject the user as shown in Figure 4. The challenge is to achieve high performance as the transmitted speech is subject to noise and coding distortion effects due to wireless communication [39]–[41].

There are different biometric modalities (fingerprint, face, speech, palmprint, iris, signature, gait, ear, retinal scan, DNA) each having practical tradeoffs [2], [22]. The choice of biometric depends on the application and there is no clearly defined optimal biometric [22]. This exemplifies the need for further research and educational activities pertaining to a variety of biometric systems. The fingerprint and iris modalities show a high distinctiveness among individuals and a high performance. The challenge is to make iris based systems more user-friendly and cost effective [22]. Fingerprint BID systems are computationally expensive [22]. Face and speech based recognition systems have high user acceptability and are particularly promising as more research is done to improve their accuracy.

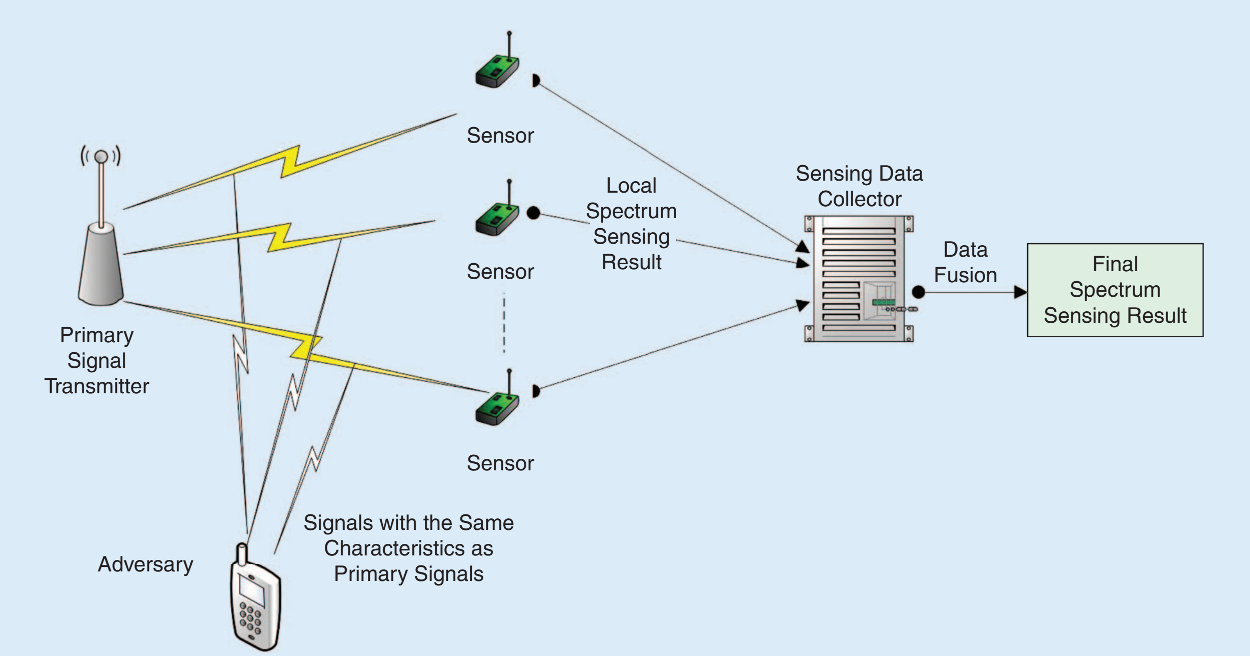

Figure 3. Spectrum sensing data falsification (SSDF) attack.

III. Freshman to Junior Levels of Curriculum

As mentioned earlier, the focus of this paper is on the senior level biometrics projects. This section discusses the freshman to junior levels to show how they lead up to the senior level in terms of students gaining design skills, software implementation skills and knowledge of STEM concepts.

A. Freshman Level

A freshman module can be fit into any Introduction to Engineering course. It is very significant in giving students a realistic understanding of engineering and realizing its potential benefits especially from the point of view of societal impact [42]. As pointed out in [43], it is important to inspire and retain freshmen students by teaching modern topics and connecting them to real-world problems and exposing the students to engineering design and testing. A freshman module is also challenging since the students may not have the adequate engineering, mathematics, design and software skills to carry out a project. Successful freshman modules for vertical integration of system-on-chip and green engineering concepts have been achieved by incorporating reverse engineering and conceptual design [18], [44].

Details on the biometrics freshman module with assessment results are given in [42]. In implementing this module, each week comprises a 50 minute lecture and a 3 hour laboratory. The learning outcomes include enhanced knowledge of STEM concepts, enhanced design and software skills and a comprehension of the ethical issues relating to biometrics. Lectures stress the concepts and basic definitions, teach biometrics from a systems perspective, summarize various biometric modalities, examine real-life applications (commercial, government and law enforcement), discuss global

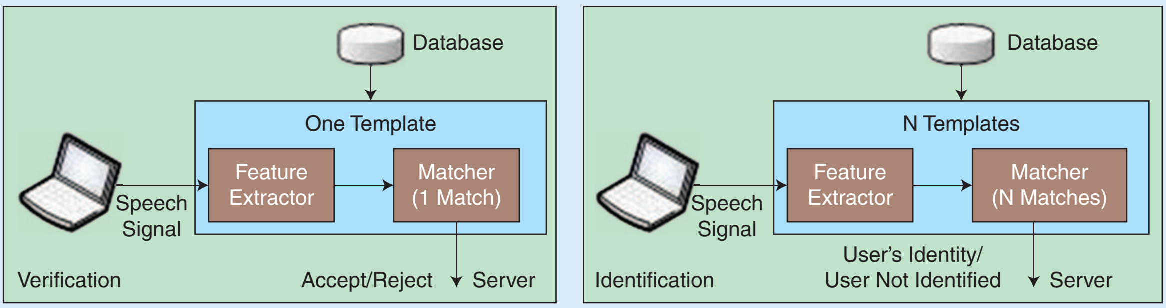

Figure 4. Application to cognitive radio.

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economic impact and cover the k-nearest neighbor (kNN) classifier using the basics of vector algebra. A hands-on tutorial introduces MATLAB. The concepts, definitions and viewing biometrics as a complete system is explained using Figure 5. The module consists of [42]:

1) Ethics component [45], [46]: This includes a classroom discussion/debate.
2) Fingerprint recognition: Students experiment with the Fingercode algorithm of [47] by using the MATLAB code obtained from [48]. The focus of the experiment is to understand the concept of performance degradation due to mismatched training and testing conditions.
3) Face recognition: A system using the DCT feature [49], [50] and a kNN classifier is simulated. The MATLAB code for training, DCT computation and part of the performance evaluation is supplied. Students write their own code to accomplish kNN classification.

B. Sophomore Level

In teaching analog circuits, it is very important to capture the students' interest and have them acquire design, testing and math skills [51]–[53]. Laboratory exercises illustrating (1) basic concepts (Kirchoff's rules, maximum power transfer and Thevenin equivalent), (2) active circuits (inverting amplifier, noninverting amplifier, differentiator and integrator) and (3) basic first order filters (both passive and active) are introduced with MATLAB fully integrated. Students accomplish their own design of a noninverting amplifier based on power dissipation constraints. The concepts of frequency response and transfer function are reinforced. Students investigate a practical filter that performs differentiation over a band of low frequencies [51]. Different inputs are applied to this filter (square wave, triangular wave and sine waves of different frequencies) such that students comprehend what the outputs are and why they result. Differentiators are further explained in terms of their importance in biometric signature recognition [54].

In the digital circuits course, students implement a circuit to find the fractional Hamming distance between two bit streams [55]. The importance of this distance metric in biometric iris recognition is explained [55], [56].

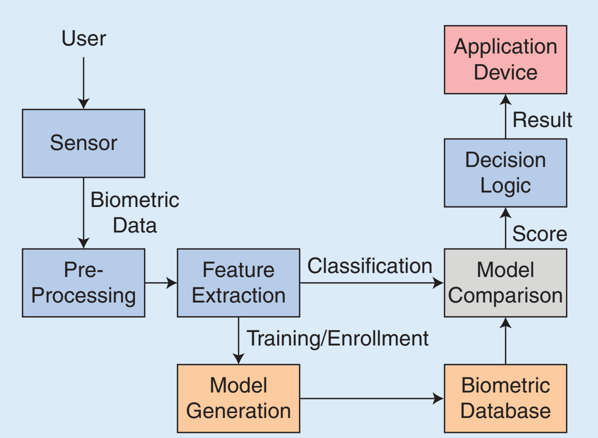

Figure 5. Block diagram of a biometric system (taken from [42]).

C. Junior Level

The experiments at the junior level can be implemented in any signals, systems and/or signal processing course. Again, MATLAB is part of every lab exercise. The basic goals are for students to improve mathematical and analytical skills, improve software design skills, see the relationship to the freshman and sophomore experiences and process biometric signals.

1) Butterworth design of digital IIR filters: This experiment builds upon the knowledge gained on analog filters in the sophomore year. Students are taught the math associated with the design formulas including the bilinear transformation. Software design of filters is performed according to given specifications and students are required to configure an active and passive circuit corresponding to the transfer function of the obtained filter.
2) Linear phase FIR filter design: Students accomplish Type 1 and Type 2 designs using the window method and the Remez exchange algorithm [57].
3) Type 3 and Type 4 FIR linear phase differentiator filters: This is a significant experiment as the filters are used in signature recognition [54]. It also naturally extends the analog differentiator concept covered at the sophomore level. Students (1) derive the impulse response of an ideal differentiator with a bandwidth $[0, \omega_c]$, (2) derive and comprehend the frequency response of practical differentiators, (3) compare the window design with the Remez design, (4) pass sample signature signals through a first order and a second order (cascade connection of two first order filters) to gain an appreciation for the velocity and acceleration of a signature signal

and (5) apply differentiators to edge detection of images and do a subjective evaluation that compares a 3 tap and a 53 tap filter.

4) One-dimensional (1-D) and two-dimensional (2-D) DCT: This is important for the face recognition project given in the senior year. The challenge is to introduce just enough math for students to appreciate the DCT (a more rigorous treatment is given at the senior level). The focus is on the processing of a face image. The 1-D DCT is studied in terms of fast computation and energy compaction [58], [59]. The DCT of specific rows or columns of face images will be studied and interpreted. The DCTs of the horizontal/vertical gray scale projections of different face images [60] will also be analyzed and compared. The 2-D DCT of an entire face image will be computed to reveal all spatial frequency components of the image and show that the DCT coefficients with large magnitude are mainly in the upper left-hand corner of the DCT matrix [50]. The 2-D DCT of two images of the same face but under different illumination conditions will be computed. The low frequency DCT coefficients will be modified to be equal for both images. Then, the inverse DCTs will be computed to reconstruct more similar face images and hence, show that the low frequencies are sensitive to illumination conditions [50].
5) Linear prediction filter for speech analysis: The concept of linear prediction of speech and consequent feature extraction [25] is commonly taught at the senior level. To facilitate instruction at the junior level, the all-pole linear prediction filter is presented as an IIR filter. The frequency response of the filter (describes the spectral envelope) of the speech is examined for a sustained vowel to demonstrate the local resonant frequencies (formants). Students will be provided with the MATLAB code to calculate the linear predictive cepstrum features for both clean speech and speech subjected to additive noise (various signal to noise ratios). Students deduce that a noise level increase reduces the magnitude of the cepstrum vector and distorts the spectral envelope. An explanation of how this phenomenon diminishes biometric system performance is provided.

IV. Senior Level Projects

The senior level projects can be applied in a variety of courses including but not limited to Biometrics, Speech Processing, Image Processing, Pattern Recognition, Machine Learning and Advanced Digital Signal Processing. The speaker and face recognition projects are in biometric identification. The iris recognition project is on biometric verification. The broad student learning outcomes of the projects are [61]–[63]:

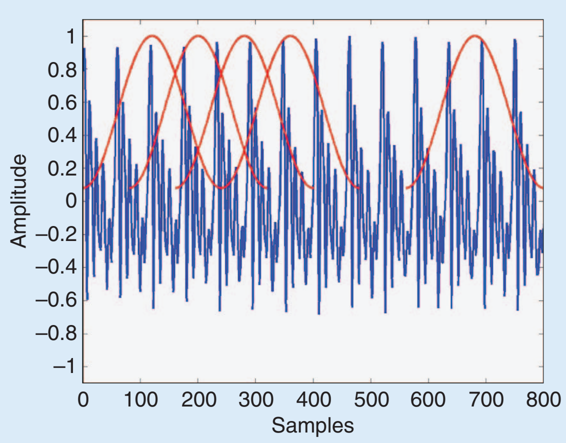

Figure 6. Frame by frame processing (taken from [61]).

1) Enhanced mathematical skills especially in terms of engineering application.
2) Enhanced software implementation skills and exposure to a modular implementation.
3) Enhanced interest in biometrics.
4) Enhanced research and design experience: Acquiring the ability to read papers, apply algorithms and achieve a performance improvement through better system design.
5) Enhanced written communication skills.
6) Comprehension of the importance of vertical integration: Students realize and appreciate the curricular flow that contributes to a unified knowledge base [61]–[63].

A. Speaker Identification Project

The initial implementation of this project is described in [61], [63]. The project has been improved and is described below. Also, as compared to the assessment results given in [61], [63], the results presented in this paper are based on running the project at two universities, namely, Rowan and Bucknell.

This project builds upon the linear prediction experiment at the junior level. At the senior level, students are taught the mathematical background and concepts of preemphasis, linear prediction, feature extraction, vector quantizer (VQ) design and the decision logic used in speaker identification [61]. Students are expected to understand and implement an entire system, use a real database (King database), comprehend performance degradation due to mismatch in training and testing conditions and achieve open-ended design to augment performance. The portion of King database [64] that is used comprises of 26 speakers in which the data is collected over 10 sessions in San Diego, California. The

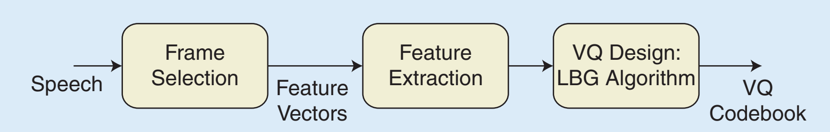

Figure 7. Vector quantizer classifier training (taken from [61]).

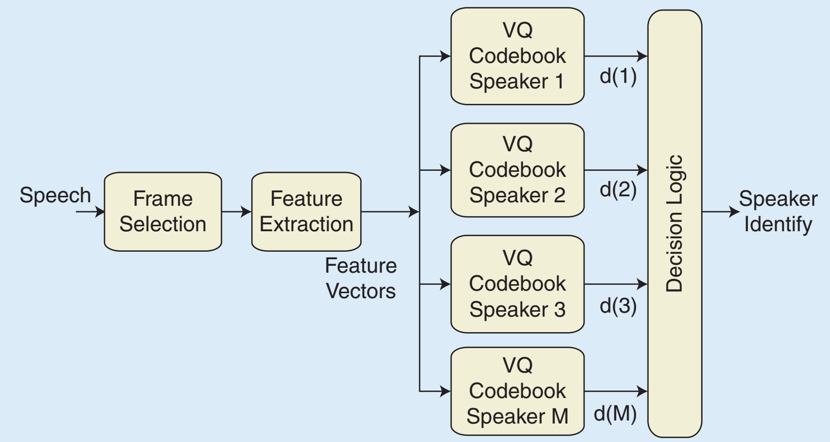

Figure 8. Vector quantizer classifier for speaker identification (taken from [61]).

database offers a train/test mismatch based upon an interesting anomaly known as "The Great Divide". This manifests itself as an apparent change in the spectral characteristics of the narrow-band channel between sessions 1-5 and sessions 6-10.

The concepts of dividing a signal into frames, doing frame selection and performing frame-by-frame processing are learned (see Figure 6). In this project, the length of each frame is 30 ms and the overlap between consecutive frames is 20 ms. Each frame is multiplied by a Hamming window and effectively represents the middle 10 ms of its entire 30 ms length. Frame selection is achieved by a voice activity detector that keeps speech-like high energy segments (usable frames [65]) and discards silence (not usable frames) [66].

The speech is preemphasized by the filter $1-0.95z^{-1}$ and for each speech-like frame, the autocorrelation method of linear prediction is used to get a 12th order polynomial $A(z)$. Knowledge of $A(z)$ leads to an additional and more stringent step of frame selection and consequent feature extraction and VQ classifier design. Linear prediction based frame selection can be done on those frames that are declared usable by the voice activity detector [64]. The procedure is to find the roots of $A(z)$ and count the number of roots that (1) have an imaginary part greater than 0, (2) a magnitude greater than or equal to 0.88 and (3) an angle between a frequency of 300 Hz and 3700 Hz. A frame is finally selected for feature extraction if the number of roots that satisfy the above criteria is greater than or equal to 3.

For each selected frame, seven 12 dimensional features are calculated: (1) linear predictive cepstrum (CEP), (2) adaptive component weighted (ACW) cepstrum [64], (3) postfilter (PFL) cepstrum [64], (4) pole filtered mean removed cepstrum (PFMRCEP) [67], (5) mean removed ACW cepstrum (MRACW), (6) pole filtered mean removed ACW cepstrum (PFMRACW) [68] and (7) mean removed PFL cepstrum (MRPFL). Seven different feature vectors of dimension 12 are computed. With seven features, there are effectively seven speaker identification systems that are configured. This motivates the use of data fusion to augment performance [69].

The VQ classifier consists of 26 codebooks. It is an unsupervised classifier [70], [71] in which each codebook is designed by the Linde-Buzo-Gray (LBG) algorithm [25] using training feature vectors (after frame selection) for one speaker only. The distortion measure is the squared Euclidean distance. A block diagram is given in Figure 7.

The VQ system for processing a test speech utterance and identifying a speaker is shown in Figure 8. There are seven such systems, one for each feature. Just as in training, a test utterance from one of the speakers is converted to a set of test feature vectors after frame selection. Each test feature vector is quantized by each of the VQ codebooks to get 26 different distances, one for each codebook. This process is repeated for every test feature vector. The distances are accumulated over the entire set of feature vectors such that $d(i)$ is the accumulated distance for codebook i. The codebook that renders the smallest accumulated distance identifies the speaker.

The specific project tasks [61] are:

1) Listen to the speech files. Are there any perceivable differences "across the divide"?
2) Read the tutorial papers [23], [24], [66] and write a critical synopsis on biometric speaker recognition.
3) Train on sessions 1 to 5, one at a time. Use VQ codebooks of size 64. Record the ISR for the nine remaining test sessions for each of the seven features. Do the speaker identification experiments with voice activity detection. How does the ISR vary with and without linear prediction based frame selection?

4) Use hypothesis testing and confidence interval estimation to see if certain features achieve a statistically better performance. Use this statistical approach to see if linear prediction based frame selection improves performance.

Some suggestions were made for open-ended design with the objective of augmenting the ISR.

1) Research and implement any other method of voice activity detection for frame selection and compare with the approaches used.
2) Research other robust features.
3) Use other classifiers like Support Vector Machines, Neural Networks and Gaussian Mixture Models. Compare with VQ and explain. Perform classifier fusion.
4) For a given classifier (VQ or other), examine feature fusion strategies. Examples are decision level fusion, probability level fusion and Borda count [69], [72].
5) Combine feature and classifier fusion.

Future offerings of this project will aim to look at speaker identification and verification for speech transmitted over wireless and VoIP networks [40], [41], [73].

B. Face Recognition Project

The project has been improved over what was described in [62], [63]. The project extends the DCT experiment at the junior level. It also reintroduces the freshman face recognition module but with more mathematical rigor (various 1-D and 2-D transforms) and software implementation in that students implement an entire face identification system with different features and classifiers. Just as in the speaker identification project, there is an open-ended design component. The detailed mathematical background on 1-D and 2-D DCTs, DSTs (discrete sine transforms) and the FWHT (fast Walsh Hadamard transform) are covered [59]. The 2-D transform (DCT, DST or FWHT) of the 256 level greyscale face image is first calculated. In the actual implementation, the 2-D DCT is scanned in a "zigzag" fashion to get a 1-D feature vector as shown in Figure 9 [59]. Students are taught the motivation and significance of this type of scanning. The kNN, VQ and neural network classifiers are covered and the concept of supervised versus unsupervised approaches explained [70].

The AT&T database [74] is used in which there are ten different images of each of 40 distinct subjects [49] [50]. This database is freely downloadable and was configured by AT&T Laboratories in Cambridge, England. For some subjects, the images were taken at different times, varying the lighting, facial expressions (open/closed eyes, smiling/not smiling), pose (left/right/center) and facial details (glasses/no glasses). The image files are in PGM format. The size of each image is 112 by 92 pixels, with 256 grey levels per pixel.

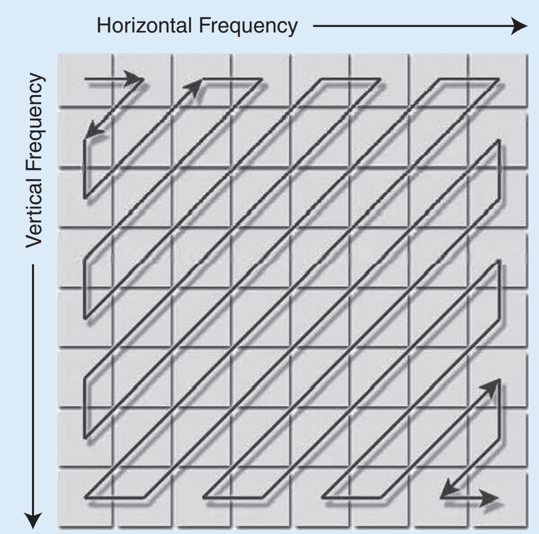

Figure 9. Feature vector from a 2-D DCT (taken from [42]).

The specific project tasks are:

1) Read the papers [22], [49], [50] and write a critical synopsis on biometrics as a whole and on face recognition.
2) Read and plot various images in the AT&T database using the MATLAB Image Processing Toolbox. What distinguishes the various images of a particular subject?
3) Plot the log magnitude of the 2-D DCT of various images and observe where most of the energy concentration is.
4) Write a general MATLAB program that (1) converts an image into a 2-D DCT, DST and FWHT and (2) scans the 2-D transform as in Figure 9 to get a 1-D feature vector. The 1-D feature vector can be truncated to any length L by retaining only the first L components. Plot the 1-D feature vectors of length 9, 35 and 100 for any image in the database and comment on your results. Do the same for an image from another subject. Do you observe any differences between the feature vectors of the two subjects?
5) For each subject, the first five image files are used to train the face identification system. The remaining five image files are used for identification success rate (ISR) computation. First, use the kNN classifier with the L2 distance measure. Investigate the ISR as a function of the dimension of the feature vectors (from 25 to 100 in steps of 15) and the variable k. Repeat for a weighted kNN and make up your own weighting scheme.

Figure 10. Pose variation of the training images of the first subject.

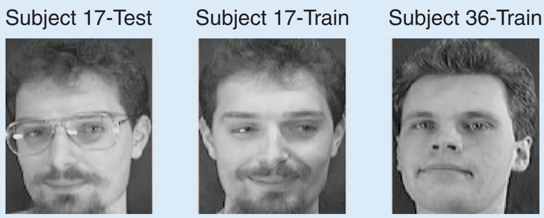

Figure 11. Illustration of a classification error.

6) Repeat above with a VQ classifier (L2 distance measure) such that the codebook size for each subject is 5 which is equal to the number of training feature vectors. No data compression is necessary. Investigate the ISR as a function of the dimension of the 1-D feature vectors (from 25 to 100 in steps of 15).
7) Repeat above by implementing a multilayer perceptron (MLP) neural network with one hidden layer. The training data of all classes are input to this network. For each experiment, perform 10 random runs to get an average ISR. Investigate the identification success rate as a function of the number of hidden layer nodes (10, 25, 40, 60, 80 and 100 nodes) and the dimension of the 1-D feature vectors (from 25 to 100 in steps of 15).
8) Perform a thorough comparison of all results.
9) Discuss one or two cases when an identification error occurs and explain.

One of the tasks above is to learn by plotting different images. Figure 10 depicts the five training images of the first subject in which there is pose variation. Another task is to comprehend why classification errors occur. An example of an error for the kNN classifier (with $k=1$) occurs for a test image of subject 17. The DCT feature vector of the test image is classified to be closest to the DCT vector of an image of subject 36 used in training. Figure 11 shows these two images along with the image of subject 17 used in training which would be the best match among the five images of subject 17 used in training. The error is due to the subject wearing glasses which is the phenomenon of occlusion.

Some suggestions were made for open-ended design:

1) Research other robust features like wavelet transforms.
2) Use the SMOTE algorithm [75] to get more training data and see if the performance improves.
3) Examine feature and classifier fusion strategies.
4) Implement an MLP classifier using a parallel structure as was done in [27] for blind signal to noise ratio estimation.
5) Read [76] and implement any ideas you find interesting.

C. Iris Recognition Project

Students experiment with the iris verification algorithm of Massek and Kovesi [55], [77] in which the iris pattern is converted into a bit stream. The distance between any two iris images is the fractional Hamming distance (FHD) between the corresponding bit streams. The freely downloadable MATLAB code [77] is appropriately modified to suit this project and is supplied to the students. The instructors also supplement the code in [77] for implementing this project. The objectives are for students to run the system and write code to plot ROC curves and estimate the equal error rate (EER) for various cases of clean images (uncorrupted bit patterns) and corrupted bit patterns. Forty subjects from the CASIA-IrisV3-Interval database [78] (configured by the Chinese Academy of Sciences) are used. The first experiment is to train and test on clean images and see the effect of establishing a verification threshold during training on the test condition.

1) Training on clean images:
   a) Use the clean images of the first 20 subjects for training.
   b) Compute the fractional Hamming distance (FHD) between the bit streams corresponding to all pairs of images of the same subject (intraclass distances), except of course between two identical images for which the FHD is 0.
   c) Compute the fractional Hamming distance (FHD) between the bit streams corresponding to all pairs of images of different subjects (interclass distances).
   d) Plot the probability density functions (histograms) of the intraclass and interclass distances on the same graph.
   e) Write code to plot the ROC for the training data. Estimate the EER and the threshold that gives this EER. Select this threshold as the one to use for the clean test condition.
2) Testing on clean images:
   a) Use the clean images of subjects 21 to 40 (inclusive).
   b) Run true and impostor trials with the threshold found for obtaining the EER on the training data. What are the resulting false accept rate

(FAR) and false reject rate (FRR) on this test data? How does it compare with what was obtained for the training data?

The second experiment is to observe the effect on the EER when the bit patterns of the clean images (subjects 21 to 40) are corrupted by random errors (equivalent to a noisy iris image). The bit error rates considered are 0.01, 0.001 and 1.0e-07. Students do the following:

1) Plot and interpret the probability density functions of the intraclass and interclass distances for the various bit error rates.
2) Use the threshold obtained from the clean training data and determine the FAR and FRR? How do these vary with bit error rate?
3) Write code to plot the ROC curve and estimate the EER for the various bit error rates. How does the EER vary with the bit error rate?

V. Assessment Results

The first set of assessment results are given for the speaker recognition project. Table 1 gives the results for the student survey taken after performing the project.

Table 1.
Project outcome survey results.

1 - Strongly disagree, 2 - Disagree, 3 - Neutral, 4 - Agree, 5 - Strongly Agree

Statement	Mean	Median	Standard Deviation
The project helped reinforce MATLAB software skills.	4.42	4	0.63
The project enriched mathematical and analytical skills.	4.31	4	0.65
The project helped reinforce written communication skills.	3.91	4	0.69
The project provided background in pattern recognition and biometrics as it applies to speech processing.	4.09	4	0.53
The open-ended part of the laboratory project helped me gain research experience on the performance aspects of speech based biometric systems.	4.25	4	0.67
The laboratory project was a good overall learning experience.	4.03	4	0.69
I believe that the knowledge set and skills I have obtained in this project/class make me better qualified for graduate study and/or career options in biometrics.	4.31	4	0.69
I am now more likely to follow popular media news/developments/programs that relate to biometrics as compared to before doing the project.	4.03	4	0.65

Table 2.
Rubrics for speaker recognition project.

Outcome	Score of 4	Score of 3	Score of 2	Score of 1
Synopsis of papers	The synopsis was well written. A clear understanding was shown.	The synopsis was well written. A complete understanding was not shown.	The synopsis was poorly written. No clear understanding was demonstrated.	The synopsis was not written.
Frame selection	Students implemented and understood both energy thresholding method based on linear prediction.	Energy thresholding implemented correctly. Minor flaws in linear predictive method.	Minor flaws when implementing both energy thresholding and linear predictive method.	Frame selection was not attempted.
Feature extraction and speaker identification performance	Students correctly implemented all six feature extraction methods and did a performance evaluation.	Students correctly implemented four or five feature extraction methods and did a performance evaluation.	Students correctly implemented two or three feature extraction methods and did a performance evaluation.	Students either implemented one method or did not attempt feature extraction.
Open-ended design component	Students implemented one idea of their own, did a performance evaluation and explained all results.	Students implemented one idea of their own, did a performance evaluation but had difficulty explaining the results.	Students explained one idea of their own but made mistakes in algorithm implementation.	Students did not explore any idea of their own.

Table 3.
Rubric statistics.

Outcome	Mean	Median
Synopsis	3.03	3
Frame selection	3.72	4
Feature extraction and performance evaluation	3.44	4
Open-ended design	2.59	3

These questions have been used before [61]–[63]. The survey results in [61]–[63] are only based on running the project at Rowan University. Table 1 gives the results based on combining the responses of Rowan University and Bucknell University students.

Students were also surveyed on their perception of vertical integration by asking about what previous courses had material which was connected with the lab project. Ninety-four percent of the students indicated that courses in Linear Systems and Signal Processing are very significant. Eighty-one percent of the students responded that courses in mathematics (calculus, linear algebra and probability) were needed for the project.

Rubrics were developed to quantify student achievement of specific speaker recognition project instructional outcomes. For each instructional outcome, a score of 1 to 4 was given based on student performance as evidenced by the project lab report. The advantages of using rubric based assessment are that it gives a quantitative judgement of student knowledge, requires little extra work in the grading process, requires no additional training for faculty to use, and avoids complete reliance on student self-reporting through surveys. Table 2 gives the outcomes and levels of achievement for the speaker recognition project. Table 3 gives the statistics based on combining the rubric assessment scores for Rowan and Bucknell students. The challenge is to have students pursue their own idea through open-ended design.

For the face recognition project, the same type of student surveys were taken and results on project outcomes and the perception of vertical integration are very similar to that of the speaker recognition project (more details are given in [62][63]). The rubrics are generally different for the face recognition project. The commonly assessed outcomes are the synopsis based on the reading assignments, feature extraction and the open-ended design. There are specific outcomes relating to the implementation of the three classifiers (kNN, vector quantizer and neural network) and the identification error analysis.

VI. Summary and Conclusions

This paper discusses the motivation of using vertical integration as a powerful curricular tool to allow students to remove artificially created course boundaries and realize that concepts gained in one course easily flow into new concepts gained in future experiences. Vertical integration is also a key factor in addressing the acute need to bring modern topics into all levels of the undergraduate curriculum particularly with little or no additional resources. This paper describes the effort at integrating biometrics throughout the curriculum. Biometrics has global significance, a growing job market and great societal impact. The focus is on three senior level projects (speaker, face and iris recognition) from a systems, software implementation, design and STEM perspective. Vertical integration at the freshman through junior levels is vital in the success of these projects. Quantitative assessment results based on student surveys and faculty formulated rubrics show that learning outcomes have been achieved.

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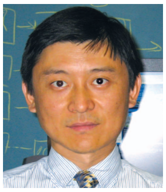

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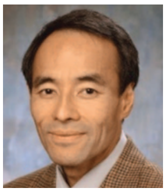

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