INTEGRATING ANALYTIC AND APPEARANCE ATTRIBUTES FOR HUMAN IDENTIFICATION FROM ECG SIGNALS

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ABSTRACT

In this paper, we investigate identification of human subjects from electrocardiogram (ECG) signals. We segment the ECG records into individual heartbeat based on the localization of R wave peaks. Two types of features, namely analytic and appearance features, are extracted to represent the characteristics of heartbeat signal of different subjects. Feature selection is performed to find out significant attributes. We compared the performance of different classification algorithms. To better utilize the advantages of different types of features, we proposed two schemes for data fusion and classification. Our system achieves promising results with 100% correct human identification rate and 98.90% accuracy for heartbeat identification. The proposed framework reveals the potential of employing appearance based analysis in ECG signal, yet demonstrates the advantage of a hierarchical architecture in pattern recognition problems.

1. INTRODUCTION

Analysis of electrocardiogram (ECG) signal has been an active research area in the past two decades. Most of the past works was motivated by applications in clinical diagnoses. Recently, another potential application of ECG analysis has drawn more attention in the research community. Human individuals presents different patterns in their ECG regarding wave shape, amplitude, PT interval etc. due to the difference in the physical conditions of the heart [1]. This characteristic of ECG signal raises the potential of applying ECG for biometric identity recognition.

A wide range of biometric techniques have been investigated in the past, such as face, fingerprint, voice, etc., each has its strengths and weaknesses. One important issue in the design of a biometric system is the robustness against attacks. However, many of the existing biometrics are easy to be spoofed. For instance, face is sensitive to artificial disguise, fingerprint can be recreated using latex, voice is easy to mimic. ECG signal is the life indicator and thus can be used as a tool for liveness detection. Comparing with some other biometrics, ECG based biometric system is expected to be more universal and hard to mimic

Recently, much effort has been put into human identification from ECG signals. Israel et al [2] extract 15 attributes from each individual heartbeat. These attributes are basically distance measures between fiducial points extracted from the heartbeat signal. A Wilks' lambda based method is applied for feature selection, and Discriminant Analysis for classification. In another paper by Israel et al [3], ECG and face information are fused for personal identification. In this paper, ECG signal is represented by the same 15 attributes as in [1], and Principle Component Analysis (PCA) is used for face representation. The paper compares three different fusion techniques, and best identification accuracy is achieved by a simple combination of all the features. Paper [4] uses 30 features that are extracted from ECG equipment. These features focus more on the amplitude and wave duration information. Feature selection is performed based on the computation of correlation between different features. A multivariate analysis method is used for classification.

All the aforementioned works use attributes that are either distance measures or amplitude differences between wave peaks or valleys. These attributes represent certain characteristics of the signal. However, focusing on only a few representative points of the signal, some useful information might missed. Furthermore, as the number of classes increases, the complexity of the data also increases. In this case, it will be hard to use one single classifier to classify all the classes. In paper [5], a template matching method is used for prescreening, and then a neural network architecture is used based on the decisions from the previous step.

In this paper, we propose a new approach for identification of human subjects from ECG signals. Taking advantage of the existing works, we combine distance measure and amplitude difference attributes as analytic features for classification. Feature selection is performed to select significant attributes. Furthermore, inspired from the great success in face recognition, we perform appearance based feature extraction using Principal Component Analysis (PCA) and Linear Discriminant Analysis (LDA). We compare the performance of different classifiers. Two different data fusion methods are proposed and compared for classification.

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The remainder of this paper is organized as follows. Section 2 describes the ECG data. The methodology and technical description of the applied algorithms, including preprocessing, feature extraction, feature selection, and classification, are detailed in Section 3. Section 4 presents our data fusion schemes and experimental results, and finally conclusion is given in Section 5.

2. ECG DATA

An electrocardiogram (ECG) describes the electrical activity of the heart. The electrical activity is related to the impulses that travel through the heart. It provides information about the heart's rate, rhythm, and morphology etc. A typical ECG wave of a normal heartbeat consists of a P wave, a QRS complex and a T wave. Figure 1 depicts the basic shape of a normal ECG signal. The P wave reflects the sequential depolarization of the right and left atria. The QRS complex corresponds to depolarization of the right and left ventricles, and the T wave reflects ventricular repolarization [6].

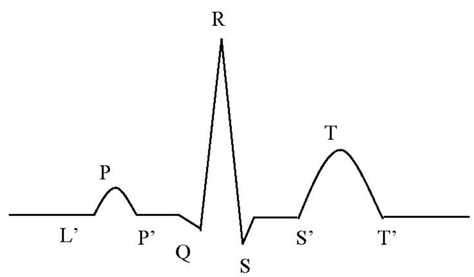

Figure 1: Basic shape of an ECG heartbeat signal

Normally, ECG is recorded by attaching a set of electrodes on the body surface such as chest, neck, arms, legs, etc. In this paper, we use ECG data from 13 normal subjects in the PTB database [7]. The ECG were recorded at a sampling rate of 1KHz with around 2 minutes each record. Figure 2 shows some of the examples.

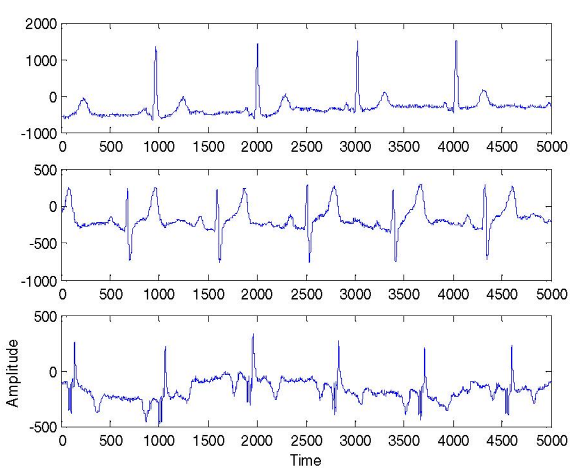

Figure 2: Examples of the applied ECG data

3. METHODOLOGY

Human identification is essentially a pattern recognition problem which basically involves four stages: preprocessing, feature extraction, feature selection, and classification. In this section, we detail the procedure and algorithms that will be applied in our system.

3.1 Pre-processing

The collected ECG data usually contain noise, which include low-frequency components that cause baseline wander, and high-frequency components such as power-line interferences. Generally, the presence of noise will corrupt the signal, and make the feature extraction and classification less accurate. To minimize the negative effects of the noises, a de-noising procedure is important. In this project, we use a Butterworth band-pass filter to perform noise reduction. The cutoff frequencies of the BP filter is selected as 1Hz-40Hz based on empirical results.

After noise reduction, we perform R peak detection using a QRS detector called ECGPUWAVE [8]. The output of this detector is a file that contains the R peak time index. We eliminate the first and last heartbeat to get full heartbeat signals. A thresholding method is then applied to remove the outliers that are not appropriate for training and classification. In the last step, the heartbeats of a record is aligned by the R peak position and truncated by a window of 0.8 second (800 samples) centered at R. This window size is estimated by heuristic and empirical results such that P and T peaks can also be included and thus most of the information retained. By preprocessing, we convert the one dimension time domain signal into a matrix of $N \times 800$, where N represents the number of valid heartbeats in a record. Figure 3 gives a graphic illustration of the applied preprocessing approaches.

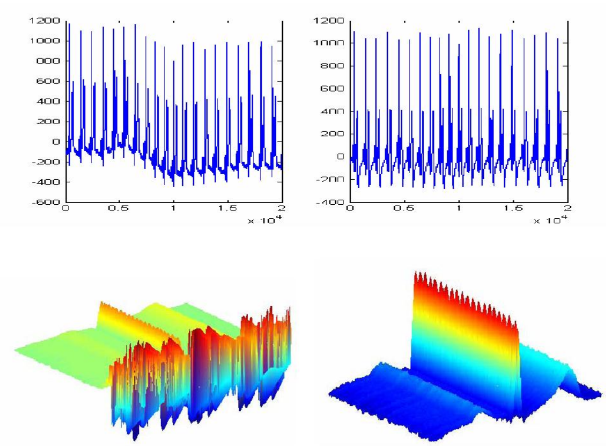

*Figure 3: Preprocessing (**Top left:** original signal; **Top right:** noise reduced signal; **Bottom left:** original aligned signal; **Bottom right:** aligned signal after outlier removal)*

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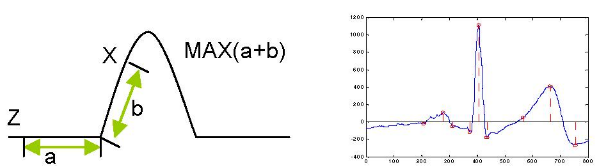
3.2 Feature Extraction

To build an efficient human identification system, the extraction of features that can truly represent the characteristics of a subject is a real challenge. Different types of features have been studied in the past. Most of these studies use distance measures [2, 3] or amplitude differences [4] as features for classification. These features are usually being extracted by analyzing and localizing some fiducial points from the signal, and we call them analytic features in our paper. The analytic features capture certain characteristics of the signal, and can achieve good recognition accuracy if the features are perfectly and properly identified. However, due to the constraint that these features are only based on a few points, some useful information might be lost.

Another intuitive method to perform classification is to use the original data directly. However, in most cases, the dimensionality of the raw data is high, and thus not suitable for classification. Furthermore, raw data may contain noise and redundant information that are not appropriate for our classification purpose. To overcome these problems, transform domain methods are usually applied to reduce the dimensionality whilst expecting better classification accuracy. Among these algorithms, PCA and LDA are two popular ones. The features that are extracted in this manner are usually called appearance features. In this project, we investigate both analytic and appearance features.

3.2.1 Analytic Feature Extraction

For the purpose of comparative study, we follow similar feature extraction procedure as described in [2]. The fiducial points are depicted in Figure 1. As we have detected R point in preprocessing step, the Q, S, P, and T positions are localized by finding local minima and maxima separately. To find the L', P', S', and T' points, we use a method as shown in Figure 4-a. The X and Z points are fixed and we search downhill from X to find the point that maximizes the sum of distances *a+b*. Figure 4-b gives an example of our fiducial points localization.



(a) *(b)*

Figure 4: Fiducial points determination

The extracted attributes are distance measures and amplitude differences between these fiducial points. We extracted 15 distance features, which are exactly the same as described in [2], and 6 amplitude features. Figure 5 depicts these features graphically, while Table 1 lists all the features.

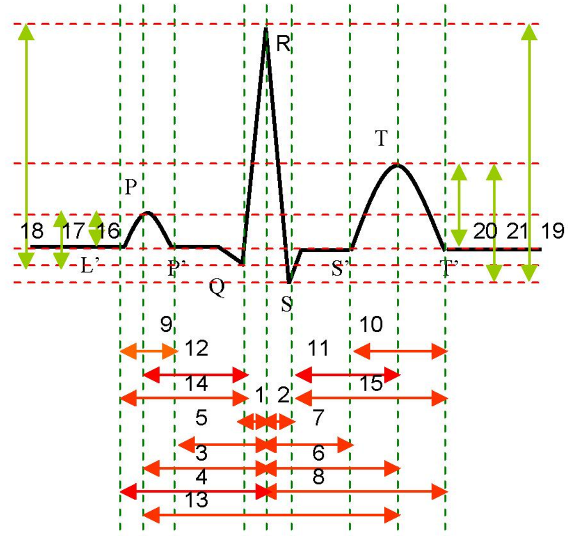


Figure 5: Graphical representation of extracted features

	Extracted Attributes				
Dis	1. RQ	4. RL'	7. RS'	10. S'T'	13. PT
	2. RS	5. RP'	8. RT'	11. ST	14. LQ
	3. RP	6. RT	9. L'P'	12. PQ	15. ST'
Amp	16. PL'		17. PQ		18. RQ
	19. RS		20. TS		21. TT'

Table 1: List of extracted analytic features

3.2.2 Appearance Feature Extraction

Principal Component Analysis (PCA) and Linear Discriminant Analysis (LDA) are transform domain methods for data reduction and feature extraction. In this section, we provide a brief description of the techniques.

PCA reduces the dimensionality of the data by performing eigen-analysis on the covariance matrix of the original data. The covariance matrix S of a set of data $\mathbf{x}$ can be computed as:

$$\mathrm{S} = \frac{1}{N}\sum_{i=1}^{C}\sum_{J=1}^{C_i}(\mathbf{x}_{ij} - \overline{\mathbf{x}})(\mathbf{x}_{ij} - \overline{\mathbf{x}})^T \tag{1}$$

where N is number of samples, C is the number of classes, C_i is the number of samples in the corresponding class, and $\overline{\mathbf{x}} = \frac{1}{N}\sum_{i=1}^{C}\sum_{j=1}^{C_i}\mathbf{x}_{ij}$ is the average of the ensemble. The covariance matrix is a square matrix, and thus the eigenvectors and associated eigenvalues can be calculated. Ordering the eigenvectors by sorting the associated eigenvalues from the highest to the lowest gives the components in order of significance. The components with less significance can be ignored and thus dimension reduction can be achieved. Once we have chosen the components that we wish to keep in our data, we can get the new dimensional-reduced data by $\mathrm{y} = \mathrm{w}^T(\mathrm{x} - \bar{\mathrm{x}})$ where w^{T} is the matrix with the eigenvectors transposed [9].

LDA is another representative approach for dimension reduction and feature extraction. Fisher's LDA find a set of M feature basis vectors w by maximizing the ratio of between-class and within-class scatter matrix. This can be deduced by solving the generalized eigenvalue problem:

$$\mathrm{w} = \arg\max_{\mathrm{w}} \frac{|\mathrm{w}^T \mathrm{S}_b \mathrm{w}|}{|\mathrm{w}^T \mathrm{S}_w \mathrm{w}|}, \mathrm{w} = \{w_1, \cdots w_M\}, \tag{2}$$

where S_b and S_w denote the between-class and within-class scatter matrix and can be computed as:

$$\mathrm{S}_b = \sum_{i=1}^{C} \frac{C_i}{N} (\overline{\mathrm{x}_i} - \overline{\mathrm{x}})(\overline{\mathrm{x}_i} - \overline{\mathrm{x}})^T \tag{3}$$

$$\mathrm{S}_w = \frac{1}{N} \sum_{i=1}^{C} \sum_{j=1}^{C_i} (\mathrm{x}_{ij} - \overline{\mathrm{x}_i})(\mathrm{x}_{ij} - \overline{\mathrm{x}_i})^T \tag{4}$$

LDA find w as the first M most significant eigenvectors of $\mathrm{S}_w^{-1}\mathrm{S}_b$ that correspond to the first M largest eigenvalues. Similar as in PCA, the original data can be mapped to the LDA domain by a simple linear projection: $\mathrm{y} = \mathrm{w}^T \mathrm{x}$ [10].

3.3 Feature Selection

The ultimate goal of feature selection is to choose a number of features from the extracted feature set that yields minimum classification error. Due to the high computational complexity in exhaustive search, suboptimal approaches are usually preferred. In this project, we perform feature selection using the stepwise method in SPSS (a trademark of SPSS Inc. USA). The stepwise method starts from one feature and adds one feature each time. The evaluation is based on Wilks' Lambda. Wilks' Lambda measures the differences between the mean of different classes on combinations of dependent variables and thus can be used as a test of the significance of the features.

3.4 Classification

In this paper, we use several different classification algorithms, including nearest center, K-nearest neighbors, and Linear Discriminant Analysis (LDA). Nearest center is a simple classification method that labels a new entry as the class that gives the minimum distance to the class center. K-nearest neighbors is a non-parametric method for classification. It assigns a class label to the new entry by examining its k nearest neighbors in the training data. The k value can be determined by using leave-one-out cross-validation. We have discussed LDA method for feature extraction in Section 3.2.2. When LDA is used as a classifier, it assumes a discriminant function for each class as a linear function of the data. The coefficients of these functions can be found by solving the eigenvalue problem as described in Section 3.2.2. An input data is classified into the class that gives the greatest discriminant function value. When LDA is used for classification, it is applied on the extracted features, while for feature extraction, it is applied on the original data.

4. EXPERIMENTS AND DISCUSSION

In this section, we present our experimental results. The experiments we performed are based on ECG signals from 13 subjects. We use one record from each subject as the training data, and use another record as the testing data. The two records were collected a few years apart. The evaluation is based on subject and heartbeat identification accuracy. Subject identification accuracy is determined by majority voting, while heartbeat identification accuracy only takes individual heartbeat sample into account.

4.1 Analytic Features

In our first experiment, we perform experiments on the 15 distance measures only to compare with [2]. A Wilks' Lambda method selects 9 features and LDA is applied for classification. This method achieves a total human identification rate of 84.61%, and heartbeat identification rate of 74.45%.

Known inputs

Detected outputs	1	2	3	4	5	6	7	8	9	10	11	12	13
1	96	0	0	0	2	0	0	0	3	0	41	0	1
2	0	84	1	0	19	3	0	4	2	17	0	0	0
3	0	20	100	0	2	2	0	0	9	0	0	0	0
4	1	4	0	94	3	0	0	0	2	21	15	0	2
5	0	0	0	0	23	0	0	0	0	1	0	0	0
6	0	0	5	5	1	107	0	1	0	0	0	0	0
7	0	0	0	6	41	5	114	0	0	4	0	0	8
8	0	0	1	18	2	0	0	110	4	3	0	0	0
9	1	1	0	0	0	0	0	0	21	0	15	0	0
10	0	0	0	0	2	0	0	0	0	61	0	0	4
11	21	0	0	0	0	0	0	0	22	0	79	0	0
12	0	0	0	0	0	1	0	0	0	0	0	91	0
13	10	0	0	0	2	0	0	0	0	13	2	0	107

Human identification rate: 11/13=84.61%, Heartbeat identification rate: 74.45%

Table 2: Confusion matrix by using distance features

As shown in Table 2, the heartbeats of individual subject are confused with many other subjects. Only the heartbeats from two subjects are 100% correctly identified. This demonstrates that the feature extraction can not efficiently distinguish different subjects. In our second experiment, we add amplitude attributes to the feature set. This approach achieves significant improvement with human identification

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rate of 100%, and heartbeat recognition rate of 92.40%. The confusion between different classes is very well alleviated, and the heartbeats form 5 subjects are 100% identified. The all-class scatter plot of the two experiments is shown in Figure 6. Different classes are much better separated by adding the amplitude features.

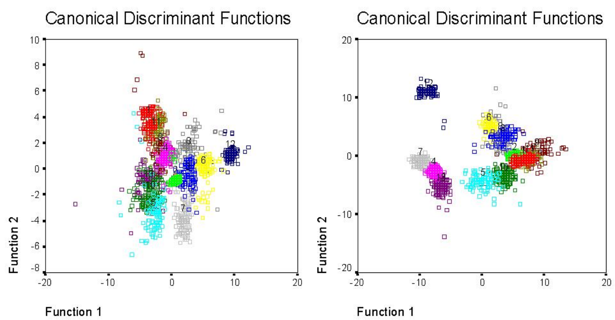


Figure 6: All-class scatter plot: Distance measures (left), and all analytic features (right)

experiment	Index of selected features
1	1,2,3,5,10,11,12,13,14
2	1,2,5,6,9,10,11,12,13,16,17,18,19,20,21

Table 3: List of selected features

Table 3 lists the selected features in both experiments. In the first experiment, 9 features are selected. It can be easily observed from Figure 5 that some of the features are actually overlapped and thus are redundant. For instance, if we use F denotes feature, then $F4=F1+F14$, and thus feature 4 is redundant and not included in our feature selection. In experiment 2, the last six selected features correspond to the six extracted amplitude features and are all retained after the selection process. This further explains that these features are significant and our results are actually greatly improved. The selected distance features are not exactly the same as selected in experiment 1. This is due to the selection algorithm also takes the amplitude features into account in the computation. Actually, the significant information in distance features is still reserved. For instance, although $F14$ is not selected, but $F9$ is included, and $F14=F5+F9-F1$.

4.2 Appearance Based Features: PCA *vs* LDA

In this paper, we compare the performance of PCA and LDA using Nearest Center (NC), and K-nearest Neighbors (K-NN). An important issue in appearance based approach is how to find the optimal parameters for classification. For a C class problem, LDA can reduce the dimensionality to C-1 due to the fact that the rank of the between-class matrix can not go beyond C-1. However, these C-1 parameters might be not the optimal ones for classification. Exhaustive search is usually applied to find the optimal LDA-domain features. In PCA parameter determination, we use a criterion by taking the first M eigenvectors that satisfy $\sum_{i=1}^{M} \lambda_i \big/ \sum_{i=1}^{N} \lambda_i \geq 90\%$, where λ_i is the eigenvalue, N is the dimension of feature space.

	NC		K-NN	
	Human	Heartbeat	Human	Heartbeat
PCA	84.61%	82.81%	100%	95.55%
LDA	100%	86.64%	100%	93.01%

Table 4: Experimental results of PCA and LDA

Table 4 shows the experimental results. The best recognition accuracy is achieved by using PCA with a K-NN classifier. Heartbeats from eight subjects are 100% correctly identified. Both PCA and LDA achieve better identification accuracy than analytic features. This reveals that the appearance based analysis is a good tool for human identification from ECG. Although LDA is more class specific and normally performs better than PCA in face recognition problem [10], the inherent characteristics of the ECG signal or the data that we applied in our experiments may accounts for this inverse situation. As PCA performs better in our particular problem, we use PCA for the analysis hereafter.

4.3 Simple Integration

A simple data fusion scheme is to put the extracted features into one vector. Figure 7 shows the block diagram of such a system. This system achieves 96.78% and 96.03% heartbeat recognition rate by using LDA and K-NN as classifiers respectively. In both cases 100% human identification rate is obtained. The combination of these two types of features indeed improves the performance of the system.

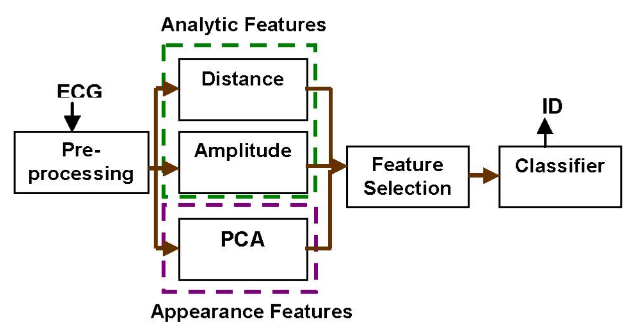


Figure 7: Block diagram of simple integration

4.4 Hierarchical Scheme

A central consideration in our development of classification scheme is trying to change a large-class-number problem into a small-class-number problem. In pattern recognition, when the number of classes is large, the boundaries between different classes tend to be complex and hard to separate. It will be much easier if we can reduce the possible number of classes and perform classification in a smaller scope. Using a hierarchical architecture, we can first classify the input into a few potential classes, and a second level classification can be performed within these classes.

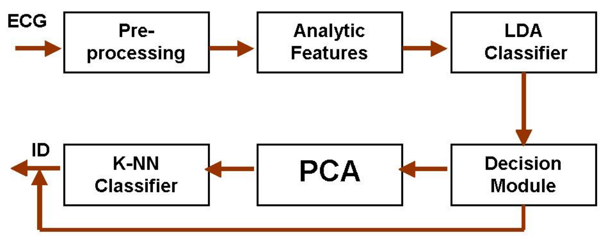


Figure 8: Block diagram of hierarchical scheme

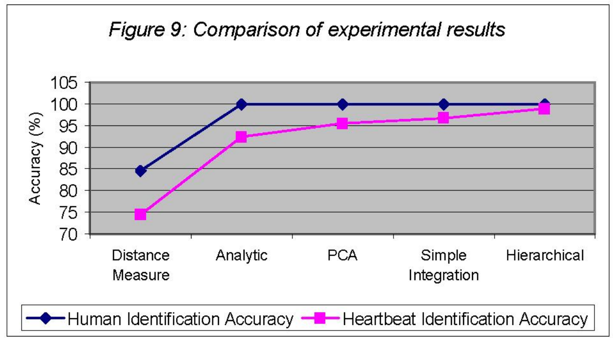
Figure 8 shows the diagram of the proposed hierarchical scheme. At the first step, only analytic features are used for classification. The output of this first level classification provides us the potential classes that the entry might belongs to. If all the heartbeats are classified as one subject, the decision module output this result directly. If the heartbeats are classified as a few different subjects, a new PCA based classification module which is dedicated to classify these confused subjects is then applied. We select to perform classification using analytic features first is due to the simplicity in feature selection. A feature selection in each of the possible combinations of the classes is computational complex. By using PCA, we can easily set the parameter selection as one criterion and important information is guaranteed to be retained. This is well supported by our experimental results. This scheme achieves 100% human identification rate and 98.90% heartbeat recognition accuracy.

The proposed hierarchical scheme outperforms simple integration. This "divide and conquer" mechanism maps global classification into local classification and thus reduces the complexity and difficulty. The advantage of such hierarchical architecture is general and can also be applied to other pattern recognition problems.

5. CONCLUSION

This paper explores a combined analysis of analytic and appearance attributes for human identification from ECG signals. Figure 9 compares the performance of different feature sets and classification schemes. Our proposed system achieves significant improvement over existing works. The experimental results demonstrate that appearance based features can successfully capture the characteristics of ECG signal of different human subjects. The combination of analytic and appearance attributes provides better representation and thus higher accuracy. The proposed hierarchical classification schemes reduce a large-class-number problem to a small-class-number problem and further enhance the performance of the system.

Figure 9: Comparison of experimental results



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