ECG Analysis: A New Approach in Human Identification

Lena Biel, Ola Pettersson, Lennart Philipson, and Peter Wide

***Abstract*—In this paper, a new approach in human identification is investigated. For this purpose, a standard 12-lead electrocardiogram (ECG) recorded during rest is used. Selected features extracted from the ECG are used to identify a person in a predetermined group. Multivariate analysis is used for the identification task.**

Experiments show that it is possible to identify a person by features extracted from one lead only. Hence, only three electrodes have to be attached on the person to be identified. This makes the method applicable without too much effort.

***Index Terms*—Data fusion, electrocardiogram (ECG), feature extraction, human identification, multivariate analysis.**

I. Introduction

A. Background

AUTOMATIC human identification has potential applications in many different areas where the identity of a person needs to be determined. In security systems, e.g., an authorization check at a door, different approaches could be used. The easiest way could be using a code lock [1]. To reach a higher security level, more complex systems are needed. Specific features from the human must be selected to recognize a person. A lot of work has been done on human face identification [2]. These methods need a high-resolution computer vision system. Here, facial features, generally anthropometric face structures, are collected. Other methods used in this area include voice recognition [3], palm recognition [4], and, the most common, finger print identification. The eye also contains specific features in both the retina and iris [5].

In virtually all of the above-mentioned identification methods, the person has to go to a special place. The person must put his hand or thumb in a scanner, his eye near a vision system, speak in to a microphone, etc. It is very difficult to implement the methods for identification on moving humans.

In this paper, we will investigate a new approach for human identification, namely electrocardiogram (ECG) analysis.

B. ECG

ECG [6] is a method to measure and record different electrical potentials of the heart. Willem Einthoven developed the ECG method in the early 1900s. The origin of the electrical activity measured by ECG is in the muscle fibers of different parts of the heart. The ECG may roughly be divided into the phases of depolarization and repolarization of the muscle fibers making up the heart. The depolarization phases correspond to the P-wave (atrial depolarization) and QRS-wave (ventricles depolarization). The repolarization phases correspond to the T-wave and U-wave (ventricular repolarization). The elements in the ECG-complex are shown in Fig. 1. The ECG is measured by placing ten electrodes on selected spots on the human body surface. Six electrodes are placed on the chest, and four electrodes are placed on the extremities.

Manuscript received May 26, 1999; revised December 18, 2000. This research work was performed within the Applied Autonomous Sensor Systems (AASS) group, the Department of Technology, Örebro University, Örebro, Sweden.

The authors are with the Technology and Science Department, Örebro University, Örebro, Sweden.

Publisher Item Identifier S 0018-9456(01)04379-0.

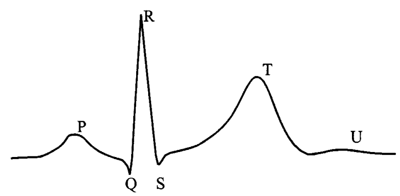

Fig. 1. Elements of the ECG-complex.

For regular ECG recordings, the variations in electrical potentials in 12 different directions out of the ten electrodes are measured. These 12 different electrical views of the activity in the heart are normally referred to as leads. The 12 leads are made up of three bipolar and nine monopolar leads. The three bipolar leads are the electrical potentials between the right and left arm (lead I), the right arm and left foot (lead II), and between the left arm and left foot (lead III). For the monopolar leads, four different artificial reference points are constructed. These reference points are the average of the signals seen at two or more electrodes [7]. Using these reference points, the potentials appearing on the left arm (aVL), the right arm (aVR), the left foot (aVF), and on the six chest electrodes (V1-V6) are measured. The right foot is normally used for grounding purposes only.

In the past, there have been many approaches to automatically generate diagnostic ECG classification based on the 12-lead electrocardiogram. Both statistical methods and artificial neural networks have been used [8]–[11].

II. Measurement Model

The information in the measured heart signal is processed in three steps

1) the ECG equipment;
2) feature selection;
3) soft independent modeling of class analogy (SIMCA).

From the digitalized signal, 30 features are generated by the ECG equipment (see Section IV-A for details). All these features are normally used for help with clinical diagnoses.

In step two, the amount of data is reduced when specific features are selected. Motivation of these selections is further described under Analysis in Section IV.

Classification is made, in the third step, using SIMCA. In order to use the SIMCA classifier for identification of a particular subject, the model has to be "taught" the specific features of the subject. This is accomplished by presenting a set of measurements for each subject to the classifier. Based on these data sets, a statistical model for each person is constructed. Thus a group of statistical models is built and stored.

Once this training process is done, the SIMCA classifier can be presented new ECG data from one randomly selected person belonging to the original group of subjects. The SIMCA classifier then picks the person providing the best match in the group as output.

III. Experiments

All measurements are done with 12-lead rest ECG recordings which are composed of six limb leads and six chest leads.

It has been shown that the variation in positioning of the chest electrodes will cause differences in the diagnosis of a disease [12]. The average difference in electrode placement on the chest is 3 cm. As shown, the placement of chest electrodes is important for diagnostics, and the same assumption has been made for person identification. The chest electrodes were, therefore, removed and replaced to start a new measurement. Since the placement of the limb electrodes is not as critical, they were not removed between the measurements.

The measurements in the experiment have been done as follows:

1) The ten electrodes were placed on the person to be identified.
2) The person was allowed to rest for a while.
3) An ECG recording was done.
4) The chest electrodes were removed.
5) The chest electrodes were replaced on the person.
6) The procedure was repeated from step 2 between four and ten times.

ECG measurements have been done on 20 persons. The ages of the persons vary between 20 to 55 years old. Both women and men have been participating in the experiment. For a minor group, ten ECG measurements have been done. For the rest of the group, four or five ECG measurements were done. All measurements are done within a time period of six weeks.

Three operators have been involved in placing the electrodes. To insure that the operator who places the electrodes does not affect the classification, all three operators have been involved in the measurements on some persons. This showed that it is not possible to distinguish a person depending on who has performed the ECG measurement.

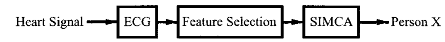

Fig. 2. Measurement model.

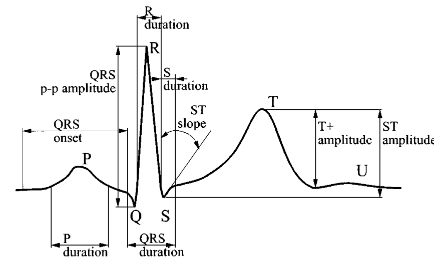

Fig. 3. Features used for classification.

IV. Analysis

A. Feature Selection

The equipment used for the measurements is a SIEMENS Megacart. The information from the SIEMENS ECG is transferred and converted to a usable format. The results from the conversion will be 360 (30 x 12 leads) features for each person to be identified. The features delivered from this device are defined in Appendix A.

Calculation of the correlation matrix shows a strong correlation between the different leads for a specific feature. The first reduction is to use data only from the chest leads or limb leads. Tests have shown small differences between using the limb leads and the chest leads. The reason for choosing the limb leads is that it is easier to attach the corresponding electrodes compared to the chest leads. Usage of just limb leads will reduce the number of features to 180.

The reason why "limb I" has been chosen for further feature reduction is the simplicity of electrode attachment. One limb lead requires that only two electrodes plus one ground electrode are placed on a person.

To reduce the amount of information further, the correlation matrix is studied again. Features with a relatively high correlation with other features are removed. This will reduce the number of features to 12. After that, the reduction must be based on tests. One possible feature set is defined in Fig. 3. This set will be used together with the T morphology.

B. Classification

The method used to classify persons is SIMCA [13]. The SIMCA model will find similarities between test objects and classes rather than find identical behavior. The first step in SIMCA modeling is to build a principal component analysis (PCA) [13] model for each class. PCA is a mathematical transform which is used to explain variance in experimental data. The data matrix consists of a number of experiments, each consisting of a number of variables (values). PCA decomposes

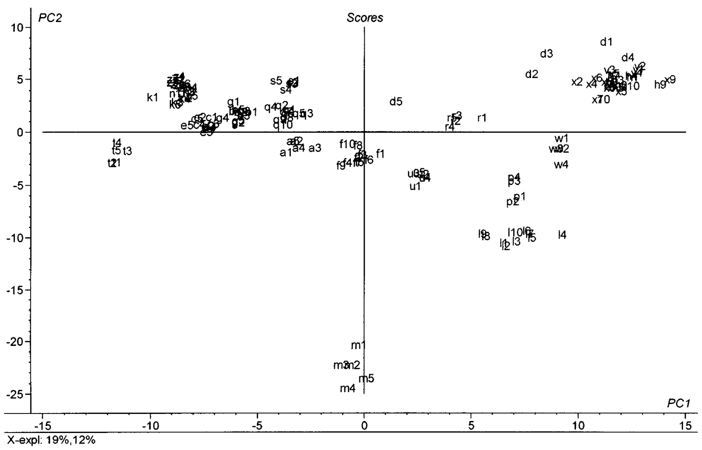

Fig. 4. PCA score plot using all data and features.

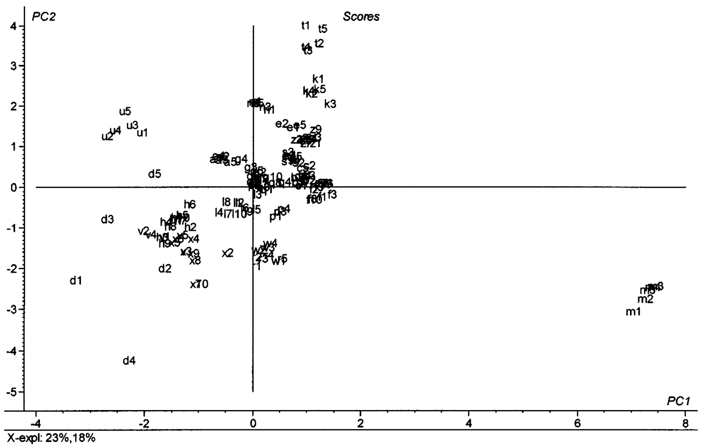

Fig. 5. PCA score plot using all data and 10 features.

the data matrix into latent variables, which, successively, account for as much variance as possible. The score vectors describe the direction of the principal components in relation to the observations. A score plot shows the relations between the observations, or experiments. Clusters of observations can be indicating classification properties. PCA is also a method for data reduction [14], [15].

Eighty-five measurement sets have been used for building models of the 20 different classes. Depending on how many measurements have been done on each person, the training set will vary.

When the training set and the different classes are known, supervised training [13] can be used. Otherwise, the classes must be identified by pattern recognition.

The classification test set consists of 50 samples. The number of samples per person will vary depending on the number of measurements that have been done on each person. The results are calculated with a significance of 5%, which means there is a 5% risk that the object will fall outside the class even if it belongs to it.

TABLE I
CLASSIFICATION RESULTS

Test	No. of features	No. of correct classified (tot)
A	360	49 (50)
B	180 (chest leads)	49 (50)
C	180 (limb leads)	49 (50)
D	30 (I lead)	49 (50)
E	21 (zeros removed)	49 (50)
F	12	49 (50)
G	10 [1]	50 (50)
H	7	45(50)

TABLE II
ALL THE 30 FEATURES DELIVERED FROM THE SIEMENS MEGACART

No.	Features
1	P wave onset
2	P wave duration (ms)
3	QRS wave onset
4	QRS wave duration (ms)
5	Q wave duration (ms)
6	R wave duration (ms)
7	S wave duration (ms)
8	R' wave duration (ms)
9	S' wave duration (ms)
10	P+ wave duration (ms)
11	QRS wave deflection (ms)
12	P+ wave amplitude (μV)
13	P- wave amplitude (μV)
14	QRS wave peak to peak amplitude (μV)
15	Q wave amplitude (μV)
16	R wave amplitude (μV)
17	S wave amplitude (μV)
18	R' wave amplitude (μV)
19	S' wave amplitude (μV)
20	ST segment amplitude (μV)
21	2/8 ST segment amplitude (μV)
22	3/8 ST segment amplitude (μV)
23	T+ wave amplitude (μV)
24	T – wave amplitude (μV)
25	QRS wave area (μV * ms)
26	T wave morphology [-2,2]
27	R wave notch existence
28	Delta wave confidence [0,100] %
29	ST segment slope [-90,90] deg
30	T wave onset

V. RESULTS

The PCA score plot can be used to interpret differences and similarities among the data samples. Fig. 4 shows a PCA score plot where all features are used. Both training and testing data are included in the plot. Each label corresponds to a measurement series. It is easy to see a number of classes in that plot. In Fig. 5, a PCA plot is shown when using all samples, but only ten features per sample. In this case, the classification properties are more difficult to distinguish.

The classification test procedure is performed as described in the previous chapter. The results are shown in Table I. The numbers of correct classifications are the same, independent of using 360 features or 21 features from one lead. We conclude that the ECG measurement contains a lot of redundant information. The misclassified sample in the measurements will vary between the tests; it is not a specific sample that is difficult to classify. This implies that each individual may have a feature making the measurement easy to classify if it is used in the classification procedure. Reducing the overall features will create new types of features to be used, and, therefore, the connections to the features are individually suited to the classification algorithm. The best results are found using ten features specified in Fig. 3. Reducing the number of features more will increase the number of misclassified samples. The sample must consist of contradictory features when they are used for classification. That is probably the reason why the best results are found for these ten features.

VI. CONCLUSIONS AND FURTHER WORK

A new approach in human identification is presented. This approach, namely ECG analysis, is shown to make it possible to identify persons from a predetermined group, e.g., a team of operators in an industry. The tests are done with a standard 12-lead rest ECG. This preliminary analyzed result shows that only one lead is enough to identify a person.

Further work will be to investigate how the ECG will vary over a longer time period and if it will affect the possibility to identify a person. Other interesting aspects are to investigate the effect of the person's normal working activities on the ECG. It would also be of interest to analyze if the proposal ECG measurement can give information about the person's state, i.e., how stressed an operator is, his/her overall physical health, etc.

APPENDIX A

Table II shows all 30 features delivered from the Siemens megacart.

ACKNOWLEDGMENT

The authors would like to thank S. Lunander for appreciated help on questions regarding medical terminology and for use of the equipment at the Department of Caring Sciences at Örebro University, Sweden. They also would like to thank the two master students, K. Hjelm and P. Johansson, who actually came up with this idea from the beginning.

REFERENCES

[1] R. Mizutani and T. Matsumoto, "Evaluating security of a simple interactive human identification scheme," *IEICE Trans. Fund. Electron., Commun. Comput. Sci.*, vol. E78A, no. 5, pp. 577–578, 1995.

[2] A. Samal and P. Iyengar, "Automatic recognition and analysis of human faces and facial expressions: A survey," *Pattern Recognit.*, vol. 25, no. 1, pp. 65–77, 1992.

[3] D. Dunn, "Using a multi-layer perceptron neural for human voice identification," in *Proc. Fourth Int. Conf. Signal Process. Applicat. Technol.*, Newton, MA, USA, 1993.

[4] W. Boles and S. Chu, "Personal identification using images of the human palm," in *Proc. IEEE TENCON Conf.*, Brisbane, Australia, 1997.

[5] W. Boles, "A security system based on human iris identification using wavelet transform," in *Proc. First Int. Conf. Knowledge-Based Intelligent Electron. Syst.*, New York, 1997.

[6] A. L. Goldberger and E. Goldberger, *Clinical Electrocardiography A Simplified Approach*, 5th ed. St. Louis, MO: Mosby, 1994, vol. 1, p. 341.

[7] J. G. Webster, *Medical Instrumentation, Application and Design*, 2nd ed. New York: Wiley, 1995, p. 814.

[8] R. Degani, *Computerized Electrocardiogram Diagnosis: Fuzzy Approach Methods of Inform. Med.*, vol. 31, pp. 225–233, 1992.

[9] P. Bozzola *et al.*, "A hybrid neuro-fuzzy system for ECG classification of myocardial infarction," in *Comput. Cardiol.*, Indianapolis, IN, 1996.

[10] G. Bortolan, C. Brohet, and S. Fusaro, "Possibilities of using neural networks for ECG classification," *J. Electrocardiol.*, vol. 29, pp. 10–16, 1996.

[11] R. Silipo and G. Bartolan, "Neural and traditional techniques in diagnositc ECG classification," in *Proc. ICASSP*, 1997.

[12] B. J. A. Schijvenaars *et al.*, "Effect of electrode positioning on ECG interpretion by computer," *J. Electrocardiol.*, vol. 30, no. 3, pp. 247–256, 1997.

[13] K. Esbensen, S. Schönkopf, and T. Midtgaard, *Multivariate Anal. in Practice*, 1st ed. Trondheim, Norway: Camo, 1994, vol. 1, p. 361.

[14] C. M. Bishop, *Neural Networks for Pattern Recognition*. New York: Oxford Univ. Press, 1995, p. 482.

[15] R. G. Gonzales and R. E. Woods, *Digital Image Processing*. Reading, MA: Addison-Wesley, 1992, p. 716.

Lena Biel received the M.S. degree in computer science and engineering at Luleå University of Technology, Luleå, Sweden, in 1993. Since 1998, she has been pursuing the Ph.D. degree at Örebro University, Örebro, Sweden, in the area of sensor fusion.

She has been employed at Bofors Defence (formerly Bofors Weapon Systems), Karlskoga, Sweden.

Ola Pettersson was born in Falkenberg, Sweden on March 7, 1972. He received the B.S. degree in electrical engineering in 1994, the M.S. degree in electrical engineering in 1995 (specialization in photonics and image analysis), both from Halmstad University, Halmstad, Sweden. In 2000, he received a Licentiate of Technology in computer science from Linköping University, Linköping, Sweden.

Since Fall 1996, he has been a graduate student at the Center for Applied Autonomous Sensor Systems, Örebro University, Örebro, Sweden. His current research interests include mobile robot action control, planning, and execution monitoring.

Lennart Philipson was born in Örebro, Sweden in 1952. He received the M.S. degree in electrical engineering from Chalmers University of Technology, Göteborg, Sweden in 1975 and the Ph.D. degree in biomedical engineering from Linköping University, Linköping, Sweden in 1987.

He has been with Örebro University, where he is the head of the Department of Technology, since 1994. He is currently interested in the detection and monitoring of physiologically generated electrical signals.

Peter Wide was born in 1955, in Karlskoga, Sweden. He received the Dipl. Eng. and Licentiate of Technology degrees in measurement and physics from the University of Linköping, Linköping, Sweden, in 1984 and 1987, respectively. He received the Ph.D.degree from Linköping University in measurement technology in 1996, with a thesis entitled "The human knowledge based sensor system—An integration between artificial intelligence and human experience."

He has been a Professor of measurement technology at Örebro University, Örebro, Sweden, since 1999. He is also the Research Director of the Center for Applied Autonomous Sensor Systems, including four research laboratories: Sensor and Measurement, Mobile Robotics, Intelligent Control, and Adaptive Learning Systems. His current research interests include sensors, feature extraction, artificial sensors, sensor data fusion, and quality measurements.