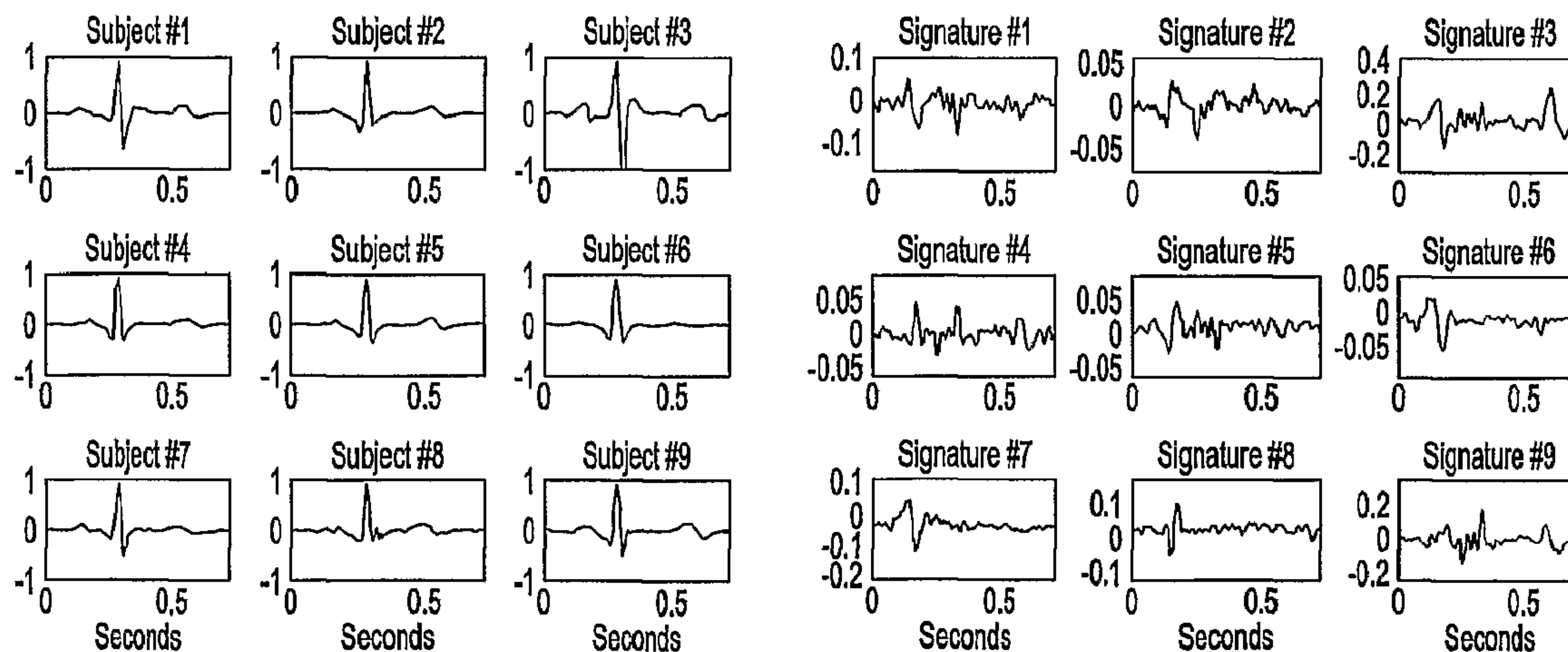




(86) **Date de dépôt PCT/PCT Filing Date:** 2005/11/08
(87) **Date publication PCT/PCT Publication Date:** 2006/06/08
(45) **Date de délivrance/Issue Date:** 2015/01/13
(85) **Entrée phase nationale/National Entry:** 2007/05/07
(86) **N° demande PCT/PCT Application No.:** IB 2005/003281
(87) **N° publication PCT/PCT Publication No.:** 2006/059190
(30) **Priorité/Priority:** 2004/11/08 (IL PCT/IB2004/03899)

(51) **Cl.Int./Int.Cl. A61B 5/117** (2006.01),
A61B 5/0452 (2006.01)
(72) **Inventeur/Inventor:**
LANGE, DANIEL H., IL
(73) **Propriétaire/Owner:**
INTEL CORPORATION, US
(74) **Agent:** SMART & BIGGAR

(54) **Titre : PROCÉDE ET APPAREIL DE RECONNAISSANCE D'IDENTITÉ ELECTRO-BIOMETRIQUE**
(54) **Title: METHOD AND APPARATUS FOR ELECTRO-BIOMETRIC IDENTITY RECOGNITION**



*ORIGINAL ELECTROCARDIOGRAPHIC SIGNALS (LEFT)
COMMON-ELIMINATED DERIVED SIGNATURES (RIGHT)*

(57) **Abrégé/Abstract:**

A method and apparatus for electro-biometric identity recognition or verification that produces and stores a first biometric signature that identifies a specific individual by forming the difference between a representation of the heartbeat pattern of the specific individual and a stored representation of common features of the heartbeat patterns of a plurality of individuals; after the producing step, the method and apparatus obtains a representation of the heartbeat pattern of a selected individual and produces a second biometric signature by forming the difference between the heartbeat pattern of the selected individual and the stored representation of common features of the heartbeat patterns of the plurality of individuals; it then compares the second biometric signature with the first biometric signature to determine whether the selected individual is the specific individual. The apparatus and method may be employed as a stand-alone unit or as part of another device pursuant to the many applications described herein.



(12) INTERNATIONAL APPLICATION PUBLISHED UNDER THE PATENT COOPERATION TREATY (PCT)

(19) World Intellectual Property Organization
International Bureau



(43) International Publication Date
8 June 2006 (08.06.2006)

PCT

(10) International Publication Number
WO 2006/059190 A2

(51) International Patent Classification: Not classified

(21) International Application Number:
PCT/IB2005/003281

(22) International Filing Date:
8 November 2005 (08.11.2005)

(25) Filing Language: English

(26) Publication Language: English

(30) Priority Data:
PCT/IB2004/03899
8 November 2004 (08.11.2004) IL

(71) Applicant (for all designated States except US): IDESIA LTD. [IL/IL]; 7, Halamish St., 38900 Caesarea (IL).

(72) Inventor; and

(75) Inventor/Applicant (for US only): LANGE, Daniel, H. [IL/IL]; Yarden 10, P.O. Box 939, 25147 Kfar Vradim (IL).

(81) Designated States (unless otherwise indicated, for every kind of national protection available): AE, AG, AL, AM,

AT, AU, AZ, BA, BB, BG, BR, BW, BY, BZ, CA, CH, CN, CO, CR, CU, CZ, DE, DK, DM, DZ, EC, EE, EG, ES, FI, GB, GD, GE, GH, GM, HR, HU, ID, IL, IN, IS, JP, KE, KG, KM, KN, KP, KR, KZ, LC, LK, LR, LS, LT, LU, LV, LY, MA, MD, MG, MK, MN, MW, MX, MZ, NA, NG, NI, NO, NZ, OM, PG, PH, PL, PT, RO, RU, SC, SD, SE, SG, SK, SL, SM, SY, TJ, TM, TN, TR, TT, TZ, UA, UG, US, UZ, VC, VN, YU, ZA, ZM, ZW.

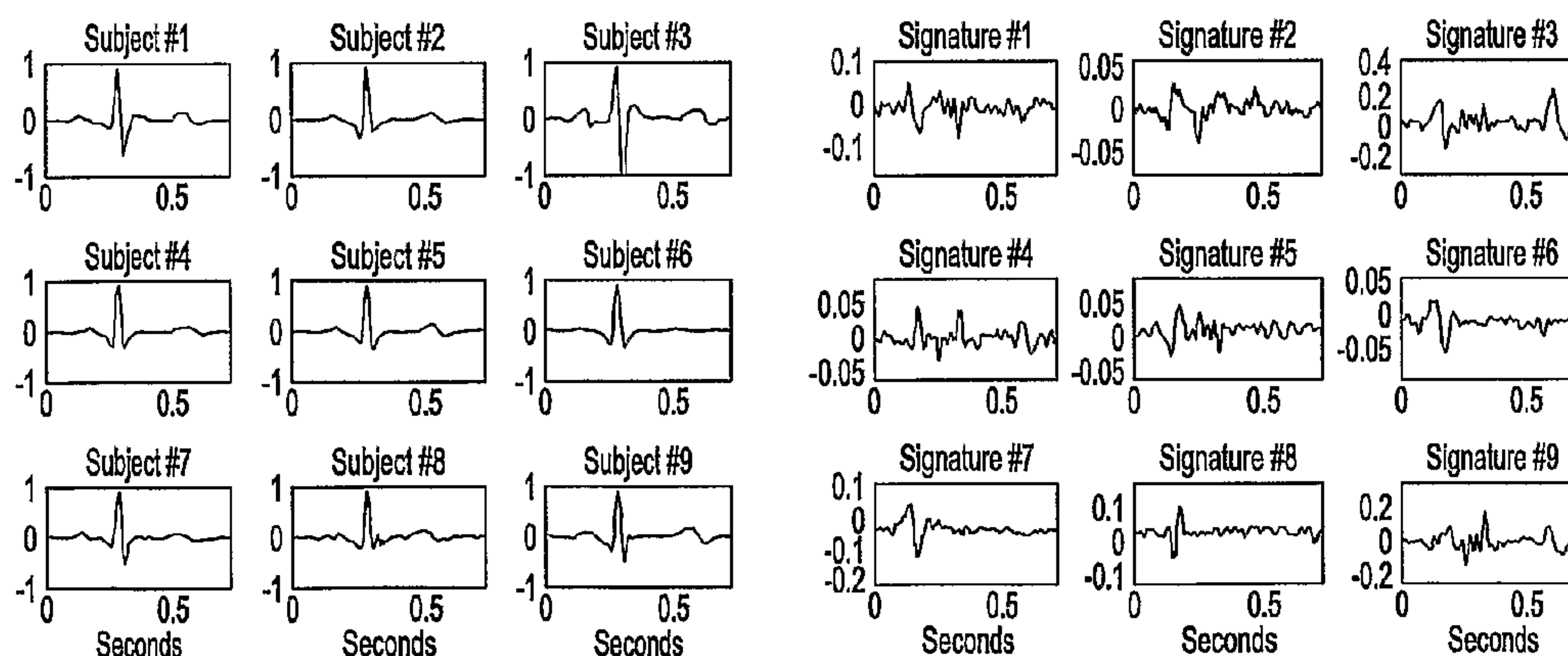
(84) Designated States (unless otherwise indicated, for every kind of regional protection available): ARIPO (BW, GH, GM, KE, LS, MW, MZ, NA, SD, SL, SZ, TZ, UG, ZM, ZW), Eurasian (AM, AZ, BY, KG, KZ, MD, RU, TJ, TM), European (AT, BE, BG, CH, CY, CZ, DE, DK, EE, ES, FI, FR, GB, GR, HU, IE, IS, IT, LT, LU, LV, MC, NL, PL, PT, RO, SE, SI, SK, TR), OAPI (BF, BJ, CF, CG, CI, CM, GA, GN, GQ, GW, ML, MR, NE, SN, TD, TG).

Published:

— without international search report and to be republished upon receipt of that report

For two-letter codes and other abbreviations, refer to the "Guidance Notes on Codes and Abbreviations" appearing at the beginning of each regular issue of the PCT Gazette.

(54) Title: METHOD AND APPARATUS FOR ELECTRO-BIOMETRIC IDENTITY RECOGNITION



ORIGINAL ELECTROCARDIOGRAPHIC SIGNALS (LEFT)
COMMON-ELIMINATED DERIVED SIGNATURES (RIGHT)

(57) Abstract: A method and apparatus for electro-biometric identity recognition or verification that produces and stores a first biometric signature that identifies a specific individual by forming the difference between a representation of the heartbeat pattern of the specific individual and a stored representation of common features of the heartbeat patterns of a plurality of individuals; after the producing step, the method and apparatus obtains a representation of the heartbeat pattern of a selected individual and produces a second biometric signature by forming the difference between the heartbeat pattern of the selected individual and the stored representation of common features of the heartbeat patterns of the plurality of individuals; it then compares the second biometric signature with the first biometric signature to determine whether the selected individual is the specific individual. The apparatus and method may be employed as a stand-alone unit or as part of another device pursuant to the many applications described herein.

73236-81

1

DESCRIPTIONMethod and Apparatus for
Electro-Biometric Identity RecognitionBACKGROUND

5 Identity recognition plays an important role in
numerous facets of life, including automatic banking
services, e-commerce, e-banking, e-investing, e-data
protection, remote access to resources, e-transactions, work
security, anti-theft devices, criminologic identification,
10 secure entry, and entry registration in the workplace.

Often computerized systems use passwords and personal
identification numbers (PIN) for user recognition. But to
maintain security, passwords have to be changed on a regular
basis, imposing a substantial burden on the users.
Likewise, signature verification methods suffer from other
15 shortcomings, including forgery and enrollment fraud. See
for example, U.S. Patent No. 5,892,824 issued to Beatson et
al.

As a result, identity recognition systems that use
measures of an individual's biological phenomena -
20 biometrics - have grown in recent years. Utilized alone or
integrated with other technologies such as smart cards,
encryption keys, and digital signatures, biometrics are

expected to pervade nearly all aspects of the economy and our daily lives.

Several advanced technologies have been developed for biometric identification, including fingerprint
5 recognition, retina and iris recognition, face recognition, and voice recognition. For example, Shockley et al., U.S. Pat. No. 5,534,855, generally describes using biometric data, such as fingerprints, to authorize computer access for individuals. Scheidt et al., U.S. Patent No. 6,490,680,
10 describes identity authentication using biometric data. Dulude et al., U.S. Patent No. 6,310,966, describes the use of fingerprints, hand geometry, iris and retina scans, and speech patterns as part of a biometric authentication certificate. Murakami et al., U.S. Patent No. 6,483,929,
15 generally describes "physiological and histological markers," including infra-red radiation, for biometric authentication. However, these types of technologies have penetrated only limited markets due to complicated and unfriendly acquisition modalities, sensitivity to
20 environmental parameters (such as lighting conditions and background noise), and high cost. In addition, due to complicated acquisition procedures, the foregoing technologies usually require operator attendance.

Fingerprint recognition is well-established and the
25 most mature technology of the group. But it has several drawbacks: a fingerprint recognition system cannot verify physical presence of the fingerprint owner and therefore is prone to deception, limiting its suitability for on-line applications; the optical sensor is a costly and fragile
30 device generally unsuitable for consumer markets; and the system suffers from negative connotations related to criminology.

Retina scanning technologies are characterized by high performance. However, they require high-precision optical sensors, and are not user friendly because they require manipulation of head posture and operate on a very sensitive
5 organ — the human eye. The optical sensor is also costly and fragile.

Iris and face recognition systems are user-friendly technologies since they record an image from afar and are not intrusive. However, they require digital photographic
10 equipment and are sensitive to lighting conditions, pupil size variations and facial expressions. In addition, iris recognition performance is degraded by the use of dark glasses and contact lens, and face recognition may be deceived by impersonation.

Voice recognition is the most user-friendly technology
15 of the group; however, it requires a low-noise setting and is highly sensitive to intrinsically variable speech parameters, including intonation. Moreover, existing conventional recording technologies may be used to deceive
20 speech-based recognition systems.

Thus, a need exists for reliable, robust, hard to deceive (on-line and off-line), low cost, user friendly identity recognition technologies that may be used in stand-alone applications or integrated with existing security
25 systems.

Over the years, electrocardiogram ("ECG") measurements have been used for many different purposes. ECG signals are electric signals generated by the heart and can be picked up using conventional surface electrodes, usually mounted on
30 the subject's chest. ECG signals are made up of several components representative of different functional stages during each heart beat and projected according to the electric orientation of the generating tissues.

73236-81

4

Individuals present different, subject-specific detail in their electro-cardiologic signals due to normal variations in the heart tissue structure, heart orientation, and electrical tissue orientation, all of which affect the electro-cardiologic signals measured from the limbs. Numerous types of systems make use of these subject-specific variations.

For example, Blazey et al., U.S. Patent No. 6,293,904, describes the use of ECG signals to evaluate or profile an individual's physiological and cognitive state. As to identification, a 2001 conference paper at the 23rd Annual International IEEE Conference on Engineering in Medicine and Biology Society (in Istanbul, Turkey) by Kyoso et al., entitled "Development of an ECG Identification System," compares a patient's ECG with previously registered ECG feature parameters for purposes of identification. Wiederhold, U.S. Application No. 20030135097, suggests using directly or remotely acquired ECG signals to identify a subject, "explores" feature extraction for identifying individuals, and provides a "preliminary analysis" of such methods.

But an ECG signal is comprised of ECG components having features that may be common to a group. None of these references describe a system or method that eliminates common features of ECG components to create a signature for subject identification. Thus, there still exists a need for systems and methods with these attributes to identify an individual.

The inclusion of the foregoing references in this Background is not an admission that they are prior art or analogous art with respect to the inventions disclosed herein.

73236-81

5

SUMMARY

Applicant provides solutions to the foregoing problems
5 of biometric identification with various apparatuses and
methods having several aspects.

In a first aspect, applicant solves each of the
foregoing problems of biometric identification through the
use of the following method and variations thereof:

10 producing and storing a first biometric signature
that identifies a specific individual by forming the
difference between a representation of the heartbeat pattern
of the specific individual and a stored representation of
common features of heartbeat patterns of a plurality of
15 individuals;

 after the producing step, obtaining a
representation of the heartbeat pattern of a selected
individual and producing a second biometric signature by
forming the difference between the heartbeat pattern of the
20 selected individual and the stored representation of the
common features of the heartbeat patterns of the plurality
of individuals; and

 comparing the second biometric signature with the
first biometric signature to determine whether the selected
25 individual is the specific individual.

A system, according to this aspect, comprises an ECG
signal acquisition module, an ECG signal processing module
that comprises an ECG signature generator, and an output
module.

30 Thus, according to this first aspect, the systems and
methods disclosed herein transform bio-electric signals into
unique electro-biometric signatures. The uniqueness of the

electro-cardiologic signatures makes the system very difficult to deceive, and the method's inherent robustness makes it ideal for local as well as for remote and on-line applications. In addition, a biometric-signature-based
5 system is characterized by high recognition performance and supports both open and closed search modes.

In one preferred method according to the first aspect, the stored representation of common features of one or more ECG components is obtained by measuring and storing such
10 representations for a plurality of individuals and then averaging all of the stored representations. Alternately, the common features may be obtained through techniques such as principal component analysis, fuzzy clustering analysis, wavelet decomposition, and the like.

15 Since electro-cardiologic methods according to this first aspect are robust, they have another important advantage: they permit a simple and straightforward acquisition technology that can be implemented as a low-cost, user friendly acquisition apparatus and also eliminate the need
20 for a skilled operator.

According to a variation on these systems and methods, the common features of one or more of a subject's ECG components may be removed using an analytical model of common features of one or more ECG components, instead of,
25 or in addition to, use of an empirical model. Likewise, the common features may be removed by first classifying the stored representations into subgroups, identifying the common features in at least one subgroup, classifying a subject signal according to subgroup, creating a subject
30 signature by removing the common features of one or more of the subgroup's ECG components from the subject signal, and identifying the subject by calculating the subject signature correlations relative to that subgroup's signatures.

Common features may be determined by averaging synchronized electrocardiograms from a group of individuals and then subtracted from the subject's electrocardiogram to determine the subject's signature. But this method assumes
5 that common features are constant across a group of individuals. In reality, certain common features are present to a greater or lesser degree in any given individual. Therefore, it is better to approximate common features so they make the best fit with a given subject's
10 electrocardiogram before removing them to obtain the subject's signature. This technique provides for a more accurate determination of the subject's signature.

According to this method, a group of electrocardiograms may be broken down (decomposed) into a set of characteristic
15 waveforms. The characteristic waveforms that represent common features of the group are then weighted to best approximate the extent of common features present in the subject's electrocardiogram. The approximation is then subtracted from the subject's electrocardiogram. What
20 remains includes the subject's electrocardiogram signature.

Multiple templates may also be kept for each subject, such as by storing multiple signatures produced by an individual at different pulse rates. In this embodiment, the subject signature may then be correlated with the
25 appropriate template, such as the one for the appropriate pulse rate. Thus, in a variation, the systems and methods disclosed herein may use multiple signature templates to identify an individual over a range of circumstances and reactions. Alternatively, or in addition, according to the
30 first aspect, the subject signal and the enrolled signals may also be normalized based on pulse rate.

According to a second aspect disclosed herein, a process for identification may set a dynamic threshold.

This dynamic threshold may be based on a desired level of confidence in the identification, such as one determined by a confidence score.

According to a third aspect disclosed herein, the systems and methods disclosed herein may employ a "Q-factor" to determine whether to reduce signal contamination due to noise. Likewise, the Q-factor or other quality of signal measurement may be used to determine the length of the subject sample required to identify a subject with a desired level of confidence. It may also be used to enroll a sample with the desired level of confidence so that the sample may be suitable for the future comparison.

In an alternate embodiment to the "Q-factor" calculation, the systems and methods disclosed herein may calculate standard deviations in the subject signature and/or enrolled signatures due to noise, and from those calculations determine whether signal quality is appropriate for identification.

Likewise, the systems and methods disclosed herein may determine the signal quality by measuring the impedance of the contact or probe. Signal quality measurements according to this aspect may also be used to inform the subject to adjust his or her contact with or position relative to the sensor or probe.

According to a fourth aspect, the subject and database signatures may be encrypted as a safety precaution against unauthorized access to and use of the signatures.

According to a fifth aspect, the ECG signal may be acquired with electrodes placed in contact with certain body sites that yield a consistent signal. For certain body locations even a slight change of electrode placement may cause drastic changes in the received signal morphology, and may even cause distinct signal components to appear or

disappear. Thus, according to this aspect, the methods and systems disclosed herein may use electrode placement sites that produce subject-specific, consistent signals, that are robust notwithstanding changes of electrode placement within
5 the sites. These sites include the arms and legs (including fingers and toes). The robustness of electrode placement within these sites stems from a constant electro-cardiologic signal projection which does not change as long as the electrodes remain close to a limb extremity.

10 According to this same fifth aspect, certain sensing probes, known as ultra-high impedance sensing probes, may also be used to acquire a signal, including a signal from a single body point such as a fingertip. Alternately, or in addition, these ultra-high impedance probes may remotely
15 sense the electro-cardiologic signal and thereby eliminate the difficulty of electrode placement while maintaining signal consistency.

According to a sixth aspect, the systems and methods disclosed herein may comprise elements and steps that
20 protect against enrollment fraud and reduce the ability of a database enrollee to misrepresent his or her identity.

According to a seventh aspect, the systems and methods disclosed herein may identify a subject by comparing his or her match scores with the match scores of database
25 enrollees.

According to an eighth aspect, the systems and methods disclosed herein may use weighted correlation techniques, ascribing different weights to different electro-cardiologic signal components for the purpose of producing a signature.
30 Alternatively, or in addition, signatures may be normalized using a variety of metrics including root-mean-square computations or L1 metrics.

50741-10

9a

According to a ninth aspect, there is provided a biometric identification system comprising a) an electrocardiogram signal acquisition module; b) an enrolled signature database; c) an electrocardiogram signal processor
5 comprising an electrocardiogram signature generator that removes characteristic waveforms, which represent common electrocardiogram features of a group of individuals, from the electrocardiogram signal acquired by the electrocardiogram signal acquisition module; d) an electrocardiogram signature
10 comparator that compares an electrocardiogram signature with at least one enrolled electrocardiogram signature; and e) an output module.

According to a tenth aspect, there is provided a method for identifying an individual comprising the steps of:
15 a) acquiring a subject's electrocardiogram; b) decomposing electrocardiograms from a group of individuals to determine a set of characteristic waveforms that represent common features of the group; c) processing said subject's electrocardiogram by removing said characteristic waveforms; and d) using the
20 subject's processed electrocardiogram to identify the subject.

According to an eleventh aspect, there is provided a method of biometric identification comprising the steps of: a) acquiring an electrocardiogram signal; b) processing said electrocardiogram signal to generate an electrocardiogram
25 signature; c) correlating said electrocardiogram signature with a plurality of synthetic electrocardiogram signatures; d) transforming one or more of said correlations; e) generating a dynamic threshold for said correlation; and f) outputting the identification result.

Some biometric technologies employ challenge-response protocols to ensure that the user data that they receive is live. In that way, they can reduce the risk that the system can be spoofed by the playback of biometric data. But, to
5 date, the challenge-response mechanisms for biometric systems have required active participation by the user. And active user participation complicates and extends the user verification process. For example, speech recognition systems typically require the user to repeat a randomly
10 selected word or sentence. Therefore, according to another aspect, a biometric ID system may reduce the risk of spoofing by beneficially employing a biological-challenge-response mechanism that does not require a conscious response from the user.

15 The systems and methods according to each of the foregoing aspects preferably perform their tasks automatically for the purpose of identity recognition. Further, these systems and methods can be incorporated into a wide range of devices and systems. A few non-limiting
20 examples are as follows: a smart card; a passport; a driver's license apparatus; a Bio-logon identification apparatus; a personal digital assistant ("PDA"); a cellular-embedded identification apparatus; an anti-theft apparatus; an ECG monitoring apparatus; an e-banking apparatus; an e-
25 transaction apparatus; a pet identification apparatus; a physical access apparatus; a logical access apparatus; and an apparatus combining ECG and fingerprint monitoring, blood pressure monitoring and/or any other form of biometric device.

30 Further, the systems and methods disclosed herein can be used to identify a person's age, such as by comparing the width of a subject's QRS complex, or more generally the

subject's QRS-related signature component, with those of an enrolled group or analytical ECG model.

In another application, the systems and methods herein may be used to identify persons on medication, such as by enrolling and calculating, or analytically deriving, a series of drug-related signature templates. This method may also be used to identify or catch subjects who would attempt to fool the system by using medication to alter their ECG signal.

Other applications include using the systems and method disclosed herein for building and room access control, surveillance system access, wireless device access, control and user verification, mobile phone activation, computer access control (including via laptop, PC, mouse, and/or keyboard), data access (such as document control), passenger identification on public transportation, elevator access control, firearm locking, vehicle control systems (including via ignition start and door locks), smart card access control and smart card credit authorization, access to online-line material (including copyright-protected works), electronic ticketing, access and control of nuclear material, robot control, aircraft access and control (passenger identity, flight control, access of maintenance workers), vending machine access and control, laundromat washer/dryer access and control, locker access, childproof locks, television and/or video access control, decryption keys access and use, moneyless slot machines, slot machine maintenance access, game console access (including on-line transaction capability), computer network security (including network access and control), point-of-sale buyer identification, on-line transactions (including customer identification and account access), cash payment service or wire transfer identification, building maintenance access

and control, and implanted medical device programming control. Other applications will be apparent to those skilled in the art and within the scope of this disclosure.

For any application, an apparatus according to any or
5 all of the foregoing aspects can operate continuously or on demand. The apparatus can be constructed to obtain the representation of the heartbeat pattern of a selected individual by having one or more electrodes in contact with individual or sensors remote from the individual. When the
10 apparatus is provided in a smart card, the card can be enabled for a limited period of time after successful recognition and disabled thereafter until the next successful recognition is performed. The apparatus can be constructed to operate with encryption keys or digital
15 signatures.

As to the methods disclosed herein, the steps of the foregoing methods may be performed sequentially or in some other order. The systems and methods disclosed herein may be used on human or other animal subjects.

20 Each of these aspects may be used in permutation and combination with one another. Further embodiments as well as modifications, variations and enhancements are also described herein.

BRIEF DESCRIPTION OF THE DRAWINGS

25 **FIG. 1** is a simplified block diagram of a system for use with the aspects disclosed herein composed of a signal acquisition module, a signal processing module, and an output module.

FIG. 2 is a block diagram of an embodiment of the
30 signal acquisition module of the system of **FIG. 1**.

FIG. 3 is a block diagram of an embodiment of the signal processing module of the system of **FIG. 1**.

FIG. 4 shows the first six most influential PCs extracted from a pool of one-hundred subjects, and the contribution of the first ten PCs to the representation of data variance.

5 **FIG. 5** shows the original electrocardiographic signals and their respective signatures constructed by eliminating the optimal combination of the three most influential PCs and their latency shifted versions.

10 **FIG. 6** is a diagram showing a grand-average electro-cardiologic signal waveform calculated from a database of 20 subjects.

FIG. 7 shows a group of electro-cardiologic signal waveforms of ten of the subjects participating in the database and contributing to the average waveform of **FIG. 4**.

15 **FIG. 8** shows a group of electro-biometric signature waveforms, or templates, derived from the signal waveforms of **FIG. 7**.

20 **FIG. 9** shows a scatter plot and distribution histograms of the sign-maintained squared correlation values of the 20 subjects who contributed to the grand average waveform of **FIG. 4**.

FIG. 10 shows a table of z-scores based on the desired degree of confidence in the identification cut-off.

FIG. 11a shows a distribution of correlation.

25 **FIG. 11b** shows a distribution of Z-transformed correlations.

FIG. 12 shows identification performance curves (static).

30 **FIG. 13** shows identification performance curves (dynamic).

FIG. 14 shows signal quality as a function of NSR.

FIG. 15 shows match score distribution as a function of signal quality for 5 second segments.

FIG. 16 shows match score distribution as a function of signal quality for 20 second segments.

FIG. 17 shows match score as a function of recording duration (for $Q=0.8$).

5 **FIG. 18** shows match score as a function of recording duration (for $Q=0.5$).

FIG. 19 shows a functional component diagram of a preferred system.

10 **FIG. 20** shows a functional component diagram of a preferred signal processor.

DETAILED DESCRIPTION

Definitions:

Unless otherwise indicated, the meaning of the terms "identify," "identifying" and "identification" include the
15 concepts of "verify identity," "verifying identity," and "verification of identity," respectively.

"Closed search" means a search in which a single stored signature is examined to verify the identity of an individual.

20 "Open search" means a search in which a plurality of stored signatures are searched to identify a subject.

First Aspect:

According to the first aspect, a bio-electric signal is acquired, processed and analyzed to identify the identity of
25 an individual. A preferred embodiment of a system and a method according to this first aspect is illustrated, by way of example, in **FIG. 1**. **FIG. 1** shows a system called an **Electro-Biometric IDentification (E-BioID)** system. In this preferred embodiment, the stored representation of the
30 common features of the one or more ECG components of the

plurality of individuals is the average of those individuals' one or more ECG components. However, other embodiments can utilize stored representations of different types of common features, such as those attainable by, for example, principal component analysis, fuzzy clustering analysis, or wavelet decomposition, or provided by an analytical model.

In the preferred embodiment, the basic elements of the E-BioID system include a signal acquisition module 12, a signal processing module 14, and an output module 16, implemented in a single housing. In another preferred embodiment, the system may provide for remote analysis of locally acquired electro-biometric signals. Each of the components shown in **FIG. 1** can be readily implemented by those skilled in the art, based on principles and techniques already well known in the art in combination with the present disclosure.

FIG. 2 shows a preferred construction of the signal acquisition module 12 in an E-BioID system. The data acquisition module preferably includes one or more sensors 22, pre-amplifiers 24, band-pass filters 26 and an analog-to-digital (A/D) converter 28. Each of these components can be readily implemented by those skilled in the art, based on principles and techniques already well known in the art in combination with the present disclosure.

Sensors 22 can be of any type capable of detecting the heartbeat pattern. For example, they can be metal plate sensors that are an "add-on" to a standard computer keyboard. According to another aspect, a single sensor may, by itself, acquire the signal from a single point of contact, such as by contacting a finger; alternately, the sensor may not need to touch the subject at all.

FIG. 3 shows preferred elements of signal processing module 14 in the E-BioID system. The signal processing module preferably includes a Digital Signal Processor (DSP) 32, a Dual Port Ram (DPR) 34, an Electrically Erasable Programmable Read Only Memory (E²PROM) 36 and an I/O port 38. Each of these components can be readily implemented by those skilled in the art, based on principles and techniques already well known in the art in combination with the present disclosure. Signal processing module 14 is connected to signal acquisition module 12 and output module 16 via port 38.

In an alternative embodiment, the signal processing module may be implemented, with suitable programming, on a personal computer, which is a flexible computation platform, allowing straight-forward integration of the system into existing computing facilities in a home, office, or institute/enterprise environments.

Output module 16 preferably consists of a dedicated display unit such as an LCD or CRT monitor, and may include a relay for activation of an external electrical apparatus such as a locking mechanism. Alternatively, the output module may include a communication line for relaying the recognition result to a remote site for further action.

SIGNAL ACQUISITION, PROCESSING AND ANALYSIS

Bioelectric signals, or heartbeat signals, are acquired in a simple manner, where the subject is instructed to touch at least one sensor 22 for a few seconds. The one or more sensors, which may be metal plates, conduct the bioelectric signals to the amplifiers 24, which amplify the bioelectric signals to the desired voltage range. In a preferred embodiment, the voltage range is zero to five volts.

The amplified signals pass through filters 26 to remove contributions outside a preferable frequency range of 4Hz – 40Hz. Alternatively, a wider range of 0.1Hz – 100Hz may be used in conjunction with a notch filter to reject mains
5 frequency interference (50/60Hz). Digitization of the signal is preferably performed with a 12-bit A/D converter 28, at a sampling frequency of preferably about 250Hz.

In module 14, the signals are normalized by the 'R' peak magnitude, to account for signal magnitude variations
10 which mostly relate to exogenic electrical properties. The normalized data is transformed into an electro-biometric signature which is compared to pre-stored electro-biometric signature templates. The result of the comparison is quantified, optionally assigned a confidence value, and then
15 transmitted to output module 16, which provides recognition feedback to the user of the E-BioID system and may also activate external apparatuses such as a lock or siren, virtual apparatuses like network login confirmation, or a communication link.

Alternately, or in addition, the signal may be
20 normalized for pulse rate. This is useful because electro-cardiologic signals are affected by changes in pulse rate, which is a well-known electro-cardiologic modifier. Pulse rate changes may cause latency, amplitude and morphological
25 changes of the 'P' and 'T' components relative to the 'QRS' component of the electro-cardiologic signal (these components appear in **FIG. 7**). However, pulse rate changes may be automatically compensated for by retrospective, pulse rate-driven adjustment of the signal complex. Moreover, an
30 adaptive operation mode of the system can track and compensate for pulse rate induced changes. This can be done by compressing or expanding the time scale of one cycle of the heartbeat waveform. More sophisticated formulations

describing the relations between waveform characteristics (e.g. S-T, P-Q segment durations) and pulse rate may be used. Thus, a method according to this variation may be based on electro-cardiologic signal discrimination, wherein
5 analysis is carried out synchronously with the heart beat, eliminating features common to the general population and thus enhancing subject-specific features that constitute an electro-biometric, or biometric, signature, normally undetectable in raw electro-cardiologic signals.

10 In another embodiment, the E-BioID system is implemented as a fully integrated compact device, where many of the functional elements are implemented on an ASIC based system.

In another embodiment, the apparatus can be
15 incorporated into a watch worn on the wrist, where the signal is measured between the wrist of the hand on which the watch is worn and the other hand of the wearer. The back side of the watch may be made of a conductive medium (e.g. a metal plate) in contact with the back of the wrist,
20 and the face of the watch can be provided with another metal contact that needs to be touched with a finger of the other hand. The watch may transmit a signal indicating confirmation of the identity of its wearer, and/or activating a physically or logically locked device such as a
25 door, a computer, a safe, etc. The watch may also transmit personal information about its wearer. In the same manner, the apparatus can be incorporated into a belt, or any other apparel item comprising a conductive medium. The belt or other apparel item may then transmit a signal indicating
30 confirmation of the identity of its wearer, and/or activating a physically or logically locked device and/or transmitting personal information about its wearer.

PRINCIPLE OF OPERATION

Biometric recognition requires comparing a newly acquired biometric signature against signature templates in a registered or enrolled biometric signature template database. This calls for two phases of system operation: Enrollment and Recognition.

ENROLLMENT PHASE

In a preferred embodiment, each new subject is instructed to touch a first sensor with a finger of the left hand, while simultaneously touching another sensor with a finger of the right. In alternative embodiments, the subject may touch the sensors, typically made of metal, with other parts of the body, preferably the hands or legs. In another embodiment, the subject may touch a single sensor with a single body point. Alternately, the subject need not touch a sensor at all. The system monitors the subject's pulse rate and initiates a recording, preferably lasting for at least 20 seconds. Shorter intervals may be used depending on the required level of accuracy. Once the recording is complete, the system may perform a self-test to verify signature consistency by comparison of at least two biometric signatures derived from two parts of the registered segment. The two parts may be two halves, or two larger, overlapping, segments. The two parts may be used to derive two biometric signatures. If the self-test result is successful, enrollment of that subject is complete, and if unsuccessful the procedure is repeated. The successful recording is used for construction of an electro-cardiologic signal or a series of electro-cardiologic signals, which are added to an electro-cardiologic signal database.

The electro-cardiologic signals are then transformed into a set of electro-biometric signature templates by

eliminating features that are common to all or a subset of the subjects participating in the dataset, thereby enhancing subject-specific discriminating features.

In a preferred embodiment, the system creates a grand-average electro-cardiologic template, which is calculated by synchronous averaging of normalized electro-cardiologic signals from the entire pool of subjects. The grand-average represents the above-mentioned common features, and thus subtraction of the grand-average from each one of the electro-cardiologic signals yields a set of distinct, subject-specific electro-biometric template signatures. In an alternative embodiment, other means for elimination of the common features may be used, such as a principal component analysis, fuzzy clustering analysis or wavelet decomposition.

In a more preferred embodiment, a group of electrocardiograms may be broken down (decomposed) into set of characteristic waveforms. According to this preferred embodiment, noise is removed from the electrocardiograms of a group of individuals. The system may use Principal Component Analysis (PCA) to decompose the group's electrocardiograms into a set of orthogonal (non-correlated) components. These non-correlated components, taken together, represent the entire energy of the signals—that is 100% of the signal variance.

The first principal components—those associated with largest eigen values of the PCA representation. Usually the first three to five components and, in any event, less than the first ten components of the group's electrocardiograms typically represent approximately 90% of the electrocardiogram's energy or variance and contain the common features. Remarkably, these first components represent common features that are present and stable across

the human population at large. As a result, these first principal components can be used to identify the signature of any human subject and need not be recalculated for each subject. The remaining smaller components (which typically
 5 can be 10% of the total waveform energy) represent noise and some individual information of the group.

The characteristic waveforms that represent common features of the group are then subtracted from the subject's electrocardiogram. What remains includes the subject's
 10 electrocardiogram signature plus some remaining noise.

Characteristic waveforms may be created in different ways, and depend on the desired "distance" or "overlap" between each waveform. For example, the correlation function may preferably be used to determine the desired
 15 distance between waveforms, although other methods also work.

Remarkably, if an electrocardiogram is taken from an individual who has not participated in the enrollment data set, it is possible to determine his or her
 20 electrocardiogram signature usually with reference to just the first three to four PCA components of the enrolled data set and time shifted versions of them.

Determining the Signature

All subjects' electrocardiograms contain each of the
 25 first principal components to greater or lesser degrees. According to this preferred embodiment, a subject's electrocardiogram may be approximated using the principal components from the sample set according to the following equation.

30
$$\sum_{i=1}^p C_i PC_i = ECG_{\text{individual}}$$

In this equation, C_i is a reconstruction coefficient, p is the model order and PC is the principal component. The goal is to find the coefficients that weight the database principal components for the best approximation of the subject's electrocardiogram. In other words, the goal is to minimize the error between an approximation of the subject signal constructed by the weighting the database's principal components and the original subject signature.

This may be done by a variety of methods. One method is to determine reconstruction coefficients using a least squares approximation to minimize the norm of the reconstruction error. This is shown below:

$$\| \text{ECG}_{\text{ind}} - \sum C_i \text{PC}_i \| \quad \text{OR} \quad \text{Error} = \sum_{n=1}^N (\text{ECG}_n - \sum C_i \bullet \text{PC}_i)^2$$

Once the optimal coefficients are determined, they may be used to sum the database's first principal components (such as the top 3 or 4) according to the following equation:

$$\sum_{i=1}^{3 \text{ or } 4} C_i \bullet \text{PC}_i = \text{Sum}$$

This sum is then subtracted from the subject signal. What remains is the subject signature and perhaps some noise.

Further, since noise, by definition, is uncorrelated, it is usually described by the last principal components — those that are associated with the smallest eigen values. As a result, noise may be optionally removed from the subject signal by weighting these last principal components to make the optimal fit with the subject signature and then removing them from the subject signal. Noise may also be removed by other methods.

Accounting for Latency Variation

Some of the variation in an electrocardiogram component database is due to latency changes, namely time variance in

enrolled data signatures. As a result, the foregoing method may be enhanced by time shifting the principal components, preferably both to the left and to the right. For example, if three principal components are used to approximate common
 5 electrocardiogram features, then six more components could be added to account for latency variation—two for each component, shifted left and shifted right.

In this example, the three principal components and the six time shifted components would be used to calculate the
 10 construction coefficients. And once the best construction coefficients are determined, the common feature components are constructed and subtracted from the original subject electrocardiogram signature to yield the individual signature:

$$15 \quad \text{Signature} = \text{ECG}_n - \sum_{i=1}^P C_i \bullet \text{PC}_i$$

FIG. 4 shows the first six most influential PCs extracted from a pool of one-hundred subjects, and the contribution of the first ten PCs to the representation of data variance. **FIG. 5** shows the original electro-
 20 cardiographic signals and their respective signatures constructed by eliminating the optimal combination of the three most influential PCs and their latency shifted versions.

Although PCA is a robust algorithm that provides a
 25 progressive, influential representation of components with clear distinctions in magnitude between the main signal, secondary variations and noise, at least two alternate techniques may be used to decompose the group's electrocardiograms. In a first alternate embodiment,
 30 independent component analysis (ICA) may be used to decompose compound signals into independent components (as opposed to the orthogonal components of PCA). These

independent components may then be used for modeling and reconstruction of electrocardiograms in a manner similar to PCA.

In a second alternate embodiment, wavelet decomposition (WD) may be used to decompose compound signals into a set of time-scaled waveforms called wavelets. WD is based on a transient wavelet waveforms, as opposed to Fourier decomposition (which is based on continuous sine and cosine decomposition). As a result, WD has an advantage over Fourier analysis in that wavelets are more efficient descriptors of transient signal components such as electrocardiograms.

Alternately, or in addition, common features may be removed by using an analytical model for common features of one or more ECG components rather than by using an empirical model calculated from the enrolled data.

In another preferred embodiment, the database is divided into several subsets in a way that enhances intra-subset similarity and inter-subset disparity. The embodiment then calculates a distinct grand-average or other common feature determination for one or more of the subsets. This database partition itself may be performed using standard pattern classification schemes such as linear classifiers, Bayesian classifiers, fuzzy classifiers, or neural networks. In case of a large database, it is useful to partition the database into subsets in order to simplify and shorten the search process as well as to ensure the validity of the grand-average as an appropriate representative of similarity among the electro-cardiologic signals. The subject signature may then be created by removing common features found in the appropriate subgroup.

FIG. 6 shows an example of a grand-average, constructed from a pool of 20 subjects participating in the database.

FIG. 7 shows 10 examples of electro-cardiologic signals, and **FIG. 8** shows the electro-biometric template signatures derived from the above electro-cardiologic signals by elimination of features common to all the subjects included in the database. Specifically, each signature of **FIG. 8** is obtained by subtracting the waveform of **FIG. 6** from the corresponding signal of **FIG. 7**. It will be observed that while the original electro-cardiologic signals are highly similar, the derived electro-biometric signatures are markedly different. These differences have been found to reflect inherently unique electro-cardiologic disparity which underlies the recognition capabilities of the E-BioID system.

RECOGNITION PHASE

In the recognition phase, the subject interacts with the system in a similar manner to that of the enrollment phase, however a shorter recording time on the order of a few seconds is sufficient.

In a preferred embodiment, the system executes a verification procedure (closed search): the system processes the acquired signals, forms an electro-biometric subject signature by removing common features found in the entire database, found in a partitioned subgroup of the database or provided by analytical ECG model, adjusts the signature according to the pulse rate, and compares the adjusted electro-biometric signature with the subject's enrolled electro-biometric signature template.

In another preferred embodiment, the system executes an identification procedure (open search): the system repeats the comparison process for the entire database or a partitioned sub-group of the database, thereby providing identification of the matching identity.

THE COMPARISON PROCESS

In a preferred embodiment, the comparison is performed by calculation of a correlation coefficient, ρ , between an electro-biometric signature σ_j and an electro-biometric signature template Φ_i , as follows:

$$\rho = \frac{COV[\sigma_j, \Phi_i]}{\sqrt{VAR[\sigma_j] \cdot VAR[\Phi_i]}}.$$

The correlation coefficient is squared, maintaining its original sign: $\eta = \text{sign}(\rho) * |\rho|^2$. In an alternative embodiment, the comparison may be based on other similarity measures, such as RMS error between the electro-biometric signatures.

The comparison may yield one or several correlation coefficients, depending on the mode of operation: closed search; or open search. In a closed search mode, the sign-maintained squared correlation coefficient (η) is used for making the recognition decision: a value greater than a preset threshold is regarded as a positive identification, or a match; borderline, near-threshold values may indicate a need for extended or repeated recording. In an open search mode, the largest sign-maintained squared correlation coefficient among all sign-maintained squared correlation coefficients yields the most likely subject identification, provided that the highest coefficient is above a selected threshold.

The preset threshold is derived from the required confidence level; higher desired confidence levels require higher thresholds. In one embodiment, sign-maintained squared correlation values larger than 0.8 are characteristic of a match and values lower than 0.7 are characteristic of a mismatch. Thus, sign-maintained squared correlation values higher than 0.8 may be considered as true matches and values lower than 0.7 as mismatches.

The upper diagrams of **FIG. 9** shows a scatter plot of sign-maintained squared correlation values, marking the 0.8 threshold with a dashed line. A clear separation between matches (circles) and mismatches (stars) is evident. The histograms in the other two diagrams provide a different view of the powerful recognition capabilities of the E-BioID system, where it can be seen that the mismatches are concentrated around the zero value (no correlation) while matches are densely distributed near 1.0 (absolute correlation).

In alternative embodiments, more sophisticated decision schemes may be used such as multi-parameter schemes (e.g. fuzzy logic schemes), which use more than one distance measure; for example, multiple correlation values can be derived from segmented data analysis.

In a preferred embodiment, the system improves its performance with time by adding electro-cardiologic signals to the subject's database file when changes in the signals are encountered. In subsequent recognitions, the system processes the newly acquired signals, calculates the pulse rate, forms an electro-biometric subject signature, selects the enrolled electro-biometric signature template with the most similar pulse rate, and compares the new electro-biometric signature with the selected enrolled electro-biometric signature template.

In another preferred embodiment, the system uses signals acquired during long-term system operation to track possible variation in the enrolled subject electro-cardiologic signal and, if consistent changes occur, the enrolled signal is automatically adjusted to reflect these changes. This tracking process compensates for gradual changes in the electro-cardiologic signal over long time periods, but does not compensate for fast, acute changes

like those expected in connection with clinical heart conditions. In another embodiment, such acute changes may be reported to the subject indicating a need for medical consultation.

5 Second Aspect:

Biometric identification methods benefit from proper determination of an identification threshold. The identification threshold may be derived from correlation analysis between candidate signatures and registered
10 database signatures. The threshold may be determined using a distribution of empirical data to achieve optimal identification performance. Yet a fixed threshold implicitly assumes deterministic signatures and stationary noise, while in practice signatures are variable and noise
15 depends on mostly unpredictable external influences. Therefore, biometric identification methods, including those according to the first aspect, may be adversely affected by signal and noise variations in database and test readings. In general, this would yield decreased correlations for both
20 matches and mismatches.

Thus, according to the second aspect, methods and systems of biometric identification, including those according to the first aspect, may use a dynamic threshold capable of compensating for the effect of signal variations
25 and noise interference. This aspect yields a dynamic, data-dependent identification threshold. In the preferred embodiment, the dynamic threshold is re-calculated in each identification attempt using a statistical approach to normalize the correlation data and thus enable calculation
30 of a quantifiable, statistically significant identification threshold. The threshold is shown to be resistant to variable signal and noise conditions.

The preferred method according to this second aspect is based on determination of a confidence limit for a correlation-based scoring between a test signature and a set of registered signatures. These ECG signatures can be empirically determined, but they may also be synthetic, in which case there is no need for a background database in the biometric matching process. Synthetic ECG signatures can be created by using random sets of reconstruction coefficients in the PCA-based ECG model. Alternately, reconstruction coefficient sets may be drawn according to a set of rules extracted from the distributions of real-life reconstruction coefficients derived from real subjects.

In any case, a confidence limit describes, with a given degree of statistical confidence, the upper and lower limits for the values in question. A two-tailed limit describes both upper and lower bounds, while a one-tailed limit describes only an upper or a lower cutoff, with the understanding that there is either no lower or no upper limit to the value of the variable. Confidence limits can be determined statistically, in several different ways, if the variable under consideration meets certain statistical criteria appropriate to each statistical method.

Most statistical methods rely on the values of a normally distributed variable, that is, according to the bell-shaped Gaussian distribution. Normally distributed variables have been well characterized statistically, and their statistical limits can be determined in a straightforward manner based on the variable average and variation.

When a variable is not distributed normally, a normalizing transformation may be used to transform the original variable into a new variable which would then be distributed normally, and may thus be used to determine

confidence limits. The appropriate mathematical transformation may be determined using statistical considerations, or by empirical examination of a sufficiently large dataset. In order to express the confidence limits in terms of the
5 original variable, a back-transformation is also required.

Signal cross-correlation analysis may be used for the matching procedure. Values range from -1 (absolute negative correlation) through 0 (no correlation) to +1 (absolute positive correlation). Generally, significantly positive
10 correlation indicates a probable true identification, and thus a one-tailed, upper confidence limit should be used to describe the dynamic identification threshold.

By definition, correlations are bounded variables and thus are not normally distributed. A mathematical
15 transformation is necessary to normalize the correlation distribution allowing determination of the upper confidence limit. Alternatively, empirical techniques which do not rely on such transformations may be used.

A preferred method, described more fully below, is particularly appropriate for correlation analysis. It is
20 based on the Fisher Z transformation, which converts correlations into a normally distributed variable.

Another method may use squared correlations. Since raw correlations are not additive, averages or other statistical
25 functions of correlations have no statistical meaning. Squared correlations are additive, but they are also not normally distributed, so that additional transformations would be required. If prior processing of the correlations changes the distribution of their values, additional
30 transformations may be necessary to account for these changes. These additional transformations include, but are not limited to, logarithms, squares, square roots, and transcendental functions.

Still another method would involve a degree of prior empirical testing, preferably where a large number of candidates are correlated to a large database. The likelihood of false identifications would be directly
5 determined by examination of this database, or appropriate transformations could be empirically determined. However, because this method is not dynamic and must be performed prior to real testing, the effects of testing conditions cannot be easily compensated, requiring development of
10 mathematical models for the influence of noise.

The preferred method according to this second aspect, the Fisher-transform method, involves transformation of the correlations between the candidate signature and the registered signatures in order to obtain a distribution of
15 scores that are more nearly normally distributed. As noted above, data that meets assumptions of normality can be used to derive parametric confidence limits.

The Fisher Z transformation was designed to normalize correlations. The transformation may be expressed as
20 follows:

$$Z_f = \operatorname{arctanh} (r)$$

Where Z_f is the transformed value, **arctanh** is the hyperbolic arc tangent function, and r is the correlation. The **arctanh** should be expressed in radians.

25 Once all the correlations are transformed, a one-tailed confidence limit for the transformed scores may be determined by taking the mean of all the transformed correlations and the standard deviations of all the transformed correlations, with the exception of the
30 candidate correlation, and calculating:

$$\text{Confidence limit} = \tanh (Z_{f \text{ mean}} + z^* \text{sd}_{Z_f})$$

where **z** is the normal distribution '**z score**', $Z_{f \text{ mean}}$ is the mean of transformed correlations with the database, and sd_{zf} is the standard deviation of the transformed correlations with the data base.

5 The lower case **z** here refers to the value of the normal distribution **z-score**, which is derived based on the desired degree of confidence in the cut-off. A table of such scores is provided in **FIG. 10**.

10 In the table of **FIG. 10**, the standard deviation is multiplied by the appropriate **z-score** and is added to the mean, and the entire quantity back-transformed to a correlation by taking the hyperbolic tangent.

For example, a 95% confidence limit could be determined using a **z** score of 1.65. So if the mean of the transformed values was 0.05, and the standard deviation was 0.25, the 15 95% confidence limit would be 0.72. That is, a correlation value over 0.72 would only occur by chance less than 5% of the time.

A reverse procedure is used to determine the likelihood 20 that any specific candidate identification is due to random chance. By solving for the **z-score**:

$$z = (Z_{fc} - Z_{f \text{ mean}}) / sd_{zf}$$

25 where **z** is the normal distribution '**z score**', Z_{fc} is the transformed candidate correlation, $Z_{f \text{ mean}}$ is the mean of transformed correlations with the database, and sd_{zf} is the standard deviation of the transformed correlations with the data base.

30 The resulting **z-score** can be converted to a 1-tailed probability value by reference to a table of the cumulative normal distribution, and interpolation if necessary. For example, with reference to the abbreviated table above, a **z-score** of 1.80 would suggest a 3.75% probability that the candidate correlated so highly by chance.

As mentioned above, if noise in the registered signatures or in the candidate signature is random, it would reduce the overall correlations with the candidate value. The true identification, if it exists, would therefore have
5 a lower correlation with the candidate. It should be noted that variability of raw correlations increases as the raw values decrease, since high raw correlations are less variable due to a ceiling effect of maximum correlation of 1, but this is compensated for by the transformation. Thus,
10 a dynamic threshold with the desired certainty may be recalculated in each identification attempt using the foregoing methods. Importantly, overall random noise still tends to drive all correlations toward zero and reduce overall true variability, thereby lowering the confidence
15 limit accordingly; yet a true match would remain significant as long as the signal to noise ratio does not fall below a certain limit.

The following examples of the second aspect are based on a 38-subject database. All subjects are healthy
20 individuals, participating in the study on a voluntary basis.

Example 1: Normalization of Correlations

A set of 703 cross-correlations was obtained by correlating all pairs in the database. The raw and z-
25 transformed correlation distributions are presented in **FIG. 11**. While raw correlations are not normally distributed (top), the transformed correlations appear to represent a near-normal distribution (bottom).

Example 2: Performance

30 The biometric identification method was implemented using analysis of 38 enrolled signatures and 38 test

signatures. **FIG. 12** presents FAR and FRR performance curves as a function of a static threshold, and **FIG. 13** presents the performance curves as a function of a dynamic threshold. Clearly, the dynamic threshold provides significantly superior results (eg. $EER_{Static}=3\%$, $EER_{Dynamic}=0\%$).

Third Aspect:

As described above, the dynamic identification threshold is a data-driven threshold, preferably recalculated in each identification session to establish a confidence limit and substantiate a statistical significance of the identification process. Yet overall scores still decrease with the drop in signal quality due to background noise, lowering the dynamic threshold and thereby reducing identification confidence. This problem calls for assessment of signal quality in both enrollment and identification phases to facilitate high performance recognition.

The third aspect solves this problem by calculation of a Q value — a type of signal quality index. A quality of signal index Q is a quantitative description of the quality of the ECG signature. It is based on an analysis of the random error in two or more ECG complexes, derived with reference to their signal average ECG.

The Q value may be used to confirm signal quality during the enrollment and identification phases, ensuring adequate system performance. In case of a Q factor lower than required by a predefined threshold (itself based on the desired level of identification confidence) the measurement may either be extended or repeated until the confidence requirement is met.

One preferred methodology derives Q in a series of steps:

(1) The input ECG signal is segmented into ECG complexes comprised of the conventional wave morphology features (e.g. P, Q-R-S, T elements).

(2) The ECG complexes are aligned ("time-locked")
5 relative to the R wave peak.

(3) An average ECG is derived from the aligned ECG complexes. The preferred method is to take an arithmetic mean, although other methods may be employed, such as the harmonic mean, geometric mean, weighted mean, or median.
10 Other alternatives include transforming the original signals by other methods such as by Principal Component Analysis.

(4) Each original ECG complex is processed relative to the average ECG, such that some difference is derived against the average ECG. The preferred method is to perform
15 subtraction, i.e. original ECG minus average ECG, although other methods may be employed (e.g. division of the original ECG by average ECG). If the average ECG is a stable and true representation of the subject's ECG, then the resulting difference is a representation of the noise inherent in each
20 individual ECG complex (ECG noise).

(5) Each sample point which corresponds in time across each ECG noise complex is processed together to derive a measure of variability. The most preferred method is to determine the variance. Other measures that may be employed
25 include standard deviation or range.

(6) An average is taken of these measures of variability. The most preferred method is to take an arithmetic average. Other methods may involve taking averages after transformation (e.g. log), or taking
30 alternative averages (geometric, harmonic, median). Other summary scores may also be employed, such as the maximum.

Noting that the signal may be normalized prior to analysis, the average may itself be employed as a Q index,

as it is directly related to the SNR. Alternatively, various other scaling transformations may be applied to the average to convert it to an index with the desired minima, maxima, and linearity characteristics.

5 Example 1 according to the Third Aspect: Q (Signal Quality) vs. NSR (Noise to Signal Ratio)

If X denotes the ECG data matrix, each row representing one ECG complex may be denoted $x_i(n)$ where i is the index of an ECG complex and n represents a discrete time unit. The
 10 average of all ECG complexes is denoted $\underline{x}(n)$. For every point in time n we calculate the error term: $e_i(n) = x_i(n) - \underline{x}(n)$, whose variance shall be denoted: $\sigma_e^2(n)$. A preferred scaling conversion, transforming the average of variability into a zero to one range is defined as follows:

15
$$Q = (1 + 100 * \sigma_e^2(n))^{-0.5}$$

A simulation shown in **FIG. 14** demonstrates the utility of using the above Q factor to assess the signal to noise level. This simulation uses real-life ECG recordings with increasing levels of Gaussian white noise added to the
 20 signal. **FIG. 14** presents Q values as a function of the Noise to Signal Ratio (NSR). It can be seen that once Q starts to decline from its plateau, it drops monotonically with the increase in NSR, until the ECG alignment procedure breaks down (NSR $\sim$ -35dB, $Q \sim 0.2$).

25 Example 2 according to the Third Aspect: Score as a function of Signal Quality

In theory, match scores close to 1 indicate a positive match, while non-match scores should tend to zero indicating complete lack of correlation. In practice, however, true
 30 match scores are influenced by temporal variations in the

ECG signature and, more significantly, from background noise. Thus, a higher signal quality is required for short time, high scored identification. It should be noted that high quality signal increases the upper bound on match
5 score, but does not influence the lower bound which depends on the cardiologic signature variability. The example represented by **FIGS. 13** and **14** demonstrates score distribution as a function of signal quality, based on a database of 38 subjects. **FIG. 15** shows short data segments
10 of 5 seconds each. In contrast, **FIG. 16** shows longer segments of 20 seconds each (**FIG. 16**). Obviously, with longer segments the effect of noise is compensated to some extent and the score distribution flattens.

Example 3 according to the Third Aspect: Signal Quality and
15 Duration of Recording

Signal quality may be quantified using the Q parameter. With smaller Q values, and provided that Q does not fall below a certain limit where the ECG alignment process breaks down, longer recordings are necessary to maintain a certain
20 level of statistical significance. **FIGS. 15** and **16** show the increase in identification score as a function of the length of recording for a given Q value.

Thus, according to this third aspect, the methods and systems disclosed herein may calculate signal quality using
25 a Q-factor or other measure, and cause the system to seek a sample with reduced noise or to take a longer sample based on the Q-factor or other signal quality measure and the desired degree of identification confidence.

Fourth Aspect:

30 According to a fourth aspect, the methods and systems disclosed herein may encrypt stored signatures. This safety

feature is designed to prevent misuse of the data in the database notwithstanding that the various methods and systems herein typically operate on stored signatures rather than raw ECG data. Thus, an added layer of security may be employed by encrypting the signatures themselves. To that end, a variety of scrambling techniques may be used including the PKI (public key infrastructure) techniques used for credit card data. This fourth aspect makes improper use of the enrolled subject's data all the more difficult, since an unauthorized person would have to decrypt the signature and then still need to convert the signature back into a raw data signal, an impossible task without knowing which common features were removed from the raw data. Thus, one advantage of the systems and methods disclosed herein is that they make it extremely difficult for anyone to misuse the stored information.

Fifth Aspect:

Biometric identification systems are in general vulnerable to enrollment fraud. The systems and methods according to this fifth aspect solve this problem by using ECG data from genetically related individuals who have enrolled in the database. Immediate family members often have ECGs that share common features. By correlating a subject's signature with the general population and/or with those enrollees he or she is purportedly related to, the system can confidently determine whether or not the subject is who they purport to be. This technique can be used in addition to confirming the individual's identity through conventional methods such as picture identification and/or fingerprint matching. However, unlike those methods, which are non-Euclidian and not amenable to clustering based on similarity, this technique can determine fraud at any stage

of enrollment process by determining a probability of a genetic relationship based on the enrollee's ECG signature.

Sixth Aspect:

The systems and methods disclosed herein may also make
5 use of ultra-high impedance probes to measure ECG. Since
reliability and ease of use is important for an ECG-based
biometric identification system, it is advantageous to
measure an ECG at a single point, or even without touching
the subject. Electric potential probes can work with
10 biometric methods and systems, including those described
herein, to increase reliability and ease of use for
biometric identification. Ultra-high impedance probes come
in a variety of forms. See e.g. Electric potential probes—
new directions in the remote sensing of the human body,
15 Harland et al., Meas. Sci. Technol. 13 (2002) 163-169. The
ultra-high input impedance probes according to this aspect
preferably have ultra-low noise characteristics, and do not
require a current conducting path in order to operate. As a
result, they work well with the foregoing methods and
20 systems even when used by a layperson without the help of an
expert system operator. Thus, these probes may be used in
airport-based biometric identification systems, such as by
acquiring an ECG signal when an individual passes through a
scanner (similar to a metal detector) in full dress.
25 Likewise, a single probe may be used to collect an ECG from
an individual's finger tip, such as at an ATM or gaming
machine. The use of a single probe contact gives the
subject more freedom of movement and makes it easier for him
or her to comply with the identification and enrollment
30 regimen. This is particularly useful when the biometric
identification systems described herein are used to control
the subject's operation of machinery, especially when the

machine requires physical contact to operate (e.g., a
firearm or vehicle). The single probe and remote probe ECG
capture systems according to this aspect may also be comple-
mented by noise reduction strategies to reduce body noise
5 and EMG.

Seventh Aspect:

According to a seventh aspect, a biometric
identification method and system may correlate the match
scores for a subject (which are created by comparing the
10 subject's signature with those of database enrollees) with
the match scores of a plurality of enrollees (which are
created by comparing the enrollees' signatures with those of
database enrollees). Thus, rather than analyzing a
distribution of a subject's correlated match scores, this
15 identification technique analyzes the distribution of the
correlation of a subject's match scores and those of the
enrollees. As with the fifth aspect, the methods and
systems according to this aspect are useful for identifying
related individuals. This is because an individual related
20 to a group of enrollees will have a Gaussian distribution of
match scores that has a substantially higher median than a
Gaussian distribution of the match scores for an individual
unrelated to the enrollees. Thus, by examining the
distribution of match scores, the probability of a subject's
25 genetic relationship with the enrollees may be confirmed.

Eighth Aspect:

Finally, in the alternative or in addition to the
correlation techniques described above, the methods and
systems described herein may employ a weighted correlation
30 for identification. According to this aspect, the
correlation may give different weights to various signature

differences. For example, signature differences due to QRS complex features may be weighted more than signature differences due to T or P complex features. The systems and methods may also use the root mean square of the signature values as part of a weighting function since T is highly variable, QRS is stable, and P is somewhere in the middle. Thus, the signatures may be normalized using root-mean-square computations, L1 metrics or another normalizing technique.

10 Preferred Embodiment That May Be Used With All Aspects:

FIG. 19 shows a functional diagram of a preferred system. Likewise, **FIG. 20** shows a functional diagram of a preferred signal processor. The term "processor" is used herein generically and the processing may be done by physically discrete components, such as with co-processors on an IC chip, or the processor may comprise a physically integral unit.

General Example That May Be Used With All Aspects: ENROLLMENT ALGORITHM

20 The following is an example algorithm for an enrollment phase that may be used with any of the foregoing aspects:

- i. Let $x_i(n)$ represent a 20-second, 250Hz digitized sample of the i^{th} new subject, where n denotes discrete units of time.
- 25 ii. $x_i(n)$ is band-pass filtered in the range 4Hz – 40Hz.
- iii. The filtered signal is denoted $y_i(n)$.
- iv. The filtered signal $y_i(n)$ is searched for QRS complexes, identifying the 'R' peaks as anchor points.
- 30

- v. The filtered signal $y_i(n)$ is maintained or inverted to obtain positive 'R' peaks.
- vi. The identified QRS complexes are counted to establish an average pulse rate reading PR_i .
- 5 vii. The filtered signal $y_i(n)$ is segmented around the anchor points, taking 50 samples before and 90 samples after each 'R' anchor point.
- viii. Each data segment is normalized by the amplitude of the 'R' anchor point.
- 10 ix. The segments are aligned around the anchor points and averaged to produce the subject electro-cardiologic signal, denoted $s_i(n)$.
- x. The subject electro-cardiologic signal $s_i(n)$ is adjusted according to the average pulse rate PR_i ,
 15 by normalizing 'P' and 'T' latencies according to the pulse rate. The adjusted electro-cardiologic signal is denoted $v_i(n)$.
- xi. The pulse rate adjusted subject's electro-cardiologic signal $v_i(n)$ is added to the database
 20 and is introduced into a grand-average $T(n)$.
- xii. A set of electro-biometric signatures Φ_i is constructed by subtraction of the grand-average $T(n)$ from each of the pulse rate adjusted electro-cardiologic signals stored in the system database.

25 EXAMPLE: RECOGNITION ALGORITHM

The following is an example an algorithm for the recognition phase:

- i. Let $x_j(n)$ represent a 10-second, 250Hz digitized sample of the tested subject.

- ii. $x_j(n)$ is band-pass filtered in the range 4Hz – 40Hz.
- iii. The filtered signal is denoted $y_j(n)$.
- iv. The filtered signal $y_j(n)$ is searched for the locations of QRS complexes, using the R peak as an anchor point.
- v. The filtered signal $y_j(n)$ is maintained or inverted to obtain positive 'R' peaks.
- vi. The identified QRS complexes are counted to establish an average pulse rate reading PR_j .
- vii. The filtered signal $y_j(n)$ is segmented around the anchor points, taking 50 samples before and 90 samples after each anchor point.
- viii. The segments are aligned around the anchor points and averaged to produce the subject electro-cardiologic signal, denoted $s_j(n)$.
- ix. The subject electro-cardiologic signal $s_j(n)$ is normalized according to the average pulse rate PR_j . The pulse rate adjusted subject electro-cardiologic signal is denoted $v_j(n)$.
- x. An electro-biometric signature σ_j is constructed by subtraction of the grand-average $T(n)$ from the pulse rate adjusted electro-cardiologic signal $v_j(n)$.
- xi. The correlation coefficients between the electro-biometric signature σ_j and all the enrolled electro-biometric signatures Φ_i are calculated and squared, maintaining their original arithmetic sign.

xii. The largest sign-maintained squared correlation value is selected and compared to a preset threshold.

5 xiii. If the selected largest sign maintained squared correlation value is larger than the preset threshold then a positive match is indicated, and the subject is identified.

10 Thus, a method and apparatus of acquisition, processing, and analysis of electro-cardiologic signals for electro-biometric identity recognition may include any subset of the following enrollment and recognition steps:

ENROLLMENT

Acquisition, digitization, and storage of electro-cardiologic signals from subjects;

- 15 a. Formation of an electro-cardiologic signal database;
- b. Partition of the template database into several subsets based on electro-cardiologic signal similarity;
- 20 c. Construction of one or more grand averages;
- d. Derivation of subject-specific electro-biometric signatures.

RECOGNITION

VERIFICATION

25 The newly captured electro-biometric signature is compared with the subject specific enrolled electro-biometric signature template;

- a. Correlation and confidence analysis of the newly captured subject electro-biometric signature with

the relevant stored electro-biometric signature template;

- b. Display and registration of the recognition result and/or activation of a physical or virtual local/remote mechanism.

IDENTIFICATION

The newly captured electro-biometric signature is compared with all of the electro-biometric signature templates participating in the database;

- a. Correlation and confidence analysis of the newly captured subject electro-biometric signature with all stored electro-biometric signature templates;
- b. Display and registration of the recognition result and/or activation of a physical or virtual local/remote mechanism.

In a preferred embodiment, the E-BioID system measures an electrical bio-signal from the human body through conductive sensor plates. These same plates may be used for bidirectional interaction with the subject's nervous system, for example, by inducing a sympathetic skin response in the user with small magnitude electrical stimulation that is provided through the plates. Such bidirectional interaction constitutes a biological challenge-response mechanism that ensures submission of a fresh bio-signal without requiring active participation of the user in the challenge-response procedure.

Others may readily modify and/or adapt the embodiments herein for various applications without undue experimentation and without departing from the generic concept. Such adaptations and modifications should and are intended to be comprehended within the meaning and range of equivalents of the disclosed embodiments. It is to be understood that the

phraseology or terminology employed herein is for the purpose of description and not of limitation. The means, materials, and steps for carrying out various disclosed functions may take a variety of alternative forms and still
5 fall within the literal or equivalent scope of the claims.

Thus the expressions "means to..." and "means for...", or any method step language, as may be found in the specification above and/or in the claims below, followed by a functional statement, are intended to define and cover
10 whatever structural, physical, chemical or electrical element or structure, or whatever method step, which may now or in the future exist which carries out the recited function, whether or not precisely equivalent to the embodiment or embodiments disclosed in the specification
15 above, i.e., other means or steps for carrying out the same functions can be used; and it is intended that such expressions be given their broadest interpretation.

73236-81

47

CLAIMS:

1. A biometric identification system comprising
 - a) an electrocardiogram signal acquisition module;
 - b) an enrolled signature database;
 - 5 c) an electrocardiogram signal processor comprising an electrocardiogram signature generator that removes characteristic waveforms, which represent common electrocardiogram features of a group of individuals, from the electrocardiogram signal acquired by the electrocardiogram signal acquisition module;
 - 10 d) an electrocardiogram signature comparator that compares an electrocardiogram signature with at least one enrolled electrocardiogram signature; and
 - e) an output module.
2. The system of claim 1 wherein said electrocardiogram
15 signature generator removes characteristic waveforms representing the first principal components derived from a principal component analysis of said group's electrocardiogram signals.
3. The system of claim 2 wherein said characteristic
20 waveforms are weighted to approximate the extent of those characteristic waveforms present in the electrocardiogram signal acquired by the electrocardiogram signal acquisition module.
4. The system of claim 3 wherein said electrocardiogram
25 signature generator removes said approximation from the electrocardiogram signal acquired by the electrocardiogram signal acquisition module.

73236-81

48

5. The system of claim 2 wherein said electrocardiogram signal acquisition module acquires an electrocardiogram signal from an individual who is not a member of said group of individuals.

5 6. The system of any one of claims 1 to 3 wherein said characteristic waveforms are derived from synthetic electrocardiograms.

7. The system of claim 1 wherein said electrocardiogram signature generator removes characteristic waveforms derived
10 from an independent component analysis of said group's electrocardiogram signals.

8. The system of claim 1 wherein said electrocardiogram signature generator removes characteristic waveforms derived from a wavelet decomposition of said group's electrocardiogram
15 signals.

9. The system of claim 3 wherein said system uses reconstruction coefficients to weight said characteristic waveforms.

10. The system of any one of claims 1 to 3 wherein said
20 electrocardiogram acquisition module comprises a bidirectional interface that provides for a biological challenge-response mechanism independent of a conscious response from the user.

11. The system of claim 10 wherein said bidirectional interface comprises a conductive medium.

25 12. The system of claim 11 wherein said conductive medium is incorporated into an apparel item.

73236-81

49

13. A method for identifying an individual comprising the steps of:

a) acquiring a subject's electrocardiogram;

5 b) decomposing electrocardiograms from a group of individuals to determine a set of characteristic waveforms that represent common features of the group;

c) processing said subject's electrocardiogram by removing said characteristic waveforms; and

10 d) using the subject's processed electrocardiogram to identify the subject.

14. The method of claim 13 wherein the subject is not a member of said group of individuals.

15. The method of claim 13 wherein said decomposed electrocardiograms are synthetic.

15 16. The method of claim 13 wherein said steps are performed in the listed order.

17. The method of claim 13 further comprising the step of weighting said characteristic waveforms to approximate the extent of common features present in the subject's
20 electrocardiogram.

18. The method of claim 17 wherein the step of removing said characteristic waveforms is accomplished by removing said approximation.

73236-81

50

19. The method of claim 17 wherein said decomposing step is performed by applying principal component analysis to the electrocardiograms from the group of individuals, and said weighting step is performed by determining reconstruction
- 5 coefficients for the principal components that represent common features so as to approximate the extent of said characteristic waveforms present in the subject's electrocardiogram.
20. The method of claim 19 wherein said approximation is removed from the subject's electrocardiogram.
- 10 21. The method of claim 19 wherein the principal components representing common features are time shifted to determine said reconstruction coefficients.
22. The method of claim 13 wherein said decomposing step is independent component analysis.
- 15 23. The method of claim 13 wherein said decomposing step is wavelet decomposition.
24. The method of any one of claims 13 to 16 further comprising the step of challenging the subject independent of the subject's conscious response.
- 20 25. The method of claim 24 wherein the challenge step includes providing an electrical stimulus through a conductive medium that is also used to acquire the subject's electrocardiogram.
26. A method of biometric identification comprising the
- 25 steps of:
- a) acquiring an electrocardiogram signal;

73236-81

51

b) processing said electrocardiogram signal to generate an electrocardiogram signature;

c) correlating said electrocardiogram signature with a plurality of synthetic electrocardiogram signatures;

5 d) transforming one or more of said correlations;

e) generating a dynamic threshold for said correlation; and

f) outputting the identification result.

27. The method of claim 26 wherein the steps are
10 performed in the listed order.

01/12

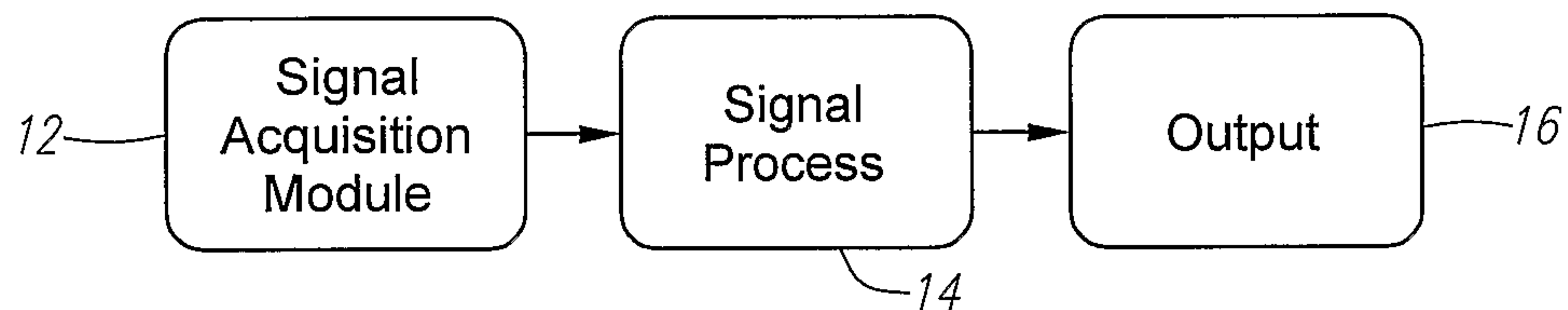


Figure 1: Block diagram of the E-BioID system

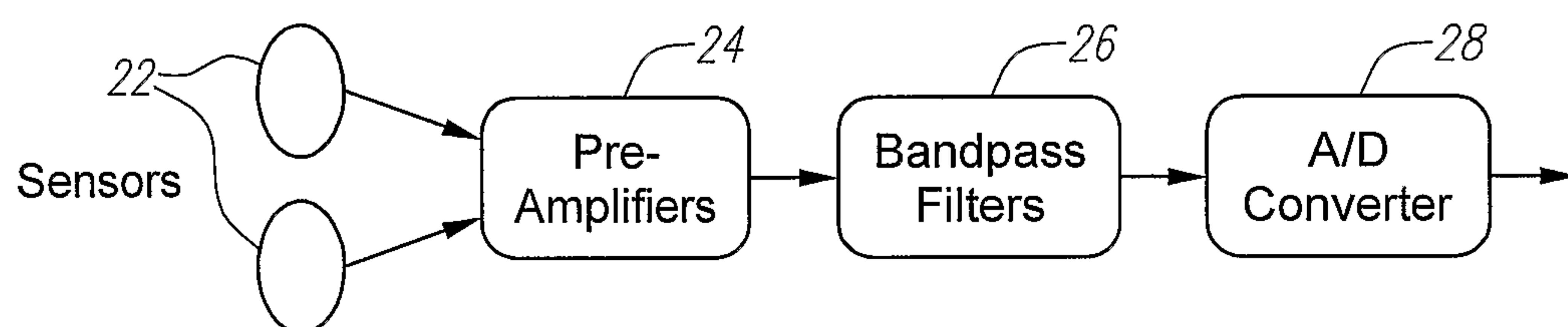


Figure 2: Block diagram of the signal acquisition module

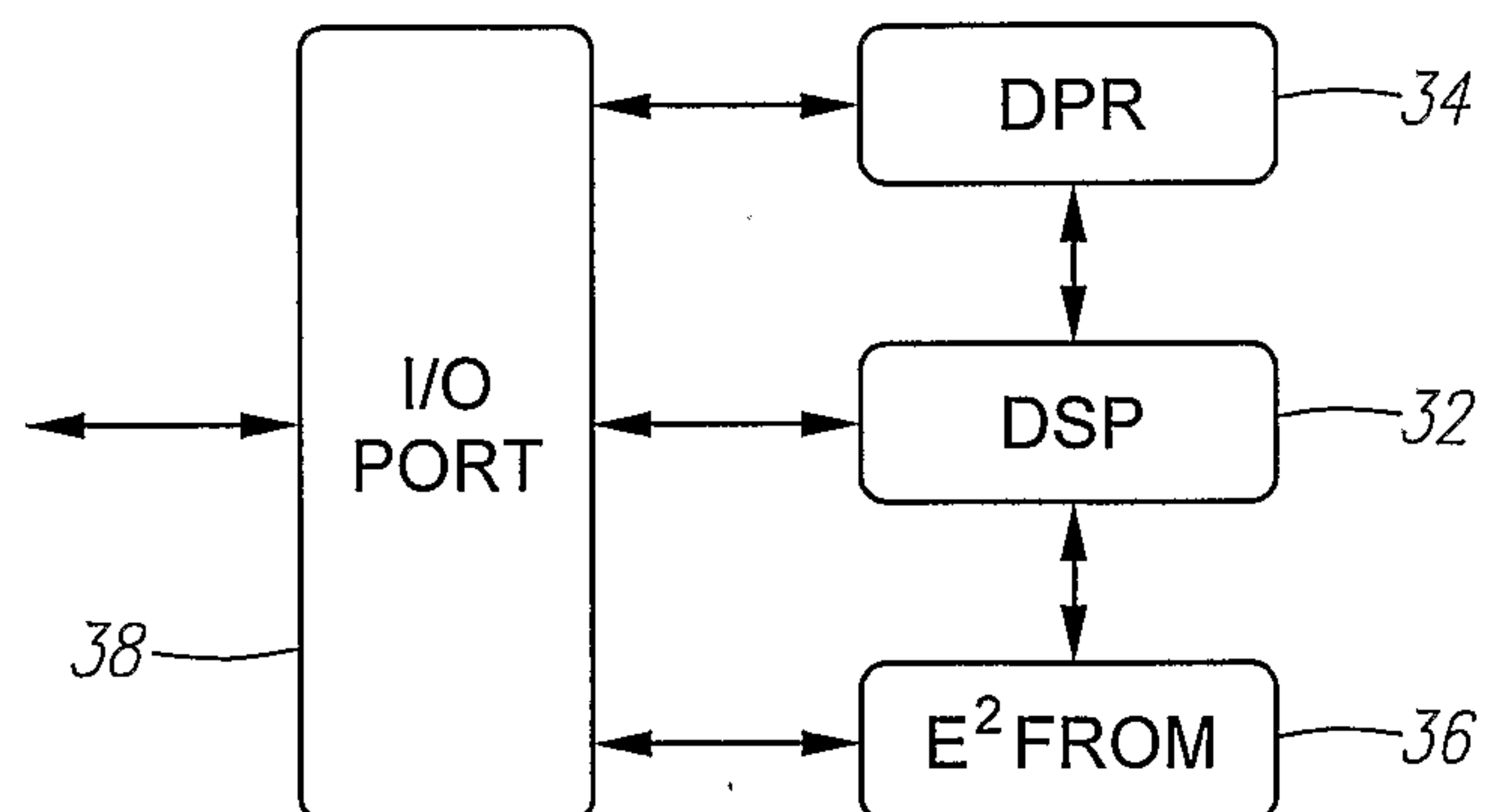
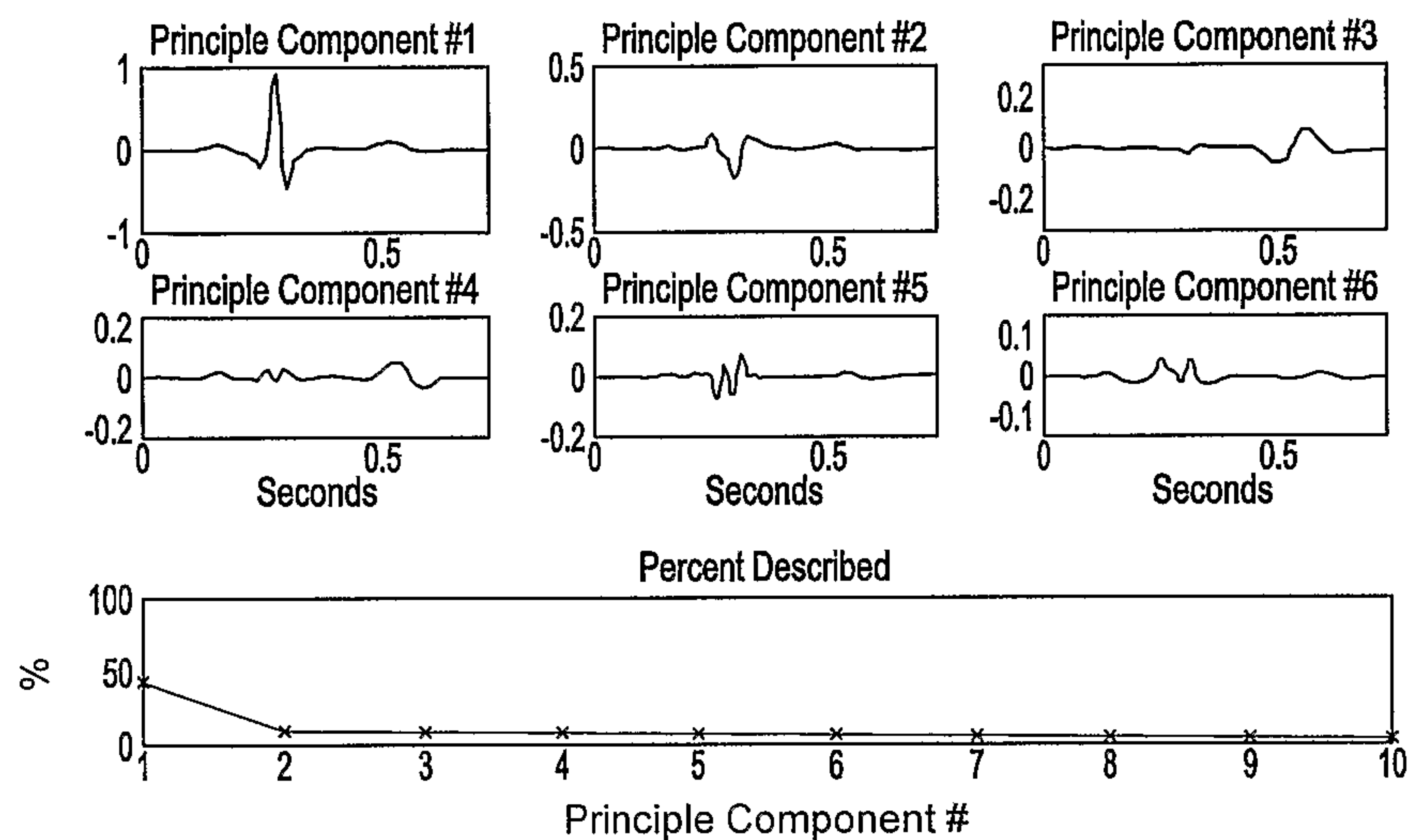


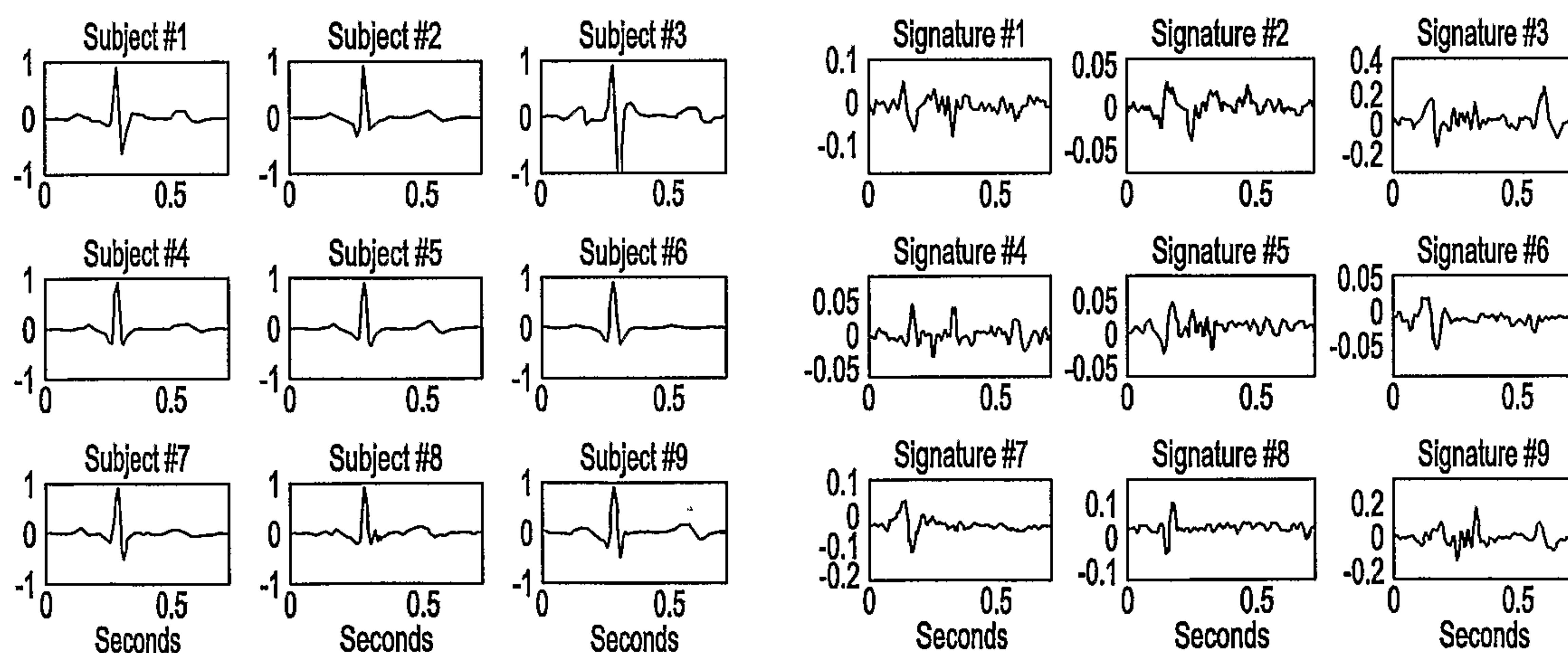
Figure 3: Block diagram of the sig. proc. module

02/12



THE MOST INFLUENTIAL 6 PCs (top)
RELATIVE CONTRIBUTION OF THE MOST INFLUENTIAL 10 PCs (bottom)

FIG. 4



ORIGINAL ELECTROCARDIOGRAPHIC SIGNALS (LEFT)
COMMON-ELIMINATED DERIVED SIGNATURES (RIGHT)

FIG. 5

03/12

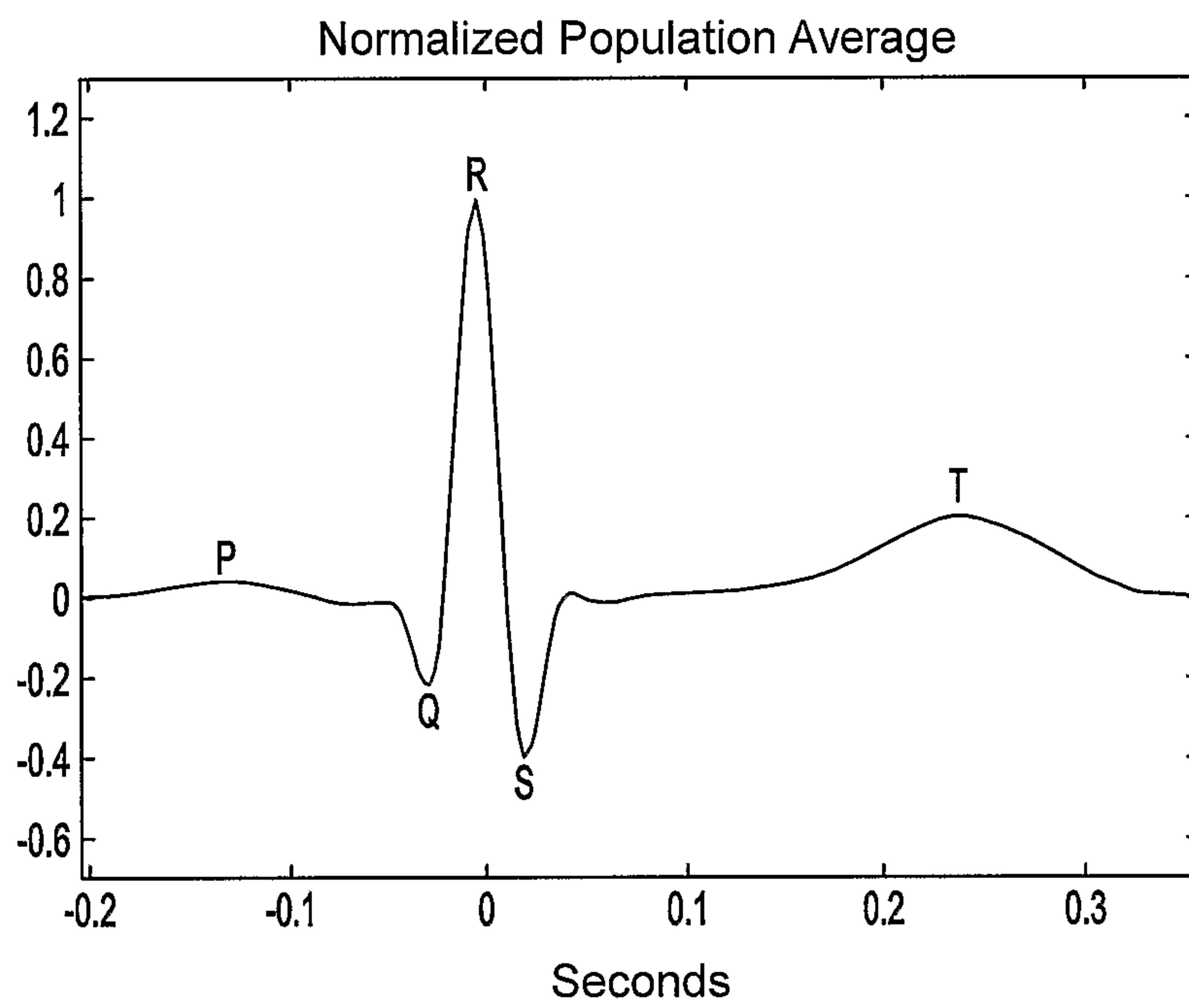


Figure 6: Normalized grand-average

04/12

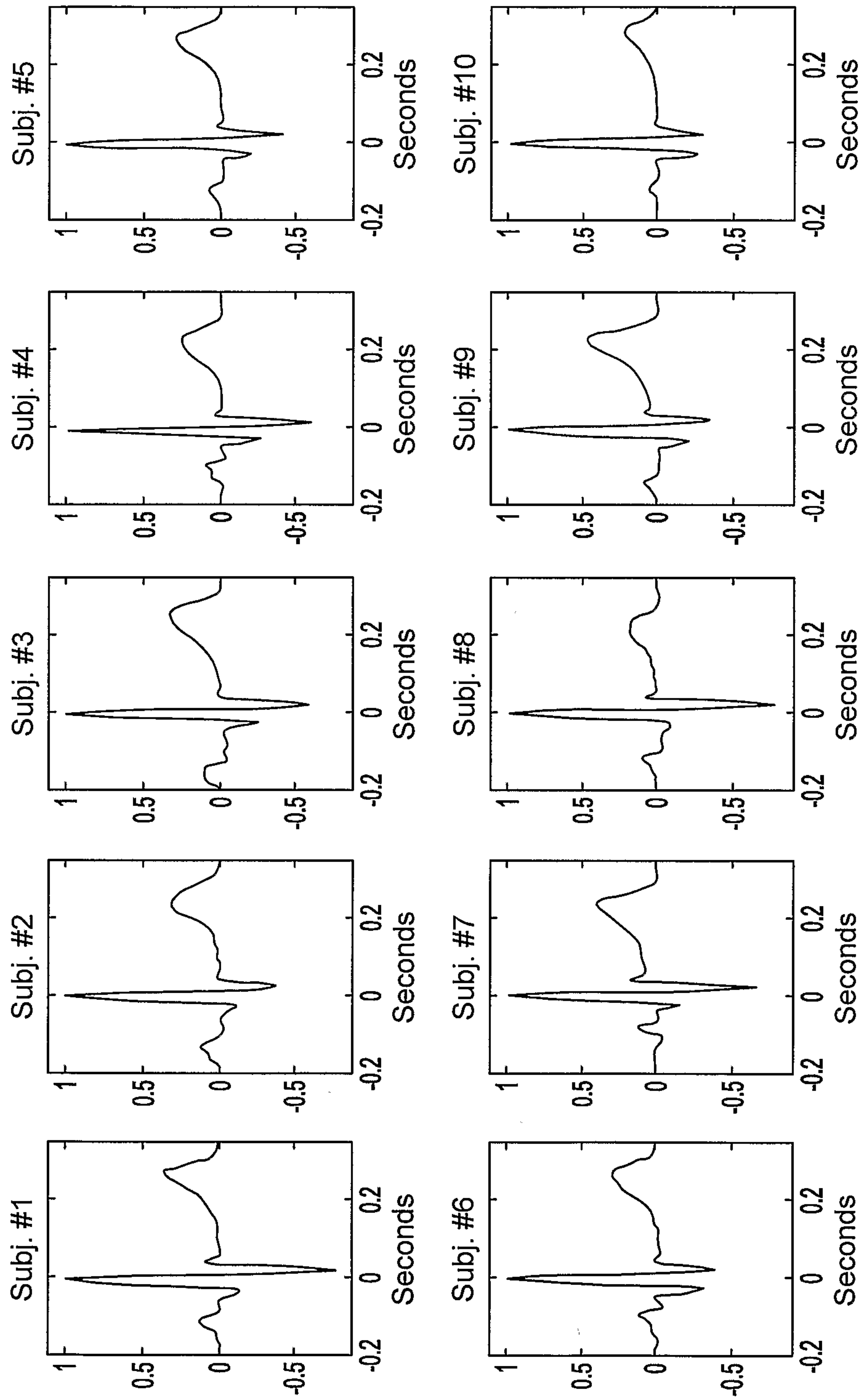


Figure 7: Electro-cardiologic signals of ten subjects

05/12

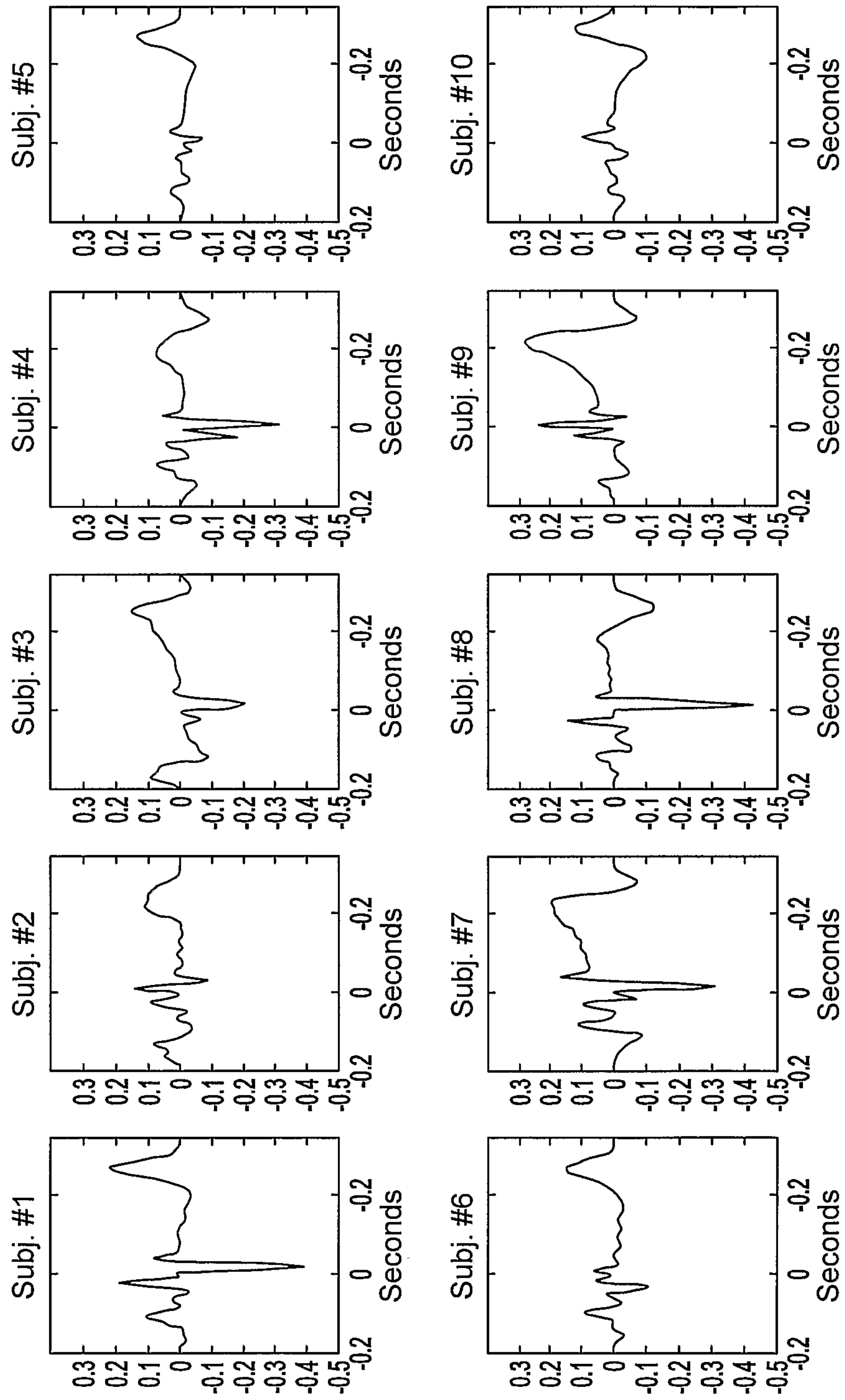


Figure 8: Signature templates of the above ten subjects

06/12

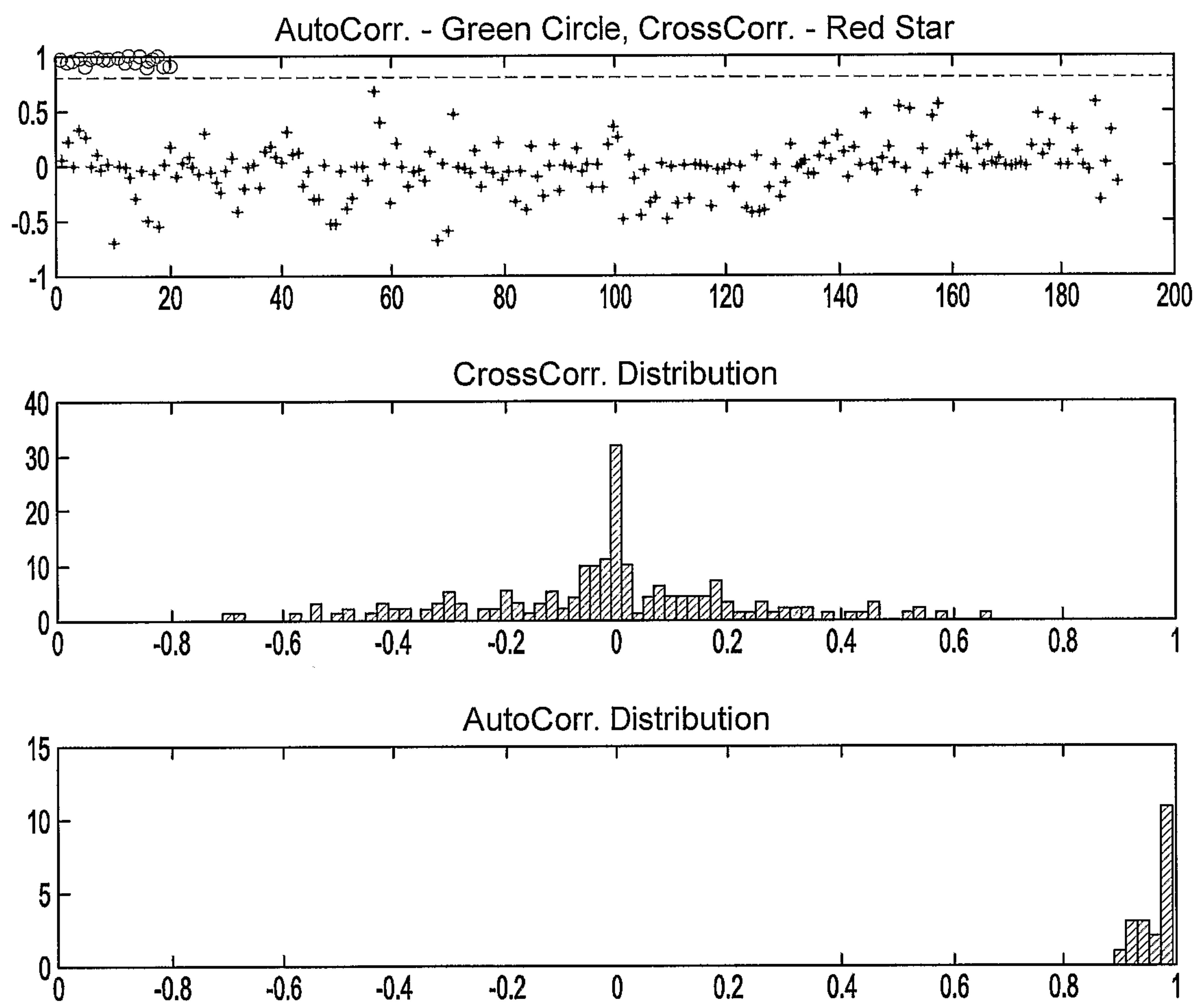
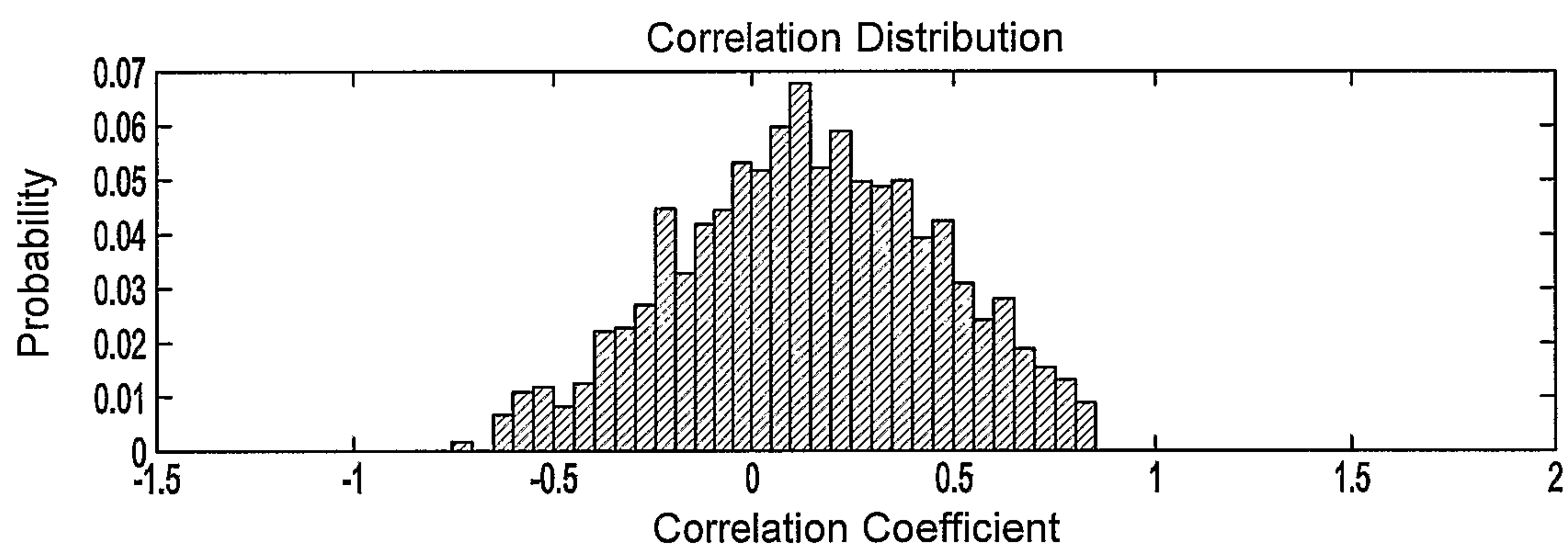
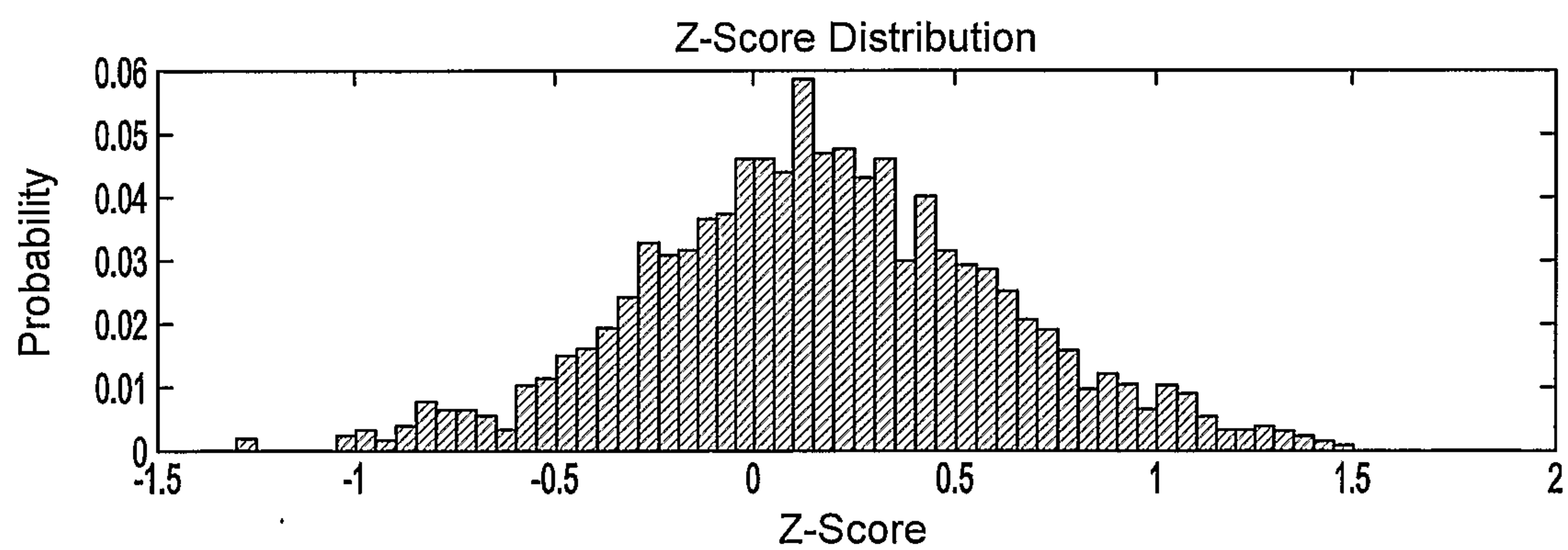


Figure 9: Distributions of correlation data

07/12

1-tailed limit	Unlikelihood	z score
99.99%	0.01%	3.71
99.90%	0.10%	3.09
99.50%	0.50%	2.58
99.00%	1.00%	2.33
97.50%	2.50%	1.96
95.00%	5.00%	1.65
90.00%	10.00%	1.28

Figure 10*Figure 11A**Figure 11B*

08/12

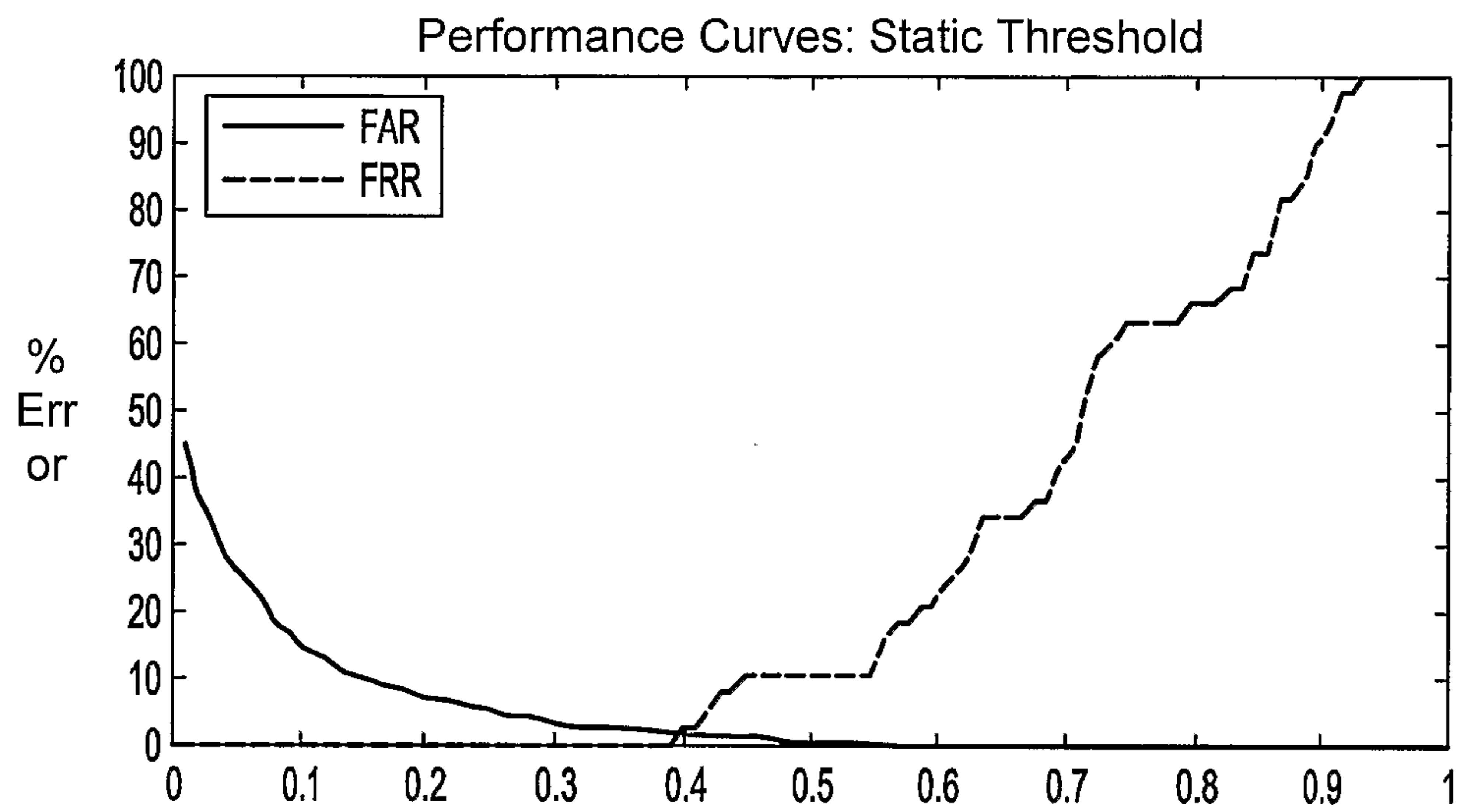


Figure 12: Identification Performance Curves (Static)

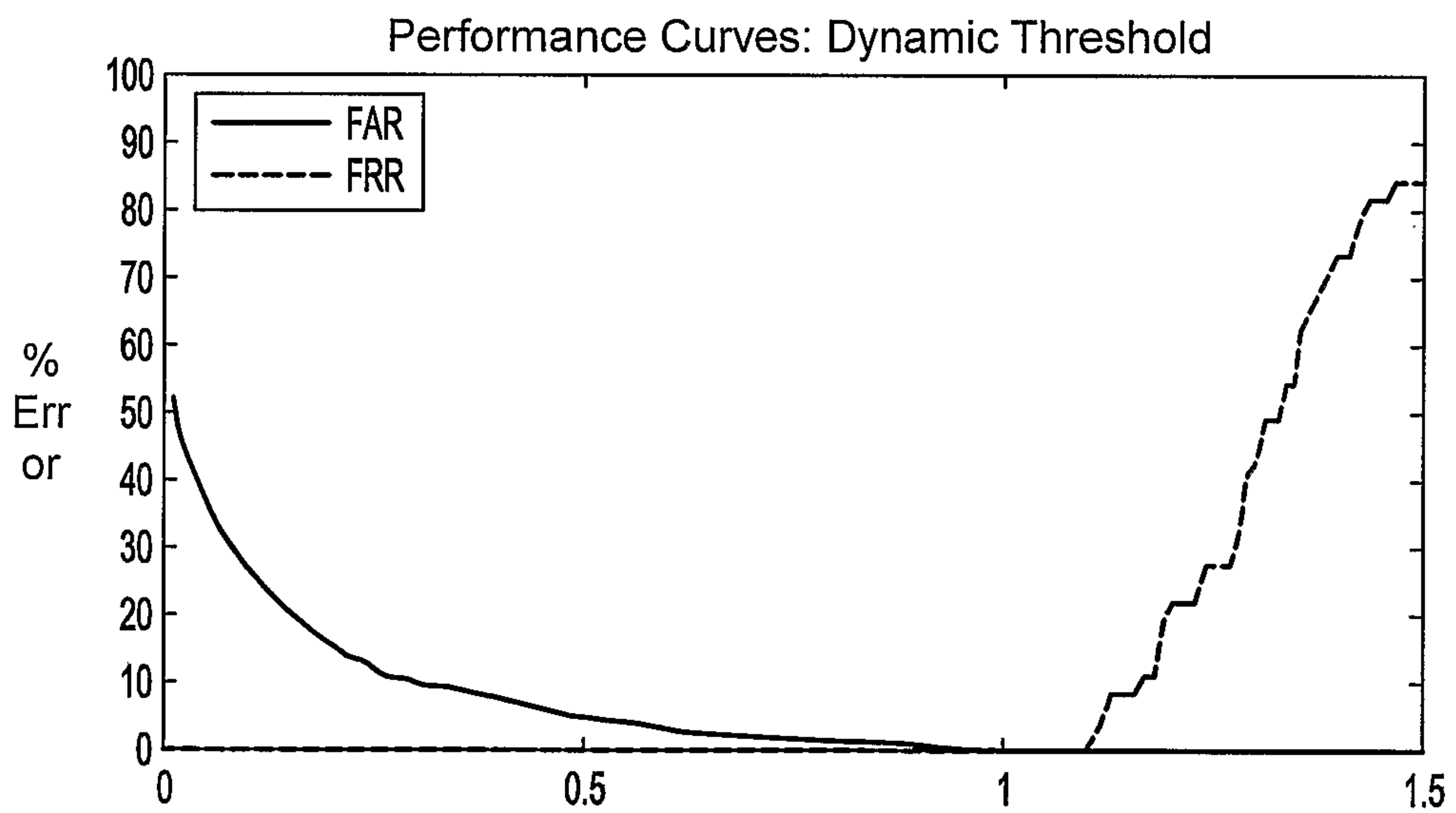


Figure 13: Identification Performance Curves (Dynamic)

09/12

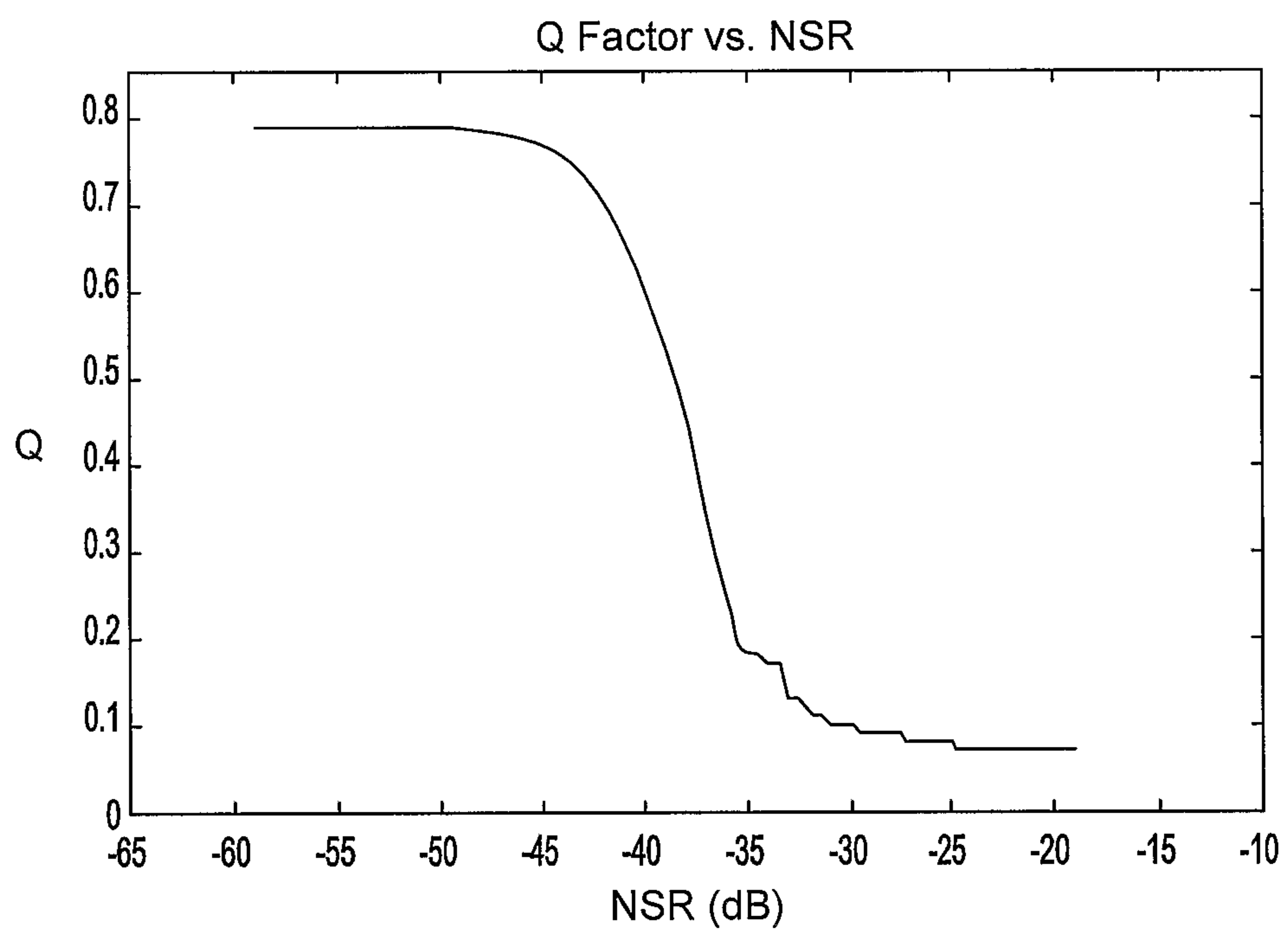


Figure 14: Signal Quality as a function of NSR

10/12

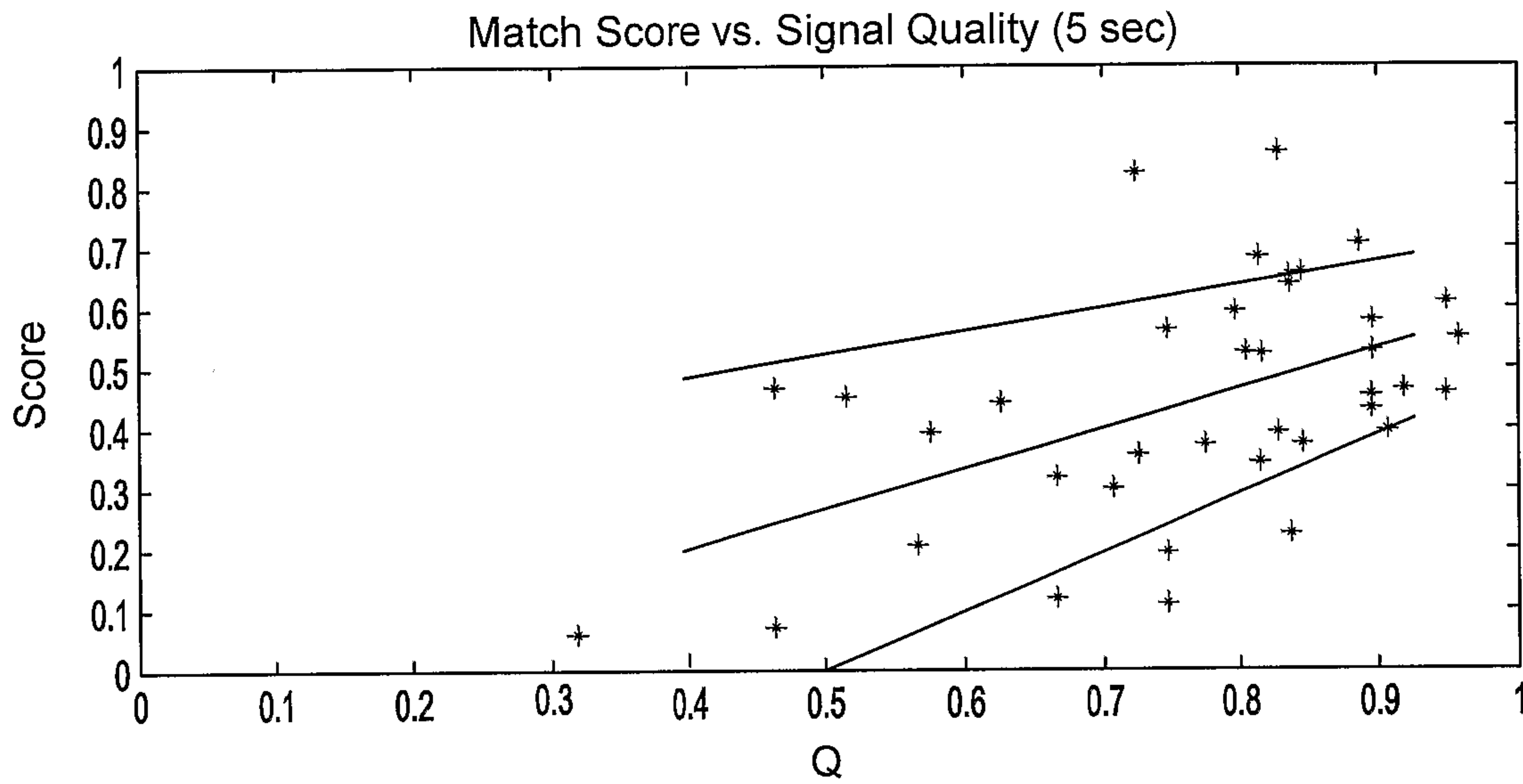


Figure 15: Match score distribution as a function of signal quality (5 sec segments)

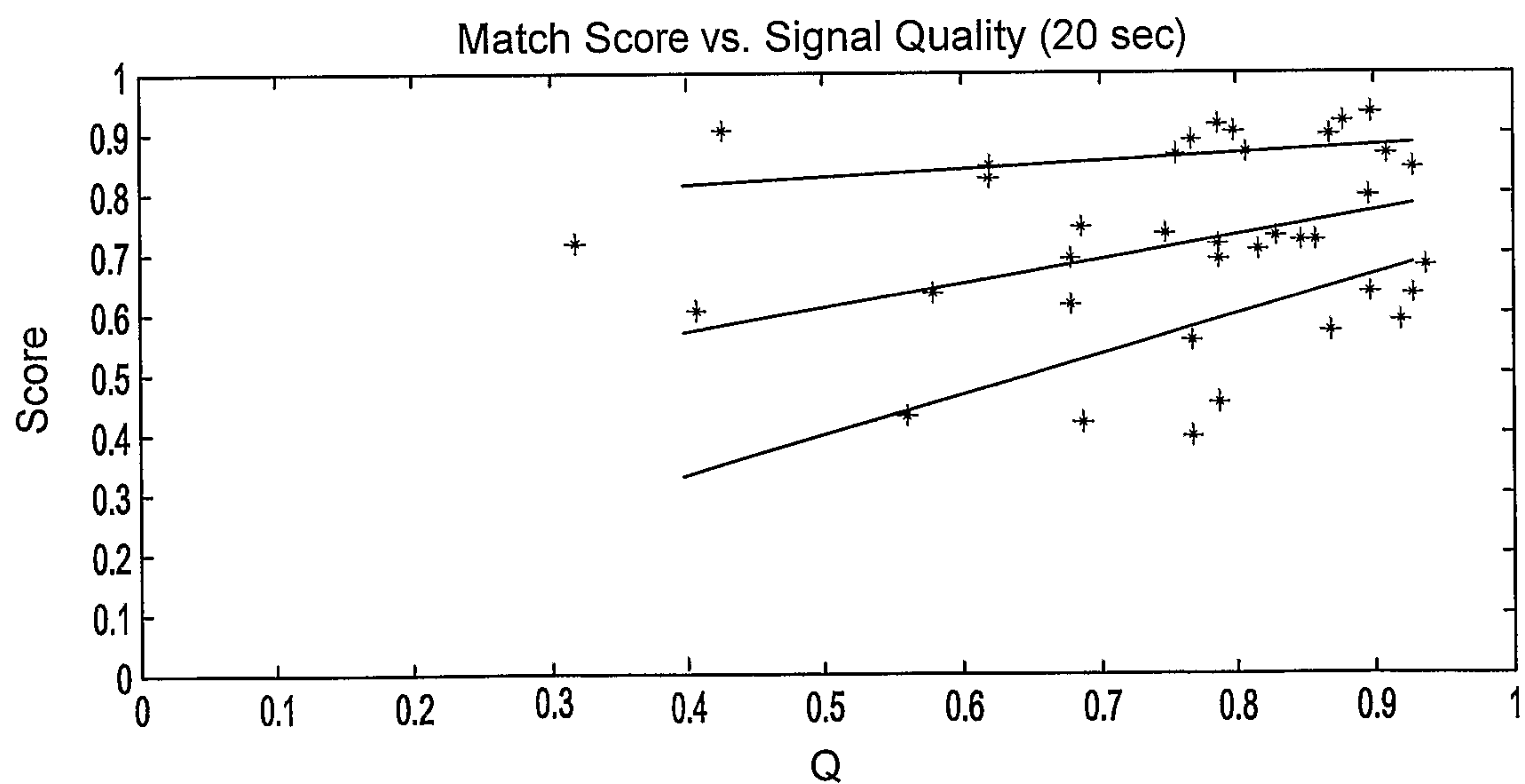


Figure 16: Match score distribution as a function of signal quality (20 sec segments)

11/12

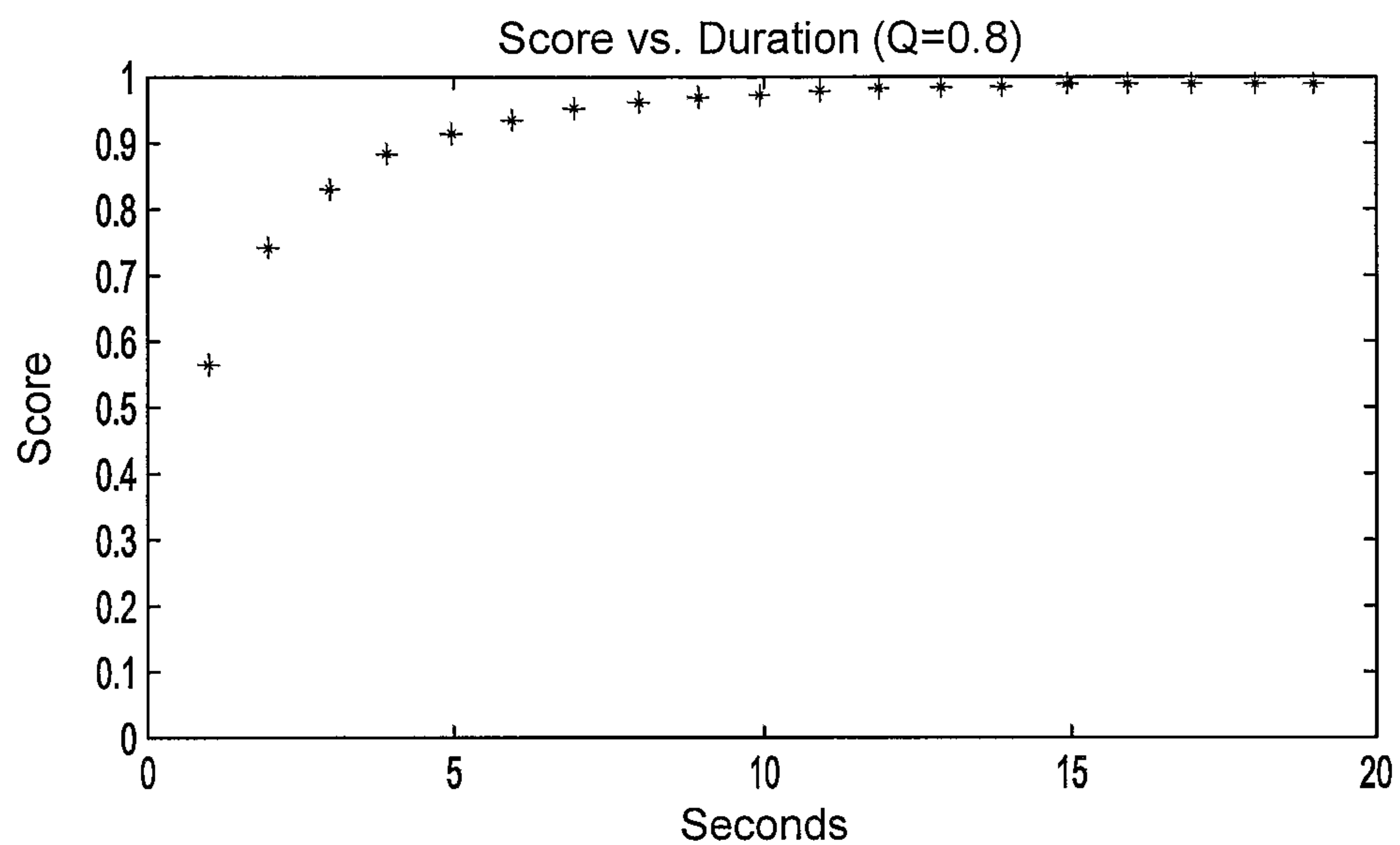


Figure 17: Match score as a function of duration of recording (Q=0.8)

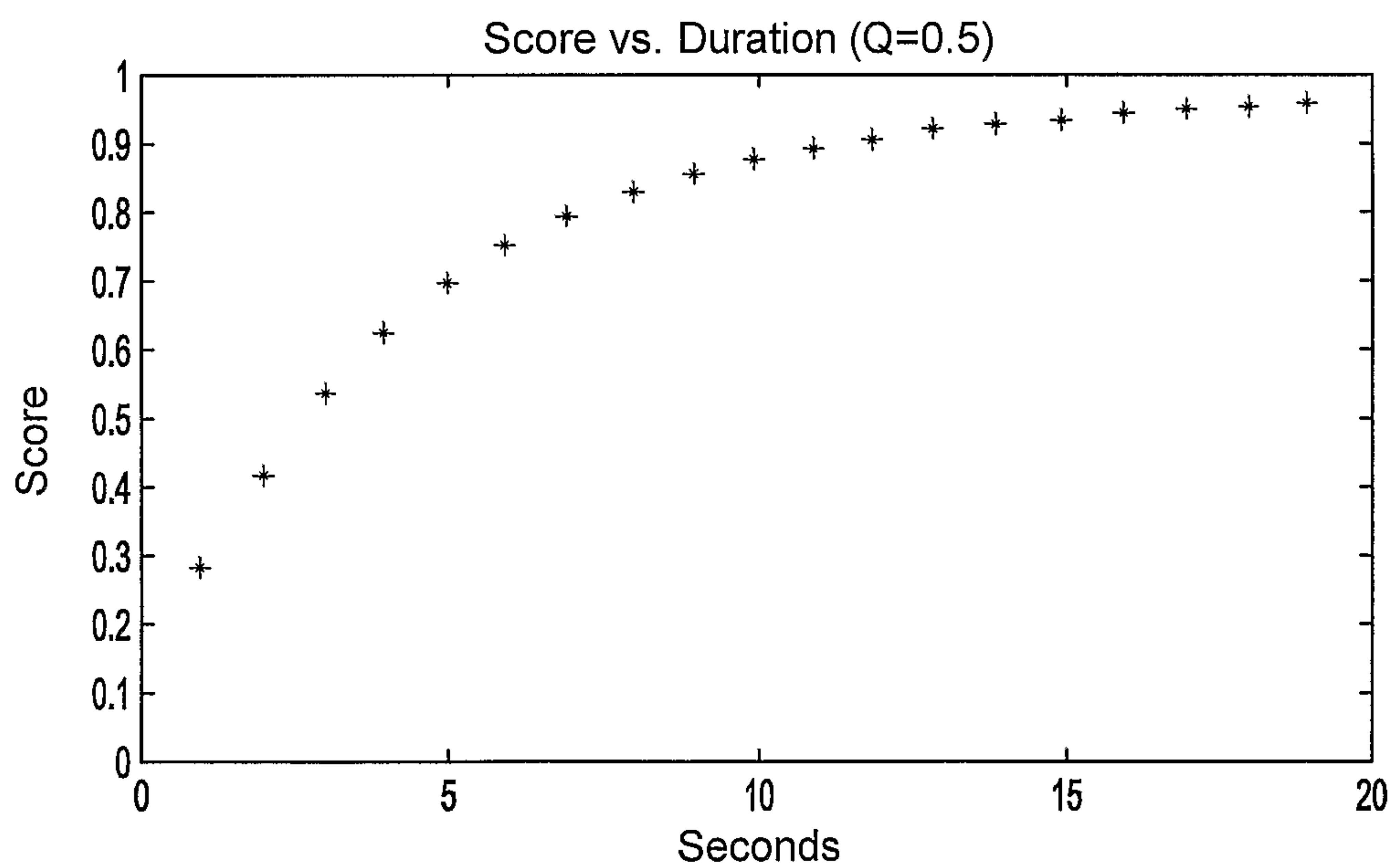
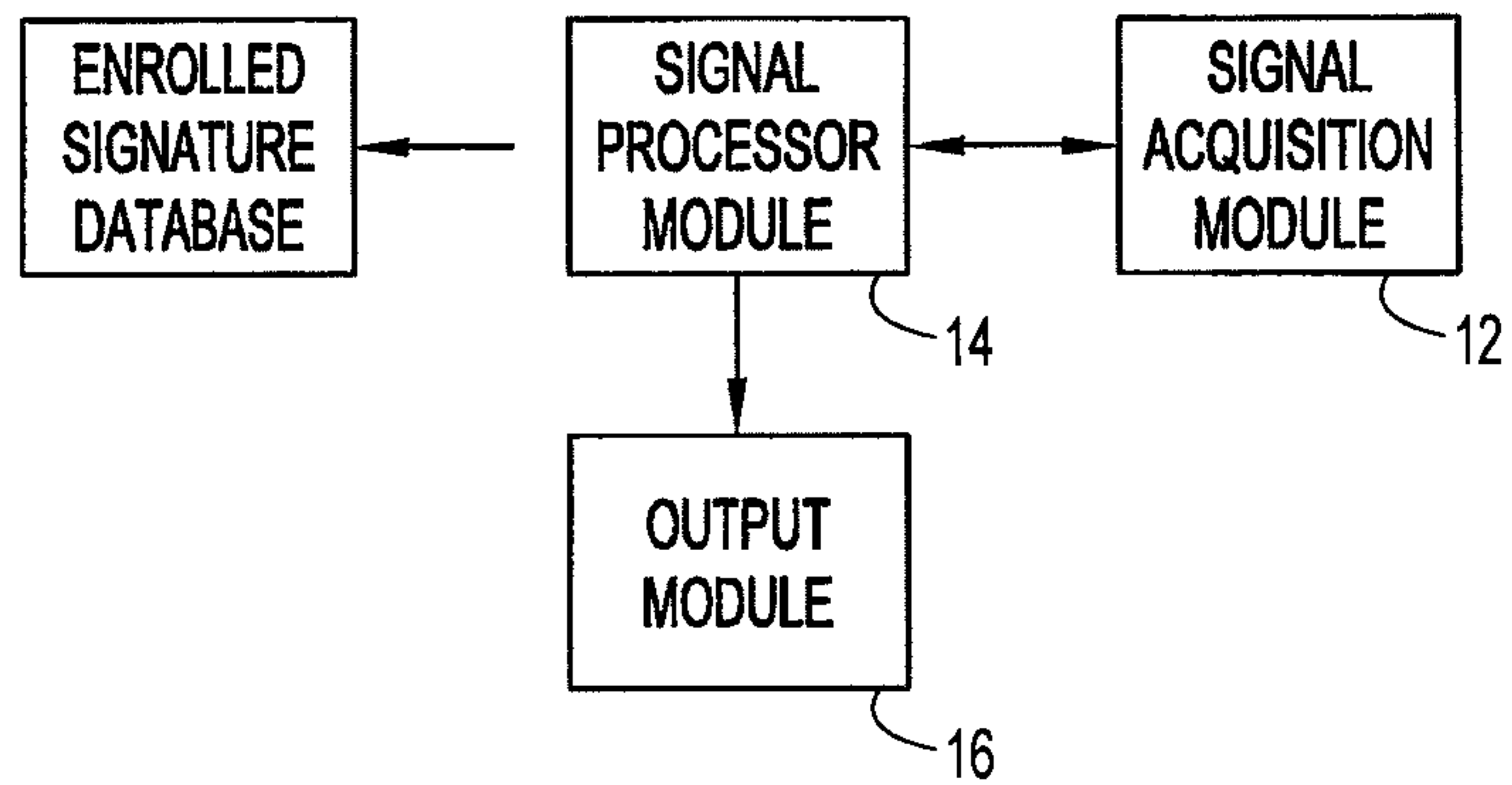
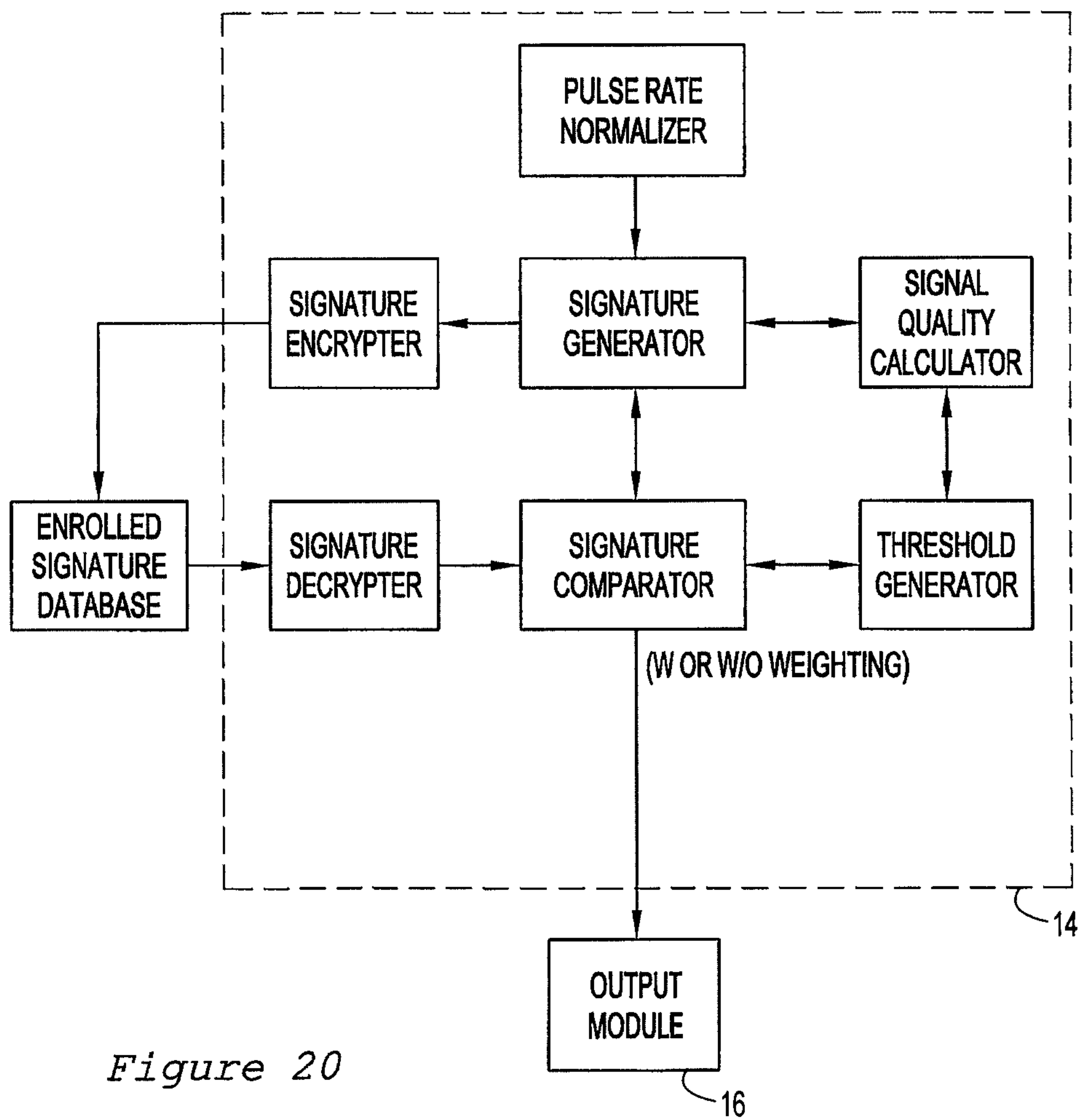
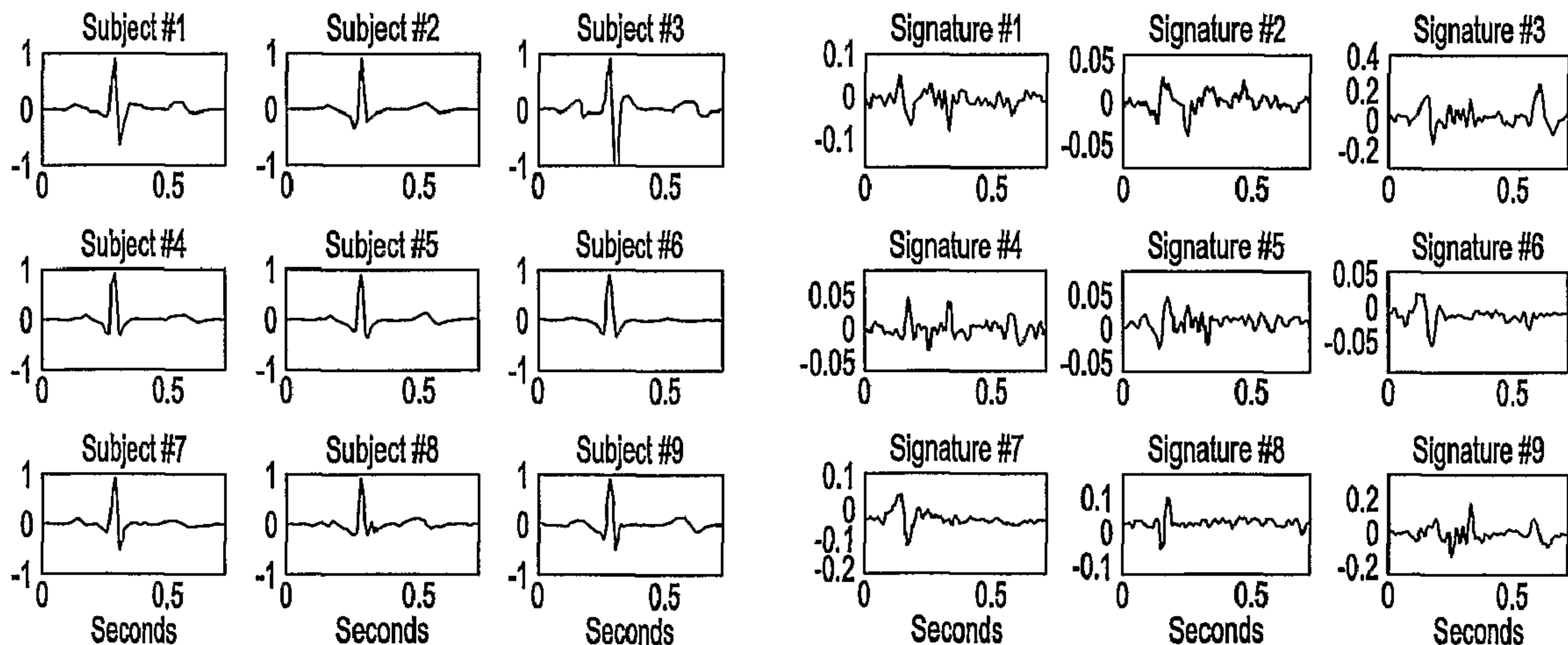


Figure 18: Match score as a function of duration of recording (Q=0.5)

12/12

*Figure 19**Figure 20*



*ORIGINAL ELECTROCARDIOGRAPHIC SIGNALS (LEFT)
COMMON-ELIMINATED DERIVED SIGNATURES (RIGHT)*