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A Chaos Based Security Approach for Data Authentication in Personal and Body Area Networks

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Abstract: Personal Area Networks (PANs) and Body Area Networks (BANs) are localized networks designed to facilitate communication between personal devices and sensors, often within a short range. PANs typically connect devices like smartphones, tablets, and wearables, while BANs are specialized networks that connect sensors directly on or near the human body. These networks are pivotal in applications ranging from health monitoring to fitness tracking and personal productivity. However, due to the sensitive nature of data transmitted, especially in BANs, securing these networks is crucial to protect user privacy and prevent unauthorized access to potentially sensitive information. This paper present a Chaos based approach for generating a pseudo random (PR) sequence based on Physiological inter pulse interval (IPI) collected from the subject. The evaluation of the strength of the PR sequence is gauged based on the hamming distance and entropy metrics. It has been shown that the proposed approach attains a higher hamming distance and entropy compared to exiting work in the domain.

Keywords: Personal and Body Area Networks, Chaos, Inter Pulse Interval, Hamming Distance, Entropy, Pseudo Random (PR) Sequence.

I. INTRODUCTION

Wireless body-area network (WBAN) is a special purpose wireless-sensor network that incorporates different networks and wireless devices to enable remote monitoring for various environments [1]. One of the targeted applications of WBAN is in medical environments where conditions of a large number of patients are continuously being monitored in real-time. Wireless monitoring of physiological signals of a large number of patients is one of the current needs in order to deploy a complete wireless sensor network in healthcare system. Such an application presents some challenges in both software and hardware designs. Some of them are as follows: reliable communication by eliminating collisions of two sensor signals and interference from other external wireless devices, low-cost, low power consumption, and providing flexibility to the patients [2]. A WBAN-based wireless medical sensor network system when implemented in medical centers has significant advantages over the traditional wired-based patient-data collection schemes by providing better rehabilitation and improved patient's quality of life. In addition a WBAN system has the potential to reduce the healthcare cost as well as the workload of medical professions, resulting in higher efficiency.

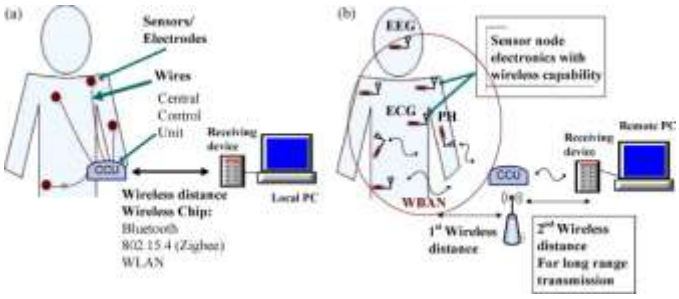

Fig.1 Concept of Wireless Personal and Body Area Networks [1]

Additionally, tiny nodes in WBSNs are resource constrained regarding battery, computation capability, and memory. Therefore, it is necessary to provide a balance between medical data security and resource consumption of sensor nodes in WBSNs. In recent times, the objectives of ECG monitoring have gone beyond mere heart rate and rhythm measurement to the analysis of chronic diseases including complex arrhythmias, stress management, and sleep disorders among others. The significance of ECG in clinical applications is because it offers a non-invasive means to evaluate the Autonomic Nervous System (ANS) which can be helpful in diagnoses of cardiac related diseases. Additionally, it has been remarkably explored in several previous studies that ECG signals possess unique characteristics to be utilized for biometric security purposes in WBSNs [3]. One of the significant benefits of ECG based security methods is that they are robust against false attacks. Moreover, ECG signal can provide the

evidence by signifying that specific application should ensure that the particular person who is posing the biometric security is certainly the same individual who is carrying it [4].

Thus, ECG signal plays an essential role in developing security mechanisms to provide secure communication between patients and physicians in real-time healthcare scenarios. However, the main limitation of WBSNs is that it should be operated under stringent constraints. Thus, to provide a balance between security and resource efficiency a biometric trait such as inter-pulse intervals (IPIs) has been widely considered. IPIs are the time intervals between two successive heartbeats also referred as RR-intervals. In order to initiate communication within sensor nodes of WBSNs, time synchronization is an essential factor [5].

II. FEATURE EXTRACTION

The regular motion of the human heart is often referred to as the cardiac cycle. The presence of sodium and potassium ions in the blood stream produces very weak electrical signals (voltages) when blood flows in and out of the heart. It has been observed that the ECG signals follow a repetitive or periodic pattern. Based on the trajectory of the ECG curve, certain fundamental features have been identified. The section that follows explains the cardiac cycle. ECG is the graphical representation of the cyclic rhythm of contraction and relaxation activity generated by the heart. An ECG is composed of the P wave, QRS complex, T and U waves [6].

They are denoted by the capital letters P, Q,R,S, and T and U. The P wave is the contraction of the atria, while the QRS complex is associated with the contraction of the ventricles. The T wave is due to the relaxation of the ventricles. The P, Q, R, S, T and U waves of the ECG signal contain all the important features that characterize the activity in the heart. The ECG signal is measured through a number of electrodes that are normally attached to a patient's body. ECG recordings usually contain high and low frequency noise. Amplitudes within beats vary from person to person [7].

a) Data Pre-Processing prior to Feature Extraction

Prior to the feature extraction stage, proper pre processing stage in very crucial for the correct extraction of features. In some ECG signals the noise level is very high and it is not possible to recognize it by single recording, it is important to gain a good understanding of the noise processes involved before one attempt to filter or preprocess a signal [8] The ECG signal is very sensitive in nature, and even if small noise mixed with original signal the characteristics of the signal changes. The most difficult problem faced by an automatic ECG analysis is the large variation in the morphologies of ECG waveforms, it happens not only for different patients or patient groups but also within the same patient. Since the ECG signal is the most affected by 50-60 Hz power line noise also called baseline drift, therefore we need to employ high pass filtering for its removal [9].

b) Extraction of Morphological Features

This stage consists of extraction of salient features which can give conclusive results for different heartbeat cases.. The heartbeat detection module attempts to locate all heartbeats .The feature extraction module forms a feature vector from each heartbeat. The feature extraction modules are required, because greater classification performance is often achieved if a smaller number of discriminating features are first extracted from the ECG [10] The Feature Extraction Parameters [11]:

- RR interval evaluation.
- SS interval evaluation.
- QQ interval evaluation.
- QRS complex evaluation.

ECG Feature Extraction plays a significant role in diagnosing most of the cardiac diseases. One cardiac cycle in an ECG signal consists of the P-QRS-T waves. This feature extraction scheme determines the amplitudes and intervals in the ECG signal for subsequent analysis. The amplitudes and intervals value of P-QRS-T segment determines the functioning of heart of every human [12].

III. GENERATION PR SEQUENCE

The random bit generation has been implemented using the Markov process. A Markov process is a random process indexed by time, and with the property that the future is independent of the past, given the present. Markov processes, named for Andrei Markov, are among the most important of all random processes. In a sense, they are the stochastic analogs of differential equations and recurrence relations, which are of course, among the most important deterministic processes [13]. The complexity of the theory of Markov processes depends greatly on whether the time space **T** is **N** (discrete time) or [0,∞] (continuous time) and whether the state space is discrete (countable, with all subsets measurable) or a more general topological space [14].

$$\text{When } T = [0, \infty] \quad (1)$$

or when the state space is a general space, continuity assumptions usually need to be imposed in order to rule out various types of weird behaviour that would otherwise complicate the theory. When the state space is discrete, Markov processes are known as Markov chains. The general theory of Markov chains is mathematically rich and relatively simple. Any process is a Markov Process if [15]:

$$P(X_{s+t} \epsilon A | F_s) = P(X_{s+t} \epsilon A | X_s) \nabla s, T \in U \quad (2)$$

Here,
X represents a state
s is the time metric
t is a delayed metric
P is the probability space
A is the state space
Xs is a previously existent state
U is the universal state of spaces

IV. PROPOSED ALGORITHM

The data is extracted from MIT-BIH db. Then the ECG signal is displayed. The signal is then passed through a high pass filter the output of which is displayed again. The baseline drift is seen to be removed from the ECG signal due to filtering [16]-[17].
Let y(t) denote the output of the filter, x(t) denote the raw ECG signal and h(t) denote the impulse response of the filter. Then:

$$y(t) = x(t) * h(t) \quad (3)$$

where * denotes convolution in the time domain.
It should be noted that the sampling frequency of the filter should follow the Nyquist criteria i.e [18].

$$f_s \geq 2 f_m \quad (4)$$

Where Fs denotes the sampling frequency and fm denotes maximum frequency of the signal. Subsequently squaring the signal is done to accurately detect R peaks as R peaks are much larger in amplitude compared to other peaks.

$$Sqr_{sig} = [y(t)]^2 \quad (5)$$

Where Sqr_sig denotes square of the filtered signal.

It should be noted that squaring is done only for detection of R peaks as other peaks cannot be discriminated after squaring and may introduce errors.
Peaks are detected after setting a threshold which varies adaptively with the concerned peak and signal under consideration [19]. Peaks are detected using the difference operation that a sample is a peak if it is greater in magnitude compared to previous and subsequent values i.e [20].

$$S_{k-1} < S_k > S_{k+1} \quad (6)$$

Then the locations of the peaks are stored and through subsequent differences, the features are extracted. The inter-pulse interval (IPI) is computed from the features using either R-R interval or QRS complex interval. This is necessary to render reliability to the system with highest amplitude. Subsequently generate the random bit stream based on the Discrete Markov Chain given by:

$$X = [X_1, X_2 \dots \dots \dots \dots \dots \dots X_n] \quad (7)$$

Subsequently, compute the hamming distance (H) and Entropy (E)
Given two vectors u, v ∈ F n, the hamming distance between u and v, d(u, v), to be the number of places where u and v differ. Mathematically,

$$H = |U| - |V| \quad (8)$$

The entropy is computed for the random process as:

$$H(X) \triangleq -\sum_{x \in X} P_x(x) log[P_x(x)] \quad (10)$$

Here,
H is the entropy
X is the random variable
x is any value that the random variable can attain
P is the probability
log represents the logarithm to the base 2.

V. RESULTS:

The results obtained are enunciated subsequently.

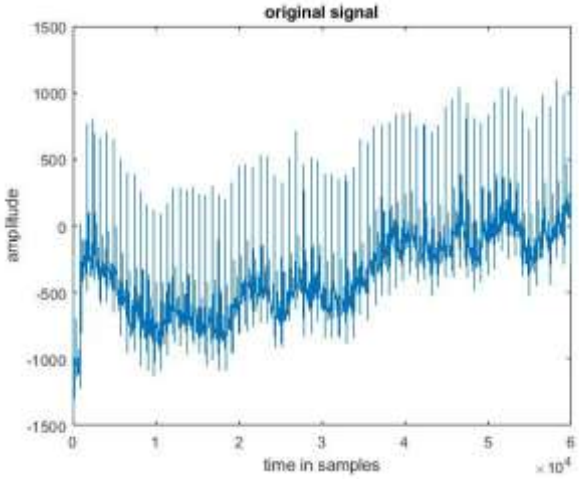

Fig.2 Original Data Sample

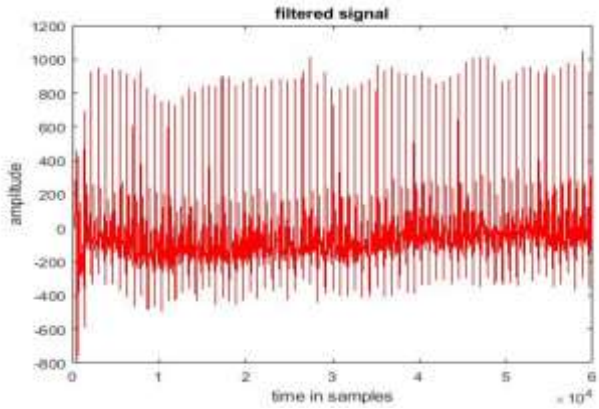

Fig.3 Filtered Data Sample

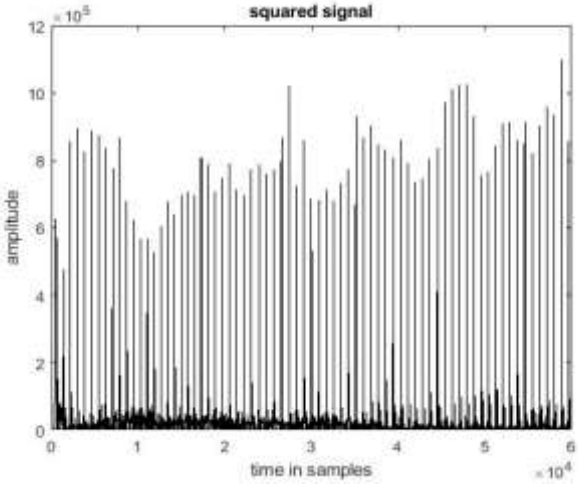

Fig.4 Squared Data Sample

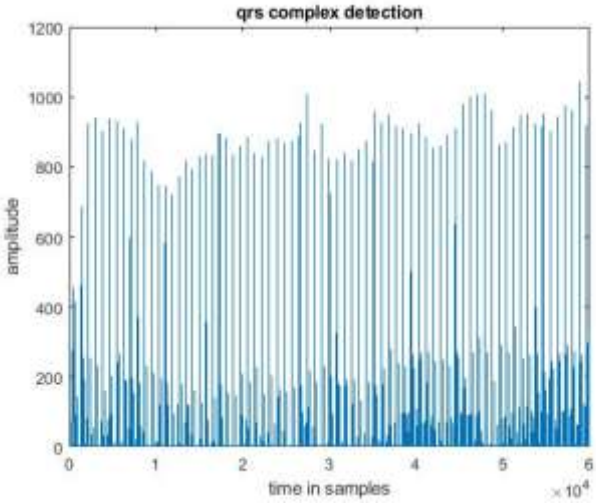

Fig.5 QRS Complex Detection

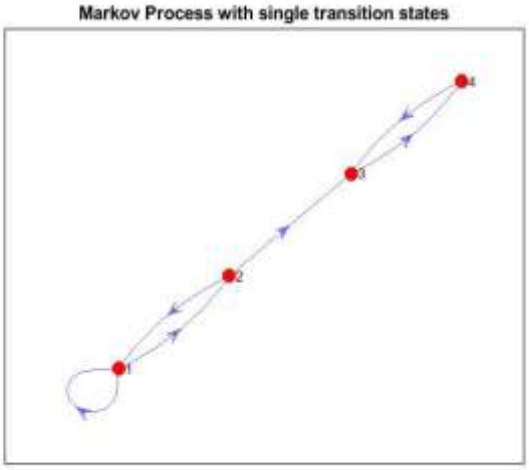

Fig.6 Single Transition Markov Chain

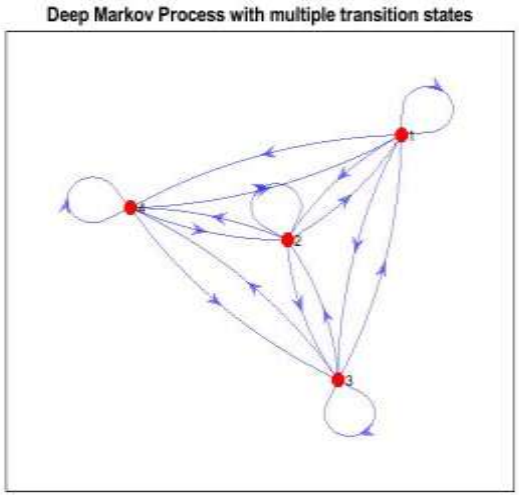

Fig.7 Multiple Transition Deep Markov Chain

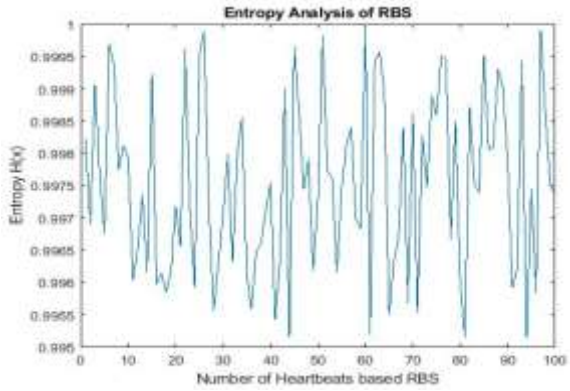

Fig.8 Variation of Entropy w.r.t. RBS

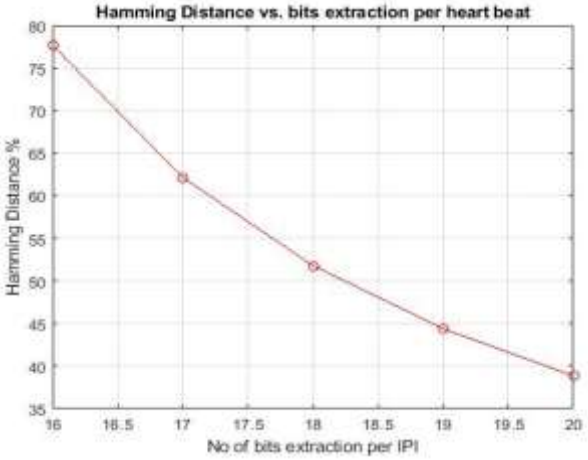

Fig.9 Variation of Hamming Distance w.r.t. No. of extracted bits/IPI

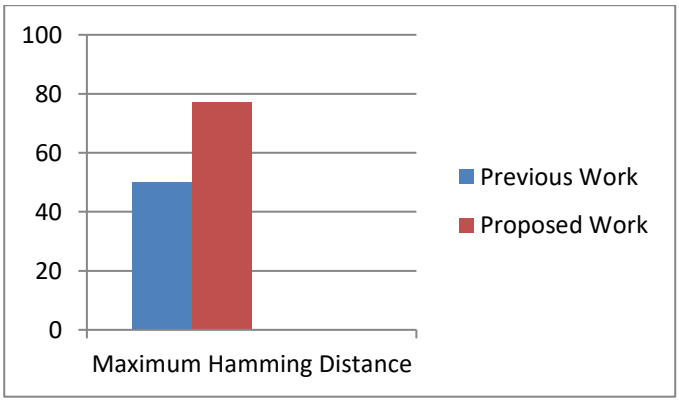

Figure.10 Comparative Hamming Distance Analysis

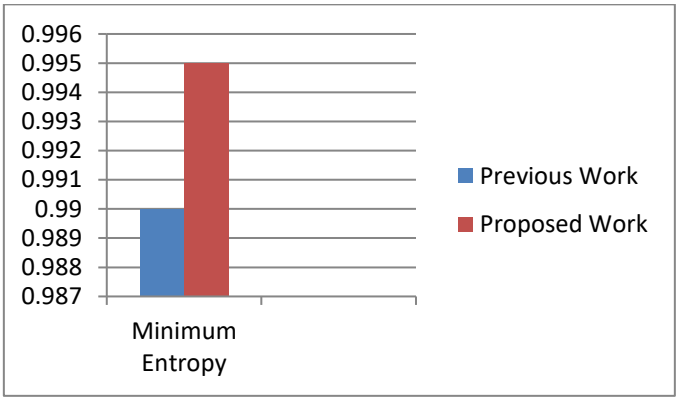

Figure.11 Comparative Entropy Analysis

The proposed work outperforms existing work [2] in the domain in terms of hamming distance and entropy.

Conclusion: Securing PANs and BANs is essential in an increasingly connected world, where personal devices and health-monitoring sensors play critical roles in daily life. By implementing encryption, secure pairing, intrusion detection, and energy-efficient protocols, PANs and BANs can effectively safeguard user data and privacy. However, the rapid growth of these networks and the sensitive nature of the data they handle demand continuous innovation in security. Through a combination of cutting-edge technology, adaptive security measures, and privacy-focused strategies, PAN and BAN networks can achieve high levels of security, ensuring that users can benefit from connected devices without compromising their personal safety and privacy. The appraoch propoed in the paper clealy outperform existing work in the domain in terms of the evalauting mettics making the system more secure for data authentication.

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