DESIGN OF A NOVEL PRESSURE SIGNAL BASED BIOMETRIC SYSTEM FOR AUTOMATED IDENTIFICATION OF COCKPIT PERSONNEL

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***Abstract*—Airplane cockpit security is a crucial function of flight management. One important aspect is the identification of the persons occupying the pilot and co-pilot seats. Existing biometric techniques have certain drawbacks, and this paper presents an automated method to identify the person sitting in a seat, based on the pressure patterns. In this paper, Principle Component Analysis is used to compute specific patterns in the pressure signature; these patterns are compared with existing patterns in a database to identify the correct person.**

Keywords- biometric system, pressure signature, PCA, Threshold.

I. INTRODUCTION

Cockpit security and pilot health are critical aspects of an airplane's functioning.

Voice biometrics is one standard approach for pilot authentication, [1]. Here the pilot is prompted, at certain intervals, for a voice sample either by the air traffic controller or the flight management system and an authentication is performed. Note that this procedure requires pilots to focus, temporarily, on the biometric tasks and may interfere with the routine flight tasks. Further, voice identification is not a fully accurate procedure, and thus cannot be used as a single biometric source of authentication. The standard biometric systems available are the on ground systems, where pilots are required to be verified before boarding a flight, [2]. In [3] aircrafts are installed with biometric systems (including retinal scanning, fingerprint identification etc) to monitor the cockpit personnel in flight. The problem with this system is that in case real time (or online) authentication is required, the pilot is forced to delay the regular flight tasks and perform a biometric authentication. This can interfere with flight procedures and could lead to potentially dangerous situations. *Ideally, the biometric system should be non-invasive and should not require the pilot to ignore any in flight task.*

In the medical rehabilitation community, when considering motion signatures of the entire human body, there is a theory that each individual has unique signatures. This is employed in various biometric applications, for e.g. in [4] the authors analyze the spatial and temporal characteristics of human motion in the frequency domain, and discriminate between two individuals based on their Fourier descriptors. In further applications of biometrics, [5] has employed gait analysis, where the gait is computed through radar signatures, in order to detect if a person is carrying a bomb. The relation with this specific paper is that it is possible to identify unique patterns in the human body through appropriate sensor measurements. Indeed, camera measurements, radar measurements, inertial sensor measurements etc can all be used to identify specific patterns in the human body. For e.g., inertial sensing is a standard tool to identify specific movement disorders in the human body [6] [7]; here machine learning techniques are used to identify specific patterns based on the motion signatures.

Finally, in the medical rehabilitation community, the pressure map of the human body is used to identify specific muscle (and joint) weakness and disorders. For e.g. in [8], the pressure signature from the forearm was used as a predictor of grip force, which is then used to model the muscle strength and related issues in rehabilitation.

The use of the whole body pressure signature in biometrics is a novel concept that we introduce in this paper. *While pressure signature itself has been traditionally used in fingerprint based biometrics, the focus of this paper is a whole body signature when the person is sitting in a chair*.

Fingerprinting is essentially a pressure signature, and based on the specific patterns the identification is made. Though this is a mature technology, there are still various failure cases, and research in this field is ongoing. For e.g., the signature obtained from two different fingerprint sensors, can be different [9]. There are various reasons for this, e.g. change in the sensor used for acquiring the raw data (e.g., optical versus solid-state sensors in a fingerprint system), even variations in environment (e.g. humidity) [9]. Thus, in the case of pilot seat pressure biometry, due to environmental variability, or variations in a person's own features (image, pressure etc) the main biometric signature will change. This necessitates the need for adaptive biometrics, and is indeed an interesting research trend [10]**.** In the current paper we do not aim to develop an adaptive biometric system, however this is clearly a requirement in our work; as various features in a person's body (such as weight, bone mass distribution etc) will vary with time.

In [9] a detailed comparison of many biometric systems has been described; in the open literature there has been no attempt at developing a biometric device for using pressure signatures from seating positions. The attempts made in this paper are a novel approach for the design and development of a pressure based biometric system.

II. PROPOSED METHOD

The biometry based identification may be stated as follows. Suppose we have a biometric system capturing some input data, from which certain features of interest are extracted. Let these features be denoted by X_{bio}. The goal would, then, be to determine which of the identities (in a database), I_k, $k \in \{1,2, \dots\}$matches with the featureX_{bio}. The match itself would be obtained by a comparison with a suitably defined threshold,
i.e.

$$X_{bio} = I_k,\ X_{bio} = I_K \quad \text{if} \quad \min_K\{S(X_{bio}, I_K)\} < \text{thresh}$$

Where $S(X_{bio}, I_K)$ can be thought of as a difference operator such that it searches for that feature in the entire database which minimizes the difference between the current feature and itself [9].

As shown in Fig. 1, the smaller circles indicate the higher pressure points. These points are in proximity to "Ischial tuberosity" [11] which is a bone protrusion and is observed that, this is the point where maximum weight is concentrated .The pressure magnitude decreases radially outward. These pressure signatures are unique for each person. Hence we need a pattern recognition technique to discriminate between signatures. In this paper, PCA is chosen for the task of authentication.

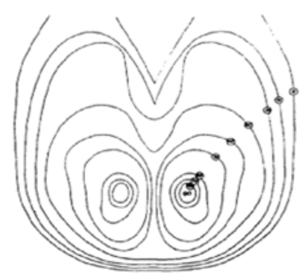

Fig. 1.Pressure distribution of a person sitting in chair

A. *Why PCA?*

While there exist many techniques to extract and compare patterns, in machine learning, we are focusing exclusively on the PCA technique mainly because it reduces the dimension of the data, which is critical in our application where we can have some 10000 cells (thus 10000 dimensions!) each capturing data at 100Hz or faster. The volume of the data will be large and thus it requires the use of dimensionality reducing techniques, such as PCA. Furthermore, PCA is computationally a powerful algorithm and is highly relevant in such real time applications. For example, while standard PCA algorithms have a computational complexity of $O(d^3 + d^2n)$ (where 'n' is the number of features), some modifications result in a complexity of $O(d^3)$, and then there is the Fast PCA where matrix inversions (which results in $O(d^3)$ type complexity in other approaches) is not even required, and the algorithm converges in a few iterations[9].Thus PCA is a well suited technique for the present application of pressure and vibration based biometry.

B. Procedure for PCA Analysis

Principle component Analysis is a statistical procedure, majorly used in face recognition. Eigen values or the prime components which accounts the best distribution of variation in the image are the basis of this procedure, which is successfully employed for authentication and identification of the pressure signatures in a controlled condition. The pressure signature matrix of a person is captured by the FSR 402(Force sensitive resistor) sensors. Because of the force repeatability error, the data got from sensors will vary ±2% each time, hence the pressure signature matrix is captured for a sequence of different time intervals and an average matrix is calculated before PCA computation. Firstly, this averaged matrix is converted into column vector by concatenating each column one after other. This vector is mean subtracted, followed by the computation of covariance matrix. From this covariance matrix, Eigen values and Eigen vectors are calculated which forms principle components.These principle components depict the amount of variation in the pattern and uniqueness of each pressure signature. Identification of new signature is done by comparing the new signature with the previously stored data set based on threshold, but the new signature has to be processed in the same manner as the stored signature. Threshold plays a vital role in recognition. Threshold is taken as some factor of maximum of Euclidean distance where the factor is chosen arbitrarily.Threshold is computed by Euclidean distance classifier method. Minimum of the Euclidean distance $\epsilon(i)$ between all the person's principle components is computed, and maximum of $\epsilon(i)$ i.e. Θ is calculated. When a new pressure signature is encountered, principle components are computed. It is compared with each of the principal components in the data base by calculating the maximum difference of the principle components $\Psi(i)$ of the new signature and each of the stored signature in the data base. $\epsilon(i)$ is compared against the threshold. If the value is less than or equal to the threshold value then the person is classified as the known person or else as unknown person.

C. Steps involved in signature discrimination

The following outlines the procedure for computing the principal components and the threshold for discriminating between pressure signatures.

Step 1: A pressure signature matrix of NxN is taken, where each pixel represents the pressure value.

$$A=\begin{bmatrix} A11 & A12 \ldots & A1N \\ A21 & A_{22} \ldots & A2N \\ .. & & \\ .. & & \\ AN1 & A_{N2} \ldots & ANN \end{bmatrix}_{NxN}$$

Step 2:Each of the matrixes is converted into column vector, V. Mean adjusted data is computed by subtracting the mean from the column vector, Covariance(X) of the mean adjusted value is calculated, Eigen value from the covariance matrix is calculated and finally the principal components, $\Psi(i)$, are computed

$$\Psi(i) = \lambda(i) * V[i]$$

Step 3: When a new pressure signature is encountered, the new principal component (Ψ) is computed and Euclidean distance between the principle component of new signature and existing signatures is calculated using,

$$[\epsilon(i)]^2 = \|\Psi - \Psi(i)\|^2 \quad \text{for } i = 1 \ldots M \quad (6)$$

If $\epsilon(i)$ exceeds a pre-defined threshold value, then we conclude that the new principal component Ψ belongs to a different person. **Choice of the threshold**: An arbitrary threshold value is initially computed as follows

$$\Theta = x*\max\{\|\Psi(i) - \Psi(j)\|^2\} \text{ where } i,j=1\ldots M \quad (7)$$

Where x is the arbitrary constant

If $\epsilon(i) < \Theta$, then pressure signature is identified

If $\epsilon(i) > \Theta$, then pressure signature is unidentified

D. Experimental results

To quantify the effect of threshold, an experiment was conducted in MATLAB with a database of twenty different pressure signatures. Each pressure signature is a 100x100 matrix, where each element of the matrix depicts the pressure value. For the ideal case, we have assumed that the pressure signature of a person radially decreases outwards. For illustration, Fig.

2 shows the data base of twenty different ideal matrices. Each one is different from other by radius, or by angle, or the distance between the two pressure distributions (i.e. circles). Principal components are computed for 20 different pressure signatures. From the observation and graph (as shown in Fig. 2) the principal components computed is found to be unique for each signature. Hence PCA was able to discriminate between different pressure signatures. Since the choice of threshold is arbitrary, in this paper, experiments are conducted for threshold varying from 0.1 to 1 times of the maximum value of minimum Euclidian distances. From the observations and experiments (as shown in Fig 3) a threshold of 0.1 is able to recognize 18 signatures whereas a threshold of
1 is able to recognize only 15 signatures. Hence 0.1 times of the maximum value of minimum Euclidian distances is chosen to be the best for distinguishing two pressure signatures.

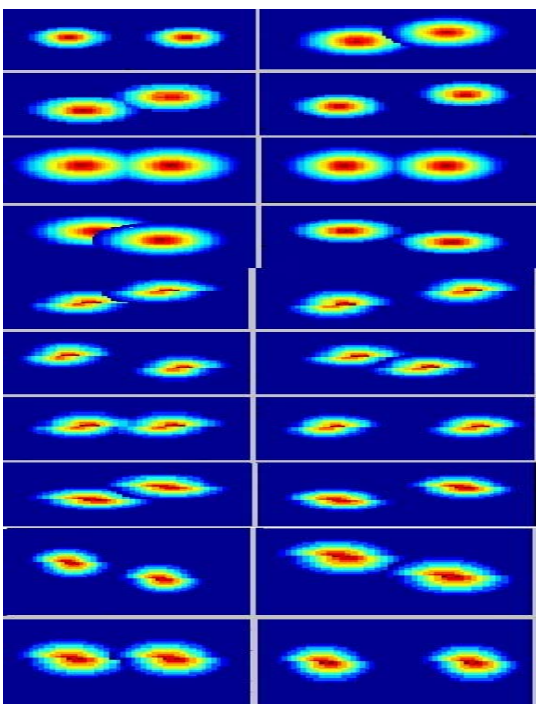

Fig. 2. Database of twenty different ideal pressure signatures

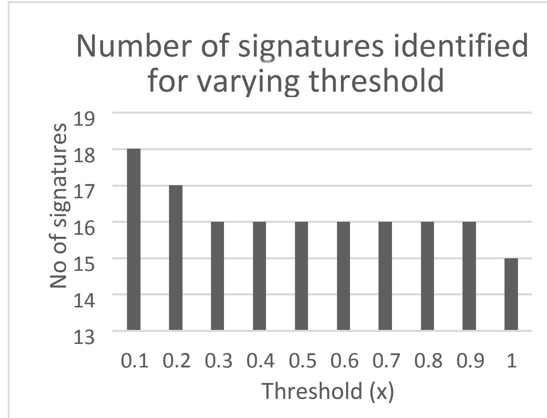

Fig. 3.Graph of number of signatures identified for varying threshold(x)

III. HARDWARE IMPLEMENTATION

The hardware implementation of the model proposed utilizes a pressure sensor testbed which outputs the required data in the matrix form, which is fed into the data base. Fig 4.shows the proposed hardware model which takes the matrix from pressure, compares with the database and identifies the pilot. Fig 5.shows the implemented hardware model which consists a testbed of FSR402 pressure sensors which has force sensitivity range between 0.1 to 10.0^2Newton , arranged in a 3x3 matrix placed on a rectangular plastic sheet of area30x42cm^2.The testbed is connected to grounding circuit which is then interfaced to Arduino mega microcontroller for the extraction of the signals from the sensors. The FSR402 sensors are robust polymer thick film devices that exhibit a decrease in resistance with increase in force applied to surface of the sensor.One lead of the sensor is pulled up to 5 Volts and the other lead is pulled down to ground by the grounding circuit.The signals from the sensors are transmitted through serial communication to Arduino microcontroller.The Arduino microcontroller converts these analog signals into digital
signals through its inbuilt ADC(Analog to digital converter).

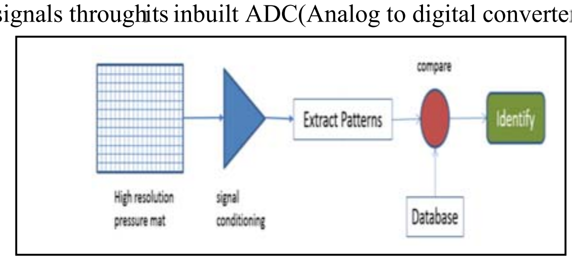

Fig. 4.Proposed hardware model

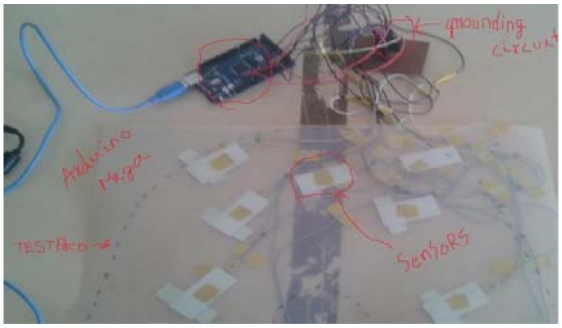

Fig .5.Implemented hardware model

CONCLUSION

This paper focuses on the development of a biometric system based on the whole body pressure signature, when a person is sitting in the pilot chair of an airplane cockpit. The hypothesis is that every individual has a unique pressure signature. Detailed simulation studies are presented in the paper, using the PCA machine learning technique, to discriminate between multiple signatures. A threshold of 0.1 is found to be having the highest recognition as per the experimentsFurther work in simulation will focus on incorporating sensor noise, and the subsequent analysis of the person identification.

ACKNOWLEDGMENT

A part of this project was funded by the Aerospace Network Research Consortium (ANRC).

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