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Dynamic fingerprint based on human motion and posture

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Abstract

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Keywords

human, posture, fingerprint, motion, dynamic

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Dynamic Fingerprint Based on Human Motion and Posture*

Amir Hesami, Fazel Naghdy, David Stirling

Abstract— **The feasibility of generating a Dynamic FingerPrint (DFP) for an individual is explored. DFP is a unique signature generated based on a combination of body part movements. The body movements are obtained using a sensor suit recording inertial signals that are subsequently modeled on a humanoid frame with 23 degrees of freedom (DOF). Measured signals include position, velocity, acceleration, orientation, angular velocity and angular acceleration. DTW (Dynamic Time Warping) is used to classify the individual's identity. The approach is described and the characteristics of the algorithms are presented. It is anticipated that these approaches will have applications in surveillance and security, medical science and animation modeling. Classification results show an accuracy rate of 100% for the 10 subjects studied during validation.**

I. INTRODUCTION

Identifying Dynamic Finger Print (DFP) as a unique signature extracted from the movement of body parts has been an active area of research [1]. Human brain is capable of building such signature for different applications such as identifying a person, categorizing a movement, or even evaluating the motion [2]. The human mind can intuitively derive rich and varied information from the characteristics of an individual movement or walk. Studies carried out in psychology confirm such observation. Johansson [2] used MLDs (Moving Light Displays; method of using markers attached to joints or points of interests) in psychophysical experiments to show that humans can recognize gaits representing different activities such as walking, stair climbing, etc. Cutting et.al [4] introduced a biomechanical invariant for gait. Richardson et al. [6] used different participants to show the possibility of recognition of a particular person among a group.

The studies reported in the literature indicate that the information produced by body movement is adequate to identify an individual [5], [6]. Based on two experiments, Stevenage et al. [7] concluded that human visual system and brain is sophisticated enough to identify six participants based on their gait under normal and adverse viewing conditions. Runeson and Frykholm [8] concluded that the kinematic structure of human movement is rich enough to elicit the underlying dynamics of the actions being performed.

There have also been a number of studies to automate the process using sensors and machine intelligence. Some researchers such as Braune and Fischer [9] attached light rods to the limbs of an individual to study body movement. Marey E.J [10] used a similar method but instead of light rods, he used white tape mounted on the limbs of the subject dressed in a black body stocking. Brenstein in a method called cyclographymounted incandescent bulbs to the joints in order to study gait with the aim of automating the motion capture [11].

This study aims at building the DFP based on kinematic and dynamic parameters of body motion obtained through inertial sensors. A Dynamic Finger Print (DFP) can be generated either for an individual (used for individual identification) or for a type of movement (used for categorizing movements).

There are applications for DFP in many disciplines including surveillance, medicine, and animation. The focus of this paper is on the application of DFP to identify an individual. Identification of an individual from his/her biometric information has always been desirable in various applications and a challenge to be achieved. Various methods have been developed in response to this need including fingerprints and pupil identification. Such methods have proved to be partially reliable.

The paper is organized as follows. Section II provides a literature review on the topic and sets the scene. In Section III the experimental set up and the characteristics of the data used in the study and the approach deployed to extract features of significance in the data for building a DFP will be provided. In section IV experimental results using the models are presented, and finally the conclusion of the paper is given in Section V.

II. LITERATURE REVIEW

There is a significant amount of work reported in the literature to mimic human brain's function in extracting identity information from the motion of an individual. Most of the studies use only part of the body or a specific movement in their classifiers. In this work, the whole body movement and posture is considered in building a unique/generic DFP.

Aristotle (384 – 322 BCE) was the first researcher who published his studies on gait analysis: "If a man were to walk on the ground alongside a wall with a reed dipped in ink attached to his head the line traced by the reed would not be straight but zig – zag, because it goes lower when he bends and higher when he stands upright and raises himself."[12]. Jaraba et al. [13] used a feature called centre of the control points and neural networks for individual recognition. Control points were coordinates of the body parts as a 2D array containing X and Y values. He used 13 control points including head, arms, elbows, hands, upper legs, knees, and foots and created a 2D matrix which was fed into a SOM (Self Organizing Maps). Using control points' coordinates were not a strong feature in recognition process.

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Lee and Grimson [14] fitted 7 ellipses to 7 regions of the body and used their locations, orientations, and aspect ratio as classification features. This was based on the assumption that the canonical view of a walking person is perpendicular to the direction of walk. Ekinci [15] used distance vectors and principal component analysis (PCA) for dimension reduction and identity identification. Campbell and Bobick [16] used phase space constraints to classify ballet movements. The proposed an algorithm based on space curves, assuming the availability of 3D Cartesian tracking data to represent movements of ballet dancers. The system could learn and recognize nine movements.

Using video recorded from body motion, Bregler [17] used coherence blob hypothesis and Hidden Markov Models (HMM) to estimate a “hidden variable” for each pixel in the image to determine the blob it belonged to. A three level framework for recognition of activities was described. Initially, probabilistic mixture models for segmentation from low-level cluttered video sequences were used. Lie et al. [18] used magnitude and phase spectra of horizontal and vertical movements of ankle as features, and used AdaBoost classifier to classify them for gait recognition purposes.

Sagawa et al. [19] performed matching of gait image sequence in the frequency domain. A volume was created by piling up the image sequences of walk. Fourier transform was applied the volume to extract its frequency characteristics as well as the similarities of the two volumes. Hoey and Little [20] presented a system that used Partially Observable Markov Decision Process (POMDF) to learn relationships between the movements of a subject and the context of the movement. Brand and Hertzmann [21] added a multidimensional style variable to HMM in order to vary its parameters and called it Stylistic HHM (SHMM). They used a cross – entropy optimization framework that makes it possible for style machines to learn from a sparse sampling of unlabeled styles. Howe et al. [22] analyzed motion from video using mixture of Gaussian models. Wilson and Bobick [23] used parametric HMM in which motion recognition models were learned from the user and labeled as styles. Caso et al[24] used hand movements to find the impact of deception and suspicion.

III. EXPERIMENTAL SET UP AND FEATURE EXTRACTION

Data is being acquired using an inertial movement suit [25], Moven®, which provides data on 23 different segments of the body kinematics such as position, orientation, velocity, acceleration, angular velocity and angular acceleration as shown in *Fig*.1 and *Fig*.2 .

In capturing human body motion, no external emitters or cameras are required. Mechanical trackers use goniometers that are worn by the user to provide joint angle data to kinematic algorithms for determining body posture. Full 6DOF tracking of the body segments are determined using connected inertial sensor modules. The orientation, position, velocity, acceleration, angular velocity and angular acceleration of the body segments are derived from the data. The kinematics data is saved in an MVNX file format.

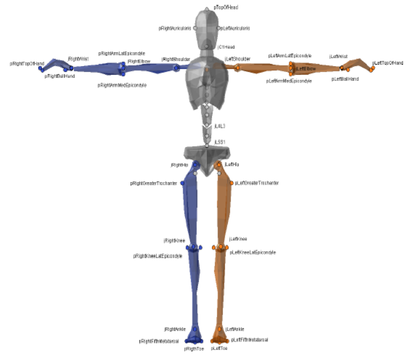

Figure 1. Anatomical Landmarks for the Moven® suit [25].

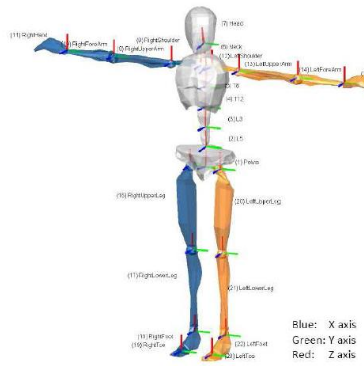

Figure 2. Body Segments defined in the Moven® suit [25].

The feature extraction is the most important stage in the process of analysis of the data and developing a classification method. The aim is to identify a simple but comprehensive method ensuring that dynamics of the motion is contained in the extracted features. The selected features should be also independent from the location, direction and path of the gait. The gait parameters for identification are categorized into spatial - temporal (step length, step width, walking speed, cycle time) and kinematic (joint rotation of the hip, knee, angle, joint angles of the hip, knee, ankle, thigh, trunk, foot) groups [26]. Our focus is on the kinematics gait parameters in this research. Features are extracted in a gait cycle for each individual. Gait cycle begins and ends when reference foot makes two consecutive contacts with the floor. The cycle is a complete stride with both legs step, starting with the right leg as shown in *Fig*.3.

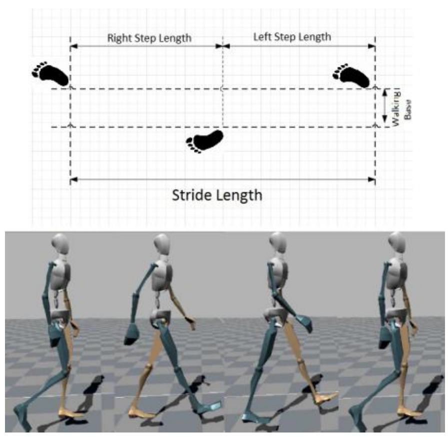

Figure 3. Anatomical Landmarks for the Moven® suit [25].

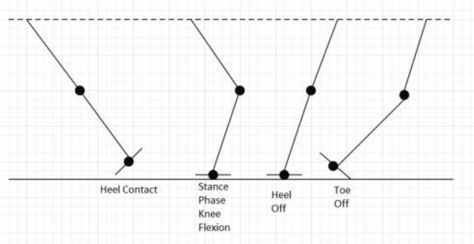

Figure 4. Lower body movement.

In studying human gait phases, we select the joints that significantly contribute more than others [27]. As shown in *Fig.*4, foot, ankle, knee and thigh angles change during the gait cycle. Arm and elbows also participate in fulfilling gait motion. Based on these observations, 12 best features that the best represent human motion during a gait cycle are extracted as show below:

- Left and Right Foot Orientation Angles (*Fig.*5).
- Left and Right Foot Angles (*Fig.*5).
- Left and Right Knee Angles (*Fig.*6).
- Left and Right Thigh Angles (*Fig.*6).
- Left and Right Elbow Angles (*Fig.*7).
- Left and Right Arm Angles (*Fig.*7).

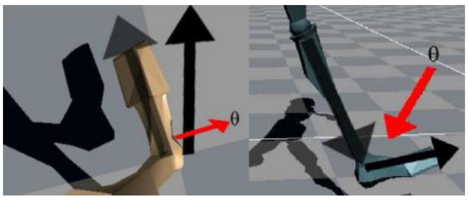

Figure 5. Foot Orientation and Foot Angle.

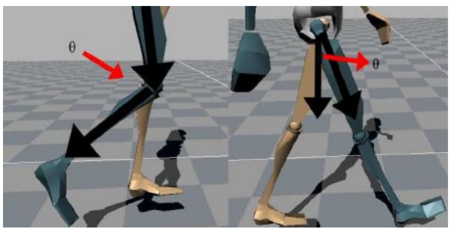

Figure 6. Knee Angle and Thigh Angle.

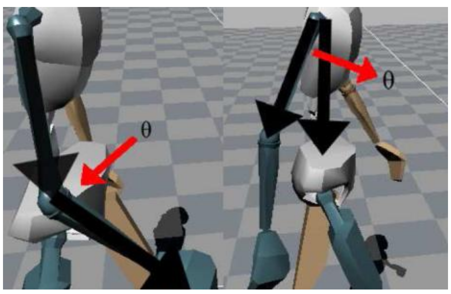

Figure 7. Elbow Angle and Arm Angle.

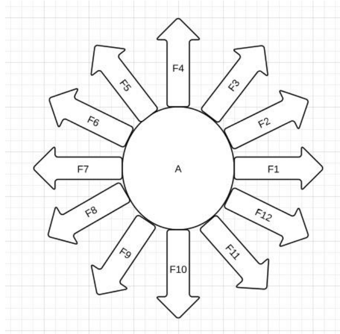

Figure 8. Features Coordinate System.

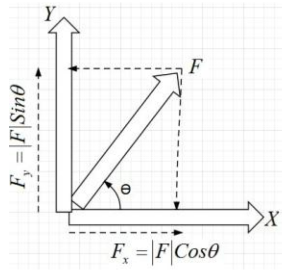

Figure 9. Feature X and Y projections.

Using features extracted, a unique dynamic fingerprint (DFP) is generated for identification of an individual. The next stage in deriving the algorithm to reduce the dimension of the feature- space from 12 to 1 to generate a time sequence which represents the individual's DFP. There are various methods which have been used in order to reduce dimension of complex data set such as principal component analysis (PCA) or singular value decomposition (SVD) [28].

This research is inspired from a method for building DNA sequence visualization. Genomic DNA sequence is usually presented with a sequence of alphabets A, C, T and G. Representation of the sequence can be challenging due to the large amount of discrete and multi - dimensional data. In [29] Chia et al. proposed a visualization technique called Visualization by Pentahedrons (VBP) algorithm to visualize and analyze similarity of DNA sequences. This simple and effective method for building a DNA sequence can be edited and optimized for building of DFP using various features deployed.

In order to develop a visualization algorithm in generating a DFP using 12 features, all extracted features and their relations were studied and a new coordinate system which showing features as vectors is proposed as shown in *Fig.*8.

In a gait cycle, as discussed in this section, right and left limbs move in opposite directions, for example while right arm is moving forward, left arm is moving backward. This can be expressed as while right arm angle is increasing, left arm angle is decreasing. Right and left angles compensate the effects of each other. A system as shown in *Fig.*8 is introduced which each feature is represented as a vector pointing to opposite direction in relation to the same vector from the other side of the body. Every feature is rotated by 30 degrees relative to the previous feature. The goal is to find a vector that is generated based on the values of all other vectors and then used as the DFP. As shown in *Fig.*9

projections of every feature on X and Y axes are calculated by:

$$\begin{cases} F_x = |F| Cos\theta \\ F_y = |F| Sin\theta \end{cases} \quad (1)$$

According to the projected values of feature space in *Fig*.8 a Dynamic Finger Print vector at every sampling time is calculated by:

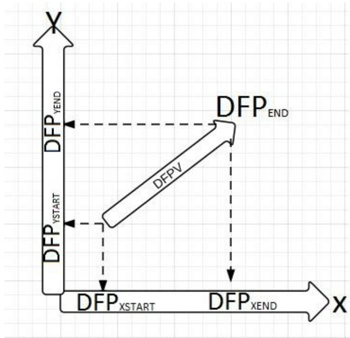

Figure 10. DFP Vector.

$$\begin{cases} DFPF_{1x} = F_1 \\ DFPF_{1y} = 0 \end{cases} \quad \begin{cases} DFPF_{2x} = |F_2| Cos(\pi/6) \\ DFPF_{2y} = |F_2| Sin(\pi/6) \end{cases}$$

$$\begin{cases} DFPF_{3x} = |F_3| Cos(\pi/3) \\ DFPF_{3y} = |F_3| Sin(\pi/3) \end{cases} \quad (2)$$

And so forth up to the 12th feature:

$$\begin{cases} DFPF_{12x} = |F_{12}| Cos(-\pi/6) \\ DFPF_{12y} = |F_{12}| Sin(-\pi/6) \end{cases} \quad (3)$$

Using all the projection values a new value can be calculated as (4):

$$\begin{cases} DFPF_{XEnd} = \sum_{i=1}^{12} F_{ix} \\ DFPF_{YEnd} = \sum_{i=1}^{12} F_{iy} \end{cases} \quad (4)$$

Using (4) calculated points $DFPF_1$ ($DFPF_{Start}$) and $DFPF_{End}$, a vector can be achieved which is the DFP vector for that instant of time as shown in *Fig*.10. Vector's magnitude and angle are calculated using (5).

$$\begin{cases} |DPFV| = \sqrt{(DFPV_{XEND} - DFPV_{XSTART})^2 + (DFPV_{YEND} - DFPV_{YSTART})^2} \\ DFP\hat{V} = \tan^{-1}\left(\frac{(DFPV_{YEND} - DFPV_{YSTART})}{(DFPV_{XEND} - DFPV_{XSTART})}\right) \end{cases} \quad (5)$$

In order to complete generation of DFP we estimate the individual's body mass and use it as a coefficient of the above vector value. Auerbach et al [30] and Ruff CB [31] propose a formula for calculating the Body mass based on the individual's skeleton lengths. According to this formula, the body mass is calculated by (6):

$$\begin{cases} BM = 0.373 \times S + 3.033 \times LBIB - 82.5(males) \\ BM = 0.522 \times S + 1.809 \times LBIB - 75.5(females) \end{cases} \quad (6)$$

Where LBIB is living bi-iliac breadth in centimeters, calculated as (7):

$$LBIB = 117 \times SKeletal\_BIB - 3 \quad (7)$$

S is the estimated stature in cm and is calculated as (8):

$$\begin{cases} S = 2.26 \times Fem_m + 66.379 - 2.5(males) \\ S = 2.59 \times Fem_m + 49.742 - 2.5(females) \end{cases}$$

(8)

Fem_m is femoral maximum length in centimeters. Using the calculated body mass as the coefficient to the DFP magnitude, the final value is as presented in (9):

$$DFP = BodyMass \times |DFPV| \quad (9)$$

After the whole gait cycle features are used in creating DFP value, it is normalized between 0 and 1.

Twelve different possible formations of features are tested using the above algorithm. As described before, we keep left and right features in opposite directions in all formations. After analysis of the results the best feature space selected is shown in *Fig*.11. A sample DFP for male subject generated using this algorithm is shown in *Fig*.12.

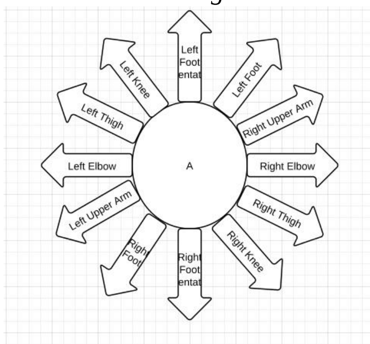

Figure 11. Feature X and Y projections.

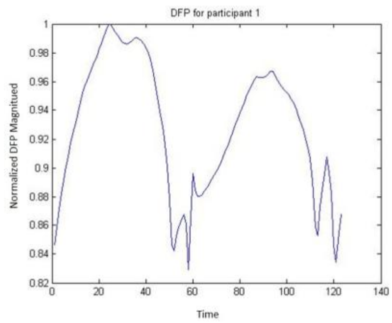

Figure 12. Sample Dynamic Finger Print.

Three gait cycles for every individual are used to extract the DFP and validating the result. The first repetition is used to generate DFP and then it is compared against all repetitions from all other subjects including the subject that the DFP was generated for to find the closest match.

IV. EXPERIMENTAL RESULTS

Ten participants between the ages of 20-35 including 4 females and 6 males participated in the experimental work. They were asked to walk normally. Data was collected and analyzed using MATLAB and 12 DFPs for every participant were generated.

Dynamic time warping (DTW) was used to compare these created DFPs as shown in *Fig*.13. DTW is mainly used in speech recognition [32]. The goal of DTW is to find the optimal path through the space that maximizes the match between the reference and subject time frames. The similarity cost or cost function can be used as a key to classify signals and select the best matching time sequence. There are variations in DTW as described in [33].

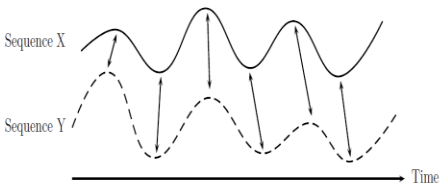

Figure 13. Dynamic Time Warping (DTW).

One of the variations of DTW which was used in this research is as described in the following pseudo code.

```
Define a new Matrix called DTWValue[n,m]
Set DTWValue[0,0] to 0
FOR i=1 to m (size of Y)
  Set DTWValue[0,i] to infinity
ENDFOR

FOR i=1 to n (size of X)
  Set DTWValue[i,0] to infinity
ENDFOR

FOR i=1 to n (size of X)
  FOR j=1 to m (size of Y)
    Set Cost to Distance between X[i] and Y[j] can be any distance such as euclidean distance
    Set DTWValue[i,j] to cost + minimum (DTWValue[i-1,j],DTWValue[i,j-1],DTWValue[i-1,j-1])
  ENDFOR
ENDFOR
```

DTW was used to compare all DFPs generated per subject. The success rate of the classification for all 12 possible generated feature spaces is shown in Table.1. The feature space with the highest classification success rate (100%) is the space shown in *Fig*.11.

TABLE I
DTW CLASSIFICATION RESULTS

Feature Space	Reference DFP P1-1	Reference DFP P2-1	Reference DFP P3-1	Reference DFP P4-1	Reference DFP P5-1	Reference DFP P6-1	Reference DFP P7-1	Reference DFP P8-1	Reference DFP P9-1	Reference DFP P10-1	Success Rate (%)
1	P1-2	P2-3	P3-2	P4-2	P5-2	**P8-1**	**P6-1**	P8-2	P9-2	P10-2	80%
2	**P6-2**	P2-3	**P2-3**	**P7-3**	P5-2	**P5-3**	P7-3	P8-2	**P8-2**	P10-2	50%
3	P1-3	P2-2	P3-2	P4-2	P5-2	**P2-1**	P7-3	P8-2	P9-2	P10-2	90%
4	**P2-1**	P2-2	P3-2	P4-2	P5-2	**P1-2**	P7-2	P8-3	P9-2	P10-2	80%
5	**P3-3**	P2-2	P3-2	P4-2	P5-2	**P1-2**	P7-3	P8-3	P9-3	P10-2	80%
6	**P2-2**	P2-2	**P6-2**	**P7-1**	P5-2	**P3-3**	P7-3	P8-2	P9-3	P10-2	60%
7	P1-3	P2-3	**P2-3**	**P6-3**	P5-2	**P10-1**	**P6-3**	P8-2	P9-3	P10-2	50%
8	P1-3	**P6-2**	**P10-3**	P4-3	P5-2	**P5-3**	P7-3	P8-3	P9-3	P10-2	70%
9	P1-2	P2-2	P3-2	P4-3	P5-2	P6-2	P7-3	P8-2	P9-3	P10-2	100%
10	P1-3	P2-2	P3-2	**P7-1**	P5-2	**P1-2**	P7-3	**P7-2**	P9-2	P10-2	70%
11	**P2-3**	P2-2	P3-3	P4-2	P5-2	**P5-1**	P7-3	P8-3	P9-2	P10-3	80%
12	P1-2	P2-2	P3-2	**P8-1**	P5-2	**P5-3**	P7-3	P8-3	P9-3	P10-3	80%

P = Participant,P1-1= Participant 1 Recording 1. Success Rate = (Correct Classification/Total Cases)x100,
Each column represents a reference DFP signal and each row shows the minimum distance in DTW for each feature space.
Bold cells show wrong classifications.

V. CONCLUSION

12 Features were extracted from a gait cycle. These 12 features were all joint angles which were significantly contributed in human walking. Using these features, a Dynamic Finger Print (DFP) was created for every individual. This DFP can be used as a motion finger print to categorize human motion into different classes. There are many applications for a DFP such as surveillance, medicine and animation industries. A sample application would be individual recognition using this finger print. Traditional methods for human identification such as finger print or face recognition can mistake by changes in face by aging or surgery or even changing one's finger print, whereas gait or motion is a subconscious action which one cannot disguise easily. The extracted DFPs were compared using Dynamic Time Warping (DTW) technique and 100% classification result was obtained in individual identification.

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