Usage of VGRF in Biometrics: Application on Healthy and Parkinson Gaits

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Abstract—**Biometric systems use unique information about or from a person to identify that person. Investments and research in this era has increased more than ever before. However, such technology is facing major fraud risks and pitfalls. This paper examines the use of VGRF in biometrics as a tool to be fused with an existing biometric system for reliable person identification. Results ensure that the use of raw data of VGRF is trustworthy if extracted from a normal subject. However, the results deteriorated in the presence of an abnormal gait. For instance, Gait subjects affected with Parkinson decreases the accuracy of classification among subjects ending up in high bias among results.**

Keywords - Biometrices, Vertical Ground Reactional Forces (VGRF), Normal gait, Parkinson gait.

I. Introduction

Technology has enabled humans to enhance the ability of object recognition based on distinctive features. It is possible to distinguish between alive and static objects based on heat emission [1], between metals and organic substances based on chemical properties, and between harmful or sab material based on radioactivity. One important notion is the ability of identifying different people based on finger prints, pupil detection, and voice recognition [2]. Researchers keep searching for innovative ways to demolish any error of identification. One of these ways is to rely on the measurement of a person's gait.

To be able to measure the pace of a person, identifying a set of features that varies upon the way a person is moving and upon time is needed. Measured vertical ground reaction force (VGRF) signals have been used in different research studies. Researchers nowadays are widely using gait for human identification and recognition. It is also proved that walking behavior identification has a 95.7% valid rate by measurements obtained from joint walking behavior and angular measurements obtained from joint movement fundamental hip angle, knee angle, and ankle angle [3].

Furthermore, a research at Universiti Kebangsaan of Malaysia highlights that the usage of VGRF signals along with the right measurement procedure and equipment set-up will yield reliable results. Researchers recommended the use of VGRF measurement during subject's assessment [4].

The results of another study using VGRF, done on elderly woman with Osteoarthritis, showed that there is no relation between knee pain and gait, meaning that the pace of a person does not change due to knee pain but might be caused by various factors, such as a changed posture or a mental condition [5]. With this information, it is noted that measuring VGRF to identify a person will not be affected with the possibility of knee pain.

The study being conducted in this paper will be using the VGRF signals measured on a group of healthy subjects and a group of subjects with Parkinson's disease. There is no specific way of diagnosing Parkinson's disease (PD). A study has been conducted at Stanford University shows that the severity of Parkinson's disease can be determined by analyzing the VGRF signals of the affected individual's gait [6]. In another research, sensors have been placed on the foot soles of the study subjects in order to measure the VGRF while they walk. The study shows that the use of gait influence diagrams can help in classifying the healthy subjects with normal gait from the PD subjects with abnormal gait [7]. However, Rami et al has investigated the importance of sensory location under foot. The research work shows that the mid-sensor give the most reliable information in classification between different walking patterns [8].

The identification of an individual based on biometric recognition using behavioral or physiological characteristics provides unquestionable security [9]. A biometric modality for human identification can be the person's gait. Gait recognition depends on the walking style of every individual [10]. Recognition grounded on human gait has the advantage of the ease of capturing the pace information. Measuring the gait can be done with different wearable sensors, such as accelerometer sensors, flexible goniometer, electromagnetic tracking systems, or force sensors [11]. The reason behind focusing on Gait biometric systems in this study is to overcome drawbacks of traditional biometric technologies that require something correlated to what a person has or knows. Moreover, this approach is feasible and easy to apply. Thus gait biometric system can be used as an alternative in which it doesn't require previous preparation of a person under examination or can be

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used to enhance other biometric systems that meets the national security concerns with sophisticated fraudsters.

II. METHODOLOGY

A. Database

The database analyzed and discussed in this research was collected from 165 subjects, where 93 subjects are diagnosed with idiopathic PD (disease stage 2-3 on the Hoehn and Yahr scale; mean age of 66.3 years; 63% of the subjects are men), and the remaining 72 subjects are healthy subjects (mean age of 66.3 years; 55% men). The database was formed by acquiring data from subjects who had sixteen sensors (Ultraflex Computer Duyno Graphy, Infotronic Inc.), eight at the bottom of each foot, measuring the VGRF in Newton, with the force as a function of time, and a sampling rate of 100 Hz. The data was gathered over a span time of two minutes, where each subject was walking back and forth in a 25-meter-long, 2-meter-wide, well-lit and obstacle free pathway. The person was not restricted to a specific pace. Figure 1 shows the approximate location of the sensors on the (X, Y) coordinate system set on a person who was standing comfortably with both feet aligned parallel; the origin (0, 0) was located between the legs with the person's front directed in the positive Y axis.

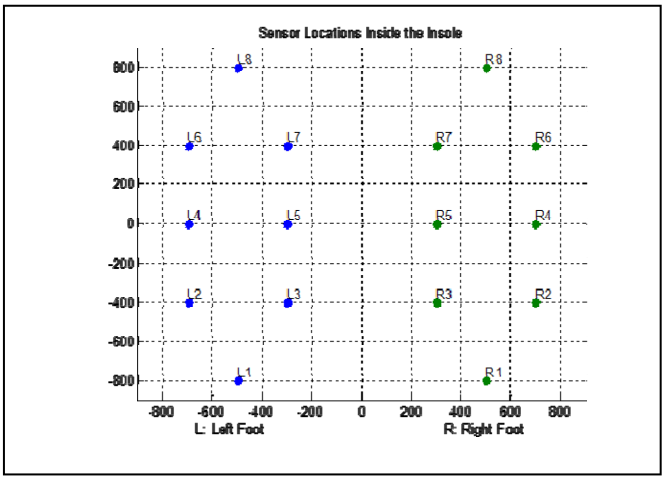

Figure 1. Approximate locations of the sensors located under the left and the right foot. Sensors under the left (right) foot are denoted by L (R)

The database used is obtained from the physionet gait database by which the subjects provided written consent prior to the data collection [12].

B. MultiClass Classification

The objective behind this paper is to examine the ability of using VGRF signals in biometric applications and not to test the learning algorithm used itself. For this, logistic classification techniques are being employed. This would give the possibility to classify the gait signals into discrete outcomes correlated to each subject given in (1):

$$y \in \{1,2,...165\} \tag{1}$$

Then the prediction of y is given by the hypothesis function ($h_\theta^i(x)$) as in (2):

$$h_\theta^i(x) = P(y = i \mid x;\theta) \tag{2}$$

Where "i" refers to subject number, θ are the parameters to be estimated using gradient descent as shown in (3) that maximizes the probability (P). "x" here represents the raw data of VGRF signals.

Repeat {

$$\begin{aligned} \theta_0 &:= \theta_0 - \alpha \frac{1}{m} \sum_{i=1}^{m} (h_\theta(x^i) - y^i) x_0^i \\ \theta_j &:= \theta_j - \alpha \left[\frac{1}{m} \sum_{i=1}^{m} (h_\theta(x^i) - y^i) x_j^i + \frac{\lambda}{m} \theta_j \right]; j \in \{1,2...n\} \end{aligned} \tag{3}$$

}

α is the learning rate which accelerates the convergence process and λ is the regularization parameter which is adjusted to overcome overfitting. Thus the overall cost function can be represented as shown in (4):

$$J(\theta) = -\frac{1}{m} \sum_{i=1}^{m} \left[y^i \log(h_\theta(x^i)) + (1 - y^i) \log(1 - h_\theta(x^i)) \right] + \frac{\lambda}{2m} \sum_{j=1}^{n} \theta_j^2 \tag{4}$$

Thus, we have to train the classifier based on logistic regression for each subject's stance VGRF signals to predict the probability of $y = i$. After all, we will use test gait steps to predict the classification of them according to which subjects' gait they belong. This is done by assigning each gait step to the class that maximizes $h_\theta(x)$.

C. Database Reforming

Since the gait signals are measured in a continuous manner over two minutes, those signals are fragmented into different stances. Signals that represent turning points, at which subjects encounter while walking back and forth, are eliminated based on previous research work [13]. This part of the VGRF signal is not correlated to other parts in terms of conditions, length, speed, weight distribution and so on.

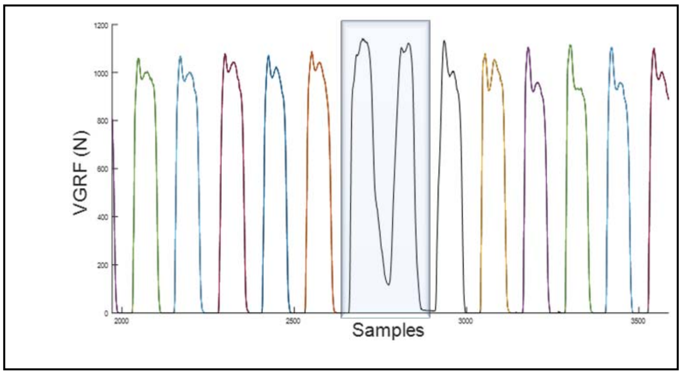

Figure 2. Highlighted preset segments are being omitted

In figure 2 the VGRF is being segmented into different steps which are highlighted with different colors. The turning point is emphasized by the rectangular box. This part is considered an outlier in the bunch of other VGRF stance segments. Then, the different gait steps are saved into a matrix and entitled by the subject's title. This has been implemented on all subjects, the normal subjects and the Parkinson subjects. However, this study is limited to the total summation of the VGRF signals of the left foot only.

III. Results and Discussion

As the training set size of the gait steps from a normal gait subject increases, the training accuracy decreases from 100 to 82 at which it then settles when the number of steps starts to exceed 17 steps. An acceptable gap between the training and the test accuracy indicates that the variance and the bias are both low and thus the results are not away from overfitting and under fitting aspects respectively. In figure 3, the size of training set increased while the test set is bounded only to one stance gait step. As the number of test set size increased, the percentage of dissimilarity among the coefficient of variation of different sizes is recorded to be 4.7%.

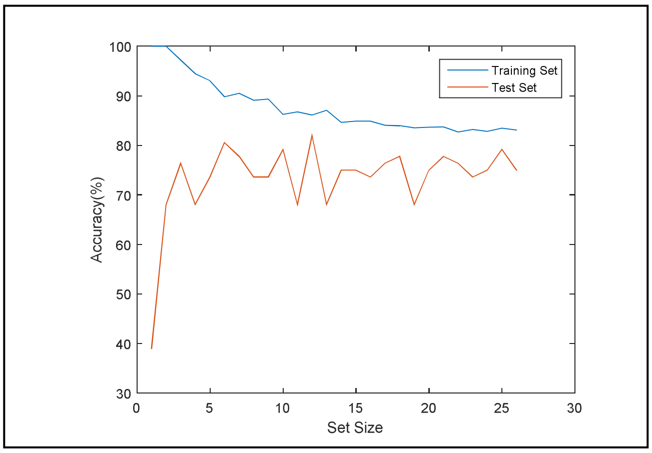

Figure 3. The variation of training and test accauracies as a function of the dataset size in a normal gait subject

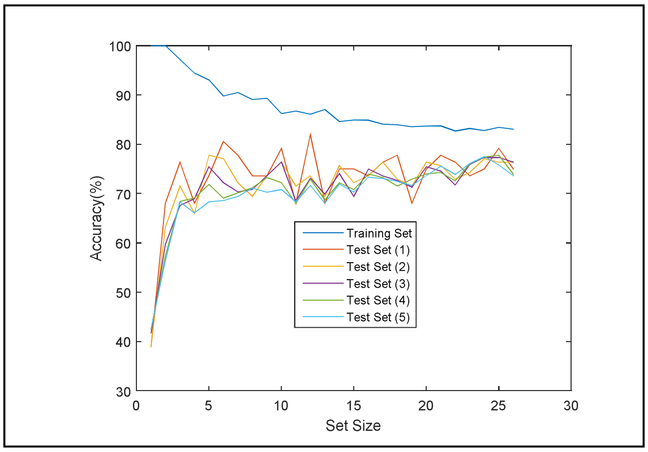

Figure 4. Different test set sizes are being varied as the training set size increases in normal gait subject

The flat part of training and test accuracies suggest that the algorithm established well parameters to identify various subjects. In the contrary, Parkinson gait subjects show a great disparity in the accuracy as shown in Figure 5. The accuracy of test set identification increased until it reached its maximum at which it stabilized when the training set was between 5 and 15, then decreased afterwards (between 15 and 20). This value started again to increase until it reaches a higher value of accuracy around 73% at a set size of 25. Such a fluctuation suggests that some measured VGRF stance gait signals do have a totally different aspect of information from one stance step into another. This is due to the existence of randomness in features that change over time which is compensated in the gait of Parkinson's subjects. The overall coefficient of variation at various used test signals is recorded to be 9.55% higher than that of the normal gait subjects as derived from Figure 6.

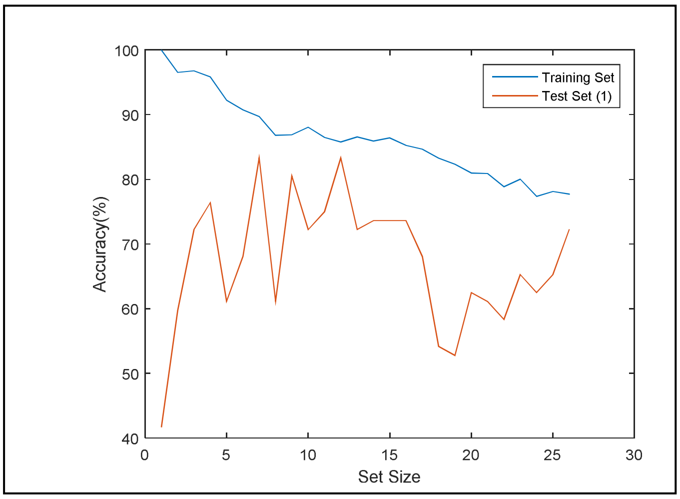

Figure 5. The variation of training and test accauracies as a function of the dataset size in a parkinson gait subject

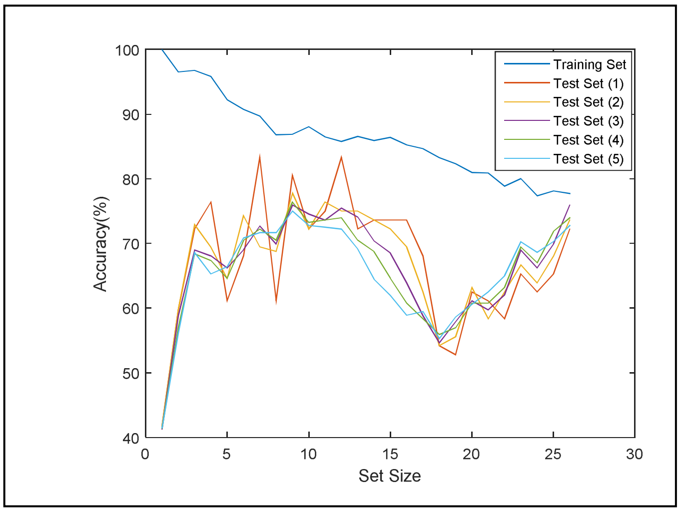

Figure 6. Different test set sizes are being varied as the examined trained set size increases in Parkinsons' gait subjects

Figure 7 shows a flat line around 74% accuracy in the training set and 65% accuracy in the test set. Here, the 5 test signals are being used and up to 26 training sets are being looped. The coefficient of variation is 7.8% in the training set and 11.5% in the test set over different training set sizes.

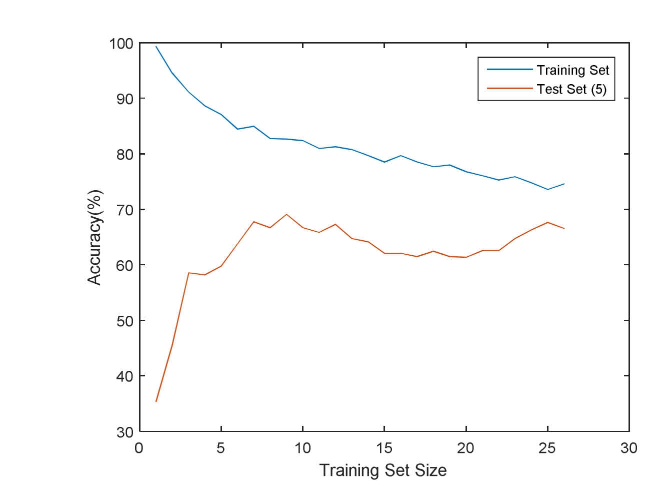

Figure 7. The accuracy varation among different trainig set sizes in the classification of the 165 subjects

IV. CONCLUSION

This study emphasizes the importance of VGRF signals in biometric systems, however under several constraints. For instance, some subjects are affected with certain diseases that in turn could affect the performance of gait classifier systems. That's why reliable features must be spotted that can't be affected by the change in the situation of the sample from time to time. This would improve the results and certainly this is directly correlated to the learning algorithm being implemented. Moreover, the signals from several sensors can be used to improve the results obtained from the research instead of using only one sensor. With a wider database that includes people who are suffering from different diseases, studies done will be more reliable in terms of gait detection. This preliminary study enlightened the way of building more reliable VGRF biometric systems.

REFERENCES

[1] A. Berg, "Detection and Tracking in Thermal Infrared Imagery" Linköping University, PhD Thesis, 2016.

[2] R. Subban, D.P. Mankame, "A Study of Biometric Approach Using Fingerprint Recognition" Lecture Notes and Software Engineering, vol. 1, no. 2, p. 209-213, 2013.

[3] C. M. Mohaisum ALi, "Human Gait identification System," *Research Journal of Mathematics and Computer Science,* pp. 1-1, 2017.

[4] F. F. Zainudin, J. H. Leonard, O. Baharudin, A. Johan and S. Riza, "Intra-Rater Reliability and Minimal Detectable Change of Vertical Ground Reaction Force Measurement during Gait and Half-Squat Tasks on Healthy," Malaysian Journal of Medical Sciences, vol. 23, no. 2, pp. 21-27, 2016.

[5] T. Takahashi, K. Ishida, D. Hirose, Y. Nagano and K. Okumiya, "Vertical Ground Reaction Force Shape is Associated with Gait Parameters , Timed Up and Go, and Functional Reach in Elderly Woman," Journal of Rehabilitation Medicine, no. 36, p. 42–45, 2004.

[6] D. Chang, M. Alban-Hidalgo and K. Hsu, "Diagnosing Parkinson's Disease From Gait," 2014.

[7] P. Ren, E. Karahan, C. Chen, R. Luo, Y. Geng, J. F. B. Bayard, M. L. Bringas, D. Yao, K. M. Kendrick and P. A. Valdes-Sosa, "Gait Influence Diagrams in Parkinson's Disease," IEEE Transactions on Neural Systems and Rehabilitation Engineering, vol. 25, no. 8, pp. 1257-1267, 2017.

[8] R.Alkhatib, M.Diab, B.Moslem, M.El Badawi, C.Corbier," gait - ground reaction force sensors selection based on roc curve evaluation", The 4th Int'l Conf. on Signal and Image Processing (CSIP 2015Mar.). Paper ID: CSIP2015Mar 80008, Scientific Research Publishing (SRP) , "Journal of Computer and Communications" (ISSN:2327-5219), California (US), article acceptance: 2014-12-28, V 3, 13-19, 2015.

[9] A. K. Jain, A. Ross and S. Prabhakar, "An introduction to biometric recognition," IEEE Transactions on Circuits and Systems for Video Technology, vol. 14, no. 1, p. 4–20, 2014.

[10] N. V. Boulgouris, D. Hatzinakos and K. N. Plataniotis, "Gait recognition: a challenging signal processing technology for biometric identification," IEEE Signal Processing Magazine, vol. 22, no. 6, p. 78–90, 2005.

[11] W. Tao, T. Liu, R. Zheng and H. Feng, "Gait Analysis Using Wearable Sensors," Sensors, vol. 12, no. 2, pp. 2255-2283, 2012.

[12] Hausdorff JM and Frenkel-Toledo S, "Gait in Parkinson's Disease," National Institutes of Health, National Parkinson Foundation, and the Parkinson's Disease Foundation, 2005. [Online]. Available: https://physionet.nlm.nih.gov/pn3/gaitpdb/?C=N;O=D.

[13] M.Diab, R.Alkhatib, B.Moslem, C.Corbier, M.El Badawi, "Synchrosqueezing Characterize Non-Stationary Signals: Application on Gait-Vertical Ground Reaction Force", Global Summit on Computer and Information Technology (GSCIT'2016), IEEE. Sousse, TUNISIA, 16-18, July, 2016.