A Nonliner Dynamics Approach to Human Activity Recognition Using Inertial Sensors

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ABSTRACT
This three month report presents several challenges for Human Activity Recognition (HAR) as well as the state-of-the-art literature in motion caputure systems, machine learning algorithms in HAR and human body analysis using nonlinear dynamics. It is also presented the proposed framework and timeline for the next six months of the PhD research.

Author Keywords
Human Activity Recognition; Body Sensor Networks; Machine Learning Algorithms; Nonliner Dynamics.

INTRODUCTION
Human Activity Recognition (HAR) has been a challenging task [1], since human body activity is complex and highly diverse [30]. HAR has many potential applications; for instance, these can be seen in personal assistants, surveillance, patient monitoring, sports analysis, dance activities, human-robot interaction and biometrics to mention but a few [2]. HAR has given several frameworks in recognizing primitive activities such as walking, jogging, cycling, jumping; nonetheless, little work has been been done in identifying complex activities that for instance involve dance.

Dance activities reflects the dancer's profile i.e., rhythmic sense, home country [28], personality, biological features (i.e., genre and age), dancing skills (i.e., fluency of the motion, adding erractical or additional movements, coordination and turbulence in dance, steadynees of the rhythm, predictability of the motion) [23]. Henceforth, for the current PhD work we are focusing on the multiattribute classification of dancing activities since these are complex and highly dinamyc activities to identify.

On the other hand, HAR deals with many issues which are a) the different types of activities to recongnise, b) the selection of motion capture system which should be unobtrusive and inexpensive, c) the selection of algorithms for feature extraction and classification, d) and the response time (offline or online) [32]. Yet, the chosen approach varies almost as greatly as the types of activities that have been recognized and types of sensor data that have been used [30]. Additionally, HAR has many challenges that motivate our work to find new techniques in order to recognize activities in more realistic conditions. Therefore, finding appropriate methods for HAR is not only motivated by the fact that the motion capture system should be non-intrusive and easy-to-wear but also that theoretical approach should be well suited for real-time applications.

We therefore hyphotesise that this work has the potential to make a major contribution to the human activity recogntion field

This three month report is organised as follows: First, the state-of-the-art in motion capture systems, machine learning approaches in HAR and human body analysis using nonlinear dynamics are reviewed in Section 2. Sencond, the proposed framework and the workplan is presented in section 3.

PREVIOUS WORK
The central goal of the research proposal is focused on a full understanding of concepts from nonlinear dynamics that can be used for human activity recognition so as to provide a robust approach for real-time identification using inertial sensors. Thus, reviews of motion capture systems are presented. Additionally, different approaches for HAR that use concepts from nonlinear dynamics are reviewed.

Motion Capture Systems
Motion capture systems can be chategorised into three approaches: vision-based [20]; floor-sensor based [38, 48, 3, 56, 59, 35, 43, 47, 41, 53, 40] ; and inertial-sensor based [42, 7, 10, 57, 26]. Although vision-based and floor-sensor based are rooted in non-intrusive motion capture systems, these are still required to be used into the space where users are constrained to move around. On the other hand, wearable systems have been proven to be the least instrusive and easy-to-use sensors. However, the choosen approach for human activity recognition varies as greately as the types of activities that have been recognized and many other factors such as type of sensors, data connection protocol, obstrusiveness, recognition performance, energy consumption, flexibility, computational processing, features, learning, and accuracy are considered for the performance of the motion capture system [32].

Machine Learning Aproaches in HAR
Much attention has also been given in recent years to use machine learning algorithms in HAR since the identification of activities entail a large number of attribute values and different transition points between activities; to this end several approaches have been used i.e. Suppor Vector Machines [21, 45, 46], template matching [36, 33], Hidden Markov Model [31, 37, 17, 11, 19, 16], Dynamic Time Warping [9, 13, 15], Neural Networks [44, 29, 34, 12], and most recently Dynamic Bayesian Networks [18, 55], Emerging Patterns [24,

30], Conditional Random Field [54] and Skip Change Conditional Random Field [30]. However, much research remains to be done to find suitable approaches in identifying activities in more realistic conditions.

Human Body Analysis Using Nonlinear Dynamics

Recently, the use of intertial-based motion capture system in human body activity and gait recognition has been proposed the use of concepts from nonlinear dynamics that implements methods to obtain; for instance, the state space reconstruction, determinism test, Lyapunov exponents and Poincaré maps. These concepts have been proven to be efficient approaches to meet the computitional requirements for processing information in real time [21, 45, 22, 39, 4, 5].

Similarly, video-based approaches have been proven to present good results to recognize more complex human body activities such as the dextery of tennis players using attractors and fractal properties [58, 49] , identification of dancing ballet, jumping, running, sitting and walking activities using the attractors of the reconstructed state space, multivariate phase space reconstruction and Maximal Lyapunov Exponent [6, 8, 51], and the recongnition of two-dimensional single-stroke patterns of 26 letters through modeling the attractor behaviors [27].

On the other hand, concepts from nonlinear dynamics also have been used to understand the behavior of human body activities for clinical applications, for instance Vieten *et al.* [52] quantify differences between gait patterns under constraints by approximating the time series data that underlying limit cycle attractors. Harbourne *et al.* [25] presented evidence to make diferentiation between health and nonhealth subjects and to identify difference between young and old people by analysing the changes in the attractor in the state space. Zhang *et al.* [60] demonstrated that the points of the Poincaré section are highly susceptible to noise; however, the use of power spectrum density analysis of the correlation coefficient demonstrate a relationship between $1/f$ noise and healthy subjects is very strong. Buzzi *et al.* [14] demonstrated satisfactorily that elderly subjects increased the inability to compensate the natural stride-to-stride variations by using the Lyapnov Exponent (LyE) and surrogate LyE (s-LyE). Terrier *et al.* [50] analysed and characterized the synchronization of steps with an auditory stimulus to evaluate gait stability and fall risk by using the maximum LyE. It is important to mention that researchers in this area have been made a greater emphasis on the need for embedded software to make accessible tools for physical therapist.

PROPOSED FRAMEWORK AND TIMELINE

The proposed framework is divided into five modules (Figure 1): 1) Data acquistion using a Bluetooth body sensor network with Inertial Measurement Units, 2) Reconstruction of the state space with a C++ class, 3) nonlinear measuraments and feature extractions by means of Principal Component Analysis, 4) classification using state-of-the-art multiatribute machine learning algorithms, and 5) application(s) such as dancing. Based on the proposed framework, tasks for the following 6 months are planned as follows:

- T1 [February]: Review of state-of-the-art machine learning methods for human activity recognition using wearable sensors.
- T2 [March]: Define the human activity experiment and recruit subjects to collect data so as to test the proposed PhD framework by means of a suitable machine learning algorithm.
- T4 [April]: Write and submit a paper in the 19th annual International Symposium on Wearable Computers (Full/Note Paper Due: 10 April)
- T5 [May-June]: Update the hardware of the body sensor network by using Bluetooth low energy devices and inductive wireless chargers.
- T6 [May-June]: Update the open source sofware library for the body sensor network.
- T6 [July]: Write the 9th month report and create a publication plan for the next year.

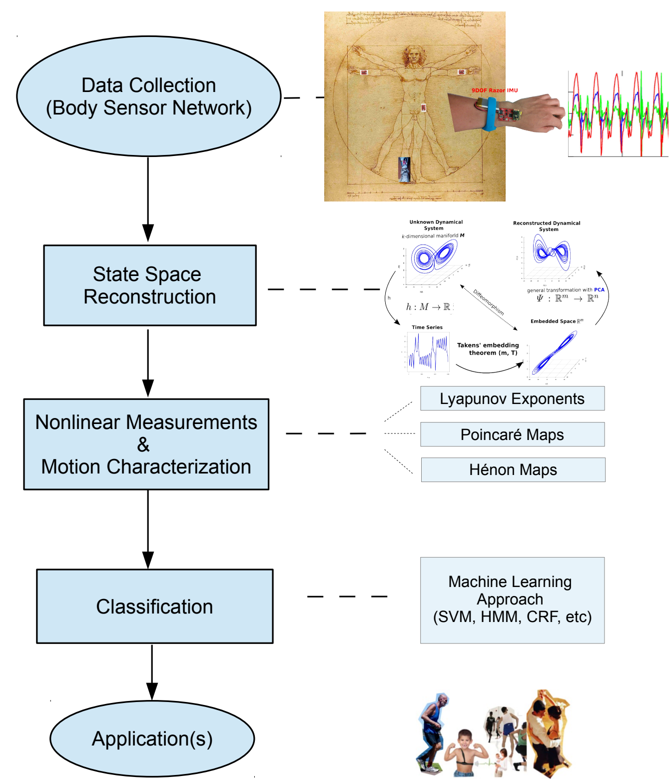

Figure 1. PhD Framework

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REFERENCES

1. Aggarwal, J., and Park, S. Human motion: modeling and recognition of actions and interactions. *Proceedings. 2nd International Symposium on 3D Data Processing, Visualization and Transmission, 2004. 3DPVT 2004.* (2004), 640–647.
2. Aggarwal, J. K., and Ryoo, M. S. Human activity analysis: A review. *ACM Computing Surveys (CSUR)* (2011).
3. Aguilar, R., Roelofsz, M., and Meijer, G. Capacitive Human-detection Systems with Auto-calibration. *smartec-sensors.com* (2007), 1–9.
4. Akiduki, T., Zhang, Z., Imamura, T., Miyake, T., Takahashi, H., and Namba, M. Toward Symbolization of Human Motion Data – Statistical Analysis in Symbol Space –. 1475–1480.
5. Akiduki, T., Zhang, Z., Imamura, T., and Takahashi, H. Toward symbolization of human motion data time-series clustering in symbol space. 1–6.
6. Ali, S., Basharat, A., and Shah, M. Chaotic Invariants for Human Action Recognition. *2007 IEEE 11th International Conference on Computer Vision* (2007), 1–8.
7. Bamberg, S. J. M., Benbasat, A. Y., Scarborough, D. M., Krebs, D. E., and Paradiso, J. a. Gait analysis using a shoe-integrated wireless sensor system. *IEEE transactions on information technology in biomedicine : a publication of the IEEE Engineering in Medicine and Biology Society 12*, 4 (July 2008), 413–23.
8. Basharat, A., and Shah, M. Time series prediction by chaotic modeling of nonlinear dynamical systems. *Computer Vision, 2009 IEEE 12th . . .* (2009).
9. Bautista, M., and Hernández-Vela, A. Probability-based dynamic time warping for gesture recognition on RGB-D data. *Advances in Depth . . .* (2013).
10. Benocci, M., and Rocchi, Laura, Elisabetta Farella, Lorenzo Chiari, L. B. A wireless system for gait and posture analysis based on pressure insoles and Inertial Measurement Units. *. . . for Healthcare, 2009. . . .* (2009).
11. Bernardin, K., Ogawara, K., Ikeuchi, K., and Dillmann, R. A Hidden Markov Model Based Sensor Fusion Approach for Recognizing Continuous Human Grasping Sequences.
12. Boesnach, I., Moldenhauer, J., Burgmer, C., Beth, T., Wank, V., and Bos, K. Classification of phases in human motions by neural networks and hidden Markov models. *IEEE Conference on Cybernetics and Intelligent Systems, 2004. 2* (2004), 976–981.
13. Boulgouris, N. V., Plataniotis, K. N., and Hatzinakos, D. Gait Recognition Using Dynamic Time Warping, 2004.
14. Buzzi, U. H., Stergiou, N., Kurz, M. J., Hageman, P. a., and Heidel, J. Nonlinear dynamics indicates aging affects variability during gait. *Clinical Biomechanics 18*, 5 (June 2003), 435–443.
15. Celebi, S., Aydin, A. S., Temiz, T. T., and Arici, T. Gesture Recognition Using Skeleton Data with Weighted Dynamic Time Warping.
16. Chang, C., and Huang, C.-l. The model-based human body motion analysis system. 1067–1083.
17. Chen, F.-S., Fu, C.-M., and Huang, C.-L. Hand gesture recognition using a real-time tracking method and hidden Markov models. *Image and Vision Computing 21*, 8 (Aug. 2003), 745–758.
18. Cuaya, G., Muñoz Meléndez, A., Nuñez Carrera, L., Morales, E. F., Quiñones, I., Pérez, A. I., and Alessi, A. A dynamic Bayesian network for estimating the risk of falls from real gait data. *Medical & biological engineering & computing 51*, 1-2 (Feb. 2013), 29–37.
19. Eickeler, S., Kosmala, A., and Rigoll, G. Hidden markov model based continuous online gesture recognition. *Pattern Recognition, 1998. . . .* (1998).
20. Forsyth, D. a., Arikan, O., Ikemoto, L., O'Brien, J., and Ramanan, D. Computational Studies of Human Motion: Part 1, Tracking and Motion Synthesis. *Foundations and Trends in Computer Graphics and Vision 1*, 2/3 (2005), 77–254.
21. Frank, J., Mannor, S., and Precup, D. Activity and Gait Recognition with Time-Delay Embeddings Time-Delay Embeddings.
22. Gouwanda, D., and Senanayake, A. Non-linear Time Analysis to Estimate Gait Stability Using Wearable Gyroscopes Network. *Journal of Robotics and . . . 24*, 4 (2012), 1–22.
23. Grammer K., Elisabeth Oberzaucher, I. H., and Atmaca, S. Dance: the Human Body as a Dynamic Motion System. *The Implications of . . .* (2011), 173–192.
24. Gu, T., Wu, Z., Tao, X., Pung, H. K., and Lu, J. epSICAR: An Emerging Patterns based approach to sequential, interleaved and Concurrent Activity Recognition. *2009 IEEE International Conference on Pervasive Computing and Communications* (Mar. 2009), 1–9.
25. Harbourne, R. T., and Stergiou, N. Movement variability and the use of nonlinear tools: principles to guide physical therapist practice. *Physical therapy 89*, 3 (Mar. 2009), 267–82.
26. Holleczek, T., and Ruegg, A, Holger Harms, G. T. Textile pressure sensors for sports applications. *Sensors, 2010 IEEE* (2010).
27. Ijspeert, A. J., Nakanishi, J., Hoffmann, H., Pastor, P., and Schaal, S. Dynamical movement primitives: learning attractor models for motor behaviors. *Neural computation 25*, 2 (Feb. 2013), 328–73.
28. Iwai, D., Felipe, T., Nagata, N., and Inokuchi, S. Identification of motion features affecting perceived rhythmic sense of virtual characters through comparison of latin american and japanese dances. *Information and Media . . .* (2011).

29. Ji, S., Yang, M., and Yu, K. 3D convolutional neural networks for human action recognition. *IEEE transactions on pattern analysis and machine intelligence 35*, 1 (Jan. 2013), 221–31.

30. Kim, E., Helal, S., and Cook, D. Human activity recognition and pattern discovery. *Pervasive Computing, IEEE 9*, 1 (Jan. 2010), 48.

31. Kohn, B., Ieee, M., Nowakowska, A., Belbachir, A. N., and Ieee, M. Real - time Body Motion Analysis For Dance Pattern Recognition AIT Austrian Institute of Technology GmbH. 48–53.

32. Lara, O. D., and Labrador, M. A. A Survey on Human Activity Recognition using. 1192–1209.

33. Lin, Z., Davis, L. S., Doermann, D., and DeMenthon, D. Hierarchical Part-Template Matching for Human Detection and Segmentation. *2007 IEEE 11th International Conference on Computer Vision* (2007), 1–8.

34. Modi, R. V. Neural Network based Approach for Recognition Human Motion using Stationary Camera. 43–47.

35. Moere, A. V., and Beilharz, K. infosense: Interaction Design for Sensate Spaces. *... of the Australian & New Zealand ...* (2004).

36. Nguyen, D. T., Li, W., and Ogunbona, P. A novel template matching method for human detection. *2009 16th IEEE International Conference on Image Processing (ICIP)* (Nov. 2009), 2549–2552.

37. Niu, W., Long, J., Han, D., and Wang, Y. Human activity detection and recognition for video surveillance. *Multimedia and Expo, 2004. ...* (2004), 2–5.

38. Paradiso, J., and Reynolds, M. The Magic Carpet : Physical Sensing for Immersive Environments.

39. Perc, M. The dynamics of human gait. *European Journal of Physics 26*, 3 (May 2005), 525–534.

40. Rajalingham, R., Visell, Y., and Cooperstock, J. R. Probabilistic Tracking of Pedestrian Movements via In-Floor Force Sensing. *2010 Canadian Conference on Computer and Robot Vision* (2010), 143–150.

41. Rangarajan, S., and Kidané, A. Design optimization of pressure sensing floor for multimodal human-computer interaction. *... Computer Interaction, I- ...* (2008).

42. Razak, A. H. A., Zayegh, A., Begg, R. K., and Wahab, Y. Foot plantar pressure measurement system: a review. *Sensors (Basel, Switzerland) 12*, 7 (Jan. 2012), 9884–912.

43. Richardson, B., Leydon, K., Fernström, M., and Paradiso, J. A. Z-Tiles : Building Blocks for Modular , Pressure-Sensing Floorspaces. 1529–1532.

44. Rosenblum, M., and Davis, L. S. Human Emotion Recognition from Motion Using a Radial Basis Function Network Architecture 1 Introduction Recent research in computer vision.

45. Samà, A., Ruiz, F. J., Agell, N., Pérez-López, C., Català, A., and Cabestany, J. Gait identification by means of box approximation geometry of reconstructed attractors in latent space. *Neurocomputing 121* (Dec. 2013), 79–88.

46. Schüldt, C., Laptev, I., and Caputo, B. Recognizing human actions: A local SVM approach. *Proceedings - International Conference on Pattern Recognition 3* (2004), 32–36.

47. Srinivasan, P., Birchfield, D., Qian, G., and Kidané, A. A pressure sensing floor for interactive media applications. *Proceedings of the 2005 ACM SIGCHI International Conference on Advances in computer entertainment technology - ACE '05* (2005), 278–281.

48. Steinhage, A., and Lauterbach, C. Monitoring Movement Behavior by Means of a Large Area Proximity Sensor Array in the Floor. *BMI* (2008), 15–27.

49. Suzuki, H., and Yamamoto, Y. Dexterity of switched hitting movement using fractal dimension analysis. *Japanese Journal of Sport Psychology 40*, 2 (2013), 91–108.

50. Terrier, P., and Deriaz, O. Nonlinear dynamics of human locomotion : effects of rhythmic auditory cueing on local dynamic stability. 1–28.

51. Venkataraman, V., Turaga, P., Lehrer, N., Baran, M., Rikakis, T., and Wolf, S. L. Attractor-Shape for Dynamical Analysis of Human Movement: Applications in Stroke Rehabilitation and Action Recognition. *2013 IEEE Conference on Computer Vision and Pattern Recognition Workshops* (June 2013), 514–520.

52. Vieten, M. M., Sehle, A., and Jensen, R. L. A novel approach to quantify time series differences of gait data using attractor attributes. *PloS one 8*, 8 (Jan. 2013), e71824.

53. Visell, Y., Smith, S., Law, A., Rajalingham, R., and Cooperstock, J. R. Contact sensing and interaction techniques for a distributed, multimodal floor display. *2010 IEEE Symposium on 3D User Interfaces (3DUI)*, 1 (Mar. 2010), 75–78.

54. Wang, S. B., Quattoni, A., Morency, L.-P., Demirdjian, D., and Darrell, T. Hidden Conditional Random Fields for Gesture Recognition. *2006 IEEE Computer Society Conference on Computer Vision and Pattern Recognition - Volume 2 (CVPR'06) 2* (2006), 1521–1527.

55. Wang, X., and Ji, Q. Context augmented Dynamic Bayesian Networks for event recognition. *Pattern Recognition Letters 43* (July 2014), 62–70.

56. Wimmer, R. Capacitive sensors for whole body interaction. *Whole Body Interaction* (2011).

57. Xu, W., and Liu, J. J. Smart Insole : A Wearable System for Gait Analysis. 1–4.

58. Yamamoto, Y., and Gohara, K. Continuous hitting movements modeled from the perspective of dynamical systems with temporal input. *Human Movement Science 19*, 3 (Aug. 2000), 341–371.

59. Yin, K., and Pai, D. Footsee: an interactive animation system. *.../Eurographics symposium on Computer animation* (2003).

60. Zhang, J., Zhang, K., Feng, J., and Small, M. Rhythmic dynamics and synchronization via dimensionality reduction: application to human gait. *PLoS computational biology 6*, 12 (Jan. 2010), e1001033.