SPWID 2018

The Fourth International Conference on Smart Portable, Wearable, Implantable and Disability-oriented Devices and Systems

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SPWID 2018

Foreword

The Fourth International Conference on Smart Portable, Wearable, Implantable and Disability-oriented Devices and Systems (SPWID 2018), held between July 22 - 26, 2018- Barcelona, Spain, is an inaugural event bridging the concepts and the communities dealing with specialized implantable, wearable, near-body or mobile devices, including artificial organs, body-driven technologies, and assistive services

Mobile communications played by the proliferation of smartphones and practical aspects of designing such systems and developing specific applications raise particular challenges for a successful acceptance and deployment.

We take here the opportunity to warmly thank all the members of the SPWID 2018 Technical Program Committee, as well as the numerous reviewers. The creation of such a broad and high quality conference program would not have been possible without their involvement. We also kindly thank all the authors who dedicated much of their time and efforts to contribute to SPWID 2018. We truly believe that, thanks to all these efforts, the final conference program consisted of top quality contributions.

Also, this event could not have been a reality without the support of many individuals, organizations, and sponsors. We are grateful to the members of the SPWID 2018 organizing committee for their help in handling the logistics and for their work to make this professional meeting a success.

We hope that SPWID 2018 was a successful international forum for the exchange of ideas and results between academia and industry and for the promotion of progress in the areas of smart portable devices and systems.

We are convinced that the participants found the event useful and communications very open. We hope that Barcelona provided a pleasant environment during the conference and everyone saved some time to enjoy the charm of the city.

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A Factor of Human-Robot Interaction on Wearable Robot: A Literature Review

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***Abstract*— The robot technology is developing to improve human life and that substitutes human function and capability. The key factor of wearable robot is a human-robot interaction. The purpose of this study is to analyze the ergonomic factors of a human-robot interaction based on literature reviews. To search for ergonomic factors on a human-robot interaction, we looked into four databases in Web of Science, Scopus, IEEE Explore, and Google Scholar. This study reviewed literature including papers, books, international standards published from January 1st, 2000 to May 1st, 2018. The title and abstract of literature was checked by authors. Selected literature was reviewed and the main factors were manually extracted. There were twelve literature that met the inclusion criteria. This study evaluated the ergonomic factors of human-robot interaction categorized as safety, human and robot factors which were warning sign, stability, fail-safe, range of motion, fatigue, contact pressure, motion intention, misalignment, power, closed-loop system, and etc. These ergonomic factors are suggested to the safety and usability evaluation systems by developing ergonomic design specifications of wearable robots.**

Keywords - Wearable Robot; Human-Robot Interaction; Ergonomic; Safety; Usability.

I. INTRODUCTION

The robot technology is developing to improve industry productivity and convenience in human life. The application of wearable robotics is growing in various fields such as industry, rehabilitation, prosthetics, space application and defense. A wearable robot can be seen as a technology that extends, complements, substitutes human function and capability or replaces [1].

Previous studies still have focused on developing and improving the mechanical performance of a wearable robot. However, the key distinctive aspect in wearable robots is their Human-Robot Interaction(HRI). An HRI is a hardware and software link that connects to both human and robot systems [2].

The purpose of this study is to analyze to the ergonomic factors of HRI on a wearable robot through a literature review.

II. METHOD

The purpose of this method is to search main factors in HRI, and to identify potential ergonomic factors. This review details the findings from four electronic databases via keyword searches in Web of Science, Scopus, IEEE Explore, and Google Scholar. For this study, we searched literature related with HRI of wearable robot including papers, public documents, books, international standards and report published from January 1st, 2000 to May 1st, 2018.

Regarding the search keyword, the search criteria used were 'human robot interaction', 'ergonomics', 'human factor', 'usability', 'safety' and 'comfortability'. To avoid literature not falling into the topic under study, the search was performed using the Boolean operator "AND", with the search term 'ergonomics' [3].

The following additional inclusion criteria were used to search the literature:

a. Published as a full text literature, or in press, in peer-reviewed journals
b. Published or in press between January 1st, 2000 and prior May 1st, 2018
c. Literature in this study includes that paper, article, public document, book, international standard and issue report
d. Literature that considered HRI on wearable robot
e. Literature with an ergonomics studies or application purpose

The process of literature review, titles and abstracts were checked separately by three of the authors. Prior to literature review, inclusion criteria were identified and corresponding relevant information required was analyzed. Then, the selected relevant literature was reviewed and the main factors manually extracted.

III. RESULT

A total of 51 literatures were searched, of which 12 literatures that met the inclusion criteria [4]-[15]. Table 1 shows the reviewed literature evaluated for the ergonomic factors. It categorized as safety, human and robot factors as follows: warning sign, emergency stop, stability, temperature, fail-safe, range of motion, fatigue, contact pressure, motion intention, misalignment, power, weight, operation type, closed-loop system, and etc.

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TABLE I. SUMMARY OF MAIN FACTOR REFERRING TO HUMAN, ROBOT AND SAFETY ON WEARABLE ROBOT.

Author and year	Main factor		
	Safety	Human	Robot
Chan and Courtney, 2001	Warning sign Emergency stop		
Copaci et al., 2017		Joint angle Range of motion	Actuator Degree of freedom Torque
d'Elia et al., 2017	Stability	Kinematic coupling Segment length Locomotion	Mechanical power
de Looze et al., 2016		Muscle load Musculoskeletal disorder	Operation type(active/passive)
De Santis et al., 2008	Control architecture	Injury Damage	Actuation Weight Sensor
ISO 13482:2014	Sharp edge Vibration Surface temperature Fail safe	Musculoskeletal disorder Fatigue	Battery Power down
Lenzi et al., 2011		Contact pressure Comfort Interaction force and torque Motion intention	Tactile sensor
Lenzi et al., 2012		Movement intention Muscle activity Muscle torque	Movement accuracy
Nguyen and Sankai, 2013		Strain of contact part Interaction force	Contact part
Nimawat and Jailiya 2015	System architecture Hyper flex human joint	User interface Misalignment Tissue load Tolerance of pressure Size weight	Sensor Actuator Energy storage
Long et al., 2006		Misalignment Discomfort	Closed-loop system Proximal elastic module
Schiele et al., 2006		Degree of freedom Misalignment	Optimal design

IV. DISCUSSION

Based on these results, this study suggested three grouped ergonomic HRI factors including the safety for human-robot interaction, the usability for human, and the mechanical specification to ensure the human safety. A factor of HRI on wearable robot are suggested to the safety and usability evaluation system by developing ergonomic design specifications of wearable robots. This study is based on content literature review techniques that briefly reviews abstracts, key contents and passages. It means that the results of this study do not represent a detailed review of literature, or the impact of their findings.

ACKNOWLEDGEMENT

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REFERENCES

[1] R. Alami et al., “Safe and dependable physical human-robot interaction in anthropic domains: State of the art and challenges”, in Proceedings of the Intelligent Robots and Systems, 2006 IEEE/RSJ International Conference, DOI: 10.1109/IROS.2006.6936985, 2006.

[2] J. L. Pons, Wearable robots: biomechatronic exoskeletons, UK: John Wiley & Sons, 2008.

[3] C. Viviani et al., “Accuracy, precision and reliability in anthropometric survey for ergonomics purposes in adult working populations: A literature review”, Int J Ind Ergon, Vol. 65, pp. 1-16, 2018.

[4] A. H. S. Chan and A. J. Courtney, “Safety and ergonomics evaluation of hybrid systems in Hong”, Accid Anal Prev, Vol. 33, pp. 563-565, 2001.

[5] D. Copaci, E. Cano, L. Moreno and D. Blanco, “New Design of a Soft Robotics Wearable Elbow Exoskeleton Based on Shape Memory Alloy Wire Actuators”, Appl Bionics Biomech, DOI: 10.1155/2017/1605101, 2017.

[6] N. d'Elia et al., “Physical human-robot interaction of an active pelvis orthosis: Toward ergonomic assessment of wearable robots”, J Neuroeng Rehabil, Vol. 14:29, 2017.

[7] M. P. de Looze, T. Bosch, F. Krause, K. S. Stadler and L. W. O'Sullivan, “Exoskeletons for industrial application and their potential effects on physical work load”, Ergonomics, Vol. 59, pp. 671–681, 2016.

[8] A. De Santis, B. Siciliano, A. De Luca and A. Bicchi, “An atlas of physical human-robot interaction”, Mech Mach Theory, Vol. 43, pp. 259-270, 2008.

[9] ISO 13482:2014, Robots and robotic devices – safety requirements for personal care robots, 2014.

[10] T. Lenzi et al., “Measuring human–robot interaction on wearable robots: A distributed approach”, Mechatronics, Vol. 21, pp. 1123–1131, 2011.

[11] T. Lenzi, S. M. M. De Rossi, N. Vitiello and M. C. Carrozza, “Intention-based EMG control for powered exoskeletons”, IEEE Trans Biomed Eng, Vol. 59, pp. 2180-2190, 2012.

[12] M. T. Nguyen and Y. Sankai, “Measurement method of interaction force between human and wearable assistive robot based on strain of contact part” Proceedings of the SICE Annual Conference, pp. 401-406, 2018.

[13] D. Nimawat and P. R. S. Jailiya, “Requirement of wearable robots in Current scenario”, Euro J Adv Engg, Vol. 2, pp. 19–23, 2015.

[14] Y. Long, Z. Du, C. Chen, W. Wang and W. Dong, “Development of a lower extremity wearable exoskeleton with double compact elastic module: Preliminary experiments”, Mech Sci, Vol. 8, pp. 249-258, 2017.

[15] T. Schiele and F. C. T. van der Helm, “Kinematic design to Improve ergonomics in human machine interaction”, IEEE Trans Neural Syst Rehabil Eng, Vol. 14, pp. 456-469, 2006.

A Single Wearable IMU-based Human Hand Activity Recognition via Deep Autoencoder and Recurrent Neural Networks

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Abstract— **Human Hand Activity Recognition (HAR) using wearable sensors can be utilized in various practical applications such as lifelogging, human-computer interaction, and gesture interfaces. Especially with the latest deep learning approaches, the feasibility of HAR in practice gets more promising. In this paper, we present a HAR system based on deep Autoencoder for denoising and deep Recurrent Neural Network (RNN) for classification. The proposed HAR system achieves a mean accuracy of 79.38% for seven complex hand activities, while only of 72.65% without the autoencoder. The presented combination of autoencoder and RNN could be useful for much improved human activity recognition.**

Keywords- Human Hand Activity Recognition; Autoencoder; Deep Learning; RNN; CNN.

I. INTRODUCTION

Human Hand Activity Recognition (HAR) is an essential technology in many user-centric applications such as human-computer interactions, assisted living, smart homes, and lifelogging [1]. In general, there are two ways for HAR: using imaging sensors or inertial sensors that capture human activities [2]. Wearable devices are generally equipped with inertial sensors such as accelerometer, gyroscope, and magnetometer, which have proven useful for HAR. There have been many studies recognizing Activities of Daily Living (ADL) with these wearable devices [1]-[10]. Besides, various classifiers have been employed such as Hidden Markov Models (HMM), Support Vector Machine (SVM), and Restricted Boltzmann Machines (RBMs) [3], [4], [5].

Recently, data-driven approaches using deep learning for HAR have led to a significant recognition improvement by self-learning without the need of handcrafting features [6], [7]. Approaches based on Convolutional Neural Networks (CNN) demonstrate the advantages of using convolutional filters to capture local dependencies and scale invariance features. Previous works, such as [8] and [9] applied CNN to extract features from multi-channel sensor data and recognized locomotion activities such as walking, sitting, walking upstairs, and walking downstairs.

Recently, there is a growing interest in hand activity recognition [10], due to the widespread use and availability of wristbands and smartwatches. In the work [11], CNN was utilized to recognize multiple daily life hand activities from multiple sensors signals. Approaches in [12] and [13] used Recurrent Neural Networks (RNN) to recognize locomotion and hand gestures using multiple Inertial Measurement Units (IMU) on the wrist and body parts. The work in [14] presented improvements in a multi-sensor based HAR combining CNN and RNN.

Although these previous studies accomplished some success recognizing hand activities, because of the delicate movements of hands and sensor noise, some additional preprocessing is needed to improve the recognition rate. One latest study in [15] examined different motion artifacts in constrained and free-mode motion sensor networks and demonstrated the effect of alleviating noise motion artifacts in HAR performance.

In this work, we present a HAR system for daily hand activities consisting of a deep autoencoder for denoising and a deep RNN for classification. As reducing signal noise and improving signal representations can be dealt with a deep autoencoder [16], we have designed a supervised autoencoder for denoising and better signal representation. Then, a classifier based on RNN recognizes daily hand activities using only the signals from a single IMU on one dominant wrist. Our results show a significant improvement in recognizing complex hand activities.

The rest of this paper is organized as follows. Section II describes the proposed methodology. In Section III, the experimental results of HAR are presented. Finally, the conclusion is given.

II. METHODS

Our proposed hand activity recognition system is shown in Figure 1. The input signal is composed of thirteen feature channels collected from a single IMU sensor at the right wrist of subjects. The Autoencoder (AE) module processes this input signal and transfers to the RNN classifier for hand activity recognition.

A. Hand Activity Database

In this study, we utilized the Opportunity public database [17], which contains continuous time-series data of various human hand activities. The database includes the recordings from four subjects: each subject performed an unscripted session of hand movements and ADL without constraints.

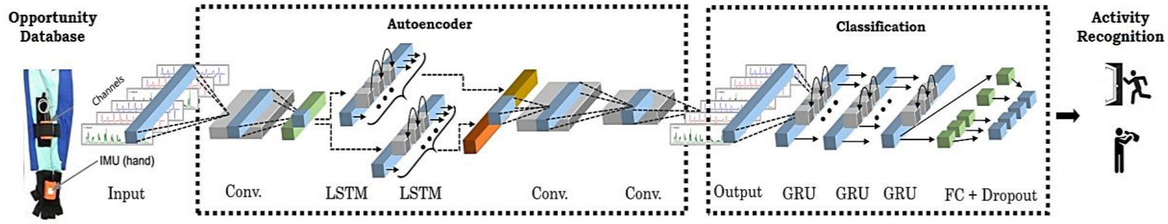

Figure 1. Proposed HAR system for hand activity recognition. From the left, signals coming from a single IMU go through our autoencoder module. Autoencoder reconstructs the data and transfer to RNN classifier. Classifier predicts activity class probabilities.

Each session was performed five times with different numbers of repetition for the activities. Additional hand activities were collected in an extra control (Drill) sessions, where each subject performed twenty scripted sequences of hand activities. We followed the Opportunity multi-modal gesture challenge guidelines in [17] to split the data into train and test datasets. We focus on data collected from a sensor placed on the right wrist of a custom jacket, which was worn by the subjects. This sensor included a commercial RS458-networked XSense IMU composed of a three-axis accelerometer, a three-axis gyroscope, a three–axis magnetometer, and four-channel quaternion orientation information.

From the total of hand gesture classes in the database, we selected thirteen activities of our interest. The activities that involve similar executions are grouped as the same class. Resultant seven classes of hand activities are Close Door (Close Door 1 and Close Door 2), Open Door (Open Door 1 and Open Door 2), Close Fridge, Open Fridge, Open Drawer (Open Drawer 1, Open Drawer 2, and Open Drawer 3), Close Drawer (Close Drawer 1, Close Drawer 2, and Close Drawer 3), and Drink from Cup.

Using a sliding window approach, the IMU signals were segmented with a window size of four seconds and an overlap of 50%. The data were normalized to a range of [-1, +1] with zero mean, which we denote them as epochs. Each epoch is tagged with a specific class label. We named these datasets of epochs as the IMU-train and IMU-test datasets respectively.

To train our supervised autoencoder, we modeled the previous datasets using an Autoregressive Moving Average (ARMA) model and named them as the ARMA-train and ARMA-test datasets. Training the AE used these ARMA datasets as the ideal targets of the reconstructed and denoised signals. Finally, the AE reconstructed outputs are named as the AE-train and AE-test datasets. The classifier uses these datasets for performance analysis of recognition.

B. Proposed Autoencoder

In this section, the proposed AE and RNN classifier are presented.

B1. Autoencoder Model

The encoder $f(x)$ in our AE architecture is a combination of a CNN layer and a Bidirectional RNN (BRNN). A convolution layer extracts features from the input signal through a one-dimensional filter. These features capture local correlations hidden in the data and form an augmented representation in a set of multiple feature maps [14]. We use the hyperbolic tangent function as a non-linear activation function for the output of the convolution. The RNN layers process sequential data, taking advantage of parameter sharing, making possible each unit in the output be a function of the previous units. BRNN takes the output from CNN and uses it in two parallel layers: forward and backward loops used for exploding context from the past and future of a specific time step. The BRNN units are based on Long Short Term Memory (LSTM) cells, which use a concept of gates that define the behavior of the memory cell. The input x_t is fed into different gates such as the forget gate f_t, input gate i_t, and output gate o_t with the previous cell output h_{t-1} to compute the current output. In the following equations, we describe the LSTM unit where σ represents a non-linear function and $[W, b]$ are the weight matrices and bias vector associated with each gate.

$$f_t = \sigma\left(W_f \cdot [h_{t-1}, x_t] + b_f\right) \tag{1}$$

$$i_t = \sigma(W_i \cdot [h_{t-1}, x_t\,] + b_i) \tag{2}$$

$$\widetilde{C}_t = \tanh(W_c \cdot [h_{t-1}, x_t] + b_c) \tag{3}$$

$$C_t = f_t * C_{t-1} + i_t * \widetilde{C}_t \tag{4}$$

$$o_t = \sigma(W_o \cdot [h_{t-1}, x_t\,] + b_o) \tag{5}$$

$$h_t = o_t * \tanh(C_t) \tag{6}$$

From the encoder hidden representation h, the decoder $g(h)$ reconstructs the signals by two stacked convolutional layers. The last decoder convolution layer has its feature map size constrained to the same size of the input channels.

B2. ARMA Modeling of IMU Activity Signals

Before training the supervised AE, the ideal target dataset is obtained by modeling the original IMU datasets via ARMA. The Akaike information criterion was used to select an appropriate order for the autoregressive and moving average models. For each channel, an optimized model was carefully chosen from a pool of different combination of orders: in most cases, the autoregressive model order of 3 and moving

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average of 4 were selected. The ARMA-train and ARMA-test datasets represent a denoised and improved representation of the signals in the IMU-train and IMU-test datasets. In Figure 2, one set of epoch instances from the IMU-test and ARMA-test datasets is shown.

B3. Training and Testing Autoencoder

The input to the AE was carried by mini-batches composed of epochs in the IMU-train dataset and target ARMA-train dataset. The AE used the Mean Square Error (MSE) as a loss function. The training algorithm iterated up to 100 training steps with a learning rate of 1e-4. Gradient decedent recursively updated the network parameters using Adam optimizer algorithm. Weights initialization used a random Gaussian distribution with a mean of zero and standard deviation of 0.5. To validate the AE performance, we quantified the similarity between the AE-test and ARMA-test datasets. This similarity is based on the overall Root Mean Square Error (RMSE) and Pearson Correlation Coefficient (R) for each corresponding channel from both datasets.

C. RNN Classifier

The classifier module is composed of three RNN layers based on Gate Recurrent Unit (GRU) memory cells. The GRU cell possesses a reset gate r and an update gate z, unlike the LSTM variant it does not have an internal memory c_t and an output gate o_t. The GRU cell combines the input gate i_t and forget gate f_t in the update gate, and directly apply the reset gate to the previously hidden state. We describe the GRU gates in the following equations:

$$z_t = \sigma(W_z \cdot [h_{t-1}, x_t]) \quad (7)$$

$$r_t = \sigma(W_r \cdot [h_{t-1}, x_t]) \quad (8)$$

$$\tilde{h}_t = tanh(W[r_t * h_{t-1}, x_t]) \quad (9)$$

$$h_t = (1 - z_t) * h_{t-1} + z_t * \tilde{h}_t \quad (10)$$

The output from last RNN layer is connected to a dense layer to obtain the class probabilities. Despite the

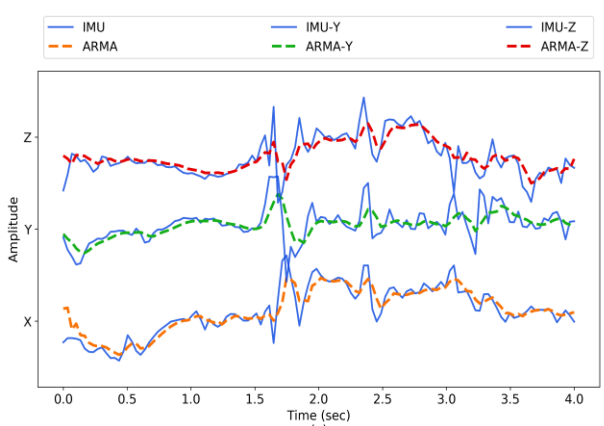

Figure 2. Time series from the 3-axis accelerometer in the "Open Door" activity: IMU (solid) and ARMA (dotted).

compelling representation from RGRU, there is still a possibility of overfitting. We address this using a dropout technique for optimization with a value of 0.4 before the dense layer. The final layer produces the class probabilities from a Softmax function. Initialization of the weights uses a random Gaussian distribution with of mean zero and standard deviation of 0.5. The network is trained over 50 training steps with a learning rate of 3e-4 with an optimization based on Adam algorithm. We compute the weighted F1-score and accuracy of classification for the given test datasets.

III. EXPERIMENTAL RESULTS

A. Validation of Autoencoder

We computed the RMSE and R coefficient between the ARMA-test and AE-test datasets to evaluate the performance of AE. Table 1 shows a summary of these values. The signals in Figure 3 illustrate an exemplary epoch of "Open Door" activity from both datasets.

TABLE 1. THE COMPUTED RMSE AND R-VALUES BETWEEN ARMA-MODELED AND AE OUTPUT DATASETS.

Channels	Axis	RMSE	R
Accelerometer	*X*	0.0441	0.9387
	Y	0.0383	0.9805
	Z	0.0359	0.9953
Gyroscope	*X*	0.0262	0.9652
	Y	0.0251	0.9820
	Z	0.0234	0.9872
Magnetometer	*X*	0.0130	0.9799
	Y	0.0111	0.9892
	Z	0.0122	0.9927
Quaternion	*Q1*	0.0328	0.9873
	Q2	0.0361	0.9914
	Q3	0.0340	0.9870
	Q4	0.0345	0.9976

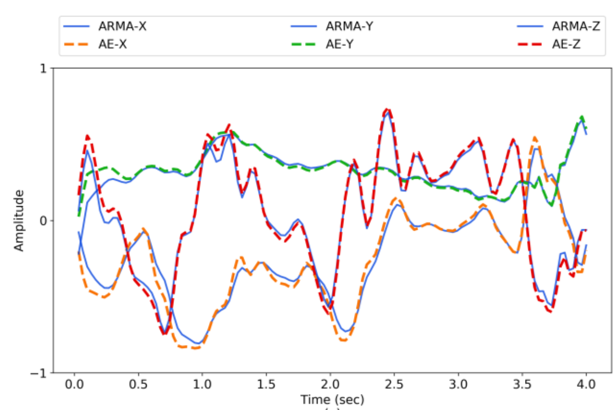

Figure 3. Time series from the 3-axis gyroscope in the "Open Door" activity: ARMA (solid) and AE (dotted).

A1. *Classification Performance*

The summary of the recall values achieved by the classifier on the IMU-test, ARMA-test, and AE-test datasets are shown in Table 2. Using the raw sensor signals in the IMU-test dataset, the classifier achieved a mean F1-score of 72.87% and accuracy of 72.65%. The recognition performance is not quite satisfactory for these complex hand activities. Using the ARMA-test dataset (i.e., modeled ideal dataset), recognition increased to a mean F1-score of 82.40% and accuracy of 82.14%. For activities such as “Open Fridge” and “Open Drawer,” their recall values increased up to 78.33% and 81.55% respectively from around 60%. Finally, using the AE-test dataset (i.e., the output of AE), the classifier achieved a mean F1-score of 79.64% and accuracy of 79.38%, reflecting a 6.75% improvement over the raw signals from the IMU-test dataset and similar to the performance of the ARMA-test dataset.

TABLE 2. SUMMARY OF CLASSIFICATION PERFORMANCE FOR THE IMU-TEST, ARMA-TEST, AND AE-TEST DATASETS WITH THE PROPOSED CLASSIFIER.

Hand Activity Recognition	**Performance on Test Datasets (%)**			
	Activity	Raw IMU	ARMA	AE
Gestures	*OD*	83.89	88.33	91.67
	CD	85.80	88.27	86.42
	OF	61.00	78.33	73.00
	CF	63.89	70.83	68.75
	DC	84.08	89.20	87.44
	ODW	60.71	81.55	69.64
	CDW	57.58	66.67	68.18
Mean	*F1-score*	72.87	82.40	79.64
	Accuracy	72.65	82.14	79.38

*OD: Open Door, CD: Close Door, OF: Open Fridge, CF: Close Fridge, DC: Drink from Cup, ODW: Open Drawer, CDW: Close Drawer

A2. *Comparison of Related Works*

In this work, we have implemented a HAR system of deep denoising AE and RNN classifier, through which the improved representation of activity signals are utilized to recognize seven daily hand activities using only a single IMU sensor.

There are rare works of HAR systems utilizing denosing AE. The HAR work in [15] used an unsupervised Variational Autoencoder (VAE) in combination of CNN with LSTM. It shown that using 75 sensor channels that presented significative motion artifacts from Opportunity the denoised signals could improve the accuracy from 72.96% to 90.81%. Also there have been HAR works utilzing multiple sensors (i.e., >70 sensor channels) to improve the performance. These studies reported F1-score of 75.4% [12], a recall value of 83.5% [13] , and F1-score of 86.6% [14] without the use of AE. In contrast with those studies, our architecture receive an input data compose of 13 feature channels extracted from only one IMU sensor, which is more practical for an end- user application.

IV. CONCLUSION

In this work, we have presented a HAR system for daily human hand activities combining a denoising autoencoder and RNN for classification. Our results prove that AE helps the deep classifier and eventually HAR by reducing noises and representing signals better. The promising results demonstrate the effectiveness of this approach, which could be used for other HAR systems.

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REFERENCES

[1] A. Bulling, U. Blanke, and B. Schiele, “A Tutorial on Human Activity Recognition Using Body-worn Inertial Sensors,” *ACM Comput. Surv.*, vol. 46, no. 3, p. 33:1--33:33, Jan. 2014.

[2] A. M. Khan, Y.-K. Lee, S. Y. Lee, and T.-S. Kim, “A Triaxial Accelerometer-based Physical-activity Recognition via Augmented-signal Features and a Hierarchical Recognizer,” *Trans. Info. Tech. Biomed.*, vol. 14, no. 5, pp. 1166–1172, Sep. 2010.

[3] E. Garcia-Ceja, R. F. Brena, J. C. Carrasco-Jimenez, and L. Garrido, “Long-Term Activity Recognition from Wristwatch Accelerometer Data,” *Sensors*, vol. 14, no. 12, pp. 22500–22524, 2014.

[4] S. Bhattacharya and N. D. Lane, “From smart to deep: Robust activity recognition on smartwatches using deep learning,” in *2016 IEEE International Conference on Pervasive Computing and Communication Workshops (PerCom Workshops)*, 2016, pp. 1–6.

[5] H. P. Gupta, H. S. Chudgar, S. Mukherjee, T. Dutta, and K. Sharma, “A Continuous Hand Gestures Recognition Technique for Human-Machine Interaction Using Accelerometer and Gyroscope Sensors,” *IEEE Sens. J.*, vol. 16, no. 16, pp. 6425–6432, Aug. 2016.

[6] M. Zeng *et al.*, “Convolutional Neural Networks for human activity recognition using mobile sensors,” in *6th International Conference on Mobile Computing, Applications and Services*, 2014, pp. 197–205.

[7] J. Wang, Y. Chen, S. Hao, X. Peng, and L. Hu, “Deep learning for sensor-based activity recognition: A Survey,” *Pattern Recognit. Lett.*, 2018.

[8] Y. Zheng, Q. Liu, E. Chen, Y. Ge, and J. L. Zhao, “Exploiting multi-channels deep convolutional neural networks for multivariate time series classification,” *Front. Comput. Sci.*, vol. 10, no. 1, pp. 96–112, Feb. 2016.

[9] H. Gjoreski, J. Bizjak, M. Gjoreski, and M. Gams, “Comparing Deep and Classical Machine Learning Methods for Human Activity Recognition using Wrist Accelerometer,” 2016.

[10] Choudhary, Santosh, and N. Choudhary, “Towards Developing an Effective Hand Gesture Recognition

System for Human Computer Interaction: A Literature Survey.," *Glob. J. Comput. Sci. Technol.*, 2016.

[11] J. B. Yang, M. N. Nguyen, P. P. San, X. L. Li, and S. Krishnaswamy, "Deep Convolutional Neural Networks on Multichannel Time Series for Human Activity Recognition," in *Proceedings of the 24th International Conference on Artificial Intelligence*, 2015, pp. 3995–4001.

[12] N. Y. Hammerla, S. Halloran, and T. Plötz, "Deep, Convolutional, and Recurrent Models for Human Activity Recognition Using Wearables," in *Proceedings of the Twenty-Fifth International Joint Conference on Artificial Intelligence*, 2016, pp. 1533–1540.

[13] A. Murad and J.-Y. Pyun, "Deep Recurrent Neural Networks for Human Activity Recognition," *Sensors*, vol. 17, no. 11, 2017.

[14] F. J. Ordóñez and D. Roggen, "Deep Convolutional and LSTM Recurrent Neural Networks for Multimodal Wearable Activity Recognition," *Sensors*, vol. 16, no. 1, p. 115, 2016.

[15] S. Mohammed and I. Tashev, "Unsupervised deep representation learning to remove motion artifacts in free-mode body sensor networks," in *2017 IEEE 14th International Conference on Wearable and Implantable Body Sensor Networks (BSN)*, 2017, pp. 183–188.

[16] S. Rifai, P. Vincent, X. Muller, X. Glorot, and Y. Bengio, "Contractive Auto-encoders: Explicit Invariance During Feature Extraction," in *Proceedings of the 28th International Conference on International Conference on Machine Learning*, 2011, pp. 833–840.

[17] R. Chavarriaga *et al.*, "The Opportunity challenge: A benchmark database for on-body sensor-based activity recognition," *Pattern Recognit. Lett.*, vol. 34, no. 15, pp. 2033–2042, 2013.

A Review of Wearable Tracking and Emotional Monitoring Solutions for Individuals with Autism and Intellectual Disability

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***Abstract*—Autism Spectrum Disorder (ASD) and Intellectual Disabilities (ID) affect an increasing proportion of today's population. Individuals with ASD/ID exhibit frequent forms of challenging behaviours such aggression and wandering off without warning. Wandering or elopement is common among such population and poses a great risk to the individuals and causes significant stress to their caregivers. Concurrent with wandering is sometimes anxiety and stress which may lead to disruptive challenging behaviours emerging from their varying internal emotional states and hyper-sensory to their surroundings. Caregivers and/or family members do need to keep track of such vulnerable population especially the ones with more severe autism/intellectual disabilities. The use of location tracking and emotional monitoring solutions can assist caregivers and family members by complementing their behavioural monitoring and intervention approaches. This paper reviews existing location tracking and physiological monitoring wearable products suited for this population. This can help caregivers and family members select suitable device for the person of concern taking account his/her unique user needs.**

Keywords-autism; assistive technology, emotional monitoring, intellectual disabilities, patient localisation, wearable sensors.

I. INTRODUCTION

Autism Spectrum Disorder (ASD) is a neurodevelopmental condition characterised by deficits in reciprocal social interactions and communication skills, accompanied by restrictive and repetitive behaviours. Intellectual disability (ID), on the other hand, can be characterised by deficits in intelligence and adaptive behaviour that is at least two standard deviations below the mean of the general population. Individuals with ASD/ID exhibit frequent forms of challenging behaviours that reduce their well-being and quality of life. Individuals with ASD are at higher risk of developing challenging behaviours compared to the general population [1].

One common kind of challenging behaviours is wandering and elopement. A recent research study reported that about half of children with autism spectrum disorder are prone to wandering [2] which can be very stressful for parents, particularly so for parents caring for children with developmental disorders, where the child's ability to communicate with strangers may be impaired. Also, it has been found that more than a quarter of children with developmental disabilities wander away from safe environments [3]. Further, researchers found that nearly a third of reported ASD missing person cases related to wandering/elopement from 2011 to 2016 in the United States ended in death or required medical attention [4].

Therefore, a mechanism that allowed parents and carers to track the locations of those individuals could have significant benefits and reduce risk. Secondly, such a device could potentially be used to monitor physiological signals which may correlate with internal emotional states, such as high levels of stress. This data may predict episodes of wandering/elopement, and could be used to ensure the intervention to reduce stress, or to identify their location in case being lost.

Since external challenging behaviour such as wandering is accompanied with anxiety issues and varying emotions, it will be very useful for caregivers to monitor the internal physiological and emotional states of the care-receiver to help them understand what such individuals are experiencing in a real-time fashion. Building on such physiological information, caregiver can take necessary actions to help the individual calm down, in case he/she is experiencing stress, for example. Also, having a wearable device may help some individuals with autism spectrum disorder to increase their self-awareness of their internal emotional state and anxiety levels so that they can follow certain behavioural techniques and coping strategies to help them self-regulate their emotions [5]. This could be particularly useful for clients with comorbid alexithymia.

This paper reviews commercial devices that can track location and physiological signals, with the potential for application to individuals with ASD/ID. Specifically, it presents the existing commercial solutions, compares their features and associated sensors, and comments on their effectiveness and open challenges for this application.

II. ASD/ID AND THEIR UNIQUE NEEDS

ASD and ID are a broad spectrum of disorders ranging from mild to profound intellectual disabilities. Individuals with these conditions experience a full range of emotional states, which can be triggered by a variety of environmental and sensory cues, and internal experiences. For example, escalated levels of anxiety can potentially lead to what is called Challenging Behaviour. Challenging behaviour is defined as a culturally abnormal behaviour(s) of such an

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intensity, frequency or duration that the physical safety of the person or others is likely to be placed in serious jeopardy [6]. Challenging behaviour include wandering/elopement, aggression, self-injury, property destruction, and tantrums. Prevalence rates as high as 94% have been reported for challenging behaviour in children with ASD [7]. Therefore, those individuals have unique needs. The widespread use of wearable technology offers an opportunity to help caregivers monitor and support such individuals. The use of wearable devices embedding sensing modalities such as location tracking and physiological sensing can offer a promising support for children and adults with ASD/ID who engage in challenging behaviour [5].

III. Related Work

A number of reviews of relevant literature have been published. For example, S. Majumder et al [8] conducted a review study on sensors used for remote monitoring for general population. The authors compared various physiological and activity monitoring solutions aimed for the elderly population. Specifically, separate comparative studies for wearable monitoring devices of cardiovascular system, body temperature, oxygen level parameters, and activity trackers were presented. Another work focused on the wearable technology from clinical perspective such as wellness, safety, and home rehabilitation for older adults and individuals with chronic conditions was conducted by S. Patel et al [9].

More recently, there has been a focus of reviews on the application of wearable technology to specific populations which bring unique design and function needs. This is because some populations have different design and wearability requirements [5]. Example of such users are the ASD/ID population. According to a survey conducted by S. H. Koo et al [5], parents of individuals with ASD were particularly interested in being able to monitor their son or daughter's physiological signals to understand anxiety levels and other emotions (72%). J. Cabibihan et al [10] surveyed the research literatures on different sensing technologies that are suitable for screening and intervention for ASD. Those sensing technologies were categorised into eye trackers, movement trackers, physiological activity monitors, tactile sensors, vocal prosody and speech detectors, and sleep quality assessment devices. The benefits and effectiveness of those devices in supporting the treatment of some symptoms of autistic individuals as well as their limitations were assessed.

According to S. H. Koo et al [5], tracking the individual's activity or location is the third most requested information by parents of individuals with ASD after the emotional state and aiding of multi-step tasks. Also, M. T. K. Tsun et al conducted a review study on tracking devices in ASD population [11]. The authors investigated potential future assistive tracking solutions for children with cognitive disabilities. Various localisation techniques have been considered such as radio frequency, inertial measurement units, and Global Positioning System which can be utilised for indoor and outdoor localisation.

As it can be seen, existing review papers either: study wearable devices for general or elderly population [8], [9] focuses on the research prototypes designed for individuals with ASD or ID [10], or target the devices offering one functionality such as the work by M. T. K. Tsun et al [11]. To the author's best knowledge, no consideration has been given to commercial solutions that enable emotional monitoring as well as location tracking devices. This paper focuses on devices that offer those two functions.

IV. Technologies and Sensing Signals Used

Building on the urgent need found in previous section, this section discusses the technologies and sensors used in the following subsections.

A. *Location Tracking Technologies*

Location tracking solutions use different technologies based on the required distance and the environment. For example, indoor monitoring devices can use accelerometer sensors, infrared tags, Bluetooth or WiFi wireless network available inside the building, or use a combination of technologies for more accurate tracking. Solutions targeted for outdoor location monitoring mostly use Global Positioning System (GPS) or cellular network service (such as GSM or third generation mobile communications).

B. *Physiological Sensing Technologies for Emotional Monitoring*

Emotional assessment for individuals with autism spectrum disorder and intellectual disabilities can provide insights into the function of the challenging behaviour and supplement costly traditional observational approaches. Physiological monitoring is found useful to assess the varying emotional levels as it can be measured noninvasively [12]. Typical physiological signals used include: Heart Rate (HR), Heart Rate Variability (HRV), Cortisol Level, Respiration Rate (RR), Electrodermal Activity (EDA), Skin Temperature (ST), and Electromyography (EMG). Other potential technologies may be useful to apply, such as eye tracking, using ElectroEncephaloGram (EEG) or brain signals but, due to the intrusive nature of the devices required for the individual with ASD/ID, they will be excluded in this study. It should be noted that various emotional states can be inferred from the measured values such as: low mood, high stress levels, agitation, excitement, and aggression.

V. Review of Existing Tracking and Monitoring Products

While the market is abundant with various products that are targeted for tracking and health monitoring of general population, there is a set of products that are designed specifically for individuals with autism and/or intellectual disabilities or can be adopted for this population. In this section, we provide a review of existing solutions listed for each category. The criteria for selection were: (1) devices that are designed specifically for individuals with ASD or ID, then (2) devices designed for general population but can

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be adopted for ASD or ID population in terms of offering the functionality that delivers the service. Selected devices are consumer electronic device or medically approved ones. If a device is clinically validated, it is noted in the tables.

This section gives an overview of the devices/solutions that can be used for monitoring the individuals with ASD/ID. Such solutions can be categorised into two groups: (a) solutions for tracking the location of the person of concern, and (b) solutions for monitoring the internal emotional state or physiological state identification. Those solutions will be reviewed in the following two subsections:

A. Location Tracking Solutions

TABLE I. lists examples of related products. The following products are either commercially available in the market or still under development. For instance, Amber Alert GPS [13] is a tracking device that can be fitted in the backpack of the child or can be worn with a lanyard around the neck and it uses 3G cellular network to track the individual. Also, Angle Sense Location Tracker [26] is a GPS device that can be inserted into a sleeve that can be put in the pocket or in the interior of the clothing. Another device called Trackimo [21], from Trackimo, uses five tracking modules: GPS, GPS-A, GSM, Wi-Fi and Bluetooth suitable for both indoor and outdoor tracking. Examples of other devices that can be attached to the person's clothing are: Pocket Finder [27], Trax GPS Tracker [28], Securus eZoom and SPOT 3 Satellite GPS Messenger [18], Yepzon One [19], My Buddy Tag [20].

TABLE I. LOCATION TRACKING PRODUCTS

Product	Device Type	Wireless Technology and Range
Amber Alert GPS [13]	wristband	GPS for outdoor tracking
Angle Sense Location Tracker [14]	Wristband	Indoor tracking using Wi-Fi
Pocket Finder [15]	Attachable device	GPS/AGPS, 3G Cell ID for outdoor location and Wi-Fi Touch for indoor locations
Trax GPS Tracker [16]	Attachable device with clips	Location tracking using GPS, Beidou, and QZSS
Securus eZoom [17]	pocket-sized device	GPS for outdoor tracking
SPOT 3 Satellite GPS Messenger [18]	pocket-sized device	GPS for outdoor tracking
Yepzon One [19]	pocket-sized device	GSM network, GPS for outdoor and Bluetooth for near distances
My Buddy Tag [20]	Tag on wristband	Bluetooth for near distances
Trackimo GPS Track Watch [21]	Watch	GPS for outdoor, Wi-Fi for indoor tracking, and Bluetooth for short range tracking
FiLIP Solution [22]	wristband	Location tracking using GPS, GSM & WiFi
BeLuvv Guardian [23]	Bracelet or necklace	Bluetooth for near distances
Polar Team Pro [24]	T- Shirt	GPS for outdoor
D-Shirt [25]	T- Shirt	GPS for outdoor, altitude and route

A recent acceptability study was conducted using questionnaires with individuals with autism spectrum disorder and their parents to see what types of devices they prefer to use. Accessories such as watches/wristband and bracelets have been found to be the most preferred wearable technology types [5]. Therefore, several companies have developed wristband/watch type devices such as FiLIP [29], for example, that can track the location of children both indoors and outdoors using GPS, GSM and WiFi with the ability to contact the caregiver in case of emergency. Another device is BeLuvv Guardian suited for short range tracking [23] that uses Bluetooth technology. Another product called, Trackimo GPS Track Watch, uses three ranges for tracking: GPS for outdoor, Wi-Fi for indoor tracking, and Bluetooth for short range tracking.

Smart clothing offers a seamless experience and thus can be used to track individuals with sensory sensitivities, who may not tolerate devices such as wristbands or watches. Furthermore, garments, such as t-shirts, have been found the second most preferred item for individuals with autism spectrum disorder [5]. Therefore, t-shirts and vests equipped with location trackers can be used to track those individuals by their parents or caregivers. Although most t-shirts with location tracking on the market are aimed for athletes, some may be adopted for individuals with autism spectrum disorder/intellectual disabilities. An example of those is Polar Team Pro that offers location and motion tracking sensors in addition to heart rate monitor [24]. Another one but still under development called D-Shirt by Cityzen Sciences which is also planned to measure heart rate, route, speed, and altitude [25].

B. Emotional State Monitoring Solutions

The list of examples of physiological and/or emotional monitoring devices is presented in TABLE II. Wristbands and watches have also been the mainstream wearable device technology for physiological monitoring and emotional assessment. A brief description of the solutions/products is presented in the following paragraphs.

Simple consumer devices like Fitbit 2 can collect some physiological data such as heart rate. However, there are concerns pertaining to the reliability of such devices and their lack of capability to provide clinical data [30]. A more reliable solution which can provide more comprehensive physiological data is E4 Wristband from Empatica, Inc. which measures heart rate, heart rate variability, electrodermal activity, and skin temperature. However, this device can only collect raw physiological signals without providing insights or assessment of the internal emotional state.

TABLE II. PHYSIOLOGICAL AND EMOTIONAL MONITORING PRODUCTS

Product/Forthcoming Device	**Purpose**	**Device Form Factor**	**Sensors/Parameters**	**Usefulness/Clinical Validation**	**Shortcomings**
E4 wristband, Empatica Inc. [31]	Collecting physiological and movement data only	Wristband	HR, HRV, EDA, ST, Acceleration	Medical Device class 2a (EU), FCC CFR 47 Part 15b IC (Industry Canada)	- Obtrusive (may not be tolerable by individuals with severe to profound ID)
TouchPoints wristband (*Forthcoming*), TouchPoints, Inc. [32]	Stress and anxiety relief	Wristband	Bi-lateral alternating stimulation –tactile (BLAST)	Patent-pending neuroscientific technology to relieve stress	Obtrusive (may not be tolerable by individuals with severe to profound ID)
MyFeel wristband, Sentio Solutions Inc. [33]	Recognising emotions	Wristband	HR, EDA, Skin temperature (ST),	Preliminary study showed usefulness on 150 subjects. However, no clinical validation	Obtrusive (may not be tolerable by individuals with severe to profound ID)
Reveal (*Forthcoming*), Awake Labs [34]	Monitoring stress and anxiety	Wristband	HR, EDA, ST	Clinical trials being conducted but not clinically validated yet.	-Initial prototype, not validated, only for anxiety. - May not be suitable by individuals with severe to profound ID
BioHarness 3.0, Zypher, Inc. [35]	Physiological and activity data collection	Chest strap	HR, HRV, EDA, body temperature, RR, activity, posture, location	Clinical HR measurements [36] but not to clinical HRV [37].	Obtrusive (may not be tolerable by individuals with severe to profound ID)
Equivital Sensor Belt [38]	Physiological and activity data collection	Chest Belt	ECG; HR, HRV, Respiratory rate (RR), EDA, ST, accelerometer, Body position	EQ02 can accurately measure ECG and HRV, its accuracy and precision is highly dependent on artifact content [39]	Obtrusive (may not be tolerable by individuals with severe to profound ID)
Zephyr belt, Medtronic, Inc. [40]	Sports health monitoring	Belt	HR, HRV, RR	Suitable for consumer electronics but no clinical validation	Obtrusive (may not be tolerable by individuals with severe to profound ID)
Hexoskin Smart Shirt, Hexoskin Inc. [41]	Physiological and activity data collection and monitoring quality of sleep	Shirt	HR, HRV, Heart rate recovery, Respiration rate (RR) and volume, Acceleration and power	Clinical validated to obtain precise ECG cardiac monitoring for long-term monitoring [42]	Does not support real-time streaming or processing, but may be suited for monitoring of certain individuals with ASD/ID who cannot tolerate wristband
Polar Team Pro Shirt, Polar Electro Oy [24]	Sports health monitoring	Shirt	HR, location and motion tracking	Not clinically validated	Could be used for individuals with ASD/ID who can tolerate wearing the shirt
AIO Sleeve, Komodo Technologies [43]	Physiological, activity data collection and monitoring quality of sleep	Sleeve	ECG, HR, HRV, accelerometer	Not clinically validated	Does not support real-time streaming/processing (may be suited for monitoring of certain individuals with ASD/ID who cannot tolerate wristband)

More advanced solutions have been developed that use emotional identification algorithms to make meaningful information out of such data. For example, MyFeel wristband, from Sentio Solutions Inc [33], uses proprietary algorithms to process the data where it collects heart rate, electrodermal activity and skin temperature.

Another device that is still under development and targeted for the population with autism spectrum disorder called Reveal, from Awake Labs [34]. This device collects heart rate, electrodermal activity and skin temperature data to assess anxiety level of the individual and can notify the caregiver when anxiety levels start to rise by applying data analytics techniques to make smart clinical decisions.

Another more advanced solution called TouchPoints wristband and produced by TouchPoints Inc. [32]. This solution provides not only emotional monitoring but also claims to relieve stress using stimulating electrical pulses [44]. Other devices that can be worn include: BioHarness, Equivital Sensor Belt, Zepher belt and Hexoskin which is clinically validated to provide reliable ECG data. The last product listed is called AIO Sleeve, developed by Komodo Technologies but it is only a consumer device which does not provide clinical grade data.

Recently, smart clothing is becoming the new trend for wearable devices especially for physiological monitoring and emotional assessment as it provides a seamless experience for the users compared to wristbands which can be obtrusive to some users. An example of such solutions is Hexoskin Smart Shirt, developed by Hexoskin Inc. [41], which incorporates fabric sensors that collect: ECG, heart rate, heart rate variability, respiration rate, and body movement data.

The need to collect multiple data (e.g., physiological and positioning), based on the listed devices, may require the use of multiple devices which can cause inconvenience to the user. Thus, it is evident that having one device that can collect all relevant data (i.e., physiological, movement, and positioning) is more practical solution. EQ02 LifeMonitor, from Equivital Inc., offers this capability where it can also collect the previous parameters and has additional features including body movement and GPS location tracking system.

VI. Discussion

The previous section has reviewed some existing or forthcoming products which are either designed for individuals with autism/intellectual disabilities or can be adopted for this population.

It can be seen that most solutions provide either tracking or emotional monitoring which can be a drawback if they lack the other capability.

As it was seen earlier, individuals with autism spectrum disorder /intellectual disabilities can exhibit different kinds of challenging behaviours such as wandering and anxiety at the same time. From the reviewed products, it can be noticed that most commercial products can only offer one type of tracking. However, it would be more useful to inform the caregivers of the internal emotional state of the individual which may precede wandering so that they can take preventative measures to avoid harm for the individual or being exposed to unsafe environment. One listed device called, EQ02 LifeMonitor, is equipped with sensors that can provide the two functionalities. Using such a solution, clinicians and caregivers can objectively identify what the individuals with ASD/ID are experiencing physiologically, which could help in understanding the internal emotional state and the contexts and locations in which such behaviour is exhibited or escalated levels of anxiety are developed. From technical perspective, the target solution can use the unlicensed Bluetooth Low-Energy Protocol to transmit the physiological and positioning data to a remote recipient (e.g., smart phone) when the data can be processed locally in the wearable device and the useful information is only sent intermittently to the recipient to reduce the communication overhead and minimise the power consumption. It should be noted that other sensing modalities can include sound sensor and light sensor which can be useful to detect verbal aggression which is another kind of challenging behaviour.

VII. Conclusion

In this work, we conducted a review on commercially off the-shelf wearable devices suitable for monitoring and tracking individuals with autism spectrum disorder and/or intellectual disability. Specifically, we briefly explained the unique issues that those individuals experience such as challenging behaviours. Then, we reviewed the related physiological, behavioural, and location related sensors that can be used to monitor the internal emotional state, their activities, and track their location. After that, we surveyed the existing and emerging products in the market with various form-factors, examined their usefulness in practice, and talked about lessons learnt and their shortcomings.

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REFERENCES

[1] K. C Dominick, N. O. Davis, J. Lainhart, H. Tager-Flusberg, and S Folstein, “Atypical behaviours in children with autism and children with a history of language impairment. Research in Developmental Disabilities,,” *Research in Developmental Disabilities*, vol. 28, no. 2, pp. 145–162, 2007.

[2] C. E. Rice, et al., “Reported Wandering Behavior among Children with Autism Spectrum,” *Journal Pediatrics*, vol. 174, pp. 232–239.e2, Jul 2016.

[3] B. Kiely, T. R. Migdal, S. Vettam, and A. Adesman, “Prevalence and Correlates of Elopement in a Nationally Representative Sample of Children with Developmental Disabilities in the United States,” *PLoS ONE*, vol. 11, no. 2 , pp. 1-11, Feb 2016.

[4] L. McIlwain and W. Fournier, “Mortality & Risk In ASD Wandering/Elopement 2011-2016,” [Online]. Available: http://nationalautismassociation.org/wp-content/uploads/2017/04/NAAMortalityRiskASDElopement.pdf. [retrieved: 06, 2018].

[5] S. H. Koo1, K. Gaul, S. Rivera, T. Pan, D. Fong, “Wearable Technology Design for Autism Spectrum Disorders.,”

Archives of Design Research, vol. 31, no. 1, pp. 37-55, 2018.

[6] E. Emerson, Challenging behaviour: Analysis and intervention in people with severe intellectual disabilities., New York: Cambridge University Press., 2001.

[7] J. L. Matson , J. Wilkins, and J. Macken, “The relationship of challenging behaviours to severity and symptoms of autism spectrum disorders.,” *Journal of Mental Health Research in Intellectual Disabilities,*, vol. 2, no. 1, pp. 29–44, 2009.

[8] S. Majumder, T. Mondal and M. J. Deen, “Wearable Sensors for Remote Health Monitoring,” *Sensors,* vol. 17, no. 130, pp. 130-175, 2017.

[9] S. Patel, H. Park, P. Bonato1, L. Chan and M. Rodgers, “A review of wearable sensors and systems with application in rehabilitation,” *Journal of NeuroEngineering and Rehabilitation* , vol. 9, no. 21, pp. 1-17, 2012.

[10] J. Cabibihan, H. Javed, M. Aldosari, T. W. Frazier and H. Elbashir, “Sensing Technologies for Autism Spectrum Disorder Screening and Intervention,” *Sensors,* vol. 17, no. 1, pp. 46-71, 2017.

[11] M. T. K. Tsun, L. B. Theng, H. Siswoyo and S. L. Lau. , “Potential of Human Tracking in Assistive Technologies for Children with Cognitive Disabilities,” in *Supporting the Education of Children with Autism Spectrum Disorders,* Philadelphia, Yefim Kats (Chestnut Hill College, USA), 2017, pp. 22.

[12] St. Balters and M. Steinert, “Capturing emotion reactivity through physiology measurement as a foundation for affective engineering in engineering design science and engineering practices,” *Journal of Intelligent Manufacturing,* vol. 28, no. 7, pp. 1585–1607, October 2017.

[13] “Amber Alert GPS - How It Works,” Amber Alert GPS, [Online]. Available: https://amberalertgps.com/. [retrieved: 05, 2018].

[14] “Angle Sense Autism Tracker Solution,” AngleSense, Inc., [Online]. Available: https://www.angelsense.com/autism-tracker/. [retrieved: 06, 2018].

[15] [Online].

[16] “Trax GPS Tracker for Kids,” Trax , [Online]. Available: https://traxfamily.com/tracker-for-kids/. [retrieved: 05, 2018].

[17] “Securus EZOOM1000 eZoom Personal GPS Locator,” Securus eZoom, [Online]. Available: https://www.amazon.com/Securus-EZOOM1000-Personal-Locator-Requires/dp/B0079SR568. [retrieved: 06 2018].

[18] “SPOT 3 Satellite GPS Messenger,” SPOT LLC, [Online]. Available: https://www.findmespot.com/en/index.php?cid=100. [retrieved: 06, 2018].

[19] “Yepzon One,” Yepzon, [Online]. Available: http://yepzon.com/product/yepzon/. [retrieved: 06, 2018].

[20] “Buddy Tag with Silicone Wristband,” Le Vise Products LLC, [Online]. Available: https://mybuddytag.com/collections/buddy-tag-with-silicone-wristband. [retrieved: 06, 2018].

[21] “Trackimo 3G GPS Watch Tracker,” Trackimo, [Online]. Available: https://store.trackimo.com/products/trackimo-watch-3g. [retrieved: 05, 2018].

[22] “FiLIP Solution,” FiLIP , [Online]. Available: http://www.myfilip.com/. [retrieved: 06, 2017].

[23] “BeLuvv Guardian - Bluetooth 4.0 Proximity Guarding Device for kids,” BeLuvv, [Online]. Available: https://www.amazon.com/BeLuvv-Guardian-Bluetooth-Proximity-Guarding/dp/B00JXDQJW8. [retrieved: 06, 2018].

[24] “Polar Team Pro | GPS player tracking system,” Polar, [Online]. Available: https://www.polar.com/en/b2b_products/team_sports/team_pro. [retrieved: 06, 2018].

[25] “Cityzen Sciences smart shirt tech to power banking ID, betting and virtual matches,” Cityzen Sciences, [Online]. Available: https://www.wareable.com/sport/cityzen-sciences-smart-shirt-tech-to-power-banking-id-betting-and-virtual-competitions-972. [retrieved: 06, 2018].

[26] “Angle Sense Autism Tracker Solution,” AngleSense, Inc., [Online]. Available: https://www.angelsense.com/autism-tracker/. [retrieved: 05, 2018].

[27] “POCKETFINDER+® PERSONAL 3G GPS / Wi-Fi / Cell ID Tracker for Locating and Monitoring People,” Pocket Finder, [Online]. Available: https://pocketfinder.myshopify.com/. [retrieved: 06, 2018].

[28] “Trax GPS Tracker for Kids,” Trax, [Online]. Available: https://traxfamily.com/tracker-for-kids/. [retrieved: 06, 2018].

[29] “FiLIP Solution,” FiLIP, [Online]. Available: http://www.myfilip.com/. [retrieved: 05, 2017].

[30] S. Benedetto, C. Caldato, E. Bazzan, D. C. Greenwood, V. Pensabene, and P. Actis, “Assessment of the Fitbit Charge 2 for monitoring heart rate,” *PLoS ONE 13(2):* , vol. 13 , no. 2, pp. 1-10, 2018.

[31] “E4 Wristband Rev. 2,” Empatica, Inc., [Online]. Available: https://store.empatica.com/products/e4-wristband?variant=39588207747. [retrieved: 06, 2018].

[32] “TouchPoint™ original Kit,” TouchPoint, Inc, [Online]. Available: https://www.touchpointeurope.com/products/touchpoint-kit-single-person. [retrieved: 06, 2018].

[33] “MyFeel Wristband,” Sentio Solutions Inc., [Online]. Available: https://www.myfeel.co/reserve. [retrieved: 05, 2018].

[34] “Reveal,” Awake Labs, Inc, [Online]. Available: http://awakelabs.com/home/. [retrieved: 06, 2018].

[35] “BioHarness 3 User Manual,” Zypher Technology, [Online]. Available: https://www.zephyranywhere.com/media/download/bioharness3-user-manual.pdf. [retrieved: 05, 2018].

[36] e. a. G. Nazari, “Psychometric properties of the Zephyr bioharness device: a systematic review,” *BMC Sports Science, Medicine and Rehabilitation* , vol. 10, no. 6, pp. 1-8, 2018.

[37] D. Nepi, A. Sbrollini, A. Agostinelli, “Validation of the heart-rate signal provided by the Zephyr bioharness 3.0,” in *Computing in Cardiology Conference (CinC)* , Vancouver, BC, Canada, 2016, 43, pp. 361-364.

[38] “Equivital™ TnR Products,” Equivital, Inc., [Online]. Available: https://www.adinstruments.com/products/equivital-sensor-belt. [retrieved: 05, 2018].

[39] A. A. Akintola, V. v. de Pol, D. Bimmel, A. C. Maan, and D. v. Heemst, "Comparative Analysis of the Equivital EQ02 Lifemonitor with Holter Ambulatory ECG Device for Continuous Measurement of ECG, Heart Rate, and Heart Rate Variability: A Validation Study for Precision and Accuracy," *Front Physiol.* , vol. 7, no. 391, pp. 1-14, 2016.

[40] "Zephyr Performance Systems," Medtronic, Inc., [Online]. Available: https://www.zephyranywhere.com/benefits/physiological-biomechanical. [retrieved: 06, 2018].

[41] "Hexoskin Smart Shirts," Hexoskin, Inc., [Online]. Available: https://www.hexoskin.com/pages/health-research. [retrieved: 06, 2018].

[42] "Health Research and Professional Solutions," Hexoskin, [Online]. Available: https://www.hexoskin.com/pages/health-research. [retrieved: 06, 2018].

[43] "AIO Sleeve," Komodo Technologies, [Online]. Available: http://komodotec.com/product/aio-sleeve/. [retrieved: 06, 2018].

[44] A. Serin, N. S. Hageman, E. Kade, "The Therapeutic Effect of Bilateral Alternating Stimulation Tactile Form Technology on the Stress Response," *Journal of Biotechnology and Biomedical Science* , vol. 1, no. 2, pp. 42-47, 2018.

Steps toward Automatic Assessment of Parkinson's Disease at Home

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***Abstract*—This work presents a non-invasive low-cost system suitable for the at home assessment of the neurological impairment of patients affected by Parkinson's Disease. The assessment is automatic and it is based on the accurate tracking of hands and fingers movements of the patient during the execution of standard upper limb tasks specified by the Unified Parkinson's Disease Rating Scale (UPDRS). The system is based on a human computer interface made by light gloves and an optical tracking RGB-Depth device. The accurate tracking and characterization of hands and fingers movements allows both the automatic and objective assessment of UPDRS tasks and the gesture-based management of the system, making it suitable for motor impaired users as are PD patients. The assessment of UPDRS tasks is performed by a machine learning approach which use the kinematic parameters that characterize the patient movements as input to trained classifiers to rate the UPDRS scores of the performance. The classifiers have been trained by an experimental campaign where cohorts of PD patients were assessed both by a neurologist and the system. Results on the assessment accuracy of the system, as compared to neurologist's assessments, are given along with preliminary results on monitoring experiments at home.**

Keywords-Parkinson's disease; UPDRS assessment; RGB-D camera; hand tracking; human computer interface; machine learning; tele-monitoring

I. INTRODUCTION

Parkinson's Disease (PD) is a chronic neurodegenerative disease characterized by a progressive impairment in motor functions (e.g., bradykinesia) [1] , with important impacts on quality of life. Unified Parkinson's Disease Rating Scale (UPDRS) [2] is commonly used by neurologists to assess the severity of the disease, whose motor aspects are an important part. Specifically defined motor tasks are used by neurologists to assess impairments and to assign a subjective score for each task on a scale of five classes of increasing severity.

The assessment process takes into account specific kinematic aspects of the movements (amplitude, speed, rhythm, hesitations) which are qualitatively and subjectively evaluated by neurologists. On the other hand, a quantitative and objective assessment of the tasks is important to increase the reliability of the clinical assessment [3]. A commonly adopted solution is to make use of the well-established correlation existing between kinematic parameters of the movements and the severity of the impairment [4][5]. This correlation is used in the automatic and objective assessment of UPDRS motor tasks by several technological approaches, among which those based on optical devices and wearable inertial sensors [6][7].

Drug treatment of the PD symptoms is crucial to reduce the effects of the impairment in daily activities but, because of possible fluctuations in impairment, it would be desirable to adjust the therapy on a weekly basis, both for the best effectiveness and to reduce side and long term effects [8]. Unfortunately, the cost of a traditional weekly assessment, preferably at home to reduce patient's discomfort, is unsustainable for the health care system. In this context, technology can support neurologists with an objective and quantitative assessment of UPDRS motor tasks. Focusing on the upper limb tasks of UPDRS, solutions based on wireless inertial measurement devices (accelerometers and gyroscopes) [8]-[10] and on resistive bend sensors [11] do not suffer of occlusion problems but they are more uncomfortable for motor impaired people respect to optical approaches and, more important, their invasiveness can affect motor performance.

Optical approaches for hand tracking of motor impaired people and for the automatic assessment of upper limb tasks of UPDRS, namely Finger Tapping (FT), Opening-Closing (OC) and Pronation-Supination (PS), have been recently proposed based on RGB cameras [12], passive markers [13] and bare hand tracking by consumer depth sensing devices [14]-[17].

Less attention is generally given to the assessment of the tracking accuracy obtainable by the proprietary hand-tracking firmware of these consumer devices. Their accuracy can be unsatisfactory especially for fast movements, as has been shown by comparisons with standard optoelectronic systems [18]; nevertheless, this is an important requirement to be considered for the reliability of kinematic parameters and the motor performance assessment. Furthermore, the short product life span of these devices and of the related

Software Development Kit (SDK) warns against solutions too dependent on proprietary hardware and software. Along this line of research, we present a low-cost system for the automatic assessment of the upper limb UPDRS tasks (FT, OC, PS) at home. The system hardware is based on lightweight coloured gloves, a RGB-Depth sensor and a monitor, while the software implements 3D tracking of the hand trajectories, characterizes them by kinematic features and assesses the motor performance by trained Machine Learning algorithms. The software performs the real-time tracking by fusion of both colour and depth information from the RGB and depth streams. The system acts at the same time as a non-invasive Human Computer Interface (HCI) which allows motor impaired PD patients to self-manage the test execution. Respect to other approaches, based only on depth information and proprietary algorithms, the hand tracking is more robust and accurate for fast movements [18], making the final assessment more reliable. Another important characteristic of our solution is that it does not relay on any particular hardware or SDK; it assumes the availability of RGB and depth streams at reasonable frame rate. The accuracies obtained by the classifiers demonstrate the feasibility of the system in remote assessment of upper limb UPDRS tasks. Some preliminary results on at-home monitoring of PD patients are given.

The paper is organized as follows. The technological solution and the methodological approach for the accurate tracking of hand and fingers movement are described in Section II. Section III reports the results of the automatic classification of motor performance and some preliminary data about the assessment of patient’s performance at home. Conclusions and future work are discussed in Section IV.

II. Systems and Methods

A. System Hardware

The hand/fingers tracking hardware consists of a low-cost RGB-Depth device (Intel Realsense SR300 ©) that provides synchronized RGB color and Depth streams at resolutions of 1920x1080 (Full HD) at 30fps and 640x480 (VGA) at 30 fps (max. 200) respectively. The RGB-Depth device is connected via a USB port to a personal computer (PC) running Microsoft Windows and equipped with a monitor positioned in front of the user (Figure 1). The monitor provides the visual feedback of the HCI for the hand and finger movements of the user. The user equipment consists of black lightweight gloves with imprinted colour markers: each colour marker corresponds to a particular part of hand to be tracked (e.g., fingertips and wrist) or to be used for colour calibration and system interaction (e.g., palm).

The device drivers and our developed software are used to implement both the hand and fingers tracking and the user interface of the HCI. The software running on the PC implements the data stream acquisition and processing for the hand/fingers tracking, the kinematic parameter estimation and the task assessment. Furthermore, the data produced in every test session, including video sequence of each performance, kinematic parameters and system scores are automatically encrypted and archived for further analysis and for clinician independent supervision and assessment.

Figure 1. Hand/fingers tracking system

B. Initial Setup

Global image brightness adjustment, hand segmentation and colour calibration for marker segmentation are performed during the initial setup phase. The Intel LibRealSense library is used for RGB and depth stream acquisition and the OpenCV library [19] is used to recover the 3D position of the hand centroid from the depth stream. A hand shaking movement of the user starts the recovering of the initial hand position. The hand centroid is used to segment the hand from the background and to define 2D and 3D hand bounding boxes, both for colour and depth images. Then RGB streams are converted from RGB to the HSV colour space, more robust to brightness variations. The design of the colour markers and the implementation of a colour constancy algorithm compensate for different ambient lighting conditions found in domestic environments. For this purpose, during the initial setup the white circular marker on the palm is detected and tracked in the HSV stream. The average levels of each HSV component of the circular marker are used to compensate for predominant colour components due to different types of lighting. Their values are used to scale each of the three HSV video sub-streams during the tracking phase.

C. Hand and Finger Tracking

During the tracking phase, the 3D position of the hand centroid is used to continuously update the 2D and 3D hand bounding boxes (Figure 2). The colour thresholds selected during the setup phase are used to detect and track all the color blobs of the markers. To improve performance and robustness, the CamShift algorithm [19] has been used in the tracking procedure. The 2D pixels of every color marker area are re-projected to their corresponding 3D points by standard re-projection, and their 3D centroids are then evaluated. Each centroid is used as an estimate of the 3D position of the corresponding part of the hand that is used for movement analysis.

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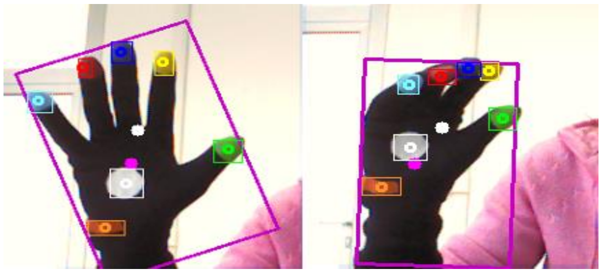

Figure 2. Hand segmentation and marker detection: color blob centroids and bounding box

D. Human Computer Interface for System Management

The real-time hand/fingers tracking software and the graphical user interface realize the human computer interface (Figure 3) where the patient can manage the test session (e.g., start and end the session, select the specific task, input information, etc.) by making simple gestures (opening and closing the hand, pointing with fingers) towards the graphical menu displayed on the monitor.

E. Clinical Assessment and Data Acquisition

The system performance was evaluated on two cohorts; one made up of forty patients (22 females, 18 males) with a diagnosis of Parkinson's Disease (PD), and the other made up of fifteen Healthy Control (HC) subjects. Patients were recruited according the UK Parkinson's Disease Society Brain Bank Clinical Diagnostic standards and met the following criteria: Hoehn and Yahr score (average 2.2, min 1, max 4); age 43–81 years; disease duration 2–29 years. Patients were excluded if they had previous neurosurgical procedures, tremor severity > 1 (UPDRS-III severity score), or cognitive impairment (Mini–Mental Score < 27/30). The HC subjects met these criteria: age, 35–78 years, not affected by neurological, motor and cognitive disorders. All subjects provided their informed consent prior to their participation.

The PD cohort was assessed for the FT, OC and PS UPDRS tasks on both hands by one neurologist expert in movement disorders and the resulting UPDRS severity scores were found between 0 (normal) and 3 (moderate impaired). The performance of the PD patients were tracked at the same time by the system and the related kinematic parameters of the hand/fingers trajectories were automatically extracted. The HC subjects performed the tests in the same environmental conditions and with the same system setup of PD patients.

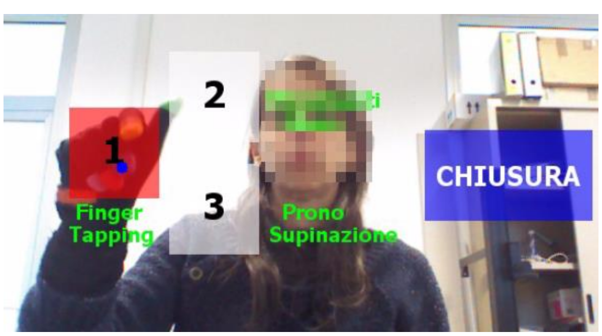

Figure 3. Human computer interface with natural gestural interaction

F. Kinematic Parameter Selection

The automatic assessment of UPDRS tasks makes use of the well establish correlation existing between the kinematic parameters of the movements, objectively evaluated by the system, and the severity of the impairment, subjectively rated by neurologists and expressed as UPDRS scores [4]. The kinematic parameters we choose are closely related to the typical characteristic of the patient movement that are used by neurologists to score the performance (amplitude, speed, rhythm, hesitations, and others). To compact the information associated to the parameters and to reduce their redundancy the most discriminative ones among them have been identified for every UPDRS tasks. First, a Principal Component Analysis (PCA) was applied to the initial set of parameters to filter out those which contribute less than 5% to represent the whole dataset. Then, the selected kinematic parameters were correlated to neurologist UPDRS scores (Spearman's correlation coefficient ρ), keeping only those ones with the best correlation with neurologist UPDRS scores, at significance level $p<0.01$ (Table I). Note that the choice of the parameters is such that increasing values of the parameters indicate a worsening of the performance.

In this context, the kinematic parameters of the HC subjects have been used to normalize the PD ones. Thanks to the better performance of HC subjects, their average score values $\mathbf{p_i}_{\,HC}$ are always better than the $\mathbf{p_i}_{\,PD}$ ones, and are used to obtain normalized PD parameters ($\mathbf{p_i}_{\,PD\ norm} = \mathbf{p_i}_{\,PD} / \mathbf{p_i}_{\,HC}$). This selection process produces normalized parameters which are able to discriminate UPDRS classes for the FT, OC and PS, highlighting the increasing severity of motor performance by the corresponding increasing of their values. This is visually confirmed by the mean values of the selected kinematic parameters versus UPDRS severity class as shown in the radar graphs of Figure 4(a) for FT, Figure 4(b) for OC and Figure 4(c) for PS tasks respectively. UPDRS classes for the FT, OC and PS, highlighting the increasing severity of motor performances by the corresponding expansion of the related radar graph representation.

G. Automatic UPDRS Assessment by Machine Learning

To implement the automatic assessment of the FT, OC and PS UPDRS tasks, three data sets of "parameter vector – neurologist UPDRS score" pairs were used to train three different classifiers. We use the LIBSVM library package [20] to implement three Support Vector Machine (SVM) classifiers with polynomial kernel. Their accuracy in assigning correctly the UPDRS scores was tested by using the *leave-one-out* cross validation method. The confusion matrices were used to characterize the classification performance of the SVM classifiers.

An interesting feature offered by the SVM classifier implementation is that, given the kinematic parameters vector as input, the classifier output is the vector **P** of

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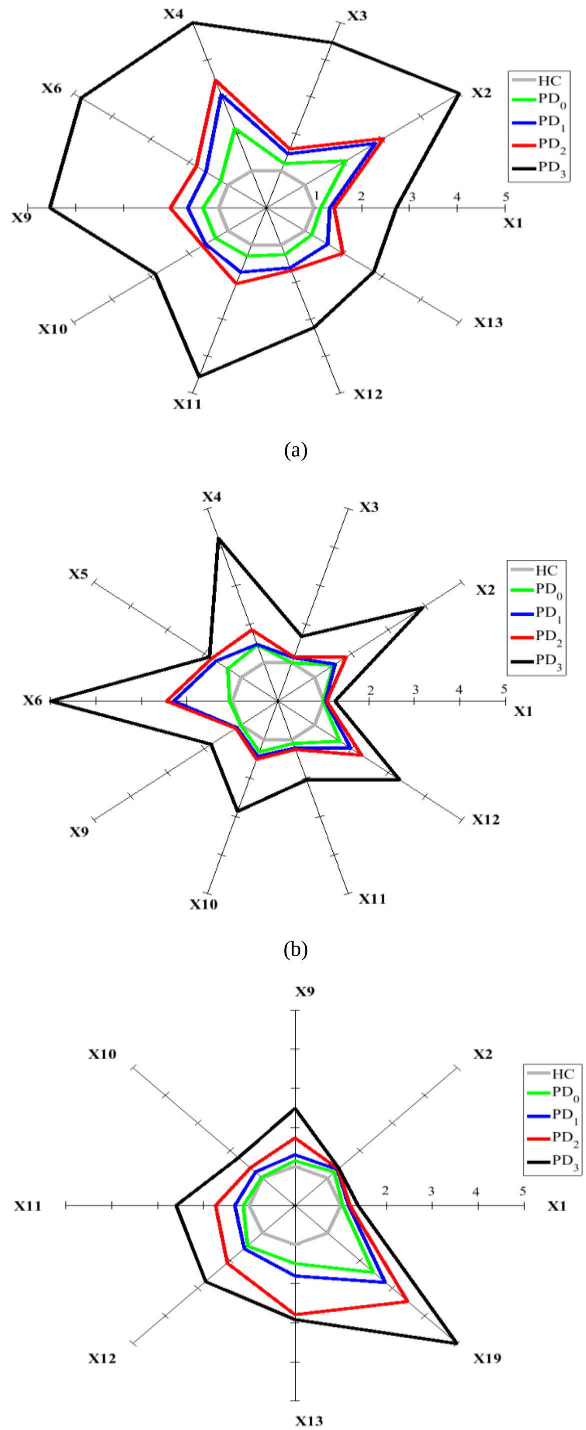
probabilities **p**j that the input vector belongs class Cj. To test the classifiers and build the confusion matrices the class Ck corresponding to the highest probability **p**k among all the probabilities in **P** is chosen.

TABLE I. SELECTED KINEMATIC PARAMETERS

Name	Finger Tapping UPDRS task		
	Meaning	***Unit***	***ρ-value***
X_1	Maximum opening (mean)	mm	-0.43
X_2	Maximum opening (CV)	-	0.35
X_3	Maximum amplitude (mean)	mm	-0.41
X_4	Maximum amplitude (CV)	-	0.39
X_6	Duration (CV)	-	0.42
X_9	Maximum opening velocity (mean)	mm/s	-0.58
X_{10}	Maximum opening velocity (CV)	-	0.39
X_{11}	Maximum closing velocity (mean)	mm/s	-0.55
X_{12}	Maximum closing velocity (CV)	-	0.43
X_{13}	Main Frequency	Hz	-0.48
Name	**Opening-Closing UPDRS task**		
	Meaning	***Unit***	***ρ-value***
X_1	Maximum opening (mean)	mm	-0.54
X_2	Maximum opening (CV)	-	0.34
X_3	Maximum amplitude (mean)	mm	-0.55
X_4	Maximum amplitude (CV)	-	0.31
X_5	Duration (mean)	s	0.25*
X_6	Duration (CV)	-	0.58
X_9	Maximum opening velocity (mean)	mm/s	-0.63
X_{10}	Maximum opening velocity (CV)	-	0.47
X_{11}	Maximum closing velocity (mean)	mm/s	-0.54
X_{12}	Maximum closing velocity (CV)	-	0.53
Name	**Pronation-Supination UPDRS task**		
	Meaning	***Unit***	***ρ-value***
X_1	Maximum supination (mean)	deg	-0.36
X_2	Maximum supination (CV)	-	0.05
X_9	Maximum supination velocity (mean)	deg/s	-0.42
X_{10}	Maximum supination velocity (CV)	-	0.35
X_{11}	Maximum pronation velocity (mean)	deg/s	-0.46
X_{12}	Maximum pronation velocity (CV)	-	0.44
X_{13}	Main Frequency	Hz	-0.47
X_{19}	Pronation Phase Duration	s	0.33

Legend
Coefficient of Variation: ratio of standard deviation (σ) to mean μ of the parameter. CV = σ/μ
Maximum Opening/Supination: peak of distance/angle in one movement
Amplitude: difference between maximum and minimum distance/angles in one movement
Duration: time elapsed between the start and the end of one movement
Maximum Opening/Supination Velocity: peak in an opening/supination phase of one movement
Maximum Closing/Pronation Velocity: peak in a closing/pronation phase of one movement
Opening/Supination Phase Duration: Time for opening/supination phase of one movement
Closing/Pronation Phase Duration: Time for closing/pronation phase of one movement
Rate: Number of movements per second
Main Frequency: Frequency with the peak in power spectrum (bandwidth 0.. 4 Hz)



(a)

(b)

(c)

Figure 4. Radar graph from selected kinematic parameters for FT task (a), OC task (b) and PS task (c)

The probabilistic assignment **P** of the classifier output allows for an interesting extension to continuous values of the discrete UPDRS classification obtained using the most probable class. For this purpose, for each task, the probabilities **p**i to belong to specific UPDRS classes (i.e., the outputs of the related classifier) have been combined in a weighted mean.

In this way, a continuous estimation (W) of the UPDRS score is obtained (1):

$$W = \sum i \cdot p_i \tag{1}$$

$i = 0..4$; p_i = probability to belong to class C_i

The advantage of this approach is the possibility to assess continuous variations of motor impairments that is not possible to obtain with a quantized (0-4) UPDRS score. A support to the correctness of the proposed extension is based on the choice of kinematic parameters, which are closely related to the clinical ones; the increase of a parameter value should correspond to an increasing of the neurologist's score. In practice, the classifiers output probabilistic assignment vectors **P** with only two significant probabilities that are related to contiguous classes. An application of the continuous UPDRS score estimate W in monitoring small fluctuation of patient impairment is presented in the preliminary experiments paragraph.

III. RESULTS

A. Accuracy of the Automatic Assessment

The confusion matrices shown in Table II, III and IV were used to characterize the classification performance of the SVM classifiers for the FT, OC and PS UPDRS tasks, both for the left and the right hand.

From them, all standard parameters for classifier evaluation (accuracy, sensitivity and so on) can be easily derived.

TABLE I. FT CONFUSION MATRIX (UPDRS CLASSES)

		SYSTEM SCORES			
		C_0	***C_1***	***C_2***	***C_3***
CLINICAL SCORES	C_0	15	3	0	0
	C_1	2	21	2	0
	C_2	0	1	18	3
	C_3	0	0	2	13

TABLE II. OC CONFUSION MATRIX (UPDRS CLASSES)

		SYSTEM SCORES			
		C_0	***C_1***	***C_2***	***C_3***
CLINICAL SCORES	C_0	14	2	0	0
	C_1	1	17	2	0
	C_2	0	1	22	3
	C_3	0	0	4	14

TABLE III. PS CONFUSION MATRIX (UPDRS CLASSES)

		SYSTEM SCORES			
		C_0	***C_1***	***C_2***	***C_3***
CLINICAL SCORES	C_0	8	3	0	0
	C_1	1	10	2	0
	C_2	0	2	30	6
	C_3	0	0	3	15

It can be noted the nonzero off diagonal elements of the matrices are one position far from the diagonal ones, meaning the classification errors were limited to one UPDRS class.

B. Preliminary Experiments on UPDRS Assessment

A preliminary experiment to assess the feasibility of the proposed system in monitoring PD patient at home has been conducted. A small group of PD patients (4 subjects) used the system at home for a period of a week. The subjects were instructed to perform FT, OC and PS task at different times (30m, 1.5h, 2.5h, 3.5h) from drug intake, every day of the week. The intent was to assess the potential fluctuations in upper limb motor performance in the period after the drug intake.

To give insight of the experiment results, a sample of the FT assessment is shown in Figure 5 for a PD patient, male, 65 years old, diagnosis at 60, non-fluctuating, and with more motor impairment on the right side. The patient was performing the upper limb UPDRS tasks daily, at different times (30m, 1.5h, 2.5h, 3.5h) from drug intake as required. Thanks to the data storage and the remote retrieving capability of the system, the session data (video, scores, parameters) and in particular the videos acquired by the system during task executions were accessed from remote, analysed and scored by the neurologist for both hands, resulting in a FT score of UPDRS 0 or UPDRS 1.

As shown in Figure 5, on the average, there is a good agreement between system and neurologist scores. Nevertheless, the system can assess tasks on a continuous scale (W score definition) respect to the standard discrete UPDRS score. This feature could open the possibility to investigate the interaction between drugs and motor effects with a more objective, sensible and hopefully accurate approach.

IV. CONCLUSIONS AND FUTURE WORKS

This work presents a non-invasive and low-cost system for the automatic assessment of PD patients performing standard upper limbs UPDRS tasks at home. The system is based on a new human computer interface that, by an accurate hand tracking allows both the system management and the automatic and objective UPDRS assessment. The hand gestural interface makes it suitable for motor impaired users, as are PD patients. The automatic assessment of UPDRS tasks is performed by a machine learning approach which uses some selected kinematic parameters that characterize the patient's movements. UPDRS task

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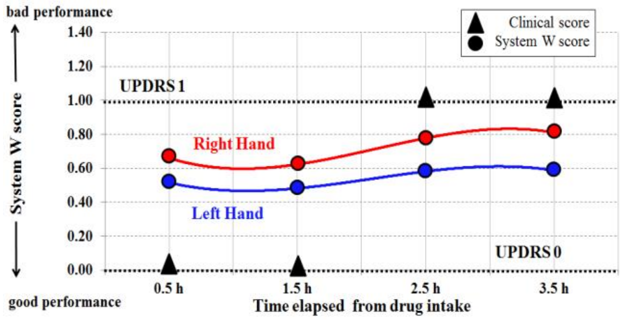

Figure 5. Automatic assessment of a FT task (left and right hand) at different times from drug intake. The continuous UPDRS assessment values and neurologist scores are shown at four different time. To facilitate the interpretation, scores are connected by coloured lines

classifiers were trained during an experimental campaign where PD patients were assessed by the neurologist and the system. The results about the obtained confusion matrices of the classifiers show the classification errors are limited to one UPDRS class and only in a few cases, making the system suitable for at home self-administrated assessment of upper limb UPDRS tasks. Based on the classifier outputs, a new continuous estimation of the UPDRS score is introduced and its potential benefit discussed.

Preliminary results about the application of the continuous UPDRS score in the at home monitoring of PD patients are presented. Further experiments are still needed to validate both the system usability and accuracy in the home environment, and the usefulness of the continuous UPDRS score here introduced in monitoring fine motor impairment fluctuations. Next steps will address also the extension of this solution to the analysis of other UPDRS tasks, aiming to obtain a global and comprehensive assessment of the neuro motor status of PD patients. It would be very important in the perspective of an optimization of the drug therapy, so improving both the clinical management and the patient's quality of life. This would be even more relevant if the overall assessment could be carried out at the patient's home, whenever more frequent observations are needed to better evaluate worsening in motor symptoms.

REFERENCES

[1] G. Pal and C. G. Goetz, “Assessing bradykinesia in Parkinsonian disorders”, Front. Neurol., vol. 4(54), Jun. 2013, pp. 1-5, eCollection, doi:10.3389/fneur.2013.00054

[2] Movement Disorder Society Task Force on Rating Scales for Parkinson's Disease, “The Unified Parkinson's Disease Rating Scale (UPDRS): status and recommendations”, Mov. Disord., vol. 18(7), Jul. 2003, pp. 738-50, doi:10.1002/mds.10473

[3] M. Richards, K. Marder, L. Cote and R. Mayeux, "Interrater reliability of the Unified Parkinson's Disease Rating Scale motor examination", Mov. Disord., vol. 9(1), Jan. 1994, pp. 89-91

[4] D. A. Heldman, J. P. Giuffrida, R. Chen., M. Payne, F. Mazzella, A. P. Duker, A. Sahay, S. J. Kim, F. J. Revilla, and A. J. Espay, “The Modified Bradykinesia Rating Scale for Parkinson’s Disease: Reliability and Comparison with Kinematic Measures”, Mov. Disord., vol. 26(10), Aug. 2011, pp. 1859-1863, doi:10.1002/mds.23740

[5] A. L. Taylor Tavares, G. S. Jefferis, M. Koop, B. C. Hill, T. Hastie, G. Heit, and H. M. Bronte-Stewart, “Quantitative measurements of alternating finger tapping in Parkinson's disease correlate with UPDRS motor disability and reveal the improvement in fine motor control from medication and deep brain stimulation”, Mov. Disord., vol. 20(10), Oct. 2005, pp. 1286-1298, doi:10.1002/mds.20556

[6] A. J. Espay, P. Bonato, F. B. Nahab, W. Maetzler, J. M. Dean, J. Kluken, B. M. Eskofier, and Movement Disorder Society Task Force on Technology, "Technology in Parkinson's disease: Challenges and opportunities", Mov. Disord., vol. 31(9), Sep. 2016, pp. 1272-1282, doi:10.1002/mds.26642

[7] S. Patel, K. Lorincz, R. Hughes, N. Huggins, J. Growdon, D. Standaert, M. Akay, J. Dy, M. Welsh, and P. Bonato, “Monitoring motor fluctuations in patients with Parkinson's disease using wearable sensors”, IEEE Trans Inf Technol Biomed., vol. 13(6), Nov. 2009, pp. 864-873, doi:10.1109/TITB.2009.2033471

[8] A. J. Espay, J. P. Giuffrida, R. Chen, M. Payne, F. Mazzella, E. Dunn, J. E. Vaughan, A. P. Duker, A. Sahay, S. J. Kim, F. J. Revilla, and D. A. Heldman, “Differential Response of Speed, Amplitude and Rhythm to Dopaminergic Medications in Parkinson’s Disease”, Mov. Disord., vol. 26(14), Dec. 2011, pp. 2504-2508, doi:10.1002/mds.23893

[9] J. Stamatakis, J. Ambroise, J. Cremers, H. Sharei, V. Delvaux, B. Macq, and G. Garraux, “Finger Tapping Clinemetric Score Prediction in Parkinson’s Disease Using Low-Cost Accelerometers”, Comput Intell Neurosci, vol. 2013, 2013, pp. 1-13, doi:10.1155/2013/717853

[10] T. O. Mera, D.A. Heldman, A. J. Espay, M. Payne, and J. P. Giuffrida, "Feasibility of home-based automated Parkinson's disease motor assessment”, J Neurosci Methods, vol. 203(1), Jan. 2012, pp. 152-156, doi:10.1016/j.jneumeth.2011.09.019

[11] N. P. Oess, J. Wanek, and A. Curt, “Design and evaluation of a low-cost instrumented glove for hand function assessment”, J Neuroeng Rehabil, vol. 9(2), Jan. 2012, doi:10.1186/1743-0003-9-2

[12] T. Khana, D. Nyholmc, J. Westina, and M. Dougherty, “A computer vision framework for finger-tapping evaluation in Parkinson's disease”, Artif Intell Med, vol. 60(1), Jan. 2014, pp. 27-40, doi:10.1016/j.artmed.2013.11.004

[13] A. Jobbagy, P. Harcos, R. Karoly, and G. Fazekas, “Analysis of finger-tapping movement”, J Neurosci Meth, vol. 141(1), Jan. 2005, pp. 29-39, doi:10.1016/j.jneumeth.2004.05.009

[14] C. Ferraris, R. Nerino, A. Chimienti, G. Pettiti, D. Pianu, G. Albani, C. Azzaro, L. Contin, V. Cimolin, and A. Mauro, “Remote monitoring and rehabilitation for patients with neurological diseases”, Proc. 10th International Conference on Body Area Networks (BodyNets 14), Oct. 2014, pp. 76-82, doi:10.4108/icst.bodynets.2014.257005

[15] A. H. Butt, E. Rovini, C. Dolciotti, P. Bongioanni, G. De Petris, and F. Cavallo, “Leap motion evaluation for assessment of upper limb motor skills in Parkinson's disease”, IEEE International Conference on Rehabilitation Robotics (ICORR 17), Jul. 2017, pp. 116-121, doi: 10.1109/ICORR.2017.8009232

[16] P. J. M. Bank, J. Marinus, C. G. M. Meskers, J. H. de Groot, and J. J. van Hilten, "Optical Hand Tracking: A Novel Technique for the Assessment of Bradykinesia in Parkinson's Disease", Mov. Disord. Clinical Practice, vol. 4(6), Dec. 2017, pp. 875-883, doi:10.1002/mdc3.12536

[17] B. Dror, E. Yanai, and A. Frid, "Automatic assessment of Parkinson's Disease from natural hands movements using 3D depth sensor", IEEE 28th Convention of Electrical & Electronics Engineers in Israel (IEEEI), Dec. 2014, doi: 10.1109/EEEI.2014.7005763

[18] C. Ferraris, D. Pianu, A. Chimienti, G. Pettiti, V. Cimolin, N. Cau, and R. Nerino, "Evaluation of Finger Tapping Test Accuracy using the LeapMotion and the Intel RealSense Sensors", IEEE 37th Annual International Conference of Engineering in Medicine and Biology Society (EMBC 15), Aug. 2015, one page abstract

[19] G. Bradski and A. Kaehler, “Learning OpenCV: Computer Vision with the OpenCV Library”, O'Reilly Media, 1 ed., Oct. 2008, pp. 1-580

[20] C. C. Chang and C. J Lin, "LIBSVM: a library for support vector machines", ACM transactions on Intelligent Systems and Technology (TIST), vol. 2(3), Apr. 2011, pp. 27:1-27:27, doi: 10.1145/1961189.1961199

Proprioceptive Focal Stimulation (Equistasi®) May Improve Motor Symptoms in Moderate Parkinson's Disease Patients

Italian Multicentric Preliminary Open Study

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***Abstract*—Object of the study was to evaluate the efficacy of propriocettive Focal Stimulation on Gait in moderate Parkinson (PD) patients by a preliminary open multicentric study, using Equistasi®, nanotechnological device of the dimension of a plaster which generates High Frequency segmental vibration. The efficacy of Gait Analysis (GA) on evaluating gait modification on Parkinson's Disease (PD) Patients is already well known. On the other hand, several studies have shown that Proprioceptive Focal Stimulation seems to be useful in symptoms amelioration in several neurological disease. Therefore, GA was recorded in a group of PD patients. Twenty-one PD patients (age 69,51 years, Duration disease 8.52 years, Duration Therapy 7,19 years; H&Y 2.46) at their best on therapy, were enrolled in the study. Two GA were performed always at the morning, before and after the treatment. Three plaques devices were put on the skin: one at C7, one at the right and the left leg, on soleus muscle. Equistasi® is a nanotechnological device of the dimension of a plaster which generates High Frequency segmental vibration. Clinical state was monitored by MDUPDRS part III. Parametric (One-way ANOVA and paired t-Student) and not – parametric statistic (Freidman ANOVA and Wilcoxon test) were used. The analysis of the Spatial –Temporal variables showed a significant improvement of Mean Velocity (MV) p=.002, Stride Lenght (SL) in right and left respectively p=.0013 and p=.017, Stance (STA) in right and left respectively p=.025 and p=.047 and Double Support Stance (DSS) in left and right stride respectively p=.034 and p=.033. MDUPDRS Part III was statistically reduced with p=0.017; furthermore the items 3.10, and 3.12 were statistically reduced respectively with p=.025 and p=.046. The results, in this group of patients, encourage to investigate the mechanical focal vibration as stimulation of proprioceptive system in PD. The effect of the device on patients may open a new possibility to the management of PD. The data indicates as the device ameliorates postural stability and gait performance and confirms the support that GA gives to underlight the modifications of gait in PD patients.**

Keywords-Parkinson; Rehabilitation; focal vibrations; Equistasi; Gait Analysis.

I. INTRODUCTION

Parkinson's Disease one of more diffuse neurodegenerative disease, second after Alzheimer's disease, present four cardinal motor symptoms: tremor, rigidity, bradykinesia, and postural instability. Last sign is the more influent on the activity of daily living, because it induces falls [10]. Pharmacological therapy as well as surgical therapy are not enough to well control this symptom, and many times the postural instability may induce fear to fall syndrome, and the PD patient are confined in wheelchair [11]. It is already know the Basal Ganglia have golden role in the pathological progression of PD patients, but it is not really true for balance and postural instability, where the Supplementary Motor Area, seems to be an important role specially, on production of Anticipatory Postural Adjustments (APAs). Humans in fact use anticipatory and compensatory postural strategies to maintain and restore balance when perturbed. Inefficient generation and utilization of anticipatory postural adjustments (APAs) is one of the reasons for postural instability [12]. SMA is a relay of many loops, not only cortical-subcortical loop (cortical-BBGG- thalamic- Cortical loop), but also vestibular loop, and proprioceptive loop and is known that gait analysis is important for the clinical evaluation of PD patients [1]. Equistasi®, nanotechnological device of the dimension of a plaster which generates High Frequency segmental vibration. It is not really known how this devise works, there are some studies indicating that this focal stimulation modifies the H wave in the medulla [13] and in PD patients, the presence of Equistasi improves effects of rehabilitation [2]. Object of the study was to evaluate the efficacy of Propriocettive Focal Stimulation in moderate Parkinson disease patients by a preliminary open study.

II. METHOD

A. Design

This is a multicentric, open study. 21 patients diagnosed with hydiopatic PD were enrolled in four rehabilitation

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centers in Italy: S. Lucia Foundation in Rome (principal center), the Auxologic Institute of Piancavallo Verbania, the Villa Margherita Clinic in Vicenza and the Mondino Neurological Institute of Pavia, each received approval from their ethics committee with protocol number respectively CE/PROG 478/15 del 19/11/2015, 58/16, 61/16, 60/16 After screening and enrollment, the patients receive a proprioceptive mechanical stimulation for 8 weeks with the Equistasi method [2], in the absence of any other rehabilitative trials. Informed consent was obtained from the participants.

B. Subjects

Participants could be included if they had consented to participation, patients with rigid akinetik form of bilateral idiopatic Parkinsons Diseasei (Hoehn and Yahr 2-3) in according to current criteria [3] for at least four years with a good response to antiparkinsonian therapy and with stable drug therapy for at least 3 months. The exclusion criteria were: presence of co-morbidity that prevent safe mobility or exercise (including clinically evident neuropathy and important medical conditions such as malignant tumors), severe dysautonomia with marked hypotension, major depression of mood, dementia, pregnancy, caridac pacer maker, deep brain stimulation (DBS) or other conditions affecting postural stability (eg poor visual acuity or vestibular dysfunction). In addition, patients had to have a MMSE > 24 points [5].

C. Instrumental assessment

As primary measures of outcome for Gait Analisys 3D the main measures of the linear path (BTS Smart system with Davis Procol in all the Centers) were evaluated: the speed (Velocity), the length of the step (Stride Length), the percentage of support times (Stance) and the percentage of the times of double support (DST).

D. Clinical assessment

Motor impairment was assessed with the parts III (motor examination) of the Unified PD Rating Scale [6] and Items 3.10, 3.11, 3.12, 3.13 were separately evaluated for underlying data on gait, freezing of gait, postural and postural instability of PD patients. Other data collected at baseline included age, gender, body mass index (BMI), disease duration, Hoehn and Yahr scale, anti Parkinsonian treatment expressed as levodopa-equivalent daily dose [7] and cognitive status assessed with the MMSE. All adverse events such as injuries, were verified and recorded during the study.

E. Statistical Analysis

This clinical trial used a sample of convenience, with the assumption that 21 participants would be ample to explore safety and feasibility. Given the small sample and the lack of normal distribution of most of the variables on Shapiro-Wilk test, nonparametric statistics were used. Treatment effect across time points were explored Wilcoxon signedrank test. we have also verified with Montecarlo method (MC) [12] [13], the adequacy of the p-value estimates. Categorical variables were compared by means of chisquare test. All values were expressed as mean and standard deviation were chosen to improve clarity of data presentation. IBM SPSS Statistics ver. 20.0 was used for all statistical analyses. All tests were two-sided with a level of significance set at P,0.05.

III. RESULT

Twenty-one subjects were enrolled in this open study (Table 1) and we have observed the clinical and instrumental assessments before (T0) and after (T1) 8 weeks of treatment. No major adverse events or death were observed during the study period.

TABLE I: BASELINE DEMOGRAPHIC AND CLINICAL VARIABLES. BMI: BODY MASS INDEX; H&Y: HOEHN & YAHR STAGE; LEDD: LEVODOPA EQUIVALENT DAILY DOSE; MMSE: MINI-MENTAL STATE EXAMINATION.

Patients	**Mean**	**stdv**
SEX (M/F)	14/7	
SIDE (R/L)	13/8	
AGE	69,51	10,1
BMI	25,89	3,7
DISEASE DURATION	8,52	3,2
YEARS OF THERAPY WITH L-DOPA	7,19	3,1
DISEASE ONSET AGE	60,04	10,4
LEDDS	697,3	110,4
H/Y	2,46	0,51
MMSE	26,4	1,46

A. Kinematic parameters

In the kinematic variables of the gait, we observed a significant improvement in Speed from 0.694 m/s to 0.756 m s p = .0002; a significant increase in the length of the Stride, both right and left respectively from 0.823 m to 0.902 m p = .0013 and from 0.835 m to 0.895 m p = .0173; Stance right and left significantly decreases, respectively from 64.65% to 62.75% p = 0.0253 and from 64,22%; to 62,75% p = .0342; the right and left DST decreases significantly, respectively from 14.02% to 12.99% p = .0342 and from 14.71% to 13.47% p = .0333 (Table 2).

TABLE II: DIFFERENCES BETWEEN T0 AND T1 IN THE TEMPORAL SPACE PARAMETERS; WE USED ANOVA FOR REPEATED MEASURES

	Pre (dst)	Post (dst)	p value
Velocity (m/s)	0,694 (0,25)	0,756 (0,24)	.0002
Stride Lenght R (m)	0,823 (0,25)	0,902 (0,22)	.0013
Stride Lenght L (m)	0,835 (0,14)	0,895 (0,19)	.0173
Stance R (%)	64,65 (3,5)	63,46 (3,4)	.0253
Stance L (%)	64,22 (2,3)	62,75 (3,5)	.0473
DST R (%)	14,02(3,2)	12,99 (3,1)	.0342
DST L (%)	14,71 (2,8)	13,47 (3,1)	.0333

B. Clinics parameters

In the clinical variables we observed a significant decrease in Total Score UPDRS Part III from 37.57 to 32.25 p = .0179; a significant decrease of ITEM 3.10 from 1.761 to 1.333 p = .025 and a significant decrease of ITEM 3.12 from 1.809 to 1.322 p = .0461. No other significant difference was observed at the end of active treatment (Table 3).

TABLE III: DIFFERENCES BETWEEN T0 AND T1 IN CLINICAL VARIABLES; WE USED WILKOXON SIGNED RANK TEST AND MC METHOD.

	Pre (dst)	Post (dst)	p value
UPDRS III	37,57 (16,4)	32,25 (12,0)	.0179
ITEM 3.10	1,761 (0.94)	1,333 (0,73)	.0250
ITEM 3.11	0,525 (0,94)	0,656 (0,92)	.1861
ITEM 3.12	1,809 (1,05)	1,322 (1,02)	.0461
ITEM 3.13	1,901 (1,17)	1,550 (1,03)	.0767

IV. CONCLUSION

It is already demonstrated that the vibration of the axial muscles, produces systematic change in the erect posture [15] and the in the orientation of the body [16], and it induces in an improvement of balance. The imperceptible vibration released from the Equistasi device, have already given a positive response in the rehabilitation of some neurodegenerative pathologies [2] [17] [18] and have also highlighted their capacity in the modulation of the spinal circuit [13]. Nevertheless, the data indicate a trend of improvement on all spatial-temporal parameters, as if the vibrations were acting even on different circuits from the dopaminergic. It is noted in literature how the rehabilitation of Parkinson's disease is centered on the stimulation of the vestibule spinal reflex (VSR), can modify those components of the ambulation more correlated with the rhythmicity and the equilibrium [19]. Furthermore precedent studies put in evidence how in PD there a compromise sense of timing [20] and of the discrimination of the proprioceptive input [21]. Therefore, the focal muscular vibration (FV) not only have an impact on the circuit on the spinal cord, but also provide a notable proprioceptive influx to different parts of the central nervous system, thus influencing the precision of the execution of the voluntary movements [14]. This open-label study has the limit of not being controlled and the number of patients must be calculated appropriately to have a power of at least 80%. Nevertheless, the results, in this group of patients, encourage to investigate the mechanical focal vibration as stimulation of proprioceptive system in Parkinson's disease patients, and open a new possibility for management of moderate PD patients. Moreover, this study confirms the importance of GA in the clinical approach of Parkinson's disease.

REFERENCES

[1] Peppe A, Chiavalon C, Pasqualetti P, Crovato D and Caltagirone C. "Does gait analysis quantify motor rehabilitation efficacy in Parkinson's disease patients?" Gait Posture. 2007 Sep;26(3):452-62.

[2] Volpe D, Giantin MG and Fasano A "A wearable proprioceptive stabilizer (Equistasi®) for rehabilitation of postural instability in Parkinson's disease: a phase II randomized double-blind, double-dummy, controlled study".PLoS One. 2014 Nov 17;9(11).

[3] Berardelli A, Wenning GK, Antonini A, Berg D, Bloem BR, Bonifati V, Brooks D, Burn DJ, Colosimo C, Fanciulli A, Ferreira J, Gasser T, Grandas F, Kanovsky P, Kostic V, Kulisevsky J, Oertel W, Poewe W, Reese JP, Relja M, Ruzicka E, Schrag A, Seppi K, Taba P and Vidailhet M. "EFNS/MDS-ES/ENS [corrected] Recommendations for the diagnosis of Parkinson's disease." Eur J Neurol 20: 16–3.

[4] Hoehn MM and Yahr MD (1967) "Parkinsonism: onset, progression and mortality. Neurology" 17: 427–442.

[5] Folstein MF, Folstein SE and McHugh PR (1975) ''Mini-mental state. A practical method for grading the cognitive state of patients for the clinician." J Psychiatr Res 12: 189–198.

[6] Fahn S and Elton R Members of the UPDRS Development Committee (1987) "Recent developments in Parkinson's disease." Fahn S, Marsden C, Calne D, Goldstein M, editors. Folorham Park, NJ: Macmillan Health Care Information. 153–163, 293–304.

[7] Tomlinson CL, Stowe R, Patel S, Rick C, Gray R, et al. (2010) "Systematic review of levodopa dose equivalency reporting in Parkinson's disease." Mov Disord 25: 2649–2653.

[8] Fay MP, Kim HJ and Hachey M. "On Using Truncated Sequential Probability Ratio Test Boundaries for Monte Carlo Implementation of Hypothesis Tests". J Comput Graph Stat. 2007;16(4):946-967.

[9] Hozo I, Tsalatsanis A and Djulbegovic B. "Monte Carlo decision curve analysis using aggregate data." Eur J Clin Invest. 2017 Feb;47(2):176-183.

[10] Benatru I, Vaugoyeau M and Azulay JP. (2008) "Postural disorders in Parkinson's disease." Neurophysiol Clin 38: 459–465

[11] Smulders K, Dale ML, Carlson-Kuhta P, Nutt JG and Horak FB. "Pharmacological treatment in Parkinson's disease: Effects on gait." Parkinsonism Relat Disord. 2016 Oct;31:3-13

[12] Schlenstedt C, Mancini M, Horak F and Peterson D. "Anticipatory Postural Adjustment During Self-Initiated, Cued, and Compensatory Stepping in Healthy Older Adults and Patients With Parkinson Disease." Arch Phys Med Rehabil. 2017 Jul;98(7):1316-1324

[13] Alfonsi E, Paone P, Tassorelli C, De Icco R, Moglia A, Alvisi E, Marchetta L, Fresia M, Montini A, Calabrese M, Versiglia V and Sandrini G. "Acute effects of high-frequency microfocal vibratory stimulation on the H reflex of the soleus muscle. A double-blind study in healthy subjects." Funct Neurol. 2015 Oct-Dec;30(4):269-74.

[14] Kording KP and Wolpert DM (2006) "Bayesian decision theory in sensorimotor control." Trends Cogn Sci 10: 319–326.

[15] Courtine G, De Nunzio AM, Schmid M, Beretta MV and Schieppati M (2007) "Stance- and locomotion-dependent processing of vibration-induced proprioceptive inflow from multiple muscles in humans." J Neurophysiol 97: 772–779.

[16] Lackner JR and Levine MS (1979) "Changes in apparent body orientation and sensory localization induced by vibration of postural muscles: vibratory myesthetic illusions." Aviat Space Environ Med 50: 346–354.

[17] Spina E, Carotenuto A, Aceto MG, Cerillo I, Silvestre F, Arace F, Paone P, Orefice G and Iodice R. "The effects of mechanical focal vibration on walking impairment in multiple sclerosis patients: A randomized, double-blinded vs placebo study." Restor Neurol Neurosci. 2016 Sep 21;34(5):869-76.

[18] Leonardi L, Aceto MG, Marcotulli C, Arcuria G, Serrao M, Pierelli F, Paone P, Filla A, Roca A and Casali C. "A wearable proprioceptive stabilizer for rehabilitation of limb and gait ataxia in hereditary cerebellar ataxias: a pilot open-labeled study." Neurol Sci. 2017 Mar;38(3):459-463.

[19] Tramontano M, Bonnì S, Martino Cinnera A, Marchetti F, Caltagirone C, Koch G and Peppe A. "Blindfolded Balance Training in Patients with Parkinson's Disease: A Sensory-Motor Strategy to Improve the Gait." Parkinsons Dis. Hindawi Publishing Corporation Parkinson's Disease Vol 2016, Article ID 7536862, 6 pages.

[20] Fiorio M, Stanzani C, Rothwell JC, Bhatia KP, Moretto G, et al. (2007) "Defective temporal discrimination of passive movements in Parkinson's disease." Neurosci Lett 417: 312–315.

[21] Jacobs JV and Horak FB (2006) "Abnormal proprioceptive-motor integration contributes to hypometric postural responses of subjects with Parkinson's disease." Neuroscience 141:999–1009.

TouchWear: Context-Dependent and Self-Learning Personal Speech Assistant for Wearable Systems with Deep Neural Networks

Using Contextual LSTMs on Recurrent Neural Networks

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***Abstract*— Context awareness in future adaptive systems for wearable computers comprise many features, such as ability to sense and perceive contexts, to be inferred by the generation of a user model, to perform the computation and present the communication interface, and to provision implemented services. In this work, we introduce a system application prototype implemented by distinguishing contexts from wearable systems. Thus, user behavior, activity, and application data are trained to generate a user model. Next, a voice interface administered by the artificial personal speech assistant not only enables conversation with the user but is also used to build a recurrent model of deep neural networks primarily based on the conversation logs. Ultimately, the service and recommendation framework are implemented and deployed so that the wearable system has the capacity to aid people in need by means of service-oriented and wearable adaptation.**

Keywords-wearable computing; personal speech assistant; context awareness; deep neural network.

I. INTRODUCTION

Using wearable devices, like smart watch and smart glasses, is more than just convenient, because they collect important information about the context according to the user's body behavior and head movement. In contrast to smartphone users who often receive limited information of little on-body context because of their 'heads-down' gesture from looking at their smartphones, users of wearable devices are able to focus more on social interactions and the surrounding views. Wearing smart watches and smart glasses permits fewer restrictions and more augmented conditions.

In recent years, artificial speech assistants like Apple Siri, Amazon Alexa, Cortana, and Google Assistant [19] have become widely adopted as a conversing medium for mobile computation. By taking advantage of acoustic and concatenative models of Text-To-Speech (TTS), speech assistants can execute and control voice commands, system recommendations and services according to user requests. In our design, recommendations and services can more effectively conform to personal intentions, activities, favorites, records, surrounding environments, social networks and crowdsourced information.

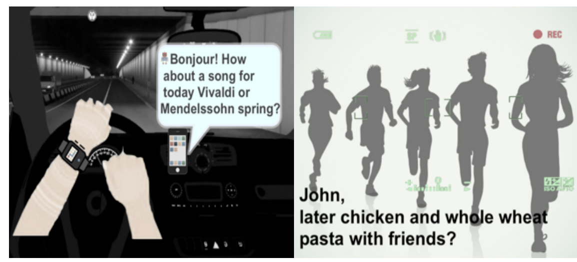

Figure 1. Context dependent states with wearable systems are automatically learned and identified by the Personal Speech Assistant of DNN, which continously offers relevant and appropriate services.

Therefore, the proposed system, TouchWear, aims to use wearable computers to present contextual, automated sensing as well as a service-oriented workflow for human computation (Figure 1). Furthermore, TouchWear is represented by the personal speech assistant (PSA) that models with continuous self-learning Deep Neural Networks (DNN), to transform and retrieve helpful, on-the-fly, historical, or even private information. Finally, the system provides mobile services that hinge on the infrastructure being successfully used in practical deployment.

This paper introduces the implementation of our prototype application for wearable devices, which is built on context dependent and continuous information from the user perspective based on modern Artificial Intelligence of DNNs. TouchWear is designed according to the following four methods: (1) integration of previous research paradigms for recognizing user activity into the system, and the design of a system adapter for context awareness through the use of wearable devices; (2) evaluation of learning patterns from a user's behavior and a conversation proposed by the PSA, and performance of continuously self-learning AI model based on DNNs, where the system adapter is flexible enough to manage either notifying the PSA of recognized contexts, or perceiving new contexts; (3) design of a message extractor and filter to better address the user's contextual query, while at the same time, personalized results retrieved and generated by the PSA processed every now and then; (4) implementation of an infrastructure for mobile service-oriented applications (SOAs), which model the business requirement and bring services via specially designed user interfaces.

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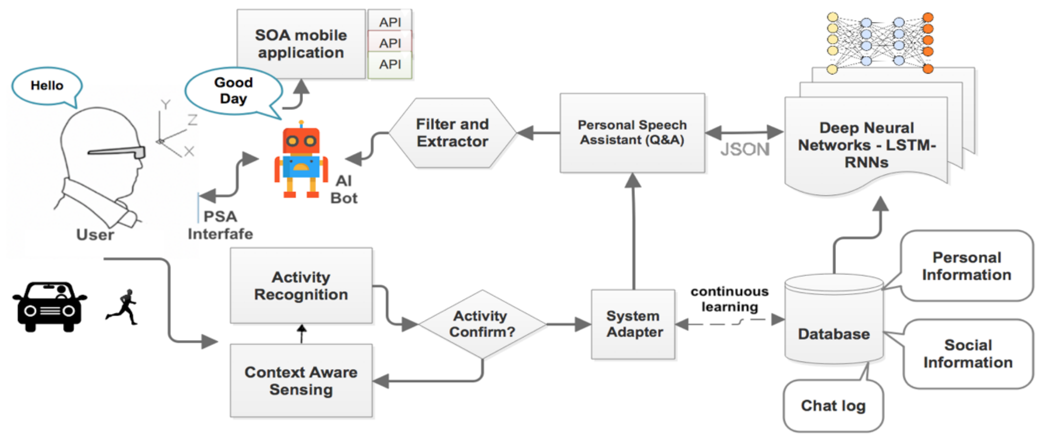

Figure 2. TouchWear system architecture – an overview of wearable application.

The organization of this paper is presented as follows: Section II provides a review of the previously related works. Section III depicts the design of the system architecture and its challenges. Section IV evaluates the use cases and preliminary results, and finally, Section V concludes the paper with our current plan for the future work.

II. RELATED WORK

In recent years, research has discussed many areas that are related to our work, such as Human Activity Recognition (HAR) [1][5][6] on mobile devices, which helps us understand how to analyze user's wearable sensory systems and the designed interfaces [2][3] for perceiving contexts. Context-awareness involves the concept of sensing oneself in a context, which means tracking 'Head-Centered and Context-Aware Learning' [12][15][16] on a wearable device, and also exploring the surrounding environments. Pervasive computing to address location-awareness [4] has also drawn considerable attentions in the development of wearable computers [7]. Other related work on wearable devices tackles privacy-preserving issues [11] on a crowd-powered system, which also inspires us for designing and enhancing our information retrieval, filtering, and extraction.

Furthermore, conversational agents with Artificial Intelligence are becoming increasingly ubiquitous in business, technology and daily life. Relevant research on these agents describe PSA to recognize the disordered speech [18], Chatbots with a Support Vector Machine (SVM) classifier [9], end-to-end systems [21][22] to play the communication role to synchronize physical motoring [10], and DNN-based agents to build embedded questions and answers, based on bidirectional long short-term memory (LSTM) network to measure the cosine similarity [8][17].

In order to achieve ubiquitous data access on mobile and wearable computing in TouchWear, SOAs are practiced and designed due to the limited memory and connection bandwidth [13]. Based on the advocated services designed and implemented by SOAs [14], our proposed system is able to consider user's adaptive contexts as predicted services via PSA more adequately and efficiently than the related works.

III. SYSTEM ARCHITECTURE

The system guides a user through the designed wearable application (Figure 2), while the PSA provides instructions and conversations on the voice-based application. The below steps present the processes, integrated frameworks, components and how they work together.

A. Context Aware Sensing and Wearable Devices

Contextual sensing is the most fundamental analysis of context-aware systems. TouchWear directly uses sensory data of Accelerometer, Gyroscope, and the signals of Global Positioning Systems (GPS) to detect a user's activity and location, where Wi-Fi signals are also considered in the indoors [24]. With our wearable devices (Google Glass [25], Sony SmartEyeglass [26]) and producing data (frequency 5Hz), the modeled SVM classifier is capable of recognizing targeted activity and location in around 3 seconds.

B. Activity Recognition and System Adapter

In Table 1, we depict six activities (both indoors and outdoors) in which TouchWear takes the detected context-aware messages as prerequisite information to prepare for the conversations with the user. The system adapter, which is based on context awareness, will inform PSA per user's request to initiate the conversation. As for the content of the conversation, the DNN will periodically notify the PSA via APIs if there is any update to the latest entropy. Furthermore, continuous self-learning occurs to conceive new contexts, such as new activities, or to improve accuracy of old ones.

APIs can be triggered by the following: highly compressed formats, publishing and exchanging protocols, Web Services with SOAP, XML-based service invocation, JSON RESTful services implementing TouchWear, and interface compliance with Open Standard Gateway initiative (OSGi). The designed adapter needs not only to implement the regulations satisfying the requirement of each application, but also to use the exact pair of enterprise public and private key infrastructure (PKI), SSL, or the secure PGP encryption system [20] to cryptographically achieve needs.

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TABLE I. RECOGNIZED ACTIVITY AND LOCATIONS

Smart Glasses Activity, Location, and Performance			
Activity	***Outdoor***	***Indoor***	***Performance***
driving	city road, highway	N/A	87%
jogging	hiking route, mountain area	gym, indoor stadium	86%
walking	side walk, street	building hallway, house	88%
sitting	outdoor bench, park, open field	office, study room, living room	89%
cooking	BBQ, brewery area	kitchen, dining room	87%
dining	places for grilling, garden	dining room, restaurant	91%

C. Database and Deep Neural Networks

Early works on computer speech systems focused on rule-based or hand-crafted implementations to simulate human conversations [9]. However, it is very difficult to enumerate the real conditions and all possible states, especially in light of the great complexity of human language. For this reason, recent speech assistants and Chatbots in Recurrent Neural Networks (RNNs) of DNN have been shown to meliorate accuracy to improve performance. After the evaluations of two large datasets, the Cornell Corpus of movie dialogues and thousands of Twitter logs with Long Short-Term Memory networks (LSTMs), TouchWear takes sequence to sequence (seq2seq) learning process [23] to construct its memory dependent network by using the conversation logs at this stage. Information of personal (such as emails) and social (Emails, tweets) is stored in the database server, and also continuously migrated to model the recurrent contextual information in the proposed system.

D. Personal Speech Assistant

The PSA, or AI Bot in TouchWear, is implemented by using the open-source project of Google Hangouts [30] to leverage current applications on our wearable platform. The AI Bot uses contextual information of activity recognition according to the wearable application; then, the AI Bot initials the automated service with example greetings such as "*Hi buddy, would you like some music while driving?*" or "*Good morning John, how may I help you?*", which are the first contextual messages. In contrast to these examples in which the AI Bot initiates the conversation, users for instance can just simply say "*Please mute, Bot*" to switch it back to the on-demand service type. So, "*OK, AI Bot*" or "*Hi Bot*" are launched by user to converse with the AI Bot.

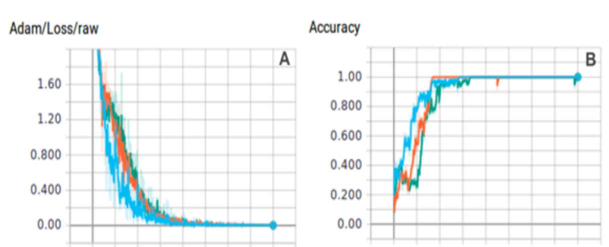

Figure 3. (A) Loss, (B) Accuracy: Training after 1000 epochs, where three testing datasets were evaluated.

There were three testing datasets that contain conversation logs trained by the LSTMs in our DNN. Since the seq2seq training processes use the same training data to validate the model in each epoch done by TensorFlow [27] and tflearn [28] frameworks, an iteration of 1000 epochs generates a loss of 0.00385 and an approaching accuracy of 1.00000 near the 400th epoch visualized on the *tensorboard* [27] (Figure 3).

E. Filter and Extractor

The retrieved responses are provided by AI Bot according to the deep learning from ongoing conversations, user Email threads, and simulated social tweets. TouchWear currently uses four categories to filter and extract the results, as shown in Table II. The four categorized directories in the system are *regular* and *critical* for *personal information*, and *regular* and *privacy preserving* for *social information*. Accordingly, the authentication plays a vital role in the '*critical*' category for *personal information*, whereas filtered datasets, using metadata and programming, are particularly essential for the '*privacy preserving*' category for *social information*.

TABLE II. INFORMATION FILTER AND EXTRACTOR

Information Type	**Category vs. Filter and Extractor**		
	Category	***Filter***	***Extractor***
personal information	*regular*	none	ranking
	critical	authenticated by secure frameworks	extracted ranking based on secure frameworks
social informaion	*regular*	defined rules	ranking
	privacy preserving	filtered datasets	extracted ranking based on filtered datasets

F. Service-Oriented Mobile Application

Mobile SOAs are examined and designed for TouchWear. The backend servers receive user commands through the PSA, and the commands are executed by contracting the system APIs of the targeted application. If the syntax is complying with the regulations and if the user's authentications are authorized, the provisioning applications will be triggered and planned toward the completion to meet business requirements. At the present time, the system has 7 mini services (or groups) to evaluate the system integrity in the experimental and validating phase. Table III below shows the list of SOA mini-services, where the services with asterisk have the permission to access the personal contacts.

TABLE III. SOA MINI SERVICE LIST

SOA Services
1. Voice or video call *
2. Search and play music (personal music albums)
3. Facility automation
4. Search 'keyword': conversation logs, Email *
5. Social networks: recommendation for shopping and entertainment *
6. GPS navigation setup
7. Food / restaurant search and reference

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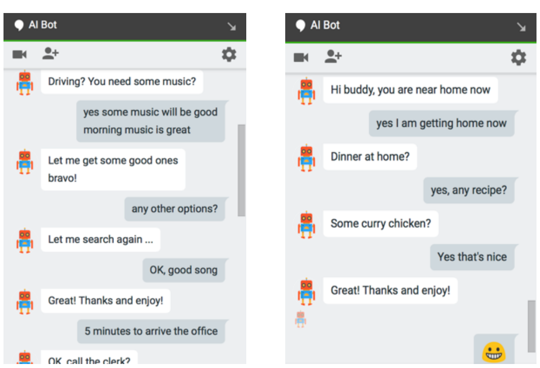
G. *Other System Frameworks*

The system stands on the top of TensorFlow to build up DNNs with LSTM RNN, which is implemented by seq2seq learning process. In seq2seq, the encoder and decoder take the input and generate the output based on the semantic contexts. In our experiments, we observed that LSTM could learn to spell words and copy general syntactic structures to capture the essence of the input sentences. Thus, the system was prepared with initial trials of training data that consisted of 1025 Email threads, 480 lines of conversation log on Hangouts, and dozens of social tweets simulated by the open-source SocialEngine [29].

IV. USE CASES AND PRELIMITARY RESULTS

We began our project with the aim of studying how to recognize activity and location by using sensors on wearable devices. The current system can recognize three activities, *driving*, *jogging*, *walking* with an accuracy up to 87% and its performance is getting better in our experiments. However, though *sitting* can be recognized with accuracy 89%, it is more difficult to distinguish *dining* and *sitting* since both are very similar, unless additional sensors like the camera and Wi-Fi signals are applied, same as for *cooking* as well. For information extraction and filtering, the current system ranks results with descending score and/or reverse chronicle order, and the top one will return to the query each time.

Initial trials of use cases were conducted using 11 types (omitting indoor *driving*) according to 6 indoor and outdoor activities that were recognized by the system. From the user's perspective, contextual services and conversing accuracy are the most important parts. Two use cases are demonstrated in Figure 4, where (a) a user is heading to work by *driving* and was successfully recommended an enjoyable song, and (b) a user is walking and located close to home or is on the way home, and the recipe recommendation of dinner is offered by AI Bot.



(a) (b)

Figure 4. Demonstrated use cases (a) driving, (b) walking.

TABLE IV. SURVEY AND POSITIVE RESPONSES

Interview Questions	Positive Responses
Q1. Are context-aware PSAs more perceived and helpful?	87.5%
Q2. How is the performance by using contextual PSA with DNNs and SOA?	83.3%

Also, the filtered datasets are designed to authenticate users before accessing their personal information so as to protect their privacy, where defined rules are given to control sharing and prevent the leaking of private information. Shared topics include food, entertainment, shopping experiences in Emails and tweets, with the removal of critical data according to filtered datasets. The initial trials were conducted in a proof-of-concept system, and the results show that the performance is very high regarding context-awareness, the conversation accuracy of LSTMs and the targeted SOAs in the laboratory, though more calibrations to our system are still further required, such as '*machine-learning search*', '*social sharing*' and '*location precision*'.

The survey from our user study with 16 participants shows that the proposed system was more preferred than systems without context-awareness (Table IV): (*i*) the wearable platform with context-aware PSAs were found to be more advantageous, as helpful aids and with more perceived accuracy; (*ii*) the performance of the contextual PSAs was seen as more resembling a real and constructive intelligent agent that assists people in their daily life. These PSAs were based on the security and the preservation of privacy of personal and social information on LSTMs, and the designed SOA mobile applications also offer contextual services per user's requests.

V. CONCLUSION AND FUTURE WORK

TouchWear proposes a unique system design for the proposed wearable application that exploits the contextual information for future wearable systems, by integrating a wearable platform, context-aware computing, PSAs, and modeling and modification of DNNs with recurrent neural networks, with the aim to design more intelligent solutions for problems that emerge in daily living. Moreover, the system is tailored to user-centric requirements and services effectively extracted by the designated information retrieval. Likewise, service operations are explicitly performed by the SOA-based mini services of mobile applications. Compared to systems without contexts, the proposed contextual DNNs significantly outperform the accuracy of conversation exchanges, start automated workflows for predicting and comprehending user's status, and take into account user favorites, demands and social associations by using the AI Bot more intimately. The continuous self-learning processes are clearly able to achieve more system genuineness, usability and user-friendliness. Our implementation was also more favored by the users according to the interviews. The insightful design of the application is promising and can be extended to the benefit of many people, their workplaces, and homes. If this forthcoming system is extensively adopted, we anticipate in the future that optimal context-awareness and context-intelligent wearable computing will be achieved in addition to Artificial Intelligence.

In our future work, we will focus other subsets of DNNs for any domain, investigate more use cases of search and social application, and identify and design more scenarios for disability-oriented systems in wearable computing. We hope our upcoming systems will assist more people in their daily living and activities.

REFERENCES

[1] Lara, Oscar D., and Miguel A. Labrador. “A Survey on Human Activity Recognition Using Wearable Sensors.” *IEEE Communications Surveys and Tutorials*, vol. 15, no. 3, 2013, pp. 1192–1209.

[2] Patel, Shyamal, et al. “A Review of Wearable Sensors and Systems with Application in Rehabilitation.” *Journal of Neuroengineering and Rehabilitation*, vol. 9, no. 1, 2012, pp. 21–21.

[3] Mistry, Pranav, et al. “WUW - Wear Ur World: A Wearable Gestural Interface.” *CHI ’09 Extended Abstracts on Human Factors in Computing Systems*, 2009, pp. 4111–4116.

[4] Ashbrook, Daniel, and Thad Starner. “Using GPS to Learn Significant Locations and Predict Movement across Multiple Users.” *Ubiquitous Computing*, vol. 7, no. 5, 2003, pp. 275–286.

[5] Lee, Seon-Woo, and Kenji Mase. “Activity and Location Recognition Using Wearable Sensors.” *IEEE Pervasive Computing*, vol. 1, no. 3, 2002, pp. 24–32.

[6] Ho, Joshua, and Chien-Min Wang. “User-Centric and Real-Time Activity Recognition Using Smart Glasses.” *GPC*, 2016, pp. 196–210.

[7] Pascoe, Jason. “Adding Generic Contextual Capabilities to Wearable Computers.” *Digest of Papers. Second International Symposium on Wearable Computers (Cat. No.98EX215)*, 1998, pp. 92–99.

[8] Tan, Ming, et al. “LSTM-Based Deep Learning Models for Non-Factoid Answer Selection.” *ArXiv Preprint ArXiv:1511.04108*, 2015.

[9] Joelianto, Endra, and Bowo Prakoso. “Support Vector Machine Classifier Based on Approximate Entropy Metric for Chatbot Text-Based Communication.” *International Journal of Artificial Intelligence*, vol. 15, no. 1, 2017, pp. 1–16.

[10] Johnson, Alex, et al. "Implementing Physical Capabilities for an Existing Chatbot by Using a Repurposed Animatronic to Synchronize Motor Positioning with Speech." *International Journal of Advanced Studies in Computers, Science and Engineering* 6.1 (2017): 20.

[11] Swaminathan, Saiganesh, et al. “WearMail: On-the-Go Access to Information in Your Email with a Privacy-Preserving Human Computation Workflow.” *Proceedings of the 30th Annual ACM Symposium on User Interface Software and Technology*, 2017, pp. 807–815.

[12] Krause, Andreas, et al. “Unsupervised, Dynamic Identification of Physiological and Activity Context in Wearable Computing.” *Seventh IEEE International Symposium on Wearable Computers, 2003. Proceedings.*, 2003, pp. 88–97.

[13] Natchetoi, Yuri, et al. “Service-Oriented Architecture for Mobile Applications.” *Proceedings of the 1st International Workshop on Software Architectures and Mobility*, 2008, pp. 27–32.

[14] Taktak, Hajer, and Faouzi Moussa. “A Service-Oriented Application Creation Process in Ubiquitous Environments: Travel Assistant Mobile Application.” *International Journal of Pervasive Computing and Communications*, vol. 13, no. 3, 2017, pp. 300–330.

[15] Kuhn, Jochen, et al. “GPhysics—Using Smart Glasses for Head-Centered, Context-Aware Learning in Physics Experiments.” *IEEE Transactions on Learning Technologies*, vol. 9, no. 4, 2016, pp. 304–317.

[16] Kim, Ki Joon, and Dong-Hee Shin. "An acceptance model for smart watches: Implications for the adoption of future wearable technology." *Internet Research* 25.4 (2015): 527-541.

[17] Kandasamy, Kirthevasan, et al. “Batch Policy Gradient Methods for Improving Neural Conversation Models.” *International Conference on Learning Representations*, 2017.

[18] Cavalcante, Agnieszka Bętkowska, and Monika Grajzer. “Mobile and Personal Speech Assistant for the Recognition of Disordered Speech.” *SPWID 2016, The Second International Conference on Smart Portable, Wearable, Implantable and Disability-Oriented Devices and Systems*, 2016, pp. 6–10.

[19] López, Gustavo, et al. “Alexa vs. Siri vs. Cortana vs. Google Assistant: A Comparison of Speech-Based Natural User Interfaces.” *International Conference on Applied Human Factors and Ergonomics*, 2017, pp. 241–250.

[20] Hankerson D. Hernandez J.L. Kirkup M.Menezes A. Brown M., Cheung D. PGP in constrained wireless devices. *In 9th USENIX Security Symposium*., 2000.

[21] Yang, X., Chen, Y.-N., Hakkani-Tur, D., Crook, P., Li, X., Gao, J., and Deng, L. (2016). End-to-End Joint Learning of Natural Language Understanding and Dialogue Manager. *ArXiv e-prints*.

[22] Ali Orkan Bayer, Evgeny A. Stepanov, and Giuseppe Riccardi. Towards end-to-end spoken dialogue systems with turn embeddings. In *Annual Conference of the International Speech Communication Association (INTERSPEECH)*, Stockholm, Sweden, August 2017. ISCA.

[23] Sutskever, I. Vinyals, O. & Le. Q. V. Sequence to sequence learning with neural networks. In *Proc. Advances in Neural Information Processing Systems 27* 3104–3112 (2014).

[24] FIND3, “FIND3,” https://github.com/schollz/find3, July 16, 2018.

[25] Glass Explorer Edition, “Glass Explorer Edition,” https://developers.google.com/glass/, July 16, 2018.

[26] Sony Smarteyeglass SED-E1, “Sony Smarteyeglass SED-E1,” https://developer.sony.com/develop/smarteyeglass-sed-e1/, July 16, 2018.

[27] TensorFlow, “TensorFlow,” https://www.tensorflow.org, July 16, 2018.

[28] tflearn, “tflearn,” https://www.github.com/tflearn/tflearn, July 16, 2018.

[29] SocialEngine, “SocialEngine,” https://www.socialengine.com, July 16, 2018.

[30] Google Hangouts, “Hangouts,” https://hangouts.google.com, July 16, 2018.

Stress Detection of the Students Studying in University using Smartphone Sensors

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***Abstract*—Stress leaves a harmful impact on the health of people and puts their health at serious risk. To assess stress, this study presents an approach to measure the stress levels of graduate and undergraduate students by analyzing the activity behavior of their daily routine. Our approach monitors the activity behavior non-invasively using the smartphone sensors. The activity behavior is classified into three classes with an accuracy of 98.0% using a support vector machine. We build linear relationship between those recognized classes of activity (explanatory variables) and stress level experienced by the students. This approach is based on multiple linear regression that computes a stress score, and categorizes stress in three levels: low, mild, and acute. Such results illustrate that the graduate students experience high stress as compared to the undergraduate students.**

Keywords–Stress; activity and sleep behavior; smartphone sensors.

I. Introduction

A natural defense of the human body, also known as stress, protects individual against any danger. Stress for a short time can be helpful, but long-term stress can negatively affect health. People suffer from stress when they are overloaded and feeling an inability to cope with the demands. Stress is a state in which individuals are expected to perform too much under sheer pressure and in which they can only marginally meet the demands. These demands can be related to psychology, finance, work, and relationships that pose a real challenge or threat to health, and well-being of individuals. If stress is not timely cured and the person is going through constant stress, it can affect human body with headache, depression [1], heart attack [2]-[4], stomachache, high blood pressure, insomnia, and weakened immune system. Clinically, subjective methods such as questionnaires and interviews are conducted to evaluate stress, whereas for objective assessment of stress, many researchers presented their works to detect stress [5]-[11]. However, they tried to measure stress using like invasive sensors EEG [5][9][10], ECG [11], and Galvanic Skin Response (GSR) [6]. EEG or ECG sensors provide state-of-the-art accuracy for stress detection. However, the usage of EEG or ECG to analyze stress is impractical in real-life settings, because people do not feel comfortable to go outside in public places wearing EEG or ECG in their daily-life. People suffering from stress may not choose to openly wear the device because stressed persons are already shy to express themselves and therefore, such wearables may not be socially acceptable to them. Moreover, the efficiency of these devices degrades as users perform any motion-related task. To the best of our knowledge, no one has designed a system for non-invasive detection of stress yet. Therefore, we are motivated to design non-invasive stress detection system.

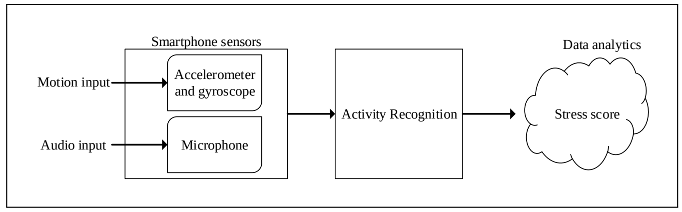

Figure 1. An architecture of stress monitoring system.

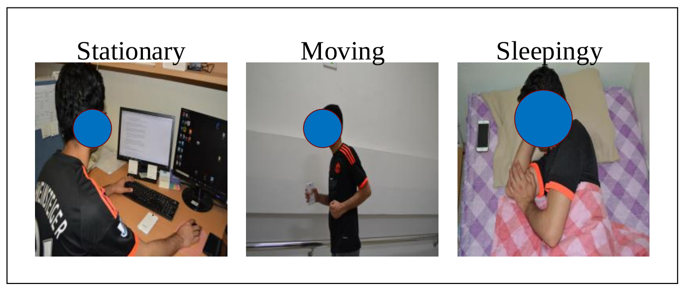

Figure 2. Subject while performing different activities.

In this paper, we present a novel system to measure the stress of the university students by analyzing their activity behavior in daily routine. We choose undergraduate and graduate students to evaluate their stress level, because they are more vulnerable to stress due to a variety of challenges such as poor academic performance [12], finances [13], poor sleep [14], and inability to cope with research demands of supervisor. Besides, high rates of suicide in American and Asian countries are associated with academic related stress [15]. It is imperative to take preventive measures for protecting the students from deleterious outcome associated with stress by monitoring their daily activity behavior.

We have broadly categorized the daily-life routine of the students into three clusters: *stationary*, *moving*, and *sleeping*. We think that poor sleep and sedentary behavior (i.e., stationary) are two main indicators of stress, whereas movement behavior of person signifies less stressed or happy man. Our system consists of motion and audio sensors that records input data with the assistance of an application (App) running on a smartphone. We exploit the motion sensors namely accelerometer and gyroscope-sensors and a microphone sensor of the smartphone as the primary sources of data input to our system. The motion sensors record the activity behavior and the audio sensor records voice signal of the participants

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at the rate of 10 samples/second and 44100 samples/second, respectively, as shown in Figure 1. The activity recognition algorithm is applied to the acquired signals, and recognized activity behavior is transmitted to the cloud server for data analysis to detect stress.

This paper is organized as follows. In Section II, we describe the experimental setup to collect raw data using the smartphone sensors and the proposed approach. In section III, we discuss and evaluate the system performance for stress detection based on the daily activity behavior.

II. Materials and Methods

Our approach employs tri-axial accelerometer, tri-axial gyroscope, and microphone of a smartphone. An accelerometer and gyroscope are dedicated to measuring acceleration and angular velocity of the subjects during *stationary*, *moving*, and *sleeping* states, whereas the microphone records surrounding noise level when subjects are in *stationary* and *sleeping* states. Figure 2 depicts the three of the activities performed by the subject while the smartphone is in the proximity to him. Smartphone app developed by MATLAB is responsible for collecting the experimental data and transmitting the data to the cloud server for further analysis.

A. Experiment Design

We recruited 32 students (16 graduate and 16 undergraduate) of Sungkyunkwan University, average age of 29.7 years with standard deviation of 10.6 years, to analyze our envisioned system. Subjects signed consent form prior to the experiment and whose rights have been protected following declaration of Helsinki. Selected Subjects had no head injury and were not using any medication. We employed same manufacturer and same model smartphone, iPhone 6, for recording the daily activity experimental data, because the majority of participants in the trial had an iPhone 6, and since the idea was to let the participants use the same type of smartphone so as to avoid the normalization problem of the activity data. Each participant recorded their 24 hour activity of daily routine which constituted experimental data of 768 hours. If a person is sleeping, the amplitude generated by a microphone is either near to zero or very small due to snoring, whereas when subject wakes up, he/she has to say “good morning” or “hello”, and as to signal the microphone that the subject has woken up, and similarly, subject has to utter “good night” to indicate beginning of sleep. The words spoken at the time of before and after the sleep helps in determining sleep duration of the subject automatically. All participants also participated in a stress-related survey. The data of 25 hours were discarded because some participants could not carry mobile in some unavoidable situations. The students were grouped into two clusters based on educational degree they are currently pursuing in the university: graduate and undergraduate. The daily routine information of both groups forms experimental data for activity recognition. Acquired signals of the sensors are segmented into non-overlapping segments of 20 seconds. The segment length of 20 seconds was selected based on the best performance of activity recognition classifier after exploring a range of 3 to 30 seconds. The activity information was annotated into three classes: stationary, moving, and sleeping.

B. Proposed Approach

Our system for stress detection has three stages. Subjective assessment is performed about stress through a survey in *stage one*. In *stage two*, subject’s activity of the whole day is recognized, and stress level is detected based on the recognized activity information in *stage three*. The activity information is comprised of three broad classes: stationary, moving, and sleeping. Our system tries to recognize these activities using an activity recognition classifier. We think that these three classes of activities are essential to determine stress of the university student. We have exploited participants’ interaction with a smartphone to indirectly determine their stress level. If participant is stressed, he/she suffers from insomnia and often remains in stationary activity. Therefore, we exploited subjective assessment and daily activity information of participants to calculate their stress levels. The proposed approach tries to exploit relation of sleep, stationary, and moving activities with stress using linear regression. We think that the pressure of supervisor and fear of failure causes the student to sleep less and study for long hours, whereas a person who sleeps less and stays stationary longer than usual becomes victim of stress. Therefore, it is very important to address the problem of stress faced by the university students using a novel non-invasive approach.

C. Activity Recognition

The distinct patterns as shown in (Figures 3(a) to 3(f)) were generated by the motion sensors of smartphone according to the activity subjects performed in their daily schedule. Three segments of 40 seconds in Figure 3 demonstrate a difference in acceleration and angular velocity of each activity. The patterns of moving activity are clearly distinguishable from the rest of the two activities. To some extent, patterns of sleeping and stationary activity are obscure due to being same in nature. For solving this problem, the microphone is used to differentiate sleeping from stationary activity as shown in Figure 4. We have modified the signal of audio input in order to keep the privacy of subjects. Amplitude signal of audio input during sleep stays approximate to zero, whereas the amplitude during stationary (awake) state is higher as shown at extreme ends of audio signal in Figure 4. Since, features play an essential role in the recognition of activities, so features must characterize the patterns effectively without carrying irrelevant and redundant information so that activity recognition classifier perform efficiently. The amplitude based features are extracted from segments of experimental data for training the activity model. Those features are arithmetic mean, standard deviation, interquartile range, kurtosis, geometric mean, median, maximum, range, skewness, energy of a signal, waveform length, entropy, RMS and ratio of RMS to maximum.

Forward Features Selection (FFS) procedure is employed on the computed features to reduce redundancy and avoid overfitting. The top 6 features are selected using FFS and those selected features are fed into Support Vector Machine (SVM) to develop the activity recognition model. The activity recognition model is trained and evaluated using a 32 fold cross-validation technique with leave-one-out. This technique allowed the training of the quadratic SVM on the features from 31 out of 32 subjects and validated the model with the remaining subject. The activity recognition algorithm has classified the acquired signals of the sensors with an accuracy

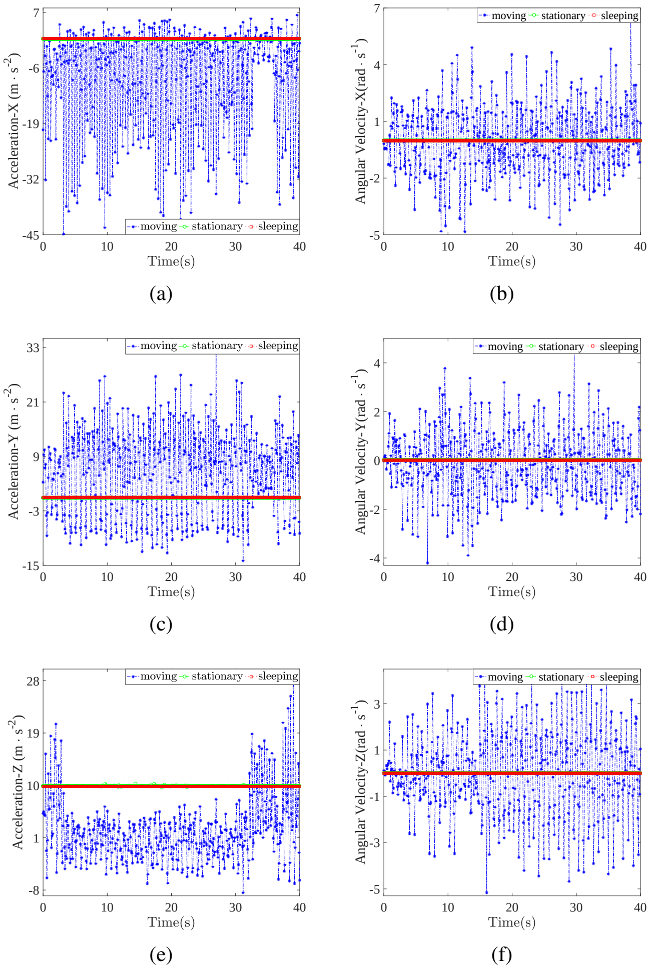

Figure 3. Motion sensors signals; (a), (c), and (e) represents Accelerometer signals in x, y and z axes, whereas (b), (d), and (f) are Gyroscope signals in x, y and z axes.

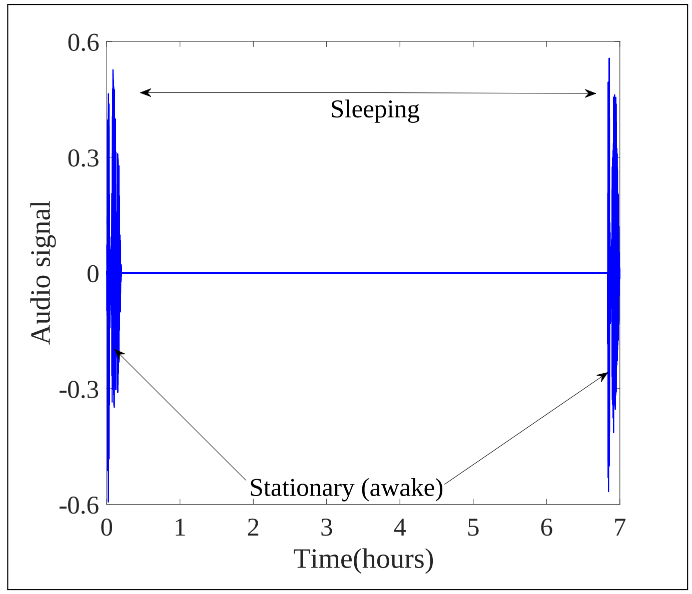

Figure 4. Audio signals for sleeping activity.

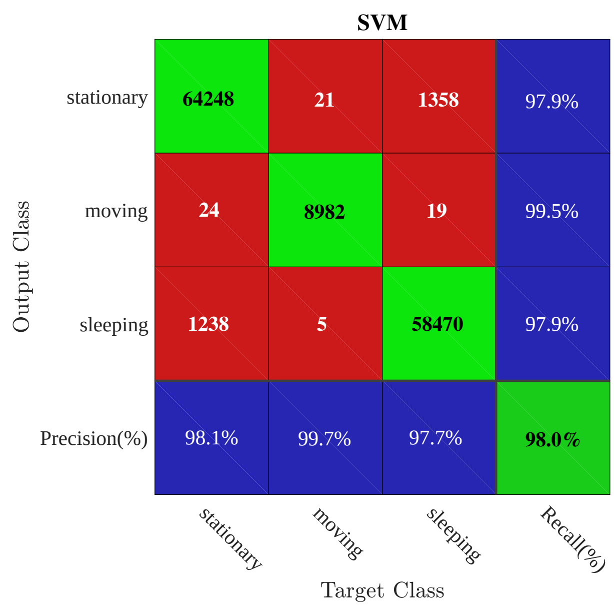

Figure 5. Activity recognition performance of SVM.

of 98.0% into three activity classes of *stationary*, *moving*, and *sleeping* as shown in Figure 5. The *moving* class is comprised of walking, running, and any other exercise involving the body motion. SVM is a supervised machine learning algorithm. We implemented SVM for activity recognition using classification learner tool in MATLAB 2016b. One-vs-all strategy and linear kernel function $k(\vec{X}_t, \vec{X}_i) = \vec{X}_t, \vec{X}_i$ is used whose penalty C parameter is 1 by default.

D. Stress Detection

The activity information recognized by SVM is transmitted to the cloud server for data analytics to detect stress (S) in the students. We tried to search relationship between stress and three activity classes: *moving*, *stationary*, *sleeping*. We exploited different linear regression models to build a robust model to estimate stress. *Stationary* and *sleeping* activities data are included to develop the stress estimation model because those two variables showed a significant relationship with stress, whereas *moving* activity data was discarded after it showed no any significant improvement in the model. We have computed stress score using (1). We think that sleep duration and stationary activity are essential explanatory variables to determine the stress levels.

$$S = aX + bY + \theta \tag{1}$$

where X and Y represents *stationary* and *sleeping* activity classes, whereas a, b, and θ are parameters.

We employed curve-fitting tool of MATLAB 2016b to evaluate the proposed model, and determined the values of a, b, and θ using least square method. As shown in Table I, the parametric values of the proposed approach are calculated as 0.176, -0.386, and 3.01 for a, b, and θ, respectively. The pvalues of *stationary* and *sleeping* variables are lower than 0.05 which proved the statistical significance of the earlier mentioned variables in estimating the stress score. The adjusted R-Squared value is 0.909 which means 90.9% variance in stress is successfully explained by the proposed model based

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on two explanatory variables (i.e., *stationary* and *sleeping*). *Stationary* has the effect of a on the stress score, whereas *sleeping* affects the stress score by factor of b. All the parameters have a partial effect on stress. The parametric values of (1) shown in Table I suggest that *sleeping* has a higher effect on stress score than *stationary*, because parameter b is higher in weight than parameter a. If both the variables are 0 in values, then parameter θ affects estimated stress highly. Stress reduces when sleep time increases and vice versa. On the contrary, *stationary* activity is directly proportional to the stress.

TABLE I. LINEAR REGRESSION ANALYSIS OF PROPOSED MODEL

	Estimated parameters	**Standard error**	**t Statistic**	**P value**
Intercept	3.01	0.78263	3.8429	0.00061
Stationary	0.176	0.04124	4.2701	0.00019
Sleeping	-0.386	0.05506	-7.011	1.0393e-07
Number of observations	32			
Root Mean Squared Error	0.287			
R-squared	0.915			
Adjusted R-Squared	0.909			

Three levels of stress are calculated based on lower and upper thresholds. Those three levels of stress are low, mild, and acute. If $S < \delta_1$, the subject is less stressed or normal, he has a mild stress if $\delta_1 \leq S \leq \delta_2$, and he has an acute stress if $S > \delta_2$. The δ_1 and δ_2 represents lower and upper thresholds. Stress level scores for all the students is computed. The result of stress computation shown in Figures (5(a) to 5(b)) has demonstrated that 2 graduate student have acute or high stress and 2 others out of 16 graduate students have mild stress, whereas only 3 out of 16 undergraduate students have mild stress. This statistics of stress experienced by students has validated our claim that graduate students have higher average stress as compared to the undergraduate students due to poor sleep and higher sedentary or stationary behavior.

III. Discussion and Conclusion

The focus of our research was to present an approach to detect stress levels experienced by the students. Our approach uses non-invasive strategy to monitor the three levels of stress in the subjects using a commonly available electronic device (smartphone). We employed the motion sensors and audio sensor of the smartphone to record the overall activity of the individuals. Prior studies have considered stress detection with EEG, ECG and Galvanic Skin Response (GSR) [3][6][9][10][11] which provide a direct method to measure stress and are preferred choice of users in indoor settings, but these devices are socially unacceptable to people going out in public places (i.e., school, office, shopping market, etc.,) while wearing these measurement devices. Our non-invasive method based on the smartphone is user friendly and socially acceptable to users, because the smartphone sensors do not interfere with their daily work and they can use the smartphone to measure their stress levels in public places without letting anybody know.

We have analyzed our approach using two groups of the students. The smartphone recorded the activity of students when they performed routine tasks without interfering in their daily-life tasks. An experiment was performed in order to obtain activity data on the basis of which, stress scores or levels

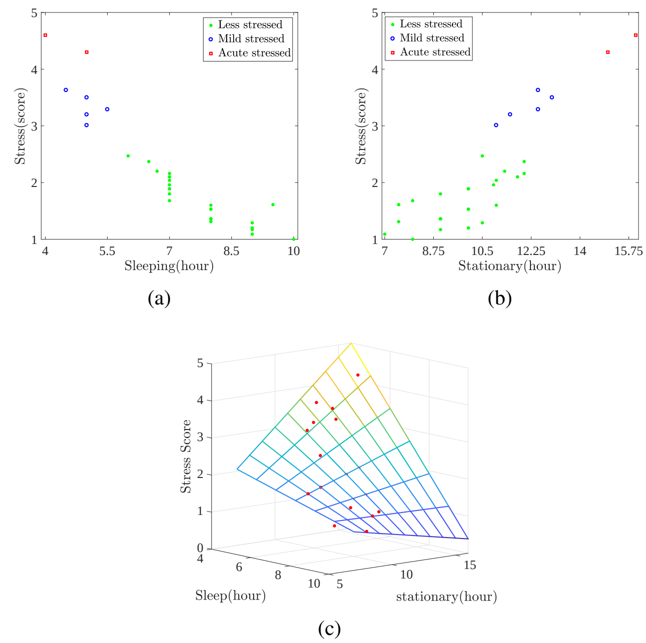

Figure 6. Stress relation with daily life activity behavior (a) Effect of Sleeping activity on Stress Score, (b) Effect of Stationary activity on Stress Score, and (c) 3D curve fitting of the proposed model.

can be detected. The activity recognition classifier grouped the daily-routine behavior of the subjects into three classes: *moving*, *stationary*, and *sleeping*. We experimentally evaluated three of the activity classes to build statistical models for stress computation, but the model is built on only *stationary* and *sleeping* classes. *Moving* activity did not contribute any significant information about stress in the model, therefore, it is discarded. *Stationary* and *sleeping* are two broad classes of activity which are essential to assess someone's stress level. The estimation of stress levels by proposed approach is demonstrated in Figures (6(a) to 6(b)). The curve fit of the stress estimation model is shown in Figure 6(c) which depicts the inverse relationship of *sleeping* with stress and direct effect of *stationary* on the stress. The conclusion drawn from proposed model also agrees with the previous studies that stress causes poor sleep [16][17] and high stationary or sedentary behavior [17] is related to stress.

We experimentally found that graduate students suffer higher stress than the undergraduate students studying in the university. Our proposed strategy determined the stress of the students and 2 out of 16 graduate students is suffering from acute or high stress, 2 out of 16 graduate students have mild stress, whereas only 3 out of 16 undergraduate students have mild stress. It is not possible that people carry the smartphone all the time, so it is a limitation of our approach. We will try to integrate motion and biological sensors in arm band or embed to T-shirt for monitoring the activity of individuals and notifying them about their stress levels in real-time as our future work.

We have presented a novel approach based on smartphone sensors to measure the stress level of graduate and undergraduate students studying in the university. Our system has determined three stress levels by analyzing the activity behavior and experimentally found that graduate students are

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more stressed than undergraduate students.

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REFERENCES

[1] R. S. Duman, "Neurobiology of stress, depression, and rapid acting antidepressants: remodeling synaptic connections," Depression and anxiety, vol. 31, no. 4, 2014, pp. 291–296.

[2] F. Lederbogen, et al., "City living and urban upbringing affect neural social stress processing in humans," Nature, vol. 474, no. 7352, 2011, p. 498.

[3] A. P. Allen, P. J. Kennedy, J. F. Cryan, T. G. Dinan, and G. Clarke, "Biological and psychological markers of stress in humans: focus on the trier social stress test," Neuroscience & Biobehavioral Reviews, vol. 38, 2014, pp. 94–124.

[4] H. Ursin and H. R. Eriksen, "The cognitive activation theory of stress," Psychoneuroendocrinology, vol. 29, no. 5, 2004, pp. 567–592.

[5] A. R. Subhani, et al., "Machine learning framework for the detection of mental stress at multiple levels," IEEE Access, vol. 5, 2017, pp. 13 545–13 556.

[6] A. de Santos Sierra, C. S. Ávila, J. G. Casanova, and G. B. del Pozo, "A stress-detection system based on physiological signals and fuzzy logic," IEEE Transactions on Industrial Electronics, vol. 58, no. 10, 2011, pp. 4857–4865.

[7] S. Kontaxis, et al., "Mental stress detection using cardiorespiratory wavelet cross-bispectrum," in Computing in Cardiology Conference (CinC), 2016. IEEE, 2016, pp. 725–728.

[8] S. Ollander, C. Godin, A. Campagne, and S. Charbonnier, "A comparison of wearable and stationary sensors for stress detection," in Systems, Man, and Cybernetics (SMC), 2016 IEEE International Conference on. IEEE, 2016, pp. 004 362–004 366.

[9] G. Jun and K. Smitha, "Eeg based stress level identification," in Systems, Man, and Cybernetics (SMC), 2016 IEEE International Conference on. IEEE, 2016, pp. 003 270–003 274.

[10] N. Adnan, Z. H. Murat, R. S. S. A. Kadir, and N. H. M. Yunos, "University students stress level and brainwave balancing index: Comparison between early and end of study semester," in Research and Development (SCOReD), 2012 IEEE Student Conference on. IEEE, 2012, pp. 42–47.

[11] A. Secerbegovic, S. Ibric, J. Nisic, N. Suljanovic, and A. Mujcic, "Mental workload vs. stress differentiation using single-channel eeg," in CMBEBIH 2017. Springer, 2017, pp. 511–515.

[12] N. Sohail, "Stress and academic performance among medical students," J Coll Physicians Surg Pak, vol. 23, no. 1, 2013, pp. 67–71.

[13] M. Ho, V. Wong, P. Chow, and W. Cheng, "A study on nursing studentsstress in hong kong," HNE Handover: For Nurses and Midwives, vol. 8, no. 2, 2015.

[14] M. A. Sawah, et al., "Perceived stress and coffee and energy drink consumption predict poor sleep quality in podiatric medical students: a cross-sectional study," Journal of the American Podiatric Medical Association, vol. 105, no. 5, 2015, pp. 429–434.

[15] F. T. Leong, M. M. Leach, C. Yeh, and E. Chou, "Suicide among asian americans: What do we know? what do we need to know?" Death Studies, vol. 31, no. 5, 2007, pp. 417–434.

[16] C. Alcántara, et al., "Stress and sleep: Results from the hispanic community health study/study of latinos sociocultural ancillary study," SSM-population health, vol. 3, 2017, pp. 713–721.

[17] J. E. Pelletier, L. A. Lytle, and M. N. Laska, "Stress, health risk behaviors, and weight status among community college students," Health Education & Behavior, vol. 43, no. 2, 2016, pp. 139–144.

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