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Wearable sensor devices for early detection of Alzheimer disease using dynamic time warping algorithm

R. Varatharajan[1] · Gunasekaran Manogaran[2] · M. K. Priyan[2] · Revathi Sundarasekar[3]

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Abstract Alzheimer disease is a significant problem in public health. Alzheimer disease causes severe problems with thinking, memory and activities. Alzheimer disease affected more on the people who are in the age group of 80-year-90. The foot movement monitoring system is used to detect the early stage of Alzheimer disease. internets of things (IoT) devices are used in this paper to monitor the patients' foot movement in continuous manner. This paper uses dynamic time warping (DTW) algorithm to compare the various shapes of foot movements collected from the wearable IoT devices. The foot movements of the normal individuals and people who are affected by Alzheimer disease are compared with the help of middle level cross identification (MidCross) function. The identified cross levels are used to classify the gait signal for Alzheimer disease diagnosis. Sensitivity and specificity are calculated to evaluate the DTW algorithm based classification model for Alzheimer disease. The classification results generated using the DTW is compared with the various classification algorithms such as inertial navigation algorithm, K-nearest neighbor classifier and support vector machines. The experimental results proved the effectiveness of the DTW method.

Keywords Internets of things · Alzheimer disease · Dynamic time warping · Middle level cross identification · Inertial navigation algorithm · K-nearest neighbor classifier · Support vector machines

✉ R. Varatharajan
varathu21@yahoo.com

1 Sri Ramanujar Engineering College, Chennai, India

2 VIT University, Vellore, India

3 Priyadarshini Engineering College, Vellore, India

1 Introduction

Recently, a report from The Hindu states that nearly 50 lakhs of people are affected by Alzheimer disease in India [1–4]. Human motion recognition is used to detect the Alzheimer disease in early stage. In order to monitor the human motion, various internet of things (IoT) devices are developed recently [5–7]. IoT is applied in many applications to get better results [8–10]. Though, implementation of above system consists of various challenges and issues [11]. For example, IoT devices are usually communicated with other devices with the help of wireless network. Hence, there is a need to improve the communication system using an efficient service oriented-architecture (SoA) [12]. In addition, there is a need of standardization to develop an efficient and effective IoT system and solve the gap between the customer and service providers [13]. IoT devices generally connect with cloud; hence, there is need of effective integration platform between cloud and IoT system [12,14].

IoT generates huge amount of data, hence, there is need of advance scalable algorithms to process such kind of data [15]. IoT devices communicate with each other, hence, there is a need to remove multicast/ broadcast flooding [16]. Similarly, when a device roaming from one place to another; it is mandatory to reduce the transmission latency between the source to destination [17]. IoT devices generates enormous amount of data, hence, there is need to have scalable data storage platform in cloud [18–21]. Moreover, IoT devices should have an appropriate security mechanism to protect and prevent from unauthorized access and data loss [22]. IoT devices should support various types of modern networking protocols such as Mobile Internet Protocol version 6 (MIPv6), Internet Control Message Protocol version 6 (ICMPv6) and so on [23]. Similarly, a modern IoT system should support star and mesh topology to provide an efficient network communication between the devices [24]. Hence, the modern IoT devices must be identified at time and location, hence, the mobile address of the devices should be enhanced. In addition, efficient handoff scheme is to be identified to avoid jitter, delays, and interruptions in Internet of Vehicles (IoV) [25]. Moreover, some major issues are found in IoV. For example, lack of coordination and communication between the vehicles in IoV implementation is considered as biggest issue [26], and lack of standards in V2V (vehicle to vehicle) wireless communication is also considered as challenging task [27]. IoT systems continuously generate huge amount of data, hence, making a decision on data is considered as another challenge. Table 1 depicts the recent development in wearable sensors for motion recognition. Table 2 depicts the various sensor devices and it uses.

The structure of this manuscript is described as follows: Sect. 1 introduces the motion detection using wearable sensor devices. Section 2 reviews the recent works in motion detection for Alzheimer disease. The proposed work is explained in Sect. 3 in detail. Sections 4 and 5 describes the result and discussion, and performance evaluation. Finally, Sect. 6 concludes the research work.

2 Related work

In the recent years, various image processing algorithms and machine learning techniques are developed for disease diagnosis of Alzheimer disease. For example, Rasta et al. have reviewed various image enhancement approaches to detect the Alzheimer disease [28]. Corrected red and green components of color retinal images are used to evaluate the existing approaches to detect the Alzheimer disease [29]. Sensitivity and specificity are calculated to find the best approach to detect the Alzheimer disease in public health. Li at al. have identified an approach to deal with complicated image segmentation [26]. Two level segmentation approach is followed in this approach namely background and target [30]. The detected retinal layer boundaries are effectively utilized to identify the Alzheimer disease and Glaucoma [31,32]. Rao et al. have used Linear mixed modeling methods to model the influences of axial length, age, TSS, and corneal birefringence on Alzheimer disease detection [33]. The proposed approach randomly selects one image out of 48 eye images to evaluate the performance of the proposed approach.

Uji et al. have proposed interpolation and super-resolution (SR) algorithms to identify the Alzheimer disease, peak signal-to-noise ratio (PSNR), photoreceptor layer status, and parallelism in each Oct images [42]. Experimental results proved the efficiency of the proposed interpolation and super-resolution (SR) algorithms to indentify the Alzheimer disease. Li at al. have identified an approach to deal with complicated image segmentation. Two level segmentation approach is followed in this approach namely background and target [43]. The detected retinal layer boundaries are effectively utilized to identify the Alzheimer disease and Glaucoma. The experimental results effectively segment the input raw OCT image into five layers accurately. The proposed algorithm initially uses factor analysis technique to categorize the well-known and unknown images generated from various sources. Space mapping approach is employed in this work to perform the objective extraction. The proposed image feature extraction with recognition approach effectively tested to detect the unfamiliar faces as well as object recognition, facial expression. LDA, MFA and LPP based image feature extraction methods are used in this work to compare and prove the effectiveness of the proposed image feature extraction with recognition approach. In addition, the structure tensor with complex diffusion filtering based image filtering method is also used to process the OCT images. This image filtering method efficiently removes the noises present in the raw OCT images. The structure tensor with complex diffusion filtering based image filtering method efficiently classifies the Alzheimer disease in public health. The detection of Alzheimer disease is done on the various cellular layers of the OCT retina images using the STRATUSOCT system.

3 Proposed framework

Dynamic time warping (DTW) is used in this paper to monitor the gait signal data from various patients [44,45]. The gait signal data is collected from various wearable sensor devices. These IoT devices continuously generate the huge amount of data [46]. The gait signal data is collected and processed with the help of DTW algorithm [47,48]. The essential goal of the DTW algorithm is to compare the various shapes of gait signals collected from each patients of Alzheimer disease and warping to align them in time [49]. In this paper, the gait signals are referred to the walking patterns of patients with Alzheimer disease. The time between strides has been reported to differ between the normal individuals and the patients who are having Alzheimer disease. The major issue with this operation is walking speed of the individuals over time [50,51]. In general, every individuals walk with different speed over time. Hence, there is a need to align them in time. In order to overcome this issue, this paper uses DTW algorithm to compare the various shapes of gait signals collected from normal individuals and people who are affected by Alzheimer disease. The comparison is done with the help of middle level cross identification function [52,53]. This cross levels is used in gait signal classification for patients who are having Alzheimer disease. Nowadays, various big data algorithms also play a significant role in

Table 1 Recent development in wearable sensors for motion recognition

	CT1/RT3	GT3X/GTM	AMP 331	IDEEA	Step watch	Active PAL	Sense wear
Monitoring parameters	Motion concentration, meteorological	Meteorological motion counts, steps, activity concentration level	Walking speed, Steps, beat, stride length, distance	Motion types, gait types	Steps gait features	Stepping time, cadence, sedentary and upright time, steps, sit-to-stand activities, meteorological	Sleep length, Motion length
Sensor size in mm	71 × 56 × 28	38 × 37 × 18	71.3 × 24 × 37.5	70 × 54 × 17	75 × 50 × 20	53 × 35 × 7	88.4 × 56.4 × 24.1
Weight in grams	71.5	27	50	59	38	20	82.2
Sampling rate	0.017–1 Hz	30 Hz	Not applicable	32 Hz	128 Hz	10 Hz	32 Hz
No. of accelerometer	One	One	Two	5	One	One	One
No. of accelerometer axis	1/3	3/1	1 single axis and 1 double axis	Two	Two	One	Two
Sensor position	Waist	Wrist	Ankle	Feet, chest, thigh	Ankle	Thigh	Upper arm
Data storage	3 hours to 21 days	40 days	Not applicable	7 days	2 months	Not applicable	Not applicable
Type of the battery	1.5V AAA × 1	3.7 V Lithium	Not applicable	1 1.5 V AA	750 mAh Lithium	3 V	1.5 V AAA × 1
Accelerometer type	Piezoelectric	Not applicable	Not applicable	Piezoelectric	Not applicable	Piezoresistive	Not applicable
Battery life	30 days	20 days	Not applicable	60 hours	Not applicable	7–10 days	3 days
Data transmission	USB	USB	916 MHz RF	USB	USB	USB	RF/USB
Sensitivity rate	Not applicable	0.05–2.5 g	Not applicable	5 g	Not applicable	2 g	2 g

Table 2 Various sensor devices and it uses

Classified event	Sensor data	Classification approach	References
Fall detection	Barometer, microphone, accelerometers	Threshold based kNN algorithm	[34]
Fall risk estimation and gait assessment	GaitShoe: accelerometer, gyroscope, bend sensor, force sensitive resistor and electric field sensor	SVM, Gaussian process	[35]
Food preparation and feeding	RFID	Threshold based algorithm	[36]
Selfcare	RFID, accelerometer	Proprietary algorithm	[37]
House keeping	RFID, accelerometer	Proprietary algorithm	[38]
Activities of daily living	Accelerometers	k-NN with Gaussian process	[39]
Leisure and communication	EOG, accelerometer, RFID	SVM	[40]
Energy expenditure	Accelerometers	Regression model	[41]

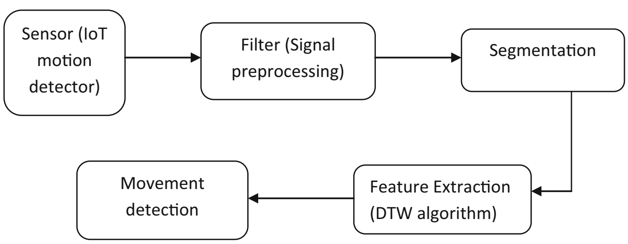


Fig. 1 Architecture for motion detection using wearable sensor devices

disease diagnosis [18,54–58]. The IoT based gait signal monitoring framework discussed in this paper is also used to monitor the various other physiological signals such as electrocardiogram (ECG) and photoplethysmogram (PPG) and so on. Figure 1 represents the architecture for motion detection using wearable sensor devices. Figure 2 represents the example motion detection device and Fig. 3 represents the Leg movement.

3.1 Dynamic time warping

Dynamic time warping is widely used to classify the multivariate time series data. DTW algorithm is more often used to classify the speech recognition and hand writing classification. In this paper, DTW algorithm is used to classify the gait signals collected from normal individuals and people who are affected by Alzheimer disease. In general, speech recognition features are more similar to the feature of gesture recognition. DTW algorithm is significantly used to measure the various similarity measures in the multivariate time-series data.

In this paper two gestures such as normal individuals and people who are affected by Alzheimer disease are to be compared against each other as, two time series X and Y.

$$X = (x_1, x_2, x_3, \ldots x_{t1}, \ldots, x_{T1},) \tag{1}$$

$$Y = (y_1, y_2, y_3, \ldots y_{t1,}, \ldots, y_{T1},) \tag{2}$$

The time series $X = (x_1, x_2, x_3, \ldots x_{t1}, \ldots, x_{T1})\, and\; Y = (y_1, y_2, y_3, \ldots y_{t1,}, \ldots, y_{T1})$ are considered as multivariate series with huge feature vectors [59–61]. The distance between the vectors of the time series $X = (x_1, x_2, x_3, \ldots x_{t1}, \ldots, x_{T1})\, and\; Y = (y_1, y_2, y_3, \ldots y_{t1,}, \ldots, y_{T1})$ are is defined by,

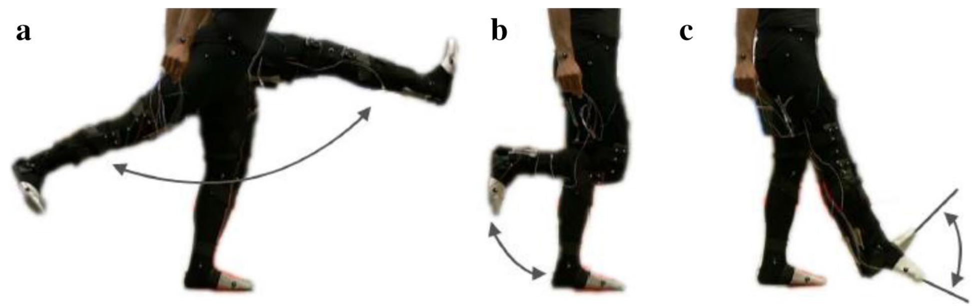
$$d : f \times f \rightarrow R > 0 \tag{3}$$

where,

$$x_{t1}, y_{t2} \in f \;\; for \;\; t1 \in [1, t_1], t2 \in [1, t_2] \tag{4}$$

Fig. 2 Motion detection device

Fig. 3 Leg movement



The above equations state that, the cost measure must be small if the time series $X = (x_1, x_2, x_3, \ldots x_{t1}, \ldots, x_{T1})$ $and Y = (y_1, y_2, y_3, \ldots y_{t1,}, \ldots, y_{T1})$ are similar and high if they are very different.

The cost matrix $C_{t1} \times C_{t2}$ is calculated for the time series $X = (x_1, x_2, x_3, \ldots x_{t1}, \ldots, x_{T1})\, and\; Y = (y_1, y_2, y_3, \ldots y_{t1,}, \ldots, y_{T1})$. The $C_{t1} \times C_{t2}$ is used to attain a association mapping elements in $X = (x_1, x_2, x_3, \ldots x_{t1}, \ldots, x_{T1},)$ to elements in $Y = (y_1, y_2, y_3, \ldots y_{t1,}, \ldots, y_{T1},)$. The mapping function is used to calculate the lowest distance measure between X and Y. The mapping function is defined by,

$$F = c(1), c(2), c(3), \ldots, c(k), \ldots, c(K) \tag{5}$$

where,

$$c(k) = c(x_k, y_k) \tag{6}$$

The time sequence order of the respective foot movement is mapped into the mapping function. In order to achieve this task, the following conditions are implemented in the proposed framework:

Step 1 The observation symbols for the initial state and end state are aligned as follows:

$$c\,(1) = (x_1, y_1) \tag{7}$$

$$c\,(K) = (x_{T1}, y_{T2}) \tag{8}$$

Step 2 The observation symbols are aligned as increasing order. The order of observation symbols is defined by,

$$k_1 \le k_2 \le \cdots \le K \tag{9}$$

Step 3 The observation symbols should not be skipped

$$k_{i+1} - k_i \le 1 \tag{10}$$

The overall distance function $C(F)$ for the time series $X = (x_1, x_2, x_3, \ldots x_{t1}, \ldots, x_{T1})\, and\; Y = (y_1, y_2, y_3, \ldots y_{t1,}, \ldots, y_{T1})$ is defined by,

$$C(F) = \sum_{k=1}^{K} c(k) \tag{11}$$

The overall distance function is used measure the overall distance between the two foot movements $X = (x_1, x_2, x_3, \ldots x_{t1}, \ldots, x_{T1})\, and\; Y = (y_1, y_2, y_3, \ldots y_{t1,}, \ldots, y_{T1})$

The DTW algorithm is to compute the lowest distance measure between the two foot movements $X = (x_1, x_2, x_3, \ldots x_{t1}, \ldots, x_{T1})\, and\; Y = (y_1, y_2, y_3, \ldots y_{t1,}, \ldots, y_{T1})$.

The dynamic programming theory is used in this paper to calculate the distance to each c(k).

We define D as the accumulated cost matrix:

Step 1 Initialize the distance $D(1, 1) = d(x_1, y_1)$

Step 2 Initialize the distance $D(T_1, T_2) = 2$ (Choose n as maximum arbitrary number)

Step 3 Calculate $D(t_1, t_2) = min\{D(t_{1-1}, t_{2-1}), D(t_{1-1}, t_2), D(t_1, t_{2-1})\} + d(X_{t1}, Y_{t2})$

The distance is calculated based on the following methods

The Euclidean distance between the two foot movement $X = (x_1, x_2, x_3, \ldots x_{t1}, \ldots, x_{T1},)$ and $Y = (y_1, y_2, y_3, \ldots y_{t1,}, \ldots, y_{T1},)$ is calculated as follows:

$$d_{mn}(X, Y) = \sqrt{\sum_{k=1}^{K} \left(x_{k,m} - y_{k,n}\right) \times \left(x_{k,m} - y_{k,n}\right)} \tag{12}$$

The absolute distance between the two foot movement $X = (x_1, x_2, x_3, \ldots x_{t1}, \ldots, x_{T1},)$ and $Y = (y_1, y_2, y_3, \ldots y_{t1,}, \ldots, y_{T1},)$ is calculated as follows:

$$\begin{aligned} d_{mn}(X, Y) &= \sum_{k=1}^{K} \left|x_{k,m} - y_{k,n}\right| \\ &= \sqrt{\sum_{k=1}^{K} \left(x_{k,m} - y_{k,n}\right) \times \left(x_{k,m} - y_{k,n}\right)} \end{aligned} \tag{13}$$

The squared distance between the two foot movement $X = (x_1, x_2, x_3, \ldots x_{t1}, \ldots, x_{T1},)$ and $Y = (y_1, y_2, y_3, \ldots y_{t1,}, \ldots, y_{T1},)$ is calculated as follows:

$$d_{mn}(X, Y) = \sum_{k=1}^{K} \left(x_{k,m} - y_{k,n}\right) \times \left(x_{k,m} - y_{k,n}\right) \tag{14}$$

The symmetric kullback leibler metric for the real and positive foot movement $X = (x_1, x_2, x_3, \ldots x_{t1}, \ldots, x_{T1},)$ and $Y = (y_1, y_2, y_3, \ldots y_{t1,}, \ldots, y_{T1},)$ is calculated as follows:

$$d_{mn}(X, Y) = \sum_{k=1}^{K} \left(x_{k,m} - y_{k,n}\right)\left(\log x_{k,m} - \log y_{k,n}\right) \quad (15)$$

changes in the foot movement are identified with the help of middle level cross function. Figure 6 represents the middle level cross identification of patients who have Alzheimer disease. The sharp changes in the foot movement of the patients who have Alzheimer disease is compared with the group of ten patients. The comparison results are depicted in Fig. 7. In general, patients do not walk at the same rate throughout the record. Hence, there is an issue in comparing the foot movement of different patients. In order to overcome this issue, DTW algorithm is significantly used to compute the distance between the segments by warping them and align them in time. Figure 8 represents the signal alignment of foot movement using DTW algorithm. Figure 9 represents the classification result of Alzheimer disease diagnosis based on the foot movement change detection using DTW algorithm.

Dynamic Time Warping Distance Calculation Algorithm

Input: *Time series input x and y with the length n and m*

Output: *Distance between the variable x and y*

```
1.    int Dynamic Time Warping Distance(s: array [1..n], t: array [1..m])
2.          {
3.          Dynamic Time Warping Distance:= array [0 to n, 0 to m]
4.          for i := 1 to n
5.                Dynamic Time Warping Distance [i, 0] := [0 to ∞]
6.          for i := 1 to m
7.                Dynamic Time Warping Distance [0, i] := [0 to ∞]
8.          Dynamic Time Warping Distance [0, 0] := 0
9.    for i := 1 to n
10.         for j := 1 to m
11.               cost := d(s[i], t[j])
12.               Dynamic Time Warping Distance [i, j] := cost +
   minimum(DTW[i-1, j ],            // insertion operation
13.                     Dynamic Time Warping Distance [i  , j-1], // deletion
   operation
14.                     Dynamic Time Warping Distance [i-1, j-1]) // match
   operation
15.         return DTW[n, m]
16.         }
```

4 Result and discussion

The walking patterns of the individuals who are affected by Alzheimer disease is collected with the help of wearable IoT devices. The walking speed of the individuals over time is analyzed with the help of DTW algorithm. In general, every individuals walk with different speed over time. Hence, there is a need to align them in time. This paper uses DTW algorithm to compare the various shapes of gait signals collected from the wearable IoT devices. The foot patterns of the normal individuals and people who are affected by Alzheimer disease are compared with the help of middle level cross identification function. The identified cross levels are used to classify the gait signal for Alzheimer disease diagnosis. Force sensitive resistor is placed on the foot of the patient to observe the force in mill volts (mV). The records are stored as one minute interval for the left and right foot. Figure 4 represents the nfoot movement of the patient who have Alzheimer disease. Every step movement of the patient is continuously monitored with the help of IoT devices. An example middle level cross identification is represented in Fig. 5. The sharp

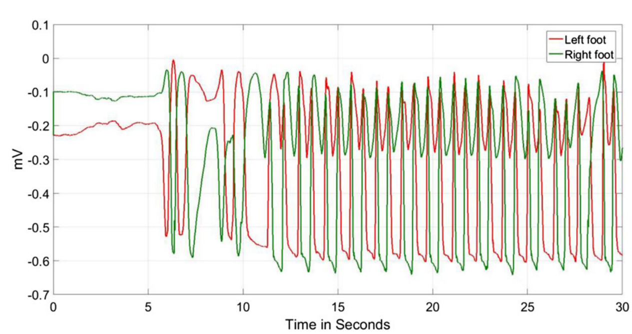


Fig. 4 Foot movement of the patient who have Alzheimer disease

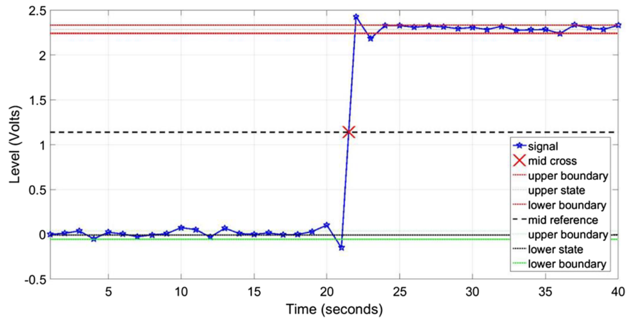


Fig. 5 Example middle level cross identification

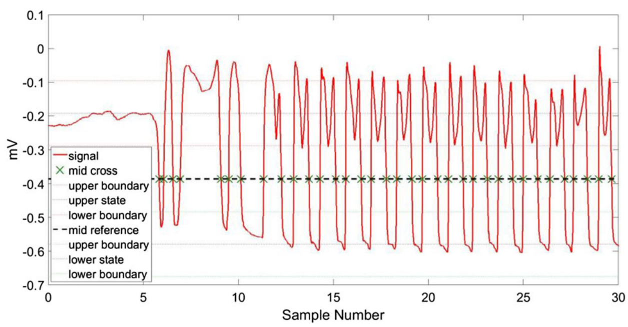


Fig. 6 Middle level cross identification of patient who have Alzheimer disease

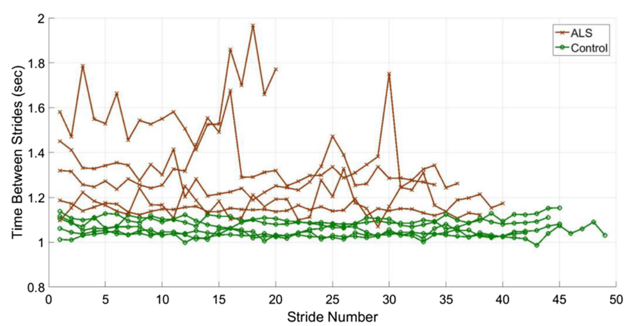


Fig. 7 Comparison of patients' foot movement with the normal individuals

5 Performance evaluation

Sensitivity and specificity are calculated to evaluate the classification model for Alzheimer disease. The classification generated by the dynamic time warping (DTW) is compared with the various classification algorithms such as inertial navigation algorithm (INA), K-nearest neighbor (k-NN) classifier and support vector machines (SVM). The validations metric are defined by,

$$Specificity = \frac{True\ Negative\ (TN)}{False\ Positive\ (FP) + True\ Negative\ (TN)}$$

$$Sensitivity = \frac{True\ Positive\ (TP)}{True\ Positive\ (TP) + False\ Negative\ (FN)}$$

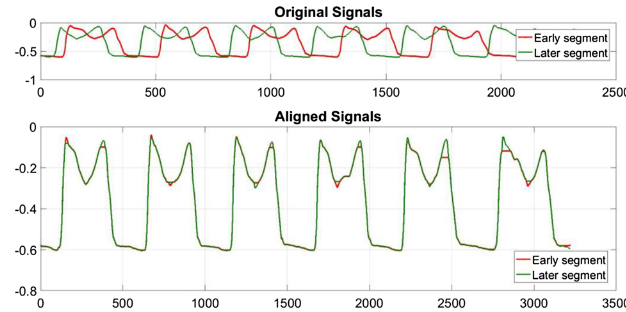


Fig. 8 Signal alignment of foot movement using DTW algorithm

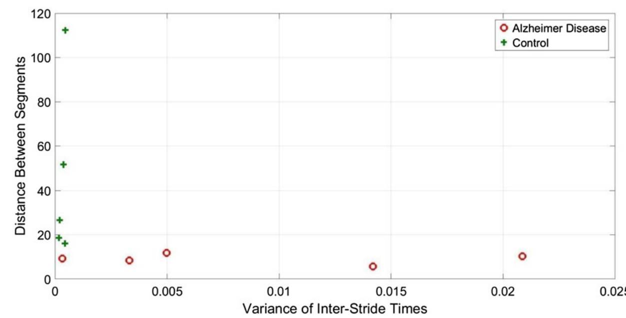


Fig. 9 Classification result of Alzheimer disease diagnosis

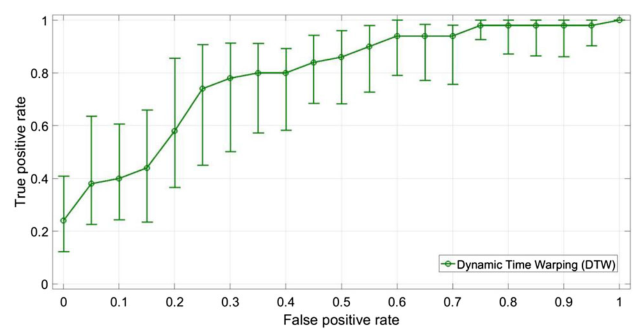


Fig. 10 ROC analysis for the DTW algorithm

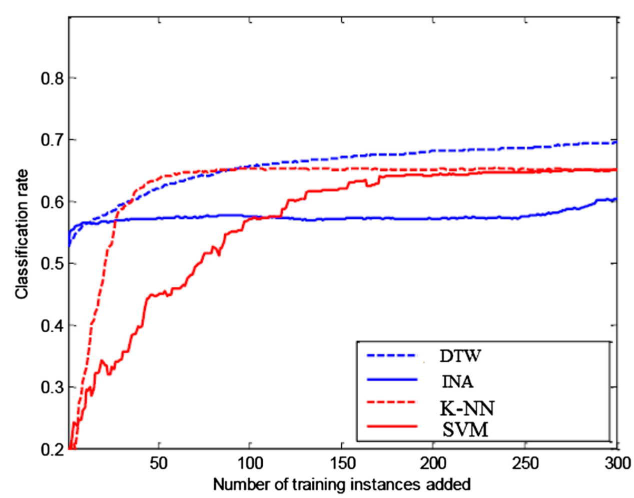


Fig. 11 Comparison of classification rate

Table 3 Performance comparison of the dynamic time warping (DTW) with various classification methods for Alzheimer disease diagnosis

S.No	Method	Disease type	No. of patients	Predicted as abnormal	Predicted as normal	SN = sensitivity (%), SP = specificity (%)
1	Dynamic time warping (DTW)	Abnormal	173	170	13	SN = 95.9
		Normal	150	147	13	SP = 94
2	Inertial navigation algorithm (INA)	Abnormal	173	169	14	SN = 94.5
		Normal	150	145	15	SP = 90
3	K-nearest neighbor (K-NN) classifier	Abnormal	173	170	13	SN = 95.9
		Normal	150	147	13	SP = 94
4	Support vector machines (SVM)	Abnormal	173	171	12	SN = 97.3
		Normal	150	146	14	SP = 92

Figures 10 and 11 represent the ROC analysis for the DTW algorithm and the comparison of classification rate respectively. Table 3 depicts the performance comparison of the dynamic time warping (DTW) with various classification methods for Alzheimer disease diagnosis. The experimental results proved the effectiveness of the dynamic time warping (DTW) method.

6 Conclusion

The human motion recognition is used to detect the early stage of Alzheimer disease. In this paper, IoT devices are used to monitor the human motion in continuous manner. The walking patterns of the individuals who are affected by Alzheimer disease is collected with the help of wearable IoT devices. The walking speed of the individuals over time is analyzed with the help of DTW algorithm. This paper uses DTW algorithm to compare the various shapes of gait signals collected from the wearable IoT devices. The foot patterns of the normal individuals and people who are affected by Alzheimer disease are compared with the help of middle level cross identification function. The identified cross levels are used to classify the gait signal for Alzheimer disease diagnosis. Force sensitive resistor is placed on the foot of the patient to observe the force in mill volts (mV). The sharp changes in the foot movement are identified with the help of middle level cross function. In general, patients do not walk at the same rate throughout the record. Hence, there is an issue in comparing the foot movement of different patients. In order to overcome this issue, DTW algorithm is significantly used to compute the distance between the segments by warping them and align them in time. Sensitivity and specificity are calculated to evaluate the classification model for Alzheimer disease. The classification generated by the dynamic time warping (DTW) is compared with the various classification algorithms such as inertial navigation algorithm (INA), K-nearest neighbor (k-NN) classifier and support vector machines (SVM). The experimental results proved the effectiveness of the dynamic time warping (DTW) method. In this study, we have observed only the foot movement from patient. The future work of this study is to use various IoT devices to collect various physiological signals from patient. The physiological signals are used to detect early stage of various diseases.

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R. Varatharajan received his B.E., M.E. and Ph.D. degrees all in Electronics and Communication Engineering from Anna University and Bharath University, India. His main area of research activity is Medical Image processing, Wireless Networks and VLSI Physical Design. He has served as a reviewer for Springer, Inderscience and Elsevier journals. He has published many research articles in refereed journals. He is a member of IEEE, IACSIT, IAENG, SCIEI and ISTE wireless research group. He has been serving as Organizing Chair and Program Chair of several International conferences and in the Program Committees of several International conferences. Currently he is working as a Associate professor in the Department of Electronics and Communication Engineering at Sri Ramanujar Engineering College, Chennai, India.

Gunasekaran Manogaran is currently pursuing Ph.D. in the Vellore Institute of Technology University. He received his Bachelor of Engineering and Master of Technology from Anna University and Vellore Institute of Technology University respectively. He has worked as a Research Assistant for a project on spatial data mining funded by Indian Council of Medical Research, Government of India. His current research interests include data mining, big data analytics and soft computing. He is the author/co-author of papers in conferences, book chapters and journals. He got an award for young investigator from India and Southeast Asia by Bill and Melinda Gates Foundation. He is a member of International Society for Infectious Diseases and Machine Intelligence Research labs.

M. K. Priyan is currently pursuing a Ph.D. in the Vellore Institute of Technology University. He received my Bachelor of Engineering and Master of Engineering degree from Anna University and Vellore Institute of Technology University, respectively. His current research interests include Big Data Analytics, Internet of Things, Internet of Everything, Internet of Vehicles in Healthcare. He is the author/co-author of papers in international journals and conferences.

Revathi Sundarasekar is currently pursuing a Master of Computer Science and Engineering in the Priyadarshini Engineering College, Vellore, Tamil Nadu, India. She received her Bachelor of Engineering in Computer Science from Priyadarshini Engineering College. She is the author/co-author of papers in international journals, book chapters and conferences. Her current research interests include Big Data analytics, and Internet of Things.