Chapter 16
Evaluation of a Time Reversal Method with Dynamic Time Warping Matching Function for Human Fall Detection Using Structural Vibrations

Ramin Madarshahian, Juan M. Caicedo, and Diego Arocha Zambrana

Abstract Falls are one of the predominant concerns of the elderly living at home. Commercial systems, such as wearable pendants that are pressed in an emergency, provide a viable solution when a fall occurs. However, wearable systems have a low compliance, especially in patients with diseases such as Alzheimer's or other forms of dementia. Monitoring changes in the environment provides the possibility of reducing the compliance challenges for those patients. Computer vision techniques is an example of environmental monitoring. However, some patients might be concerned about their privacy when having cameras in their homes. Monitoring the vibrations of the patient's dwelling is another alternative. Classification of the acceleration recorded signals becomes important to determine if a fall has occurred. This paper proposes the use of the Time Reversal Method (TRM) with Dynamic Time Warping (DTW) for classifying structural accelerations produced by different human actions. The potential classification is studied by releasing objects at different heights. A statistical study is performed to determine the importance of different factors to the application of the proposed technique. These factors are distance to the sensor, type of object used to impact the floor and intensity of the impact. Results indicate that the technique is most sensitive to the type of object, indicating the potential for human fall detection. Results also show interaction between the height in which the object was released and the type of object. Distance between the location of impact and the sensor is not an important factor but has an effect on the standard deviation of results.

Keywords Fall detection • Factorial design • Dynamic time warping (DTW) • Structural vibration • Classification

16.1 Introduction

Falls is one of the main reasons for hospitalization due to accidents in elder populations [1–3]. Furthermore, serious falls are usually not quickly reported to medical personnel or caregivers because the patient is unable to call for help [4]. Fall detection systems can reduce the time between the incident and the arrival time of medical attention. Fall detection systems can be classified in wearable, vision based, and ambient systems [5]. Wearable sensor, which are directly attached to the body of patient have been found reliable for fall detection, but difficult to wear in some situations, especially while taking showers [6, 7]. Moreover, some patients such as Alzheimer patients might forget or decide not to wear the devices [8]. Computer vision techniques solves the compliance problem but raises privacy concerns. Furthermore, falls should happen in the visual range of the camera to be detected. The use of accelerometers to monitor floor vibrations can be considered as an alternative ambient fall system. Tracking vibration on the patient's dwelling, have the potential to solve both compliance challenges and privacy concerns [9–12]. Vibration-based methods are feasible because accelerometers are not expensive and installation is easy. Previous work performed at the Structural Dynamics and Intelligent Infrastructure (SDII) laboratory at the University of South Carolina and by other research groups shows that events are easily detectible [9, 13]. However, little work has been done in the classification of the events. This paper investigates what factors are important for event classification. The Dynamic Time Warping (DTW) is used for event classification for comparing a potential event with a series of reference signals. An experimental test is designed to study the effect of several parameters in the signal classification. These are:

R. Madarshahian (✉) • J.M. Caicedo • D.A. Zambrana
University South Carolina, 300 Main St., Columbia, SC 29208, USA
e-mail: mdrshhn@email.sc.edu; caicedo@cec.sc.edu; arochazd@email.sc.edu

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Height of the fallen object (Height), its type (Type), and the distance between point of impact and the sensor location. Two levels are considered for each factor. Factorial analysis is used to study the effect of each factor and also their interactions.

16.2 Dynamic Time Warping

Dynamic Time Warping (DTW) is a popular method in the field of speech recognition [14, 15]. DTW is used, for example, in speech recognition, by comparing a signal with a bank of reference signals. The technique determines the closest reference signal after considering warping and time delay. DTW provides a factor calculated between the newly recorded signal, and each of the reference signals available. The higher the value the more similar the signals are. The procedure to apply DTW starts by formulating a distance matrix between the new recorded signal, and one of the reference signals. The $n \times m$ distance matrix, δ, is obtained from the difference of all samples of first signal, γ, with length of n, and second the signal, β, of length of m. The element δ_{ij} corresponding to the i-th row and j-th column of distance matrix δ is calculated as $\delta_{ij} = \gamma_i - \beta_j$. The next step is to find the shortest path from the first element of the distance matrix, δ_{11}, to the last element δ_{mn} should be obtained. The indices i, and j of the elements of δ_{ij} which are located on the path should increases monotonically. This is, considering two consecutive elements on the path shown by δ_{ab}, and δ_{cd}; c, and d shouldn't be smaller than a, and b respectively. The cost of each path is defined as summation of all arrays in that path. The path with the smallest cost corresponds to the best alignment between two signals. In this paper the summation of the elements on the on the shortest path is called 'DTW.'

$$DTW = \sum \zeta_i \tag{16.1}$$

where ζ_i is i-th element on the path. DTW is a number equal or greater than Zero. If the shortest path is diagonal two signals match without any warping.

16.3 Experiment Setup

A set of experiments were designed to study the effect of three factors in the classification of floor vibration signals using DTW. The three parameters considered are: (1) height of the object being thrown, (2) type of object, and (3) distance between point of impact and sensor location. The type of excitation is changed by using objects with different characteristics to hit the floor. The amplitude of the excitation is varied by releasing objects at different heights. The low and high amplitude are achieved by releasing objects from 145 cm and 208 cm respectively (Fig. 16.1). A basketball and a bag of K-Nex (Fig. 16.2) are selected to represent two different type of objects.

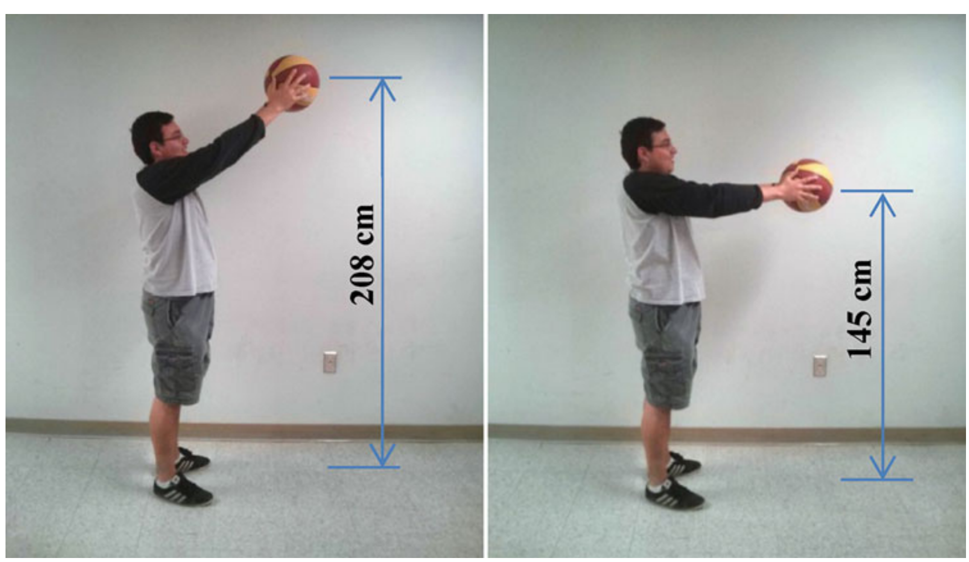

Fig. 16.1 Height, *left*: high, *right*: low

Fig. 16.2 Type, *left*: basketball, *right*: K-next bag

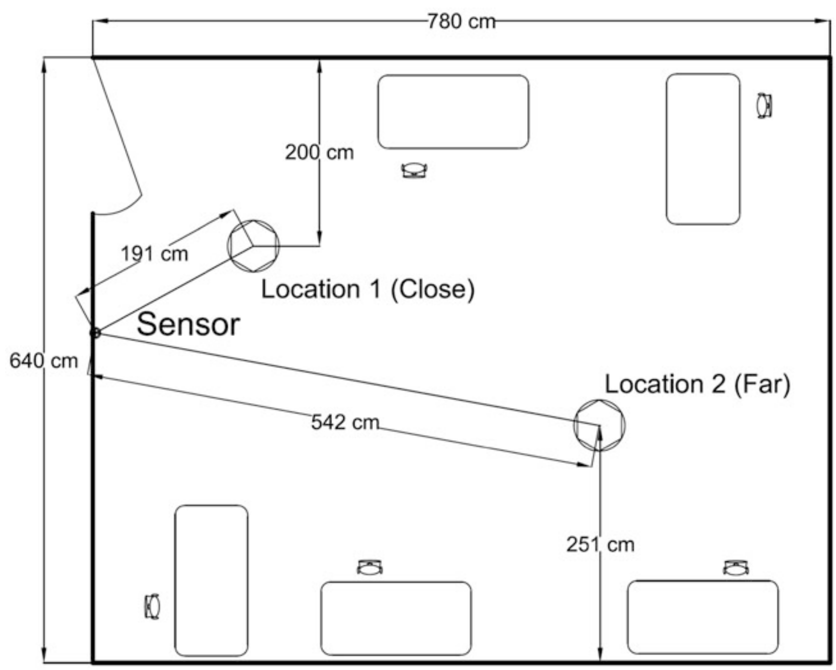

Fig. 16.3 Layout of sensor and fall locations

Table 16.1 Factors and their levels

Factors		Levels	
Name	Abbreviation	Level 1	Level 2
Height	A	High	Low
Type	B	K-Nex bag	Basketball
Distance	C	Close	Far

Figure 16.3 shows the layout of the room where the experiment was conducted. The room is in the second floor of a building with a steel structural system, standard concrete floors and plastic tails. The location where the sensor is installed and the location of the excitation are also shown in Fig. 16.3. Location 1 is 191 cm from the sensor and location 2 is 542 cm from the sensor.

Table 16.1 shows the factors, levels, and their abbreviations. A total of eight combinations are possible with the three factors considered in this paper (amplitude, type, and distance). Each combination was repeated 115 times, for a total of 920 accelerations records. Fifteen signals for each possible combination are used to generate reference signals, and the additional records are used for factorial analysis (100 replications per case).

16.4 Fall Signals

Traditionally, the DTW is applied using the acceleration signals directly. In this paper, the autocorrelation function is used in an effort to reduce any experimental noise. The reference signals shown in Fig. 16.4 are obtained as the average of 15 auto-correlations.

16.5 Results

The auto-correlation of the 100 signals is compared with the corresponding reference signal using DTW. The mean, median and standard deviation of the results are shown in Table 16.2. Generally speaking, DTW decreases from bag to ball, likewise standard deviation, but for getting more information it is needed to do factorial analysis on the data.

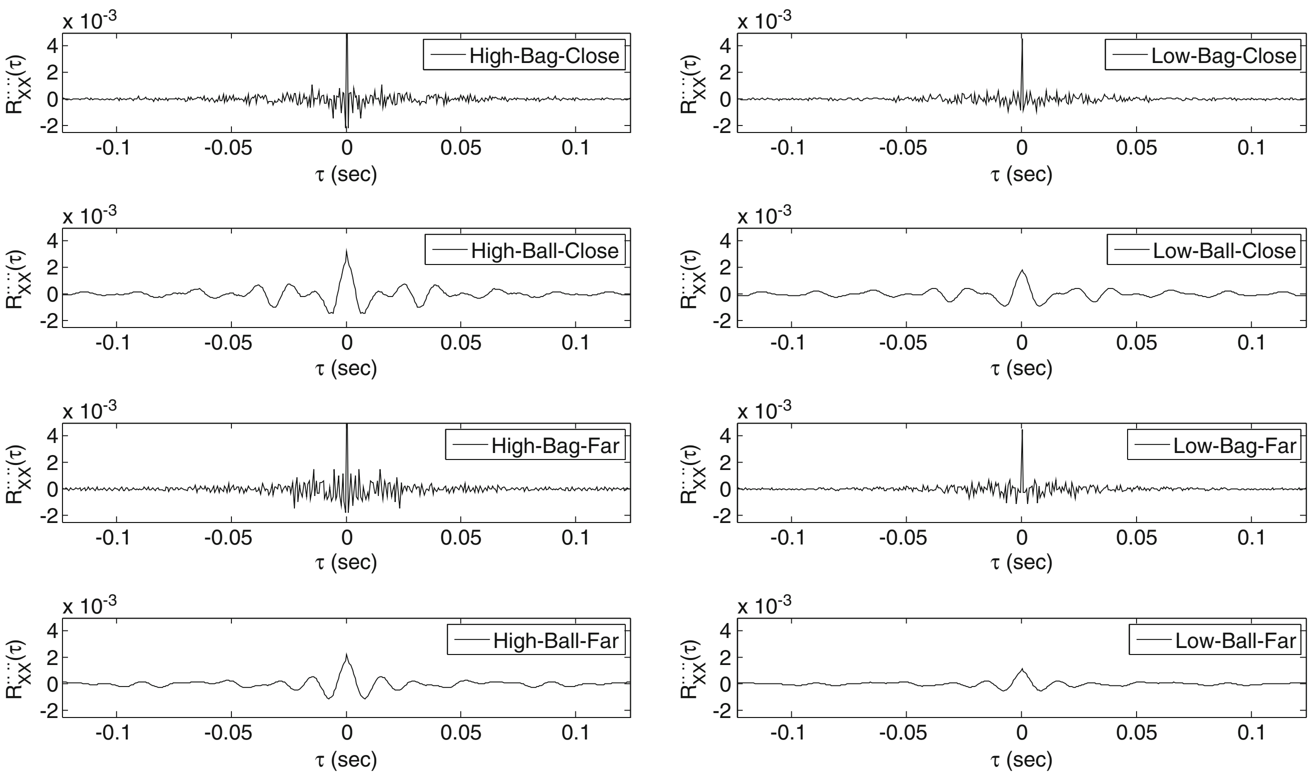

Fig. 16.4 Reference signals

Table 16.2 Statistical summary of response for DTW

Run	Factors			DTW × (10^4)		
	Height	Type	Distance	Mean	Median	Standard deviation
1	High	Bag	Close	0.6269	0.3332	1.0072
2	Low	Bag	Close	0.3607	0.1271	0.7939
3	High	Ball	Close	0.0224	0.0191	0.0119
4	Low	Ball	Close	0.0105	0.0095	0.0055
5	High	Bag	Far	1.2080	0.6511	1.4445
6	Low	Bag	Far	0.4573	0.1475	1.4092
7	High	Ball	Far	0.0107	0.0061	0.0118
8	Low	Ball	Far	0.0029	0.0021	0.0040

16.6 Post processing of Results

Factorial analysis is performed to study which of the factors considered (e.g. distance to the sensors, height, and type of object) have the biggest effect in the use of DTW for classification. The effect of factors and all their possible combinations are studied. The raw DTW metrics, obtained from comparison of autocorrelation of signals with reference signals, did not comply with the assumptions (normality of errors and homogeneity of variance) for factorial design. Therefore the Box-Cox method is used to transform the DTW results and perform the analysis. The response (y) is transformed as follow:

$$Y = \begin{cases} \frac{y^{\lambda}-1}{\lambda} & \lambda \neq 0 \\ \ln y & \lambda = 0 \end{cases} \tag{16.2}$$

The power transformation parameter was found to be $\lambda = -0.12$ using maximum likelihood. Both equation shown in (2) provide a similar transformation since λ is close to Zero. Therefore, the transformation $Y = \ln(y)$ was used because of its simplicity. Since insignificant effects are expected to have a Gaussian distribution. Any effect far from a straight line can be considered as a significant effect.

Figures 16.5 and 16.6 show the normal plot and cube plot respectively. Cube plot shows fitted values of different combination on a cube. Numbers (1) and (−1) show level 1 and level 2 respectively (Table 16.1). There is a considerable change in values when type changes from bag to basketball. Figure 16.6 shows effects and their combinations on a normal paper. It indicates that 'Type' is the most significant effect, and response is decreases when 'Type' changes from ball to bag. Another significance effect is interaction of 'height' and 'type.'

16.7 Conclusion

Falls is one of the main causes for accidental hospitalization in elder populations. Monitoring structural vibrations has the potential to be an environmental monitoring method to detect these falls and send the appropriate medical help. Classifying signals becomes fundamental to determine if a person has fallen or any other event has occurred. This paper presents a factorial analysis to identify the most important factors when using the Dynamic Time Warping technique for signal classification. The results show that distance between the location of impact and the sensor location has little effect in the classification. In addition, the magnitude of the impact, simulated by the height in which an object is released had little importance on the methodology. The type of object used to strike the floor was the only important parameter of those studied. These results indicate that the potential of using structural vibration for the identification of human falls.

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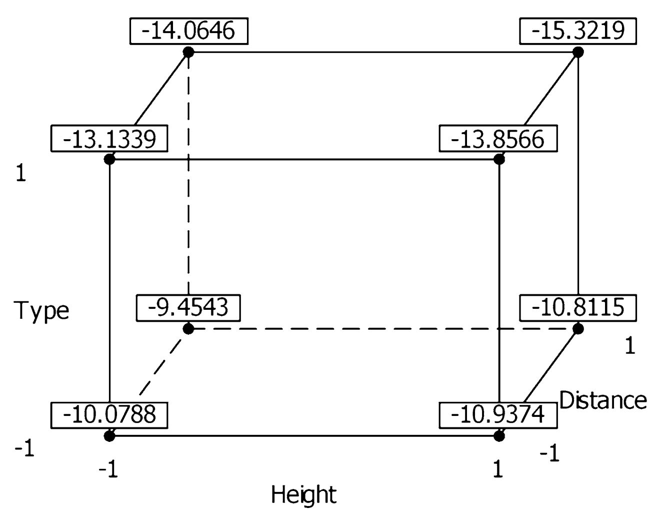

Fig. 16.5 Cube plot of mean value of transformed data

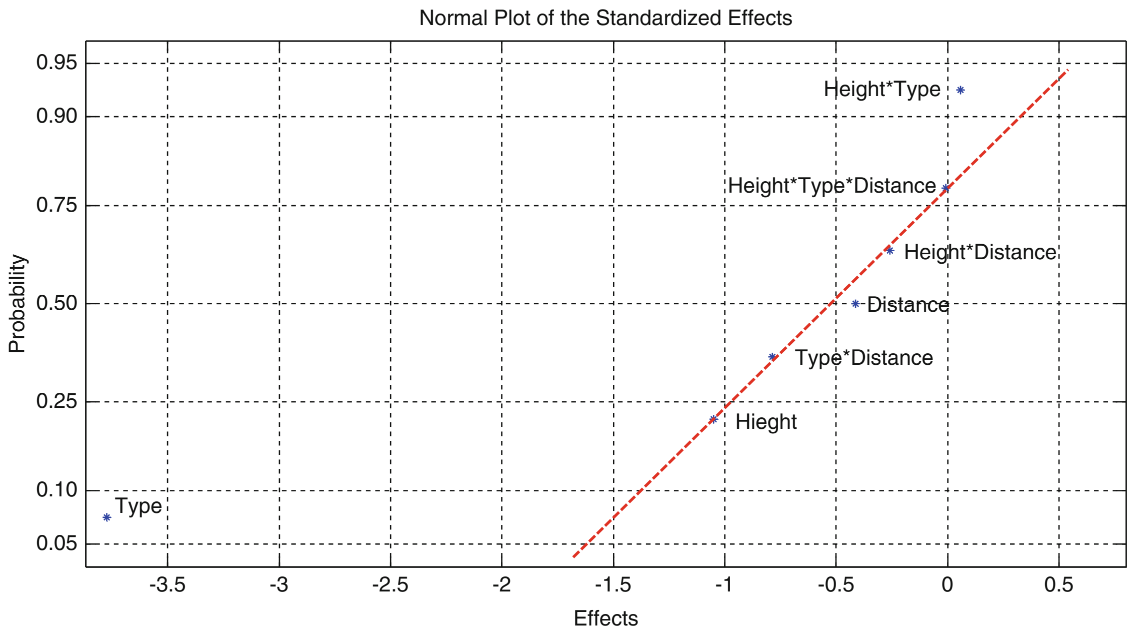

Fig. 16.6 Normal plot of effects for transformed DTW

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