A Time Series Classification Approach for Motion Analysis Using Ensembles in Ubiquitous Healthcare Systems

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Abstract. Human motion analysis is a vital research area for healthcare systems. The increasing need for automated activity analysis inspired the design of low cost wireless sensors that can capture information under free living conditions. Body and Visual Sensor Networks can easily record human behavior within a home environment. In this paper we propose a multiple classifier system that uses time series data for human motion analysis. The proposed approach adaptively integrates feature extraction and distance based techniques for classifying impaired and normal walking gaits. Information from body sensors and multiple vision nodes are used to extract local and global features. Our proposed method is tested against various classifiers trained using different feature spaces. The results for the different training schemes are presented. We demonstrate that the proposed model outperforms the other presented classification methods.

Keywords: human motion analysis, time series classification, multiple classifier systems.

1 Introduction

Human health monitoring continues to be an increasingly active research area. Ubiquitous healthcare systems provide information necessary to recognize emerging physical problems. This is useful for monitoring and controlling the elderly and chronically ill patients inside their homes [1]. In general, human activity can be captured within a home environment. This can automatically provide an online analysis of the user's health status [2]. One of the most promising health care areas is human motion analysis. Understanding user walking patterns and identifying changes in everyday behavior can reveal the onset of adverse health problems. Moreover, capturing walking abnormalities is important for assessing people who may have a greater risk of falling [3]. A set of sensors is used to capture information of human activity patterns. Recognizing various activities requires different sensors at different locations and time. Among sensors that are helpful in context recognition tasks are Body Sensor Networks and Visual Sensor Networks. Body Sensor Networks (BSNs) are wireless wearable sensors that capture continuous data over extended periods of time [4].

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BSNs can be easily worn with minimal inconvenience. Wearable sensors prove to be helpful in health monitoring of patients in ambulatory settings [5,6] and in measuring gait parameters [7,8]. Visual Sensor Networks (VSNs) are ambient sensors that contain a number of low cost vision sensor nodes [9]. Information computed from distributed multiple vision nodes can monitor the movement of human body.

In this paper we address the problem of human motion analysis from a time series perspective. Sensor data is a typical form of time series observations captured along a period of time. We propose a new methodology for classification of human motion activity by retaining the temporal aspect found in sensor captured measurements. The proposed architecture performs automated differentiation between impaired and normal walking gaits. Real time motion monitoring and recognition is implemented for gait analysis. The objective is to identify walking patterns for unseen individuals using a training set of different subjects. We previously tested the model on character and sign language recognition applications and produced satisfactory results [10].

The proposed model uses multiple classifiers to integrate feature and distance based methods extracted from body sensor and multiple vision nodes. The aim of this study is to investigate the different classifier integration methods for the problem of human motion analysis. Different types of local and global features are explored. Our model is mainly though for real time classification, however we also investigate the performance in an offline setting and discuss impact of preprocessing and feature effectiveness in this case.

The data set used represents information captured by an ear worn body sensor node and four wireless cameras. A home care environment is simulated to record motion information for different targets.

The paper is organized as follows: The following section highlights important background related to human motion analysis, time series classification and multiple classifier systems. Section 3 presents the proposed ensemble. Section 4 introduces the data set, experimental setup and results. The discussion is presented in section 5. The final section concludes the paper and discusses future work.

2 Background

2.1 Human Motion Analysis

The process of human motion analysis can be classified into three parts: human detection, tracking and behavior recognition [11]. In this work, we are concerned with human behavior understanding. Most techniques for activity recognition using sensor data follow a number of steps [12]: First the captured signal is divided into windows. The windowing technique segments the signal sequentially into smaller parts with or without overlap [13-16]. The second step is to extract features from each window. These features should be able to discriminate between different classes of action. Widely used features include mean, variance, entropy, energy, skewness and kurtosis [16-20]. Also the frequency content of a signal is analyzed using extracted frequency domain features. Some of these features such as the fast Fourier transform entropy can be used to differentiate between actions with highly varying acceleration patterns [13].

Finally, the generated features are used as input to a classification process. The last step is applying a classification algorithm to distinguish between different human activities. Comparisons of different classifiers for activity recognition are found in [13] and [21].

2.2 Time Series Classification

Time series data is a sequence of observation values ordered with respect to time in ascending order [22]. Time series analysis studies the structural dependencies between the observations. Among the challenging tasks in time series analysis is time series classification. Similar to conventional supervised classification, each series is associated with a class label. During training phase, examples of series with known classes are presented. The goal is to learn patterns and assign unlabeled time series into predefined classes.

Three main approaches are used along the literature for time series classification; distance based methods, feature extraction followed by a classification method, and finally model based classification [23]. In the distance based method approach a distance function is used to define the similarity between time series data [24]. Many methods have been proposed to define similarity between time series data. Some of these techniques are listed in [24]. The most widely popular techniques are Euclidean distance (ED) and Dynamic Time warping (DTW) [25]. Another approach for time series classification is transforming the observations into a feature vector thus allowing the usage of a conventional pattern recognition scheme [26,27]. Global and local features are extracted from each time series sample. These features represent the global characteristics and the temporal aspect of a time series respectively [26]. Other methods include classifying time series using modeled based algorithms such as Recurrent Neural Networks (RNN) [28,29] and Hidden Markov Models (HMM) [30].

The field of Multiple Classifier Systems (MCS) has attracted great interest in pattern recognition research. The main objective is based on the continuous need for improving the classification accuracy. The idea of MCS is combining learners to generate more precise results than individual classifiers [31]. The decision aggregation is dependent on using competitive experts as single classifier, and combining their different predictions to provide complementary information about the problem. MCS works best when base classifiers produce accurate and diverse results [32].

3 Proposed Ensemble Model

A multiple classifier systems approach is proposed for human motion recognition using time series analysis. The proposed architecture is a two layer ensemble; it combines classifiers trained with different features and distance measures. The decision fusion is performed using a trainable combiner that learns the class from the outputs of classifiers in the first layer.

Figure 1 shows the model architecture. Initially three base classifiers are trained independently with a different set of features. The first classifier is trained using local features while the second classifier is trained using global features. The third classifier is a K Nearest Neighbor classifier with Dynamic Time Warping similarity distance function. Next, a fusion layer is trained to perform mapping of the classifiers' outputs into the set of desired class labels.

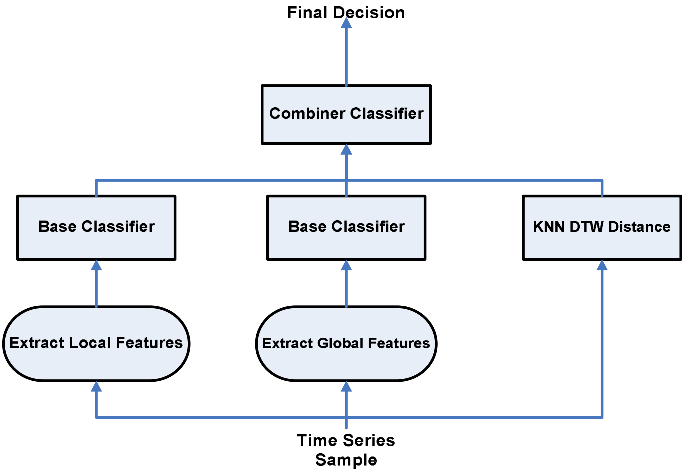

Fig. 1. Ensemble Architecture Block Diagram

The success of the ensemble depends on the use of different models and feature spaces for training the base classifiers. This provides complementary and diverse information about each subject's walking pattern. The model captures differing information from sensors, and uses them to train individual classifiers to produce independent errors. The outputs of the three base classifiers are used as training data for the fusion classifier to make an improved estimate of the activity pattern. The combiner classifier is adaptive enough to learn the weights of different classifiers and the best combination of base classifiers' decisions. As follows we present the details of the proposed ensemble model.

3.1 Feature Extraction

The precision of the classification process is highly related to the selection of attributes. Both local and global features are used in order to capture the fundamental trends in the motion activity. Each type will represent a different aspect of the structure of patterns, thus generate accurate approximations.

Local features are features extracted from interval regions of a time series [33]. Sliding time windows are used to divide the sensor signals into segments. A sliding window covers a small portion and moves along the series, extracting a set of features from each window. The number of windows varies from a time series to another. For time series T, a sliding window W^J is moved along the series dividing it into parts $T(i)_{i=1}^{I}$ for each window$W^j, j = 1, \ldots J$. Starting from the first observation, the sliding window extracts the features until the whole time series is covered. This method will reveal temporal information in BSN and VSN sequences. Spikes, edges or sudden abrupt changes in time domain of a walking pattern are defined. Local features extracted are the average of raw values, minimum, maximum, amplitude and standard deviation.

Global features are based on the global characteristics and information of the whole time series instead of the temporal property [26]. Global features give a measure of the overall properties of a subject's complete walking activity. By following the general trend of the entire movement, valuable gait information is extracted. This information is not affected by the contrasting sub regions in the pattern. Each sequence is analyzed independently and also the association between different series is examined. The total distance covered by each time series is calculated. Also we compute the Euclidean distance between each pair of series, the minimum and maximum of each attribute and the mean of each sequence.

3.2 Similarity Measure

Dynamic time warping (DTW) [25] is an algorithm that measures the similarity among sequences of data. The algorithm computes the best alignment between two walking patterns that can be of different length. DTW can find the likeness between sequences that are warped non-linearly in time dimension. Unlike Euclidean distance, if two similar gait measurements are not exactly timely aligned, DTW algorithm can map them to the same class. In other words, the algorithm is able to examine two series very much like the way humans may compare and recognize the similarity between them.

The DTW algorithm can be formulated as follows:
Given two sequences X and Y of length m and n respectively:

$$X = x_1, x_2, \dots, x_m \quad Y = y_1, y_2, \dots, y_n$$

The goal is to find a path which minimizes the total distance between the two sequences.
The sequences are used to form a matrix M of size [m, n]. Each cell in M denotes an alignment between elements $x_i \in X$ and $y_j \in Y$ where:
$0 \leq i < m \; and \; 0 \leq j < n$
This alignment is denoted by the squared distance between the points x_i and y_j.

$$d(x_i, y_j) = (x_i - y_j)^2$$

The matrix is searched to find an optimal distance path W between the two sequences.

$$W = w_1, w_2, \dots, w_K$$

Each $w_k$corresponds to a d(i, j) point in the matrix M. The optimal path is the one that minimizes the distance:

$$DTW(X, Y) = \min[\sum_{k=1}^{K} (w_k)]$$

Where (w_k) is the k^{th} matrix element in the warping path W.

Dynamic programming is used to find the minimal warping path W. Dynamic Programming divides the problem into sub problems, and uses the solutions repeatedly to solve the original problem [34].
The path is discovered using the following recurrence:

$$\gamma(i,j) = d(i,j) + \min\{\gamma(i-1,j-1), \gamma(i-1,j), \gamma(i,j-1)\}$$

For each element in the matrix d(i,j), the three adjacent elements are examined, and the minimum cumulative distance $\gamma(i,j)$ is selected in a recursive way.

The proposed ensemble uses KNN classifier with DTW algorithm applied as a similarity measure. When minimal distance is found between a given sequence and a class label, the pattern is assigned to this particular label. A warping path is calculated between each series in the training data and in the test sequence. An unknown input pattern is compared to all labeled series. The classification is based on ranking the labeled instances by their similarity measure to the unlabeled pattern.

3.3 Ensemble Fusion

The fusion layer for the architecture is a classifier which adaptively combines the outputs of the three classifiers to produce the final class label. The fusion classifier is trained on a separate data set that has not been used to train the base classifiers. This means that a training set is used to build the base classifiers, and a validation set is used to train the combiner classifier using the outputs from the base classifiers as features. This two layered ensemble architecture allows the combiner classifier to learn the mapping between the labels produced from the base classifiers and the desired class labels. Since the base classifiers are trained using different feature spaces, each classifier makes different mistakes and produces independent errors. Thus, the trainable combiner learns the different outputs of each classifier (including their individual errors). After training level one and two of the architecture, a separate test set is used to evaluate the classification process.

4 Data and Experiments

4.1 Data Set

The data set represents motion information of different targets. It is obtained from [35] and experiments were carried out in a lab-based home monitoring environment. The data set contains accelerometer information from a wearable body sensor and information from multiple vision nodes. The cameras simulate visual information from vision sensor nodes by capturing and sending images at 10 frames per second. The proposed framework in [35] employs ubiquitous sensing to acquire non redundant, complimentary features for improved motion analysis. The data set consists of two classes; impaired walking (limping) and normal walking patterns. Ten subjects are used, and for each subject four different examples for each limping and walking patterns are recorded.

4.2 Setup and Results

Data from body and visual sensors are captured in frames per second. Thus information from each sensor is considered a time series sample. The temporal aspect in the measured data is used to build the classification model. A set of experiments are carried out for evaluating the proposed model. Experiments are performed for real time and offline motion classification.

For the DTW approach, data abstraction is performed for reducing the size of the input time series. This helps in speeding up the algorithm. The time series is reduced and the warping path is found by DTW on lower resolution time series. Each pair of adjacent observations in the series is averaged, this way the size is reduced by the factor of two every time resolution is decreased.

In the first experiment we test the efficiency of our proposed ensemble compared to conventional single classification techniques using both local and global features. The effect of these features on classification accuracy is analyzed. In this experiment, our objective is real time classification; to recognize the motion pattern instantly. We also test the impact of different sensor nodes on motion analysis and present the results for training with BSN and VSN data. Next we explain the set up for the first experiment followed by the results.

The following single classifiers are used: support vector machines, decision trees, K - Nearest Neighbor and naïve bayes classifiers. As for the proposed ensemble, it's diversity depends on the different feature representations. Two base classifiers are trained using local and global features, and a KNN classifier that uses DTW as the similarity measure. To train the combiner classifier the output labels from the base classifiers are used as features. These features along with the actual labels from the training set are the input to the second fusion layer. Support vector machine classifier with polynomial kernel is used for combination due to its generalization capability. WEKA [36] is used for our implementation. All experiments are conducted using leave one out method. The classification accuracy of the proposed framework is tested using unseen subjects.

A window of three seconds is used for training. This decreases the delay, and also increases the number of training samples used in classification, since each subject's recordings are divided into many training samples, three seconds each. We test whether the time series model can represent the short window well enough to recognize the subject's motion pattern. Global features are extracted from the whole motion sample. Windows representing one second each are defined concurrently, these windows are used to extract local features.

Below are the findings of the first experiment. Tables 1 and 2 present the results for classification using BSN and VSN respectively. The tables demonstrate the results for classification using local and global features. Also, the accuracy of the proposed ensemble architecture (section 2) is presented. The mean and standard deviation for the different classification accuracies are shown.

Table 1. Percentage accuracy for single classifiers and proposed ensemble - BSN data set – real time experiments

Single Classifiers	Local Features	Global Features
Naïve Bayes	72.03% ±8.42	84.78% ±2.11
Decision Tree	78.89% ±6.34	81.20% ±2.53

Table1. (*Continued*)

KNN	80.01% ±3.52	92.94% ±1.90
SVM	**80.66% ±3.54**	**93.94% ±0.9**
Proposed Ensemble	***96.48±0.47***	

Table 2. Percentage accuracy for single classifiers and proposed ensemble - VSN data set – real time experiments

Single Classifiers	Local Features	Global Features
Naïve Bayes	74.64±12.76	81.45±1.89
Decision Tree	79.34±10.40	93.75±0.9
KNN	84.2±9.48	93.23±0.89
SVM	**86.43±8.58**	**94.11±0.88**
Proposed Ensemble	***98.48±0.52***	

In general, results reveal that using global features outperforms local features. Additionally, Support Vector Machine is the winning 'single' model using local and global features for both data sets. As for the sensor recordings, training using BSN and VSN data yield similar results. We should note that the result of training single classifiers using both BSN and VSN data yields close results to when only BSN data is used. Finally, the proposed ensemble architecture outperforms the performance of single classifiers. The classification is improved significantly by combining feature and distance based techniques and introducing the trainable fusion layer.

The second experiment is presented next. To verify the usefulness of our approach, we test offline classification using the whole sensor recordings. In some applications it is useful to use the whole subject's motion pattern as input data, this provides more information about the motion pattern, but does not allow online classification. Similar to real time classification, smaller windows are moved along each sensor recording to extract the local features. The number of windows varies for each series under consideration; and depends on the number of instances produced from each subject's recordings.

Table 3. Percentage accuracy for single classifiers trained using different features – BSN and VSN combined – offline experiments

Single Classifiers	Local Features	Global Features
Naïve Bayes	91.78±6.2	**85.34±4.81**
Decision Tree	**93.52±5.95**	81.89±7.29
KNN	89.65± 7.23	76.72±9.25
SVM	90.89±6.11	84.91±5.29

Table 3 shows the accuracies of single classifiers trained using local and global features from both sensors. Here, global features are clearly performing worse in offline experiments than in real time results. The table also indicates that Decision Tree produces best results for local features while Naïve Bayes outputs the best results for global features. This is different from previous experiments where Support Vector Machines outperformed other single classifiers.

Finally, studies have indicated the need for preprocessing the data before classification [35]. In the next experiment we evaluate the usefulness of preprocessing. We note that the preprocessing is performed for the offline experiment, which makes this step unsuitable for real time continuous classification.

The average and variance of the signals are used as features instead of the raw data. For each sensor signal, a time window of size 4 seconds and a step of one eighth of a second are used to calculate the average and variance of each time series. The average and variance of the features from the four cameras and from the BSN node are augmented together to form the feature vector used for classification.

Consistent with the previous experiments, the results of training using individual sensors is not different from combining them together. We choose to present the result of concatenating BSN and VSN data. Below are the results for single classifiers using data from both sensors.

Table 4. Percentage accuracy for single classifiers trained using different features – BSN and VSN combined – offline experiments- with preprocessing

Single Classifiers	Local Features	Global Features
Naïve Bayes	**100.00±0.00**	91.25±13.93
Decision Tree	**100.00±0.00**	**95.00±10.05**
KNN	97.50±7.54	77.00±20.93
SVM	**100.00±0.00**	92.25±14.08

Table 4 presents the results for training single classifiers using the offline recognition scheme. Most classifiers trained using local and concatenated features achieve accuracies close to 100%. Also, in this experiment the local features produce better results than global features for all classifiers. This result will be further analyzed in the discussion section. The table displays the results for using both BSN and VSN data combined. The K Nearest Neighbor yields worse results than other three single models using local features.

5 Discussion

The results show that the proposed ensemble architecture outperforms the single classification methods in case of real time experiments. The classification is improved because of the multiple representation of information extracted from each sensor.

In particular, the classification is boosted by combining feature and distance based techniques and introducing the trainable fusion layer. The combiner classifier can effectively learn the errors of the base classifiers. The choice of diverse base classifiers produces independent errors and the process of aggregating the decisions results in better accuracy.

It is worth noting that our experiments reveal that there is a relation between the time series length and the impact of both local and global feature vectors. As the size of the data set decreases the global features become more effective than the local features. This happens because as the width of the local feature windows decreases, the features become less meaningful and do not truly discriminate among the extracted subsets, thus the trained model is unable to describe the classes at hand. To illustrate this observation, we note that the offline experiments are performed with the whole data series, while the real time experiments use a shorter window. In offline experiments, local features seem to outperform global features since the temporal aspect is fully maintained in the time series data. Alternatively, in the real time experiments, when only a significantly smaller portion of the series is used for training, global features have better impact on classification accuracy over other features.

Combining the two sensor data together does not boost the accuracy of classifiers. There is no significant difference over the results using BSN or VSN individually.

It is clear that classification accuracy increases significantly when preprocessing the data before classification instead of using the raw series. The processed values provide more useful information about the motion pattern over the individual samples.

6 Conclusion and Future Work

The focus of this work is using pattern recognition techniques to analyze human motion patterns and classify an unknown motion sequence. In this paper, an efficient multiple classifier design is proposed. The ensemble is capable of recognizing the difference between normal and impaired walking gaits. We show the results for training classifiers using local and global features extracted from sensor data. Future work includes speeding up the distance calculations for reducing the computational cost of real time experiments [37]. Also we are going to analyze the effect of different components of the ensemble on the results and compare it to other techniques such as Recurrent Neural Networks. Also the dataset will be extended to cover a wider range of subjects. Finally, the proposed method is intended to be tested in a wider range of applications in the ubiquitous computing field, such as activity recognition.

References

1. Aziz, O., Atallah, L., Lo, B., ElHelw, M., Wang, L., Yang, G.Z., Darzi, A.: A pervasive body sensor network for measuring postoperative recovery at home. Surgical Innovation 14(2), 83–90 (2007)
2. Lukowicz, P., Anliker, U., Ward, J., Tröster, G., Hirt, E., Neufelt, C.: Amon: A wearable medical computer for high risk patients. In: 2012 16th International Symposium on Wearable Computers, p. 0133. IEEE Computer Society (October 2002)
3. Gurley, R.J., Lum, N., Sande, M., Lo, B., Katz, M.H.: Persons found in their homes helpless or dead. New England Journal of Medicine 334(26), 1710–1716 (1996)
4. Yang, G.Z., Yacoub, M.: Body sensor networks (2006)
5. Jovanov, E., Milenkovic, A., Otto, C., De Groen, P.C.: A wireless body area network of intelligent motion sensors for computer assisted physical rehabilitation. Journal of Neuro Engineering and Rehabilitation 2(1) 6 (2005)
6. Istepanian, R.S., Jovanov, E., Zhang, Y.T.: Guest editorial introduction to the special section on m-health: Beyond seamless mobility and global wireless health-care connectivity. IEEE Transactions on Information Technology in Biomedicine 8(4), 405–414 (2004)

7. Bamberg, S.J.M., Benbasat, A.Y., Scarborough, D.M., Krebs, D.E., Paradiso, J.A.: Gait analysis using a shoe-integrated wireless sensor system. IEEE Transactions on Information Technology in Biomedicine 12(4), 413–423 (2008)
8. Ramachandran, R., Ramanna, L., Ghasemzadeh, H., Pradhan, G., Jafari, R., Prabhakaran, B.: Body sensor networks to evaluate standing balance: interpreting muscular activities based on inertial sensors. In: Proceedings of the 2nd International Workshop on Systems and Networking Support for Health Care and Assisted Living Environments, p. 4. ACM (June 2008)
9. Akyildiz, I.F., Melodia, T., Chowdhury, K.R.: A survey on wireless multimedia sensor networks. Computer Networks 51(4), 921–960 (2007)
10. Salaheldin, R., El Gayar, N.: Multiple Classifiers for Time Series Classification Using Adaptive Fusion of Feature and Distance Based Methods. In: UKCI 2011, p. 114 (2011)
11. Aggarwal, J.K., Cai, Q.: Human motion analysis: A review. In: IEEE Proceedings of the Nonrigid and Articulated Motion Workshop, pp. 90–102. IEEE (June 1997)
12. Preece, S.J., Goulermas, J.Y., Kenney, L.P., Howard, D., Meijer, K., Crompton, R.: Activity identification using body-mounted sensors—a review of classification techniques. Physiological Measurement 30(4), R1 (2009)
13. Bao, L., Intille, S.S.: Activity recognition from user-annotated acceleration data. In: Ferscha, A., Mattern, F. (eds.) PERVASIVE 2004. LNCS, vol. 3001, pp. 1–17. Springer, Heidelberg (2004)
14. Ge, X., Smyth, P.: Segmental semi-markov models for endpoint detection in plasma etching. IEEE Transactions on Semiconductor Engineering (2001)
15. Huynh, T., Schiele, B.: Analyzing features for activity recognition. In: Proceedings of the 2005 Joint Conference on Smart Objects and Ambient Intelligence: Innovative Context-Aware Services: Usages and Technologies, pp. 159–163. ACM (October 2005)
16. Kern, N., Schiele, B., Schmidt, A.: Multi-sensor activity context detection for wearable computing. In: Aarts, E., Collier, R.W., van Loenen, E., de Ruyter, B. (eds.) EUSAI 2003. LNCS, vol. 2875, pp. 220–232. Springer, Heidelberg (2003)
17. Thiemjarus, S.: A device-orientation independent method for activity recognition. In: 2010 International Conference on Body Sensor Networks (BSN), pp. 19–23. IEEE (June 2010)
18. Atallah, L., Lo, B., King, R., Yang, G.Z.: Sensor placement for activity detection using wearable accelerometers. In: 2010 International Conference on Body Sensor Networks (BSN), pp. 24–29. IEEE (June 2010)
19. Heinz, E.A., Kunze, K.S., Sulistyo, S., Junker, H., Lukowicz, P., Tröster, G.: Experimental evaluation of variations in primary features used for accelerometric context recognition. In: Aarts, E., Collier, R.W., van Loenen, E., de Ruyter, B. (eds.) EUSAI 2003. LNCS, vol. 2875, pp. 252–263. Springer, Heidelberg (2003)
20. Zheng, Y., Wong, W.K., Guan, X., Trost, S.: Physical Activity Recognition from Accelerometer Data Using a Multi-Scale Ensemble Method. In: IAAI (July 2013)
21. Ravi, N., Dandekar, N., Mysore, P., Littman, M.L.: Activity recognition from accelerometer data. In: AAAI, vol. 5, pp. 1541–1546 (July 2005)
22. Palit, A.K., Popovic, D.: Computational intelligence in time series forecasting: theory and engineering applications. Springer (2006)
23. Xing, Z., Pei, J., Keogh, E.: A brief survey on sequence classification. ACM SIGKDD Explorations Newsletter 12(1), 40–48 (2010)
24. Wang, X., Mueen, A., Ding, H., Trajcevski, G., Scheuermann, P., Keogh, E.: Experimental comparison of representation methods and distance measures for time series data. Data Mining and Knowledge Discovery 26(2), 275–309 (2013)

25. Berndt, D.J., Clifford, J.: Using Dynamic Time Warping to Find Patterns in Time Series. In: KDD Workshop, vol. 10(16), pp. 359–370 (1994)
26. Dietrich, C., Schwenker, F., Riede, K., Palm, G.: Classification of bioacoustic time series utilizing pulse detection, time and frequency features and data fusion, pp. 2001–2004. Univ., Fak. für Informatik (2001)
27. Ghosh, J., Beck, S.D., Chu, C.C.: Evidence combination techniques for robust classification of short-duration oceanic signals. In: Aerospace Sensing, pp. 266–276. International Society for Optics and Photonics (August 1992)
28. Elman, J.L.: Finding structure in time. Cognitive Science 14(2), 179–211 (1990)
29. Williams, R.J., Zipser, D.: A learning algorithm for continually running fully recurrent neural networks. Neural Computation 1(2), 270–280 (1989)
30. Rabiner, L.: A tutorial on hidden Markov models and selected applications in speech recognition. Proceedings of the IEEE 77(2), 257–286 (1989)
31. Kuncheva, L.I.: Combining pattern classifiers: methods and algorithms. John Wiley & Sons (2004)
32. Kittler, J., Hatef, M., Duin, R.P., Matas, J.: On combining classifiers. IEEE Transactions on Pattern Analysis and Machine Intelligence 20(3), 226–239 (1998)
33. Dietrich, C., Palm, G., Riede, K., Schwenker, F.: Classification of bioacoustic time series based on the combination of global and local decisions. Pattern Recognition 37(12), 2293–2305 (2004)
34. Sakoe, H., Chiba, S.: Dynamic programming algorithm optimization for spoken word recognition. IEEE Transactions on Acoustics, Speech and Signal Processing 26(1), 43–49 (1978)
35. ElSayed, M., Alsebai, A., Salaheldin, A., El Gayar, N., ElHelw, M.: Body and Visual Sensor Fusion for Motion Analysis in Ubiquitous Healthcare Systems. In: 2010 International Conference on Body Sensor Networks (BSN), pp. 250–254. IEEE (June 2010)
36. Hall, M., Frank, E., Holmes, G., Pfahringer, B., Reutemann, P., Witten, I.H.: The WEKA data mining software: An update. ACM SIGKDD explorations newsletter 11(1), 10–18 (2009)
37. Xi, X., Keogh, E., Shelton, C., Wei, L., Ratanamahatana, C.A.: Fast time series classification using numerosity reduction. In: Proceedings of the 23rd International Conference on Machine Learning, pp. 1033–1040. ACM (June 2006)