10

Sensor Fusion-Based Activity Recognition for Parkinson Patients

Majid Bahrepour, Nirvana Meratnia,
Zahra Taghikhaki and Paul J. M. Havinga
*Pervasive Systems Group, University of Twente,
Netherlands*

1. Introduction

Parkinson disease (PD) is a slow destructive disorder of the central nervous system in which dopamine, i.e., catecholamine neurotransmitter in the central nervous system is lost. PD hurts patients' movement and speech ability. Sometimes, it can also affect patients' mood, behavior, and thinking ability. Falling down is a common problem in PD patients and on time fall detection is important to assist PD patients and prevent them from being injured. To this end, being able to correctly distinguish various activities, e.g. walking, sitting, standing still, is a must. To monitor activities and moving patterns of PD patients, a wireless body sensor network (BSN) may prove to be useful. By attaching various wireless sensor nodes on the body of PD patients or integrating them into their shoes or cloths, their activities and physiological conditions can be checked regularly and an alarm can be generated in case of emergency or need for additional assistances.

A wireless body sensor network consists of a number of wireless sensor nodes that cooperatively monitor physical (e.g. motion) and physiological (e.g. heart rate) conditions of a person. In addition to sensors, each sensor node is typically equipped with a radio transceiver or other wireless communication devices, a small microcontroller as processing unit, and an energy source in a form of a battery. Sensor nodes may vary in size and type of sensors they are equipped with. Size and cost constraints on sensor nodes cause limitations on their resources in terms of energy, memory, and computational processing. Figure 1 shows an example of a body sensor network.

Previous studies for activity recognition of PD patients mostly use accelerometer and occasionally gyroscope sensors attached to various parts of patients' body (JJ., HA. et al. 1991; Aminian, Robert et al. 1999; JI., AA. et al. 2001; JI., V. et al. 2004; N., T. et al. 2004; White, Wagenaar et al. 2006; Moorea, MacDougalla et al. 2007; Salarian, Russmann et al. 2007). One of the main criticisms on the previous studies is that they use centralized techniques which not only require expensive equipments to monitor physiological conditions and activities of patients [e.g. Vitaport 3 (White, Wagenaar et al. 2006)] but also introduce delays in the detection process. Also due to having a single point of failure they are more prone to failures and crashes. In contrary, we propose a fusion-based distributed algorithm which can be easily implemented on resource constrained wireless sensor nodes and detect and distinguish activities in (near) real-time. Our approach offers three main advantages: (i) distributed processing and reasoning which decreases the data processing time and provides fast activity detection and classification, (ii) robustness against sensors failure, and (iii) accurate detection through use of sensor fusion.

Fig. 1. An example of a body sensor network.

Our approach is based on implementing classification techniques on wireless sensor nodes attached to patients' body, online evaluation of the classification results on individual nodes, and fusing results of various nodes to resolve possible conflicts between sensor nodes and reach a consensus. Previously in (Bahrepour, Meratnia et al. 2009; Bahrepour, Meratnia et al. 2009; Bahrepour, Zhang et al. 2009; Bahrepour, Meratnia et al. 2010; Bahrepour, Meratnia et al. 2010; Bahrepour, van der Zwaag et al. 2010), we have shown capability of machine learning based classification techniques in distributed detection of environmental events such as fire. There is no reason to believe that classification techniques used in other domains are not applicable for medical domain. The challenge here, however, is twofold: (i) investigating capabilities of these classification techniques for a more complex data such as activity data, and (ii) being able to determine the most relevant sensor data among a large number of sensor types for a specific purpose, e.g., fall detection of PD patients. In what follows we address both challenges.

The organization of this paper is as follows. Section 2 provides an overview of the related work. Section 3 introduces the machine learning based classification and sensor fusion techniques that will be used in this study for the purpose of activity recognition. In section 4, our processing models are introduced, which will be followed by our proposed approach explained in Section 5. Section 6 describes the dataset and presents experimental results. Conclusions are drawn in Section 7 and the obtained results are discussed.

2. Related work

Related work on use of wireless body sensor network in medical domain can be generally classified into three groups:

i. those related to hardware platform design [e.g. (Kern, Schiele et al. 2003; Park, Liu et al. 2005; Lorincz, Kuris et al. 2007; Ying, Schlösser et al. 2008; Nabar, Banerjee et al. 2010)];
ii. those related to activity recognition methods and algorithms (Aminian, Robert et al. 1999; Veld, M.H.A. et al. 2005; Moorea, MacDougalla et al. 2007; Osmani, Balasubramaniam et al. 2007; Salarian, Russmann et al. 2007; Osmani, Balasubramaniam et al. 2008; Lee, Kim et al. 2009; Khattak, Vinh et al. 2010);
iii. those related to making the information flow between patients and medical team more efficient [e.g. (Centeno, Giachetti et al. 2003; Martinez-Garcia and Menndez-Olague 2003; Wijewickrama and Takakuwa 2006; Sanchez, Tentori et al. 2008)].

While the first group focuses on design and implementation of small, easy to wear, and cheap sensor node platforms equipped with a set of sensors, the second group focuses on design of computationally light signal processing, feature extraction, classification, and pattern recognition techniques. The focus of the third group is on providing timely information to the doctors in charge, reducing patients waiting time, and improving interaction between doctors and patients, etc.

The main objectives of performing activity recognition in medical domain are:

- Prevention (e.g., (Steele, Belza et al. 2003; Wu, Bui et al. 2008; Le and Pan 2009; Benocci, Tacconi et al. 2010)
- Rehabilitation (e.g., (Jarochowski, Shin et al. 2007; Soini, Nummela et al. 2008; Zhang and Sawchuk 2009)
- Assistance and care giving (e.g., (Hou, Wang et al. 2007; S. Bosch 2009)

To perform activity recognition usually the following steps are taken (Krishnan, Juillard et al. 2009; Avci, Bosch et al. 2010; Horst and Meratnia 2011):

- Sampling, which refers to the process of taking measurements from the body sensors. Success of this process heavily depends on robustness of the sensor node platform, radio communication, as well as availability of accurate timing.
- Preprocessing, which involves refining the sensor data. More specifically this step deals with noise reduction through for example filtering (Yun, Lizarraga et al. 2003) as well as signal transformation through use of for example Fourier transformation (Wu, Pan et al. 2009).
- Segmentation, which is the process of identification of beginning and end of an important feature in the sensor data stream. Segmentation can be performed manually, e.g., (Jafari, Li et al. 2007) or automatically, e.g., (Guenterberg, Bajcsy et al. 2007; Guenterberg, Ostadabbas et al. 2009).
- Feature extraction, classification, and pattern recognition, which refer to the process of giving semantic to the identified feature and identification of repeated patterns and trends. During feature extraction, time-domain, frequency-domain, or time-frequency domain features can be identified. Techniques such as neural network, Bayes network, hidden markov model, support vector machine, and decision trees are often used for the classification purpose.
- Pattern matching, which deals with comparing the identified patterns and features either with those identified on other nodes or with pre-defined templates.
- Feedback, which is the process of taking appropriate action based on output of classification.

For a more elaborate overview of state of the art on use of wireless body sensor networks in medical domain, reader is referred to (Abbate, Avvenuti et al. 2010; Avci, Bosch et al. 2010; Horst and Meratnia 2011).

3. Classification and fusion techniques

For the purpose of activity recognition and classification, we use Feed Forward Neural Network (FFNN), Naïve Bayes (NB), and Decision Tree (DT). For the purpose of sensor fusion, we use reputation-based voting and majority voting. In this section, we first provide a short explanation of the concepts used by these techniques.

3.1 Feed forward neural network (FFNN)

Feed forward neural network (FFNN) is a type of the neural network, in which each layer is fed by its back layer (Mehrotra, Mohan et al. 1996). FFNN consists of one input layer, one or more hidden layers and one output layer. The challenge faced in using FFNN as a classifier is finding correct weights. The process of finding these weights, which is called 'learning', can be carried out using algorithms such as gradient descent (GD) algorithm (Wikipedia ; ALPAYDIN 2004).

3.2 Naïve bayes classifier (NB)

A Naïve Bayes classifier uses Bayesian statistics and Bayes theorem to find the probability of each instance belonging to a specific class. It is called Naïve because of its emphasis on independency of the assumptions. Naïve Bayes classifier finds the probability of belongingness of each instant to a specific class.

3.3 Decision tress

A decision tree is a learning algorithm that uses tree-like graphs to model and evaluate discrete functions (Russell and Norvig 2003; ALPAYDIN 2004). Construction of a decision tree for classification purpose requires a training phase (ALPAYDIN 2004), which employs a set of data and a learning algorithm to find a minimum depth decision tree. The tree should contain the minimum required nodes (or minimum depth) to reduce time and memory complexities. Therefore, the training algorithm is usually a local search greedy algorithm to find an optimum decision tree (ALPAYDIN 2004). Once the decision tree is created, the tree can be used by evaluating nodes from the root down to the leaves. The final leaf contains a value that shows the result of the classification. After the decision tree is constructed in the learning phase, it can be pruned to save memory. Pruning is only required for large trees to alleviate computational complexity.

3.4 Reputation-based voting

Reputation based voting is a fusion technique that happens after classification. Once each classifying entity makes its individual decision about belogness of an instance to a class, a consensus needs to be reached among the classifying entities. Reputation-based voting approaches are based on finding reputation of individual classifying entity and choosing the decision made by the classifying entities having the highest reputation. Assuming that classifying entities have correctly classified instances, they should judge how well the other entities have performed the classification. To do the judgment, each entity first sends its classification result, called Detection Value (DV), to all other entities in its neighborhood. The DVs received from the neighbors will be stored in a table called Neighbors Detection Value Table (NDVT). In the next step, each entity should judge about its neighboring entity by considering itself as the reference. The judgment is accomplished by comparing the difference between value of entity itself and value of the other neighboring classifying entities. If the difference is less than a threshold value θ (which is chosen based on the context), the "judging" entity gives a positive vote ($V^{new} = V^{old} + 1$) to the other entities. Otherwise, the "being judged" entity receives a negative vote ($V^{new} = V^{old} - 1$). Finally, NDVT tables are sent to a voter to reach a consensus among different opinions. The challenging part of reputation-based voting is how to assign a global reputation value to each entity in order to choose high reputed entity and its classification result. There are various ways to do so, two of which are explained here:

3.4.1 Reputation technique 1

This reputation technique checks local reputation of every individual entity from the other entities' perspective. The local reputation value is obtained based on average value of V_i (positive or negative votes which were given by the other entities) for each classifying entity. Then, the average local reputation is multiplied by the weight of sensor nodes calculated using Equation 1 to assign global reputation values. The class with the highest reputation weight (W) is the result of the voting procedure. Equation 1 shows how the weights are calculated.

$$W_i = R_i \times Acc_i \tag{1}$$

where W_i is the reputation value corresponding to classifying entity i, R_i is the local reputation value of classifying entity i from other entities' perspective, and Acc_i is weight of classifying entity *i* (Bahrepour, Meratnia et al. 2010).

3.4.2 Reputation technique 2

In this reputation technique, two threshold values, i.e., θ_1, θ_2 are used. Comparing the local reputation value (R_i) with θ_1 and θ_2 gives an insight about how well classification is performed. If ($R_i \geq \theta_1$), then classifying entities have made perfect decisions, if ($\theta_1 > R_i \geq \theta_2$) then classifying entities have made OK decisions, and if ($\theta_2 \geq R_i$) then classifying entities have made poor decisions. We assign 0.5 to poor classification performance, 1 to normal classification performance, and 2 to perfect classification performance. Based on these values, this reputation technique uses Equation 2 to assign reputation to each classifying entity.

$$W_i = S_i \times Acc_i \tag{2}$$

where W_i is the reputation value corresponding to classifying entity i, S_i is obtained from Eq. 3, and Acc_i is weight of classifying entities (Bahrepour, Meratnia et al. 2010).

$$S_i = \begin{cases} 2 & if\ (R_i \geq \theta_1) \\ 1 & if\ (\theta_1 > R_i \geq \theta_2) \\ 0.5 & if\ (\theta_2 \geq R_i) \end{cases} \tag{3}$$

θ1 and θ2 are application dependant.

3.5 Majority voting

Majority voting is a simple voting technique, which selects the classification result obtained from majority of sensor nodes.

4. Classification models

In this section, we present our general classification models regardless of which classifier is being used for the classification purpose. For more information about properties of these models and their performance, reader is referred to (Bahrepour, Meratnia et al. 2009; Bahrepour, Meratnia et al. 2009).

4.1 Local classification model

Local model assumes that each sensor node performs classification individually without communicating and cooperating with others. Figure 2 illustrates processing model of local classification, which consists of (i) a number of sensors providing input to the classifier, (ii) the classifier, which is responsible for activity recognition and determining the belogness of each instance to an activity class, and (iii) classification output, which is called activity. One should note that not all sensor nodes need to have the same classifiers.

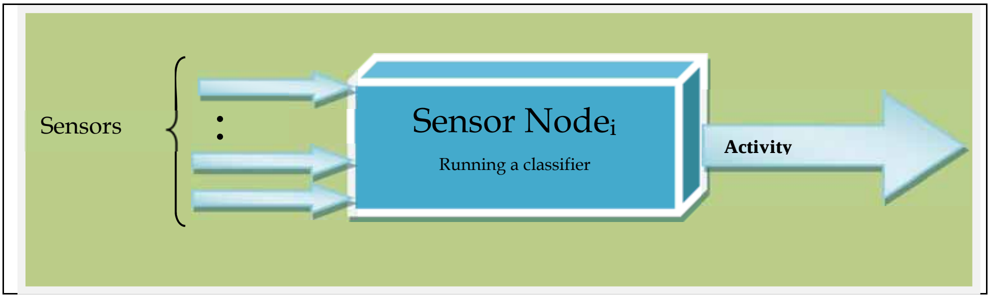


Fig. 2. Local classification model

4.2 Fusion-based classification model

The local approach is simple and works fine in situations, in which the sensor nodes are highly accurate and not prone to noises. However, generally speaking sensors, sensor nodes, and communication links are not always reliable and their failure is a common practice. Fusion-based classification model tolerates individual sensor and sensor node failures and involves more than one sensor node in the classification process. By doing so, it ensures that there are always some sensor nodes contributing to the classification process and compensating for the errors. The fusion-based approach uses the basic notions of the local approach and lets individual sensor nodes first classify and detect activities on their own. Then, the classification results are all sent to a fuser/ voter node (e.g., a cluster head) to reach a consensus. Figure 3 illustrates processing model of fusion-based classification. Similar to the local model, not all sensor nodes (including the fuser node) need to have the same classifiers.

In this study we use fusion-based classification model for activity recognition and investigate its performance by making use of various classifiers. Choice of classifier not only has direct effect on classification accuracy but also on complexity, as presented in the following sections.

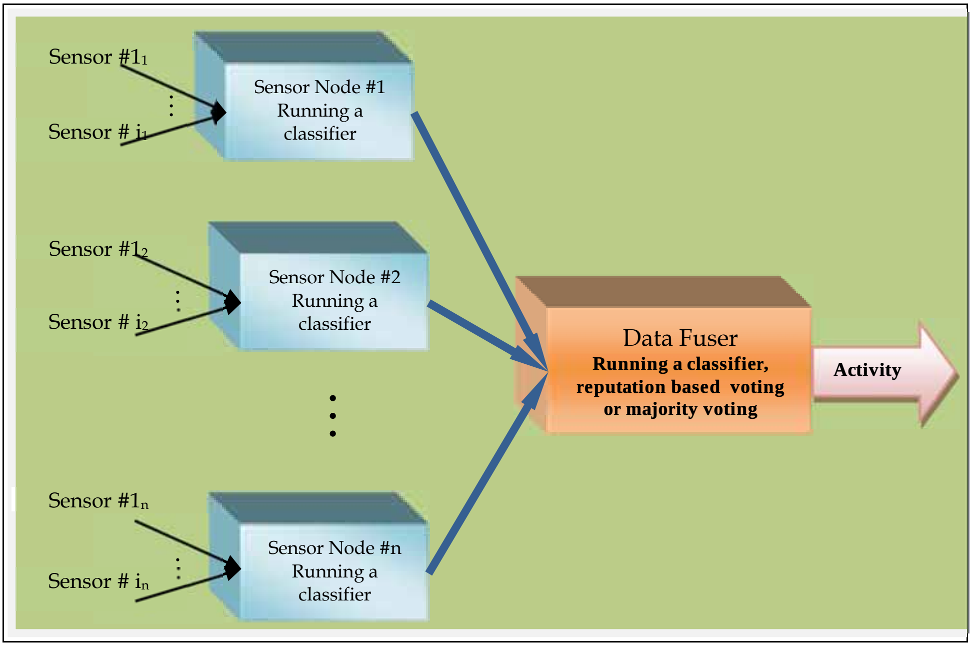


Fig. 3. Fusion-based classification model

4.3 Computational complexity consideration

4.3.1 Complexity of local model using FFNN and naïve bayes

Complexity of FFNN is function of m(number of features or number of nodes in the input layer),z (number of neurons in the hidden layer), and p(number of neurons in output layer). Equation 4 presents time complexity of FFNN in the local model (Bahrepour, Meratnia et al. 2009):

$$O_{FFNN} = O(m \times z \times p) \tag{4}$$

Complexity of Naïve Bayes is a function of m (number of features), c (number of classes), and j (number of partitions for distribution estimation). Equation 5 presents time complexity of Naïve Bayes classifier (Bahrepour, Meratnia et al. 2009) in the local model:

$$O_{NaiveBayes} = O(m \times c \times j) \tag{5}$$

Since training phase of FFNN and Naïve Bayes is conducted offline and only once, the computational complexity of training part can be disregarded.

4.3.2 Complexity of fusion-based model using FFNN and naïve bayes

When naïve Bayes or FFNN are used in the fusion-based model, the data-fuser has to wait till all classification results from the sensor nodes are available. In the worst case for n time duration (where, n is the number of sensor nodes involved in the classification process)

FFNN or naïve Bayes classifiers on sensor nodes run in parallel. In this case, computational complexities of classifiers running on the fuser and on the sensor nodes are added together. The computational complexities of the fusion-based model using FFNN and Naïve Bayes are presented by Equation 6 and Equation 7, respectively (Bahrepour, Zhang et al. 2009).

$$O_{FFNN} = O[(m \times z \times p) + (m \times z \times p)] = O(m \times z \times p) \tag{6}$$

$$O_{NaiveBayes} = O[(m \times c \times j) + (m \times c \times j)] = O(m \times c \times j) \tag{7}$$

4.3.3 Complexity of local model using Decision Tree

Complexity of decision tree appraisal is a function of the depth of decision tree. Equation 9 presents this time complexity:

$$O(local\ approach) = O(Decision\ tree\ appraisal) \tag{8}$$

$$O(Local\ approach) = O(m)O(Local\ approach) = O(m) \tag{9}$$

where m is depth of the decision tree

4.3.4 Complexity of fusion-based model using decision tree and reputation theory

Time complexity of the fusion-based model using decision tree as classifier and reputation theory as fuser is a function of three parameters: (i) complexity of making the decision tree on each node, (ii) complexity of performing local classification on each node, and (iii) complexity of performing fusion and reaching consensus between classification results. Equation 12 presents the final complexity.

$$\begin{aligned} &O(Fusion\ based\ decision\ tree\ with\ reputation) \\ &= \max[O(Decision\ tree\ appraisal) + O(process\ on\ the\ node) + O(reputation\ voting)] \end{aligned} \tag{10}$$

$$\begin{aligned} &O(Fusion\ based\ decision\ tree\ with\ reputation) = \\ &Max[O(m) + O(n(n-1)) + O((n(n-1)) + n + c)] \end{aligned} \tag{11}$$

$$O(Fusion\ based\ decision\ tree\ with\ reputation) = O(n^2) \tag{12}$$

where n is the number of nodes

4.3.5 Complexity of fusion-based model using decision tree and majority voting

Complexity of classification process of fusion-based model using decision trees is $O(m_1 + m_2 + \cdots + m_n) = O(m)$; where n is the number of nodes involved in the classification and m is depth of the decision tree. Since the voting is independent from the classification, its time complexity is added to the classification time as shown in Equation 13. Equation 16 presents the final complexity of fusion-based model using decision trees and majority voting.

$$\begin{aligned} &OO(Distributed\ approach\ using\ majority\ voting) = \\ &O([m]) + O[Majority\ voting 1]) = Max[(m), Majority\ voting] \end{aligned} \tag{13}$$

$$O(\text{Distributed approach using majority voting}) = O(\text{Max finding}) + \mathrm{O(m)} \tag{14}$$

$$O(\max finding) = O(\mathrm{c}) \tag{15}$$

$$O(O(\text{Distributed approach using majority voting}) = O(c) + 0(\mathrm{m})) = O(m) \tag{16}$$

where m is depth of the decision tree, and n is number of nodes in the network.

4.4 Computational comparison

The time complexities of local and fusion-based models using different classifiers and fusers are summarized in Table 1.

Model	Time complexity
Fusion based model using FFNN	$O = O(m \times z \times p)$
Fusion based model using Naïve Bayes	$O = O(m \times c \times j)$
Fusion based model using Decision Tree and Reputation-based voting	$O(n^2)$
Fusion based model using Decision Tree with majority voting	$O(m)$

Table 1. Complexity comparison of local and fusion-based classification models with different classifiers

where n is the number of sensor nodes in the network, c is number of classes, m is number of features, and j is number of partitions for distribution estimation.

5. Data description and empirical results

5.1 Activity dataset and feature reduction process

To investigate applicability of the aforementioned classifiers for the activity recognition task in the medical domain, we used an activity dataset provided by Enschede Hospital (Medisch Spectrum Twente). The dataset consists of data from sensors attached to a 25 year old person, while he had been walking, sitting and standing still. The dataset contains 30 features from 5 tri-axial accelerometers and 5 tri-axial gyroscope sensors located on feet, shank, thigh and trunk. To find the most important features of the dataset, we first developed a feature reduction technique using genetic algorithm and decision tree. Feature reduction is the technique of selecting a subset of relevant features for making robust learning models. By removing redundant features from the dataset, feature selection helps improve the performance of learning models by (i) alleviating the effect of the curse of dimensionality, (ii) enhancing generalization capability, and (iii) speeding up learning process (Isabelle Guyon 2006). Genetic algorithms (GAs) belong to the larger classes of evolutionary algorithms (EAs) that generate solutions to optimization problems using techniques inspired by natural evolution, e.g., inheritance, mutation, selection, and crossover (Goldberg 1989). GA optimizes the features in order to find those most contributing to the classification process. Using GA for feature reduction, we first selected four most contributing features from the dataset. A decision tree was then created using these four features and its classification accuracy was considered as the fitness value for the four features. After the feature reduction process, our activity dataset contained four features, 8330 instances of data and three classes namely walking, sitting, and standing still. Figure 4 shows data distribution for these three classes and Table 2 presents statistical information of dataset, while the four features of the dataset are: 'Z' vector of gyroscope installed on the right foot, 'Y' vector of accelerometer installed on trunk, 'Z' vector of accelerometer installed on trunk, and 'X' vector of accelerometer installed on left foot. As it can be seen from Figure 4, data representing three classes have a high degree of overlap, which makes the dataset very complex for the classification process.

Feature	Min	Max	Mean	STD	Info
1	9.233	10.7756	-0.040	1.4355	right foot gyroscope Z vector
2	78.7644	50.0057	-3.9921	6.942	trunk accelerometer Y vector
3	-24.5415	20.3732	-2.8579	2.2486	trunk accelerometer Z vector
4	29.8074	1.8017	-4.4615	2.753	left foot gyroscope X vector

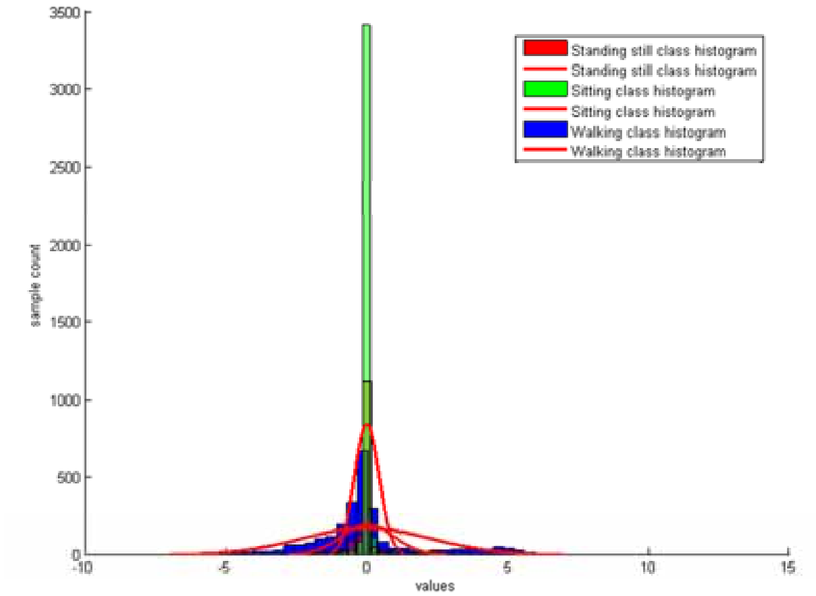
Table 2. Activity data set information (8360 instances, 3 classes: stand still, walking, sitting)

To simulate the classification process, we use Matlab® to train and test every individual node separately. In the training phase, first the classifiers (local model) running on the sensor nodes are trained. Then, according to the trained classifiers on sensor nodes, the fuser (fusion-based model) is trained. In the test phase, an instance of data is given to all sensor nodes and then their outputs are fused using either another classifier or a voting technique. Training phase is conducted with 2/3 of data and testing is performed with 1/3 of data.

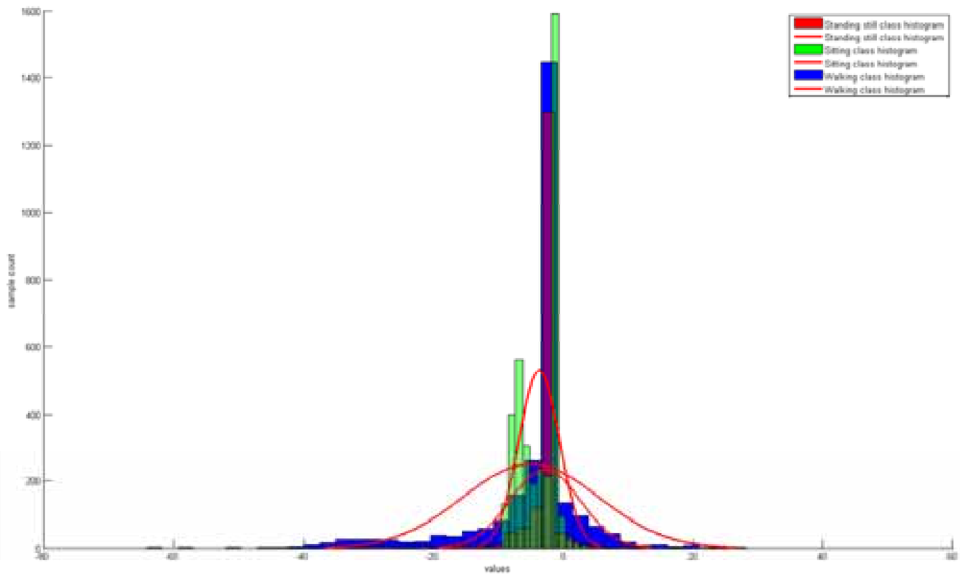
5.2 Empirical results

We perform each activity classification experiment ten times and accuracy ratios are reported in Table 3.

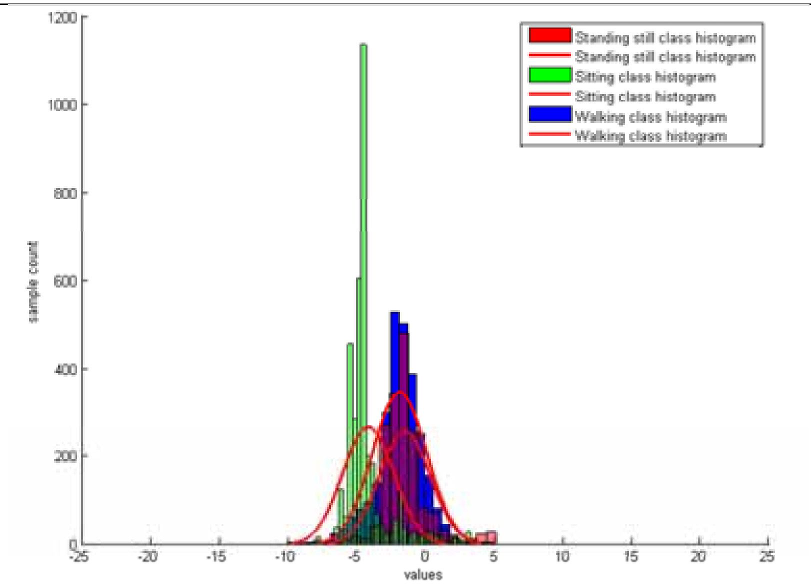
According to Table 3, fusion based models using decision trees and reputation-based voting (technique 1 and 2) and using majority voting provides more accurate activity recognition. Additionally, in this specific dataset (activity dataset) reputation based voting technique 1 and 2 provides the same accuracy ratio.


Standing still class histogram
Standing still class histogram
Sitting class histogram
Sitting class histogram
Walking class histogram
Walking class histogram
3500
3000
2500
2000
1500
1000
500
0
sample count
-10
-5
0
5
10
15
values

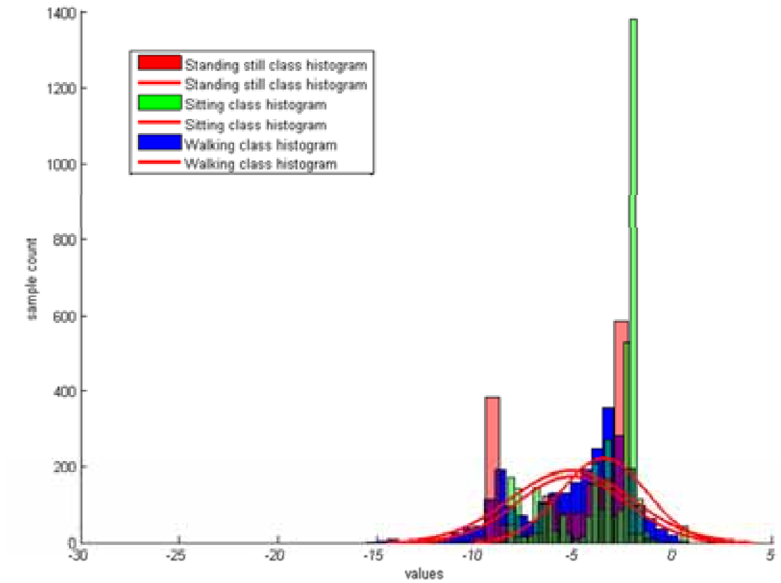
(a)


Standing still class histogram
Standing still class histogram
Sitting class histogram
Sitting class histogram
Walking class histogram
Walking class histogram
sample count
values

(b)



(c)



(d)

Fig. 4. Data distribution of three classes per each feature: (a) 'Z' vector of gyroscope installed on the right foot, (b) 'Y' vector of accelerometer installed on trunk, (c) 'Z' vector of accelerometer installed on trunk, (d) 'X' vector of accelerometer installed on left foot

Model	Classification Accuracy (Mean)	Standard Deviation
Fusion based model using FFNN	73.6022	1.4858
Fusion based model using Naïve Bayes	73.4624	1.2771
Fusion based model using Decision Tree and Reputation-based voting (technique 1)	78.9881	0.7820
Fusion based model using Decision Tree and Reputation-based voting (technique 2)	78.9881	0.7820
Fusion based model using Decision Tree with majority voting	78.6712	0.9836

Table 3. Accuracy and standard deviation of activity classification and recognition

5.3 Parameter study

There are some parameters in our classification process, which can affect classification accuracy. These parameters include (i) type of the classifiers, (ii) internal parameters of the classifiers (e.g. number neurons in hidden layer for FFNN), (iii) number of sensors, and (iv) type of sensors. In (Bahrepour, Meratnia et al. 2010), we have shown that the most effective parameter in fusion-based classification is the sensor types. This means that it is important to identify the most contributing sensors and ensure their presence in the classification process. As mentioned in Subsection 5.1, using a genetic algorithm and decision tree in the feature reduction process, we have identified the most contributing features of the dataset. In this section we study internals parameters of classifiers and their effects on classification accuracy.

5.3.1 Effects of internal parameters of feed forward neural network (FFNN) on classification

Internal parameters for FFNN are number of hidden layers and number of neurons in each hidden layer. The hidden layer in FFNN can grow vertically, horizontally and bi-directional (in both horizontal and vertical). The vertical growth means keeping number of hidden layers as low as possible and increasing the number of neurons in hidden layers. Number of neurons can also be kept as low as possible while number of hidden layers is increased. This process is called horizontal growth. A combination of both vertical and horizontal growth is also possible (bi-directional growth). To see the effects of growth in different directions, we performed several experiences, whose results are reported in Table 4.

Generally speaking, vertical growth of neural network leads to more accurate results comparing to horizontal growth. Moreover, by increasing number of hidden layers and/or neurons in the hidden layers, the accuracy enhances; however, at a certain point increasing hidden layer elements decreases the accuracy. Therefore, number of hidden layers as well as their neurons in each layer should be increased to the point which generates the highest accuracy. This is obtained experimentally.

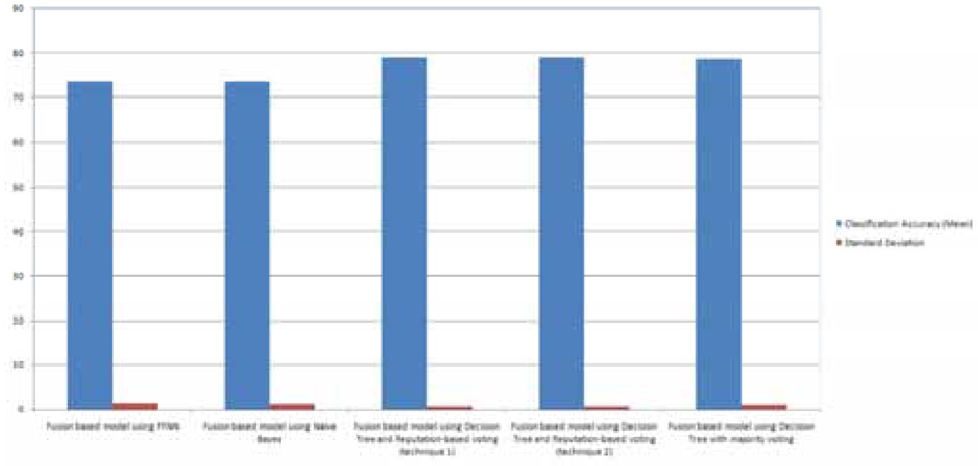


Fig. 5. Accuracy and standard deviation of activity classification and recognition.

	Hidden Layers	Neurons	Accuracy	STD
Horizontal growth	1	1	45.52	0.92
	10	1	46.33	0.61
	100	1	46.59	1.01
	1000	1	64.27	13.07
Vertical growth	1	10	55.77	1.37
	1	100	58.53	1.22
	1	1000	44.57	18.49
Bi-directional growth	10	10	51.44	0.92

Table 4. Effect of neural network's internal parameters on classification accuracy

5.3.2 Effects of internal parameters of naïve bayes (NB) classifier on classification

The only parameter for Naïve Bayes classifier is number of partitions for making a histogram. Table 5 shows how this parameter affects classification accuracy.

Partitions	Accuracy	STD
10	55.81	1.61
100	66.34	2.00
1,000	67.81	1.01
10,000	66.51	0.76
100,000	57.99	1.2

Table 5. Effect of Naïve Bayes' internal parameters on classification accuracy

As it can be seen in Table 5, generally speaking increasing number of partitions leads to increase of the classification accuracy. However, at a certain point either the accuracy stays roughly the same or drops.

5.3.3 Effects of internal parameters of decision tree (DT) on classification

Decision trees have almost no internal parameter because the whole tree is made during the training phase. However, after the training phase, the obtained tree can be pruned and some less-contributing branches can be removed. We performed a number of experiments, in which we prune the decision tree created for the activity dataset to a degree that tree has only one node. Figure 6 illustrates the effect of this pruning on classification accuracy. As it can be seen, pruning causes degradation of classification accuracy, in general. One also notices that for our activity dataset, pruning first increases the accuracy to some extent and then decreases it. The reason for this behavior is that the tree is over branched (i.e., almost 240 level tree is sophisticated enough to create some ambiguity and inaccuracy in the classification). Reducing some branches helps tree be simpler and perform classification slightly more accurate. However, at a certain point the accuracy drops. A general conclusion is, pruning causes reduction in accuracy ratio because the decision tree has to perform classification with fewer nodes.

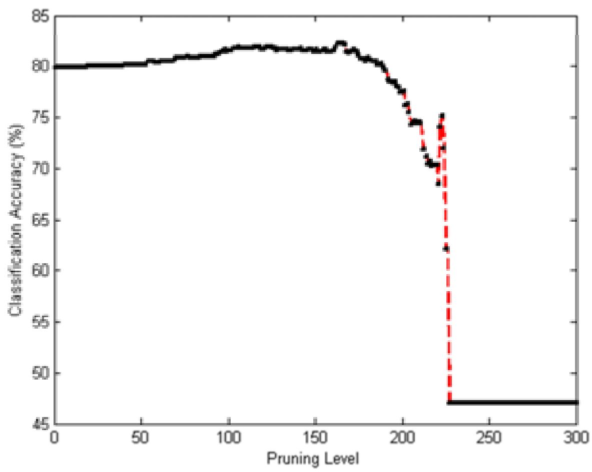


Fig. 6. Pruning and its effect on classification accuracy

6. Conclusion

Fall detection is a common problem in PD patients. Accurate activity classification and recognition is one of the first steps towards on time fall detection. Body senor networks are an emerging technology enabling online and distributed monitoring of both physical and physiological conditions of patients. Integrating this monitoring capability with (near) real-time activity recognition and classification can speed up the fall detection process and enable provision of timely feedback and assistance. To this end, having a thorough understanding of capabilities and performance of classification techniques is essential.

In this paper we investigated applicability of three classification techniques, i.e., Naïve Bayes, Feed Forward Neural Network, and Decision Tree for activity recognition in medical domain and showed how fusion-based classification can improve classification accuracy. In addition to considering classification accuracy, we studied effects of internal parameters of the classifiers on the classification performance and compared various techniques in terms of their complexity.

Activity recognition in medical domains requires inexpensive and easy wearing hardware components and computationally-light algorithms. To this end, our fusion-based classification technique offers three main advantages: (i) distributed processing and reasoning which decreases the data processing time and provides fast activity detection, (ii) robustness against sensors failure, and (iii) accurate detection through use of sensor fusion.

We performed a number of experiments using an activity dataset collected from a 25 year old person walking, sitting, and standing still. Performing an offline analysis shows high complexity of the dataset, as data representing three classes have a high degree of overlap. The evaluation results show that, considering this high complexity of the dataset, our fusion-based technique can reach reasonable classification accuracy.

Our future plans include design of temporal learning techniques to increase detection accuracy over time.

7. Acknowledgment

The authors would like to acknowledge Dr. J. P. P. van Vugt from Medisch Spectrum Twente and Sarvi Sharifi from the University of Twente for sharing their activity dataset. This work is supported by the EU Seventh Framework Programme and the SENSEI project.

8. References

Abbate, S., M. Avvenuti, et al. (2010). Monitoring of Human Movements for Fall Detection and Activities Recognition in Elderly Care Using Wireless Sensor Network: a Survey. *Wireless Sensor Networks: Application-Centric Design Book.*

ALPAYDIN, E. (2004). *Introduction to Machine Learning*, The MIT Press.

Aminian, K., P. Robert, et al. (1999). "Physical activity monitoring based on accelerometry: validation and comparison with video observation " *Medical & biological engineering & computing* 37(3).

Avci, A., S. Bosch, et al. (2010). Activity Recognition Using Inertial Sensing for Healthcare, Wellbeing and Sports Applications: A Survey. *23rd International Conference on Architecture of Computing Systems, ARCS 2010*. Hannover, Germany.

Bahrepour, M., N. Meratnia, et al. (2009). Sensor Fusion-based Event Detection in Wireless Sensor Networks. *SensorFusion'09*. IEEE. Toronto, Canada.

Bahrepour, M., N. Meratnia, et al. (2009). Use of AI Techniques for Residential Fire Detection in Wireless Sensor Networks. A*rtificial Intelligence Applications in Environmental Protection Workshop, AIAEP 2009*, Thessaloniki, Greece.

Bahrepour, M., N. Meratnia, et al. (2010). "Fast and Accurate Residential Fire Detection Using Wireless Sensor Networks." *Environmental Engineering and Management Journal* 9(2): 215-221.

Bahrepour, M., N. Meratnia, et al. (2010). Distributed Event Detection in Wireless Sensor Networks for Disaster Management. *International Conference on Intelligent Networking and Collaborative Systems, INCoS 2010*. Thessaloniki, Greece, IEEE Computer Society.

Bahrepour, M., B. J. van der Zwaag, et al. (2010). Fire data analysis and feature reduction using computational intelligence methods. *Advances in Intelligent Decision Technologies - Proceedings of the Second KES International Symposium IDT 2010*. Baltimore, Maryland, USA: 289-298.

Bahrepour, M., Y. Zhang, et al. (2009). Use of Event Detection Approaches for Outlier Detection in Wireless Sensor Networks. *Proceedings of Symposium on Theoretical and Practical Aspects of Large-scale Wireless Sensor Networks, The 5th International Conference on Intelligent Sensors, Sensor Networks and Information Processing 2009 (ISSNIP 2009)*, Melbourne, Australia.

Benocci, M., C. Tacconi, et al. (2010). "Accelerometer-based fall detection using optimized ZigBee data streaming." *Microelectron Journal*.

Centeno, M., R. Giachetti, et al. (2003). A simulation-ILP based tool for scheduling ER staff. *2003 winter simulation conference*.

Goldberg, D. E. (1989). *Genetic Algorithms in Search, Optimization, and Machine Learning*, Addison-Wesley Professional.

Guenterberg, E., R. Bajcsy, et al. (2007). A segmentation technique based on standard deviation in body sensor networks. *EEE Dallas Engineering in Medicine and Biology Workshop*.

Guenterberg, E., S. Ostadabbas, et al. (2009). "An automatic segmentation technique in body sensor networks based on signal energy." B*odyNets '09 - Fourth International Conference on Body Area Networks*.

Horst, A. and N. Meratnia (2011). Online Activity Matching using Wireless Sensor Network. *1st International Conference on Pervasive and Embedded Computing and Communication Systems (PECCS 2011), In conjunction with VISIGRAPP 2011*,.

Hou, J., Q. Wang, et al. (2007). Pas: A wireless-enabled, sensor-integrated personal assistance system for independent and assisted living. *HCMDSS-MDPnP*.

Isabelle Guyon , S. G., Masoud Nikravesh , Lofti A. Zadeh (2006). *Feature Extraction: Foundations and Applications (Studies in Fuzziness and Soft Computing),* Springer.

Jafari, R., W. Li, et al. (2007). Physical activity monitoring for assisted living at home. *4th International Workshop on Wearable and Implantable Body Sensor Networks*. Berlin.

Jarochowski, B. P., S. Shin, et al. (2007). Ubiquitous Rehabilitation Center: An Implementation of a Wireless Sensor Network Based Rehabilitation Management System. *International Conference on Convergence Information Technology*, IEEE Computer Society.

JI., H., v. d. P. AA., et al. (2001). "Accelerometric assessment of levodopa-induced dyskinesias in Parkinson's disease." *Mov Disord* 16: 58-61.

JI., H., v. d. M. V., et al. (2004). "Accuracy of objective ambulatory accelerometry in detecting motor complications in patients with Parkinson's disease." *Clin Neuropharmacol* 27: 53-57.

JJ., v. H., M. HA., et al. (1991). "A new approach in the assessment of motor activity in Parkinson's disease." *Neurol Neurosurg Psychiatry* 54: 976–979.

Kern, N., B. Schiele, et al. (2003). *Multi-sensor activity context detection for wearable computing*. Proceedings of European symposium on ambient intelligence (EUSAI03).

Khattak, A. M., L. T. Vinh, et al. (2010). Context-aware Human Activity Recognition and Decision Making. *12th International Conference on e-Health Networking, Application Services (IEEE HealthCom 2010)*. Lyon, France.

Krishnan, N. C., C. Juillard, et al. (2009). "Recognition of hand movements using wearable accelerometers." *JAISE*.

Le, T. M. and R. Pan (2009). Accelerometer-based sensor network for fall detection. *Biomedical Circuits and Systems Conference*.

Lee, M.-H., J. Kim, et al. (2009). Physical Activity Recognition Using a Single Tri-Axis Accelerometer. *WCECS 2009*. San Francisco, USA.

Lorincz, K., B. Kuris, et al. (2007). Wearable wireless sensor network to assess clinical status in patients with neurological disorders. *6th international conference on Information processing in sensor networks*, ACM.

Martinez-Garcia, A. and R. Menndez-Olague (2003). "Process improvement with simulation in the health sector." *e-Health:application of computing science in medicine and health care*.

Mehrotra, K., C. K. Mohan, et al. (1996). Elements of Artificial Neural Networks, MIT Press.

Moorea, S. T., H. G. MacDougalla, et al. (2007). "Long-term monitoring of gait in Parkinson's disease." *Gait & Posture* 26(2): 200-207.

N., S., Y. T., et al. (2004). "Lifecorder: A new device for the long-term monitoring of motor activities for Parkinson's disease." *Intern Med* 43: 685-392.

Nabar, S., A. Banerjee, et al. (2010). Evaluation of body sensor network platforms: a design space and benchmarking analysis. *In Wireless Health 2010 (WH '10)*. New York, NY, USA: 118-127.

Osmani, V., S. Balasubramaniam, et al. (2007). Self-organising object networks using context zones for distributed activity recognition. *ICST2007*. Florence, Italy.

Osmani, V., S. Balasubramaniam, et al. (2008). "Human activity recognition in pervasive health-care: Supporting efficient remote collaboration." *Journal of Network and Computer Applications:* 628-655.

Park, C., J. Liu, et al. (2005). Eco: an ultra-compact low-power wireless sensor node for real-time motion monitoring. *IPSN 2005*: 398-403.

Russell, S. J. and P. Norvig (2003). *Artificial Intelligence: A Modern Approach*, *2 edition*, Pearson Education

S. Bosch, M. M.-P., R. S. Marin-Perianu, P. J. M. Havinga, and H. J. Hermens, Keep on moving! activity monitoring and stimulation using wireless sensor networks, in the Proceedings of the 4th EuroSSC conference, vol. 5741, September 2009, pp. 11–23 (2009). Keep on moving! activity monitoring and stimulation using wireless sensor networks.

Salarian, A., H. Russmann, et al. (2007). "Ambulatory Monitoring of Physical Activities in Patients With Parkinson's Disease." *IEEE Transactions on Biomedical Engineering* 54(12): 2296 - 2299.

Sanchez, D., M. Tentori, et al. (2008). Activity Recognition for the Smart Hospital. *IEEE Intelligent Systems*: 50-57.

Soini, M., J. Nummela, et al. (2008). "Wireless Body Area Network for Hip Rehabilitation System." *Ubiquitous Computing and Communication Journal* 3(5).

Steele, B. G., B. Belza, et al. (2003). "Bodies in motion: Monitoring daily activity and exercise with motion sensors in people with chronic pulmonary disease." *Rehabilitation Research and Development* 40(5).

Veld, H. i. t., O. M.H.A., et al. (2005). "Context aware algorithm for epileptic seizure detection." *Awareness deliverables*.

White, D. K., R. Wagenaar, et al. (2006). "Monitoring Activity in Individuals with Parkinson Disease: A Validity Study." *Journal of Neurologic Physical Therapy* 30(1): 12-21.

Wijewickrama, A. and S. Takakuwa (2006). Simulation analysis of an outpatient department of internal medicine in a university hospital. *2006 winter simulation conference WSC 06*.

Wikipedia Decision tree, http://en.wikipedia.org/wiki/Decision_tree.

Wu, J., G. Pan, et al. (2009). Gesture recognition with a 3-d accelerometer. *UIC 2009*: 25-38.

Wu, W. H., A. A. Bui, et al. (2008). "MEDIC: medical embedded device for individualized care." *Artificial Intelligence in Medicine* 42(2): 137-152.

Ying, H., M. Schlösser, et al. (2008). Distributed Intelligent Sensor Network for Neurological Rehabilitation Research. *4th European Conference of the International Federation for Medical and Biological Engineering (EMBEC 2008 - ESEM 2008)*. Antwerp, Belgium.

Yun, X., M. Lizarraga, et al. (2003). An improved quaternion-based kalman filter for real-time tracking of rigid body orientation. *International Conference on Intelligent Robots and Systems*.

Zhang, M. and A. Sawchuk (2009). A Customizable Framework of Body Area Sensor Network for Rehabilitation. *2nd International Symposium on Applied Sciences in Biomedical and Communication Technologies (Isabel).*