Classifying Posture Based on Location of Radio Tags

Violeta MIRČEVSKA[a], Mitja LUŠTREK[a], Igone VÉLEZ[b], Narciso GONZÁLEZ VEGA[c], Matjaž GAMS[a]
[a]*Dept. of Intelligent Systems, Jožef Stefan Institute, Slovenia*
[b]*CEIT, Spain*
[c]*Agora Center, University of Jyväskylä, Finland*
violeta.mircevska@ijs.si

Abstract. CONFIDENCE FP7 project is developing a care system for the elderly based on measurements of locations of radio tags attached to a human body. Posture classification is the basis of reasoning in CONFIDENCE. We first applied a data mining approach to recordings of human behavior in order to develop classifier of posture. However, evaluations with separate training and test set scenario show over fitting. Therefore, we considered enriching classifier by human modification. Posture classifier was developed by human modification of induced decision trees. Besides the 5% improvement in accuracy compared to support vector machines and a significant 11% compared to decision trees, we also expect better robustness of this classifier in real-life tests.

Keywords. care system, radio tags, posture, machine learning, common sense

Introduction

The Statistical Office of the European Communities (Eurostat) predicts that the over-65 population in EU27 will rise from 17.1% in 2008 to 30.0% in 2060 [1]. Since aging is often accompanied by health problems, this process will increase the need for medical services. Therefore, it is reasonable to expect increase in costs for health care services and burden on the working age population.

The European FP7 project CONFIDENCE – Ubiquitous Care System to Support Independent Living [2][3][4] aims at developing a system that will monitor health conditions of its elderly user in real-time. In case of health problems, the system will issue a warning to the user or alert a caregiver if necessary. This way the elderly should gain the needed confidence and security to continue their independent participation in the society, thus reducing the costs of medical services and the burden on the working age population.

The CONFIDENCE system monitors health conditions of the elderly based on the measurements of locations of radio tags attached to the user's body. Because there are no cameras, there is little privacy intrusion. Polls revealed that the majority of the elderly are willing to wear tags even in toilet, during bathing and sleeping. The major difficulty faced by the project is low accuracy of the existing equipment for measuring the locations of radio tags. Therefore, new hardware and software is being designed and implemented.

Health problems are detected from the characteristics of the user's posture and movement. Therefore, posture classification is the basis of reasoning in CONFIDENCE. This study presents two approaches for posture classification.

The first approach is completely based on machine learning. The performance of several induction techniques and sets of attributes were examined for the task of posture classification. Due to the wide variety of body constitutions and postures, it is difficult to record all possible situations and to obtain representative training dataset for posture classification. Since machine learning techniques extract statistically relevant patterns about the training data, non representative training dataset may lead to over fitting.

The second approach applies common sense to knowledge extracted with machine learning. We post-processed decision trees and modified them into rules to encapsulate human common sense. Since humans are good at imagining body structures and postures not represented in the training data, application of common sense should improve the accuracy and robustness of the classifier.

Section 1 presents an overview of the CONFIDENCE system. Previous work on posture classification is given in Section 2. The data on which the new software approaches are tested is presented in Section 3. Then posture detection based purely on machine learning (Section 4) and a novel approach of systematically transforming induced decision trees into rules incorporating human common sense (Section 5) are described.

1. The CONFIDENCE System

The CONFIDENCE system is designed to monitor the health conditions of the elderly both indoor and outdoor. Depending on the severity of the health problem, the system will issue a warning to the user or an alarm to a caregiver. Several technological challenges arise from the given task.

On the hardware side, a real-time system that will accurately measure the locations of radio tags is needed. Moreover, since the user's home must not be obstructed by installation of the CONFIDENCE system, the hardware must enable seamless integration in the user's environment. The proposed solution for the indoor version will use ultra-wideband technology and will be implemented in the form of a base station, which could be designed to look like a decorative item. For the outdoor version, a portable device will play the role of base station. The technologies for the outdoor version are still being evaluated.

On the software side, the system must extract information about the user's health conditions based only on measured locations of radio tags affixed to user's body. This task is divided into several sub-problems as shown in Figure 1. The CONFIDENCE system will recognize two types of behavior that indicate health problems: falls and those manifesting in unusual changes in behavior. Falls are easier to detect than unusual changes in behavior, so the initial idea was to use rules for falls. For changes in behavior, data-mining approaches based on training recordings were considered from the start.

Behavior is described by a set of data encompassing time, location and type of user's postures, frequency of activities and similar. Accurate posture classification, the problem examined in this paper, is essential for correct behavior description.

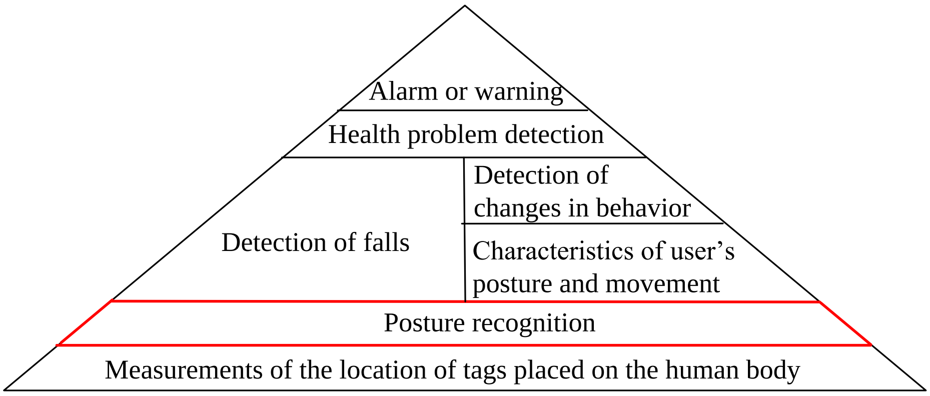

Figure 1. Schema of reasoning in CONFIDENCE

2. Related Work on Posture Recognitions

Posture recognition based on measurements of tags on the human body, a setup similar to the one used in CONFIDENCE, is reported in [5]. In this work, seven postures related to military operations were detected using 43 body tags sampled with frequency of 30Hz. Accuracy of 76.9% was achieved with the support vector machines algorithm whose features were the tag coordinates belonging to two postures separated by 1/3 second.

Posture recognition based on accelerometers is often found in the literature. Using five tri-axial accelerometers, 30 physical postures were distinguished with accuracy of 94.9% with person-dependent training and 56.3% with person-independent training [6]. Accuracy of 96.7% was reported in [7] for fall detection using One-Class SVM machine learning algorithm whose features, among other, had accelerations and changes in acceleration.

Posture recognition can be done from video data, as well. An overview of vision-based human motion analysis is presented in [8]. In [9], the recognition of ten states related to activities of daily living with accuracy of 74.1% was reported.

3. Data

Two sets of examples of human behavior were recorded. The first contains 135 sequences of behavior of three persons. The recordings include examples of standing/walking, lying down, sitting down, and falling. In the second set there are 775 sequences of behavior of five people. Beside the basic behaviors recorded in the first set, these recordings include examples of several kinds of falls and, based on discussions with physicians, examples of walking and lying of people with different health problems, such as Parkinson's disease, hemiplegia etc.

Since the CONFIDENCE hardware is not available yet, the recordings were made with the use of the Smart infrared motion capture system [10]. The locations of twelve tags were measured, one on each shoulder, hip, knee, ankle, elbow and wrist. The location of a virtual tag on the neck was computed as the middle point between the shoulders due to difficulties in attaching a tag there and tracking it during forward falls. The coordinates of the tags were sampled at a frequency of 60 Hz. The data obtained with the Smart system was then transformed so that it corresponds to the characteristics of the Ubisense real-time location system [11]. We expect that the properties of the data obtained with the CONFIDENCE hardware will be the similar to the ones of the Ubisense system, because this system uses the ultra-wideband technology, the same technology on which also the CONFIDANCE hardware is being built. Two transformations were done for this purpose. First, the sampling frequency was reduced to 10 Hz. Then, Gaussian noise with standard deviation of 4.36cm horizontally and 5.44cm vertically was added to the data. The values of the standard deviation of the noise in the Ubisense system were obtained experimentally.

4. Posture Recognition with Machine Learning

Several posture representations and machine learning algorithms were examined for the problem of posture classification.

The posture of the user was represented with three sets of attributes: reference, body (with the variant body with reference Z) and angles. The reference attributes contain the location of tags with respect to the reference coordinate system presented in [12], the velocity of the tags and the Z component of their velocity, as well as the absolute distance between all pairs of tags and their distance in Z and XY direction. The body attributes are same, except the fact that the location of tags is presented with respect to the body coordinate system [12]. Finally, the angle attributes represent the angle between different parts of the body [12].

The training dataset was formed by combining the proposed attribute sets. Each instance of the training dataset contains the concatenated values of the attributes for the measured data of the 12 tags in ten overlapping consecutive time intervals separated by 0.1 seconds. The length of attribute vectors in this setting ranges from 240 to 5700.

Table 1. Classification accuracy of the best four machine learning techniques on all reasonable attribute set combinations

Attribute set combination / **Algorithm**	reference + body	reference + body with ref. z	reference + angles	body + angles	body with ref. z + angles	all	all (ref. z)
Support Vector Machines	95.5	95.4	**96.5**	91.9	92.5	95.6	95.5
Random Forest	93.8	**94.2**	94.1	91.8	93.5	93.9	94.0
Bagging	93.8	**94.1**	93.7	92.4	93.4	93.8	**94.1**
Adaboost M1 boosting	93.6	**93.7**	93.2	93.2	93.3	93.6	**93.7**

The instances were classified as one of the six postures: standing/walking, sitting, lying, sitting down, lying down and falling.

Eight machine learning algorithms were examined for classifying the human posture with Weka [13]. The best four (support vector machines, random forest, bagging and Adaboost M1 boosting) were tested on all combinations of proposed attribute sets. The classification accuracy of these algorithms with 10-fold cross validation on the first set of recordings is presented in Table 1.

The 10-fold cross validation accuracy of 96.5% achieved with the support vector machines classifier using the reference and angle attributes is very encouraging. However, machine learning can over fit if a limited set of learning data is used. In order to examine this, the classifier was tested on data recorded in the second set of recordings. Since the two sets of behavior are recorded on two different occasions, they prevent people from performing the postures and movements in exactly the same way. The 19% fall in accuracy when the support vector machines are trained on the first set of recordings and tested on data in the second set of recordings (Table 2) is an indication of classifier over fitting to the training data.

Table 2. Comparison of the classification accuracy of SVM using 10-fold cross validation and separate training and test set to show over fitting in the first case

SVM	10-fold cross validation on first set	Train on first set and test on subset of second set of recordings	Difference
Classification accuracy	96.5%	77.7%	**18.8**

Due to the wide variety of possible body constitutions and postures, it is difficult to capture all possible posture variants in the training dataset. Since humans can imagine constitution and posture variations, including those not present in the training recordings, application of common sense should improve the accuracy and robustness of the classifier.

5. Incorporation of Human Knowledge

In order to include common sense in a posture classifier, it must be understandable. Since the support vector machines are not understandable, another model was needed. Rules were selected because besides being understandable, they can be easily modified. Moreover, their execution is computationally cheap. This is critical for the outdoor version of the system in which the software will run on small portable devices.

5.1. Rule Extraction and Model Construction

The rule extraction procedure follows the steps presented in Figure 2.

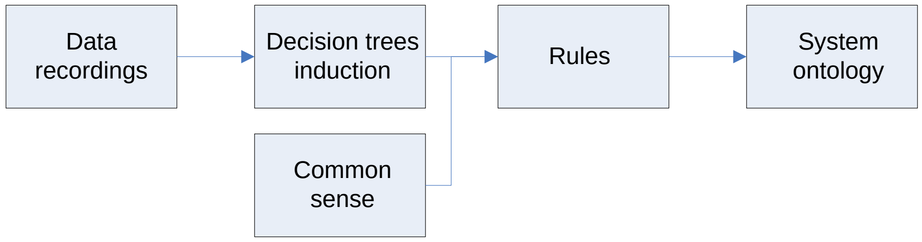

Figure 2: Knowledge induction and encapsulation for posture diagnosing in CONFIDENCE

First of all, decision trees were generated with the purpose of identifying the attributes that best separate the examples of a particular posture form all other postures. Since the decision trees perform general-to-specific hill-climbing search through the space of possible hypotheses, they show only the best hypothesis. Other hypotheses, even if they are somewhat less accurate, may be interesting from the common-sense perspective. To find them, several decision trees were induced with different sets of attributes. First of all, a decision tree was built with all attributes. Then, the procedure was repeated by removing the attribute at the root node or attribute near the root node, with the aim of finding relevant hidden hypotheses, until the classification accuracy of the resultant tree significantly dropped.

From the trees, rules with high accuracy and high precision were extracted. The conditions of the extracted rules were made stricter, especially for the classes standing/walking, sitting, lying and falling, improving their precision at the expense of recall. The aim was to correctly classifying pure postures, neglecting the borderline cases.

Then additional logic was added so that all examples were covered by the rules. Since the current posture of a person is highly correlated with the posture he/she had in the previous time interval, if an example is not covered by any of the rules, it is considered to be the same posture as the posture in the previous time interval.

Finally, conflicts between the rules were solved as indicated in Table 3. Conflicts appear only between adjacent postures. Since the rules for standing/walking, sitting, lying and falling were constructed in a way that only pure postures are captured, they are chosen when there is a conflict with a rule for moving downwards/upwards.

All knowledge developed in CONFIDENCE will be included in ontology which will simplify the sharing of knowledge and ensure reusability of the approaches developed in the project.

Table 3: Resolution of conflicts between rules

Conflict	Result
Standing/Walking and Moving Down/Up	Standing/Walking
Sitting and Moving Down/Up	Sitting
Lying and Moving Down/Up	Lying
Falling and Moving Down/Up	Falling

5.2. Measurements

A model for classifying six postures (standing/walking, sitting, lying, falling, moving downwards and moving upwards) was induced with the procedure described in Subsection 5.1. The training dataset used for the induction contains only reference attributes computed over half a second overlapping sequences of user behavior. Each instance contains only the average attribute value in the half second interval, since it is difficult for humans to consider several concatenated values at once. The locations of three tags on the user's body were considered: neck and both ankles. It seems that the relationship between the location of the neck and the ankles and their velocity contains the information needed for distinguishing the classes of interest. Being one of the highest tags of the body, the height of the neck with respect to the ankles is important for distinguishing among standing, sitting and lying. Moreover, the neck has the highest velocity in the Z direction, making it suitable for distinguishing among falls, moving downwards and upwards.

The performance of this rules model was compared with the performance of the decision tree and support vector machine classifier with the use of Weka [13]. Three comparisons with a separate training and test set were made. In the first and second comparison, the classifier was induced on the data from one session of recordings and tested on the other. In the third comparison, the classifier was trained on the recordings of two persons from both phases and tested on the recordings of a third person.

As seen in Table 4, the classification accuracy of the decision trees is more than 10% lower than the classification accuracy of the rules model when the classifier is trained on one phase of recordings and tested on the other with 2% minimal number of instances per leaf (experimentally the best). There was no significant difference in accuracy between the trees and the rules model when the trees were trained on the data of two persons and tested on the third. It seems that the difference in postures between persons is smaller than the difference in postures between the phases. The accuracy of the support vector machines when trained on one set of recordings and tested on the other is also smaller than in the case when the training is done on two persons and tested on a third. The higher classification accuracy of the rule model, however, still suggests that the incorporation of common sense improves the generality of the classifier.

Table 4: Comparison of the classification accuracy of decision trees, SVM and rules

Training dataset	Test dataset	Trees (%)	SVM (%)	Rules (%)
First set	Second set	79.92	84.68	90.91
Second set	First set	70.78	77.96	81.76
Two persons	Third person	87.24	86.89	89.42
10-fold cross validation on merged data from the two sets		87.66	89.51	

6. Conclusion

This paper presents posture classification with the use of data mining techniques and a novel approach of systematically transforming induced decision trees into rules model by incorporating human common sense. The experiments were made on around 1000 recordings of posture-related activities which were measured with state of the art hardware. The final goal is transforming the constructed knowledge into the system ontology in OWL.

The approach achieved 5% increase in classification accuracy compared to SVM with only tree radio tags on the user's body. Compared to the decision trees, the improvement was a very significant 11%. Combining machine learning technologies with human common sense proved to be successful at least in the experiments performed. We expect that the constructed rules model will be even more robust in real-life circumstances.

It should be noted that CONFIDENCE combines several software modules, some based on data mining and machine learning. The output of the modules is combined to verify and improve the quality of alarms and warnings. Systems that incorporate multiple modules in general achieve improvements over "single" modules [14]. Overall system performance is therefore expected to further increase when the system becomes fully operational.

References

[1] Eurostat, http://epp.eurostat.ec.europa.eu. [2009-04-20]

[2] CONFIDENCE, http://www.confidence-eu.org/. [2009-04-20]

[3] N. González, I. Vélez, CONFIDENCE: Support To Older People's Independent Living, *Proceedings of Psykologia* (2008).

[4] C.Quemada, I.Val, M.Pietrzyk, T.Von der Grün, N.González, I.Vélez, A Smart Care System for Elderly People to Support Independent Living: CONFIDENCE, *Smart Systems Integration* (2009).

[5] G. Sukthankar, and K. Sycara, A cost minimization approach to human behavior recognition, *Proceedings of AAMAS 2005* (2005), 1067–1074.

[6] E. M. Tapia, S. S. Intille, W. Haskell, K. Larson, J. Wright, A. King, and R. Friedman, Real-time recognition of physical activities and their intensities using wireless accelerometers and a heart rate monitor, *Proceedings of ISWC 2007* (2007), 37–40.

[7] T. Zhang, J. Wang, P. Liu, and J. Hou, Fall detection by wearable sensor and One-Class SVM algorithm, *Lecture Notes in Control and Information Science 345* (2006), 858–863.

[8] J. K. Aggarval, Q. Cai, Human motion Analysis: A review, *Compute Vision and Image Understanding* (1999), vol. 73, 428-440.

[9] N. Zouba, B. Boulay, F. Bremond, and M. Thonnat, Monitoring activities of daily living (ADLs) of elderly based on 3D key human postures, *Proceedings of ICVW 2008* (2008), 37–50.

[10] eMotion, Smart motion capture system, http://www. emotion3d.com/smart/smart.html. [2009-04-20]

[11] Ubisense, http://www.ubisense.net/. [2009-04-20]

[12] M. Luštrek, and B. Kaluža, Fall detection and activity recognition with machine learning, *Informatica 33 2* (2009). (accepted for publication)

[13] I. H. Witten, and E. Frank, *Data Mining: Practical machine learning tools and techniques*, 2nd Edition, Morgan Kaufmann, San Francisco, USA, 2005.

[14] M. Gams, Weak Intelligence: Through the Principle and Paradox of Multiple Knowledge, *Advances in computation*, vol. 6, Huntington, New York, Nova Science, 2001.