Posture and movement monitoring for ambient assisted living

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Abstract: We present the current work on posture and movement recognition in the European FP7 project CONFIDENCE – Ubiquitous Care System to Support Independent Living. CONFIDENCE aims at providing care for the elderly using radio tags attached to the body. The part of the project described in this paper deals with the reconstruction and interpretation of the user's behavior in order to raise an alarm or issue a warning if a fall or some other unusual activity is detected. We compared several machine learning algorithms and various attributes characterizing the user's behavior in order to obtain accurate classification of the behavior into predefined activities. The first results show sufficient accuracy so that the final system is expected to substantially help the elderly and enable them to gain confidence in the late years.

Keywords: ambient assisted living, reconstruction, interpretation, intelligence, machine learning

1. Introduction

The world population is aging due to the increase in life expectancy and decrease in birth rate. This is an immediate concern in developed countries, but it is becoming increasingly problematic in many developing countries as well [10]. As a consequence of this process, the number of the elderly will exceed the society's capacity for taking care of them. Therefore technical solutions are being sought by the EU other countries to ensure that the elderly can live longer independently with minimal support of the working-age population. Many of these efforts belong to the area of ambient assisted living, whose objective is to make daily life easier and safer by placing unobtrusive smart devices and services into the environment [6]. This is also the goal of the European FP7 project CONFIDENCE – Ubiquitous Care System to Support Independent Living [3].

The CONFIDENCE system will unobtrusively monitor the user in order to detect health problems, such as falls and some diseases. Literature suggests that the fear of falling or being left unattended in case of trouble can lead the elderly to the refusal of mobility, isolation, decline in the ability to perform daily activities and eventually admission to institution care [4]. Therefore our target group are the elderly aged over 65 who live on their own, do not have serious mobility problems, but are afraid of falling. With the CONFIDENCE system, such people will gain confidence and security and will have a better quality of life and a longer active participation in the society. The beneficiaries will be not only the elderly, but also their families and caregivers, since the burden on them will be reduced. In practical terms, the goal of the project is to extend the independent life of the elderly by several years, which will also save the cost of institutional care.

The CONFIDENCE system will be able to reconstruct the user's posture and movement, recognize abnormal situations, and raise an alarm if a critical situation such as a fall is detected. It will also be able to detect changes in the user's behavior that may indicate a health problem and issue a warning. For instance, if the system notices changes in the user's gait that may indicate a lack of stability, it will warn the user about an increased risk of falling, and prevent an accident. The system will also detect changes in behavior over longer periods of time, e.g., if an increased danger of falling may appear with time. In this case it will warn the user so that he/she can start walking with a cane or a walker.

It is important that care systems such as CONFIDENCE introduce only small changes in the user's home. The system must be as simple as possible from the user's point of view. A complex system would cause reluctance among the users, who would regard it as a problem rather than as a solution. Therefore, the CONFIDENCE system will be easy to setup and to use, so that it does not limit the user's daily activity in any way. The system will consist of a central base station, which could be designed to look like a decorative item, a small portable device, which will look like a mobile phone, and several tags. The base station will be able to determine the 3D location of each tag in the home using radio technology. The portable device will serve the same role outdoors. In addition, the portable device will guide the user during the installation process. Small and inexpensive tags will be attached to the user, either in the form of bracelets, necklaces etc. or sewn into the clothes. These tags will be easy to wear and, due to their small size, easy to hide.

A lot of research has been done on fall detection and there are also some commercial systems available [1]. Most research used accelerometers [8] and gyroscopes [2] combined with threshold algorithms that simply raise an alarm if a certain acceleration or velocity threshold is reached. Some approaches replaced threshold algorithms with machine learning [15]. There were also attempts to recognize activities using cameras and visual markers [12]. However, we are aware of no system detecting health problems from locations of body tags, so we believe the CONFIDENCE system is breaking new ground.

This paper presents the first results of the work package 3 (WP3) of the CONFIDENCE project – "Design, implementation and test of the reconstruction and interpretation subsystem" [9]. The aim of this work package is to develop the reconstruction and interpretation algorithms for the recognition of abnormal situations. In the reconstruction step, the algorithms reconstruct the user's posture and activity. In the interpretation step, the user's situation is interpreted as normal or abnormal. The input to the WP3 algorithms are 3D coordinates of tags. The equipment to determine the tag coordinates will also be developed within the project. The alarms and warnings raised by WP3 will first be communicated to the user, so that the user will have the opportunity to indicate he/she is feeling fine. If the user confirms that there is a problem or does not respond, the caregivers are notified by phone.

In the first year of the project, a number of behaviors performed by volunteers were recorded. Then machine learning methods for the reconstruction of activities were developed, which is what this paper is mostly concerned with. Because the interpretation algorithms are still under development, the paper deals with them only to a small extent: if the user's activity is recognized as falling, this can be immediately interpreted as abnormal. Section 2 describes the recorded behaviors, Section 3 details the attributes characterizing them and Section 4 reports the results of machine learning experiments for classifying the behaviors into activities.

2. Input data

The goal of the research described in this paper was to classify the user's behavior into one of the following activities: standing/walking, sitting, lying, the process of sitting down, the process of lying down, and falling. In order to develop a classifier for recognizing these activities, we recorded 135 examples of the behavior of three persons:

- 3 × 15 recordings of falling, consisting of standing/walking, falling and lying. Fall detection is one of the main objectives of the CONFIDENCE project.
- 3 × 10 recordings of lying down, consisting of standing/walking, lying down and lying. Lying down is similar to falling, so we wanted to verify whether the classifiers can distinguish between the two.
- 3 × 10 recordings of sitting down, consisting of walking, sitting down and sitting. Sitting down may also resemble falling and is a common action whose recognition is important for the analysis of the user's behavior.
- 3 × 10 recordings of walking. Walking is also common and we wanted unambiguous examples of it to test the classifiers.

The recordings consisted of the coordinates of 12 body tags attached to the shoulders, elbows, wrists, hips, knees and ankles, sampled with 10 Hz. Since the equipment with which the CONFIDENCE system will determine tag coordinates is still under development, the commercially available Smart infrared motion capture system [5] was used. To make the recordings similar to what we expect of the CONFIDENCE equipment, we added Gaussian noise to them. The standard deviation of the noise was 4.36 cm horizontally and 5.44 cm vertically. This corresponds to the noise measured in the Ubisense real time location system [13], which is similar to the equipment planned CONFIDENCE. The noise in the recordings was smoothed with Kalman filter [11].

3. Attributes characterizing the user's behavior

Finding the appropriate representation of the user's behavior activity was probably the most challenging task in our research. The behavior needs to be represented with simple and general attributes, so that the classifier using these attributes would also be general. Attributes overly specific to our recordings would likely fail on general behavior, since the recordings captured only a small part of the whole range of human behavior.

We designed three sets of attributes describing the user's behavior. Reference attributes are expressed in the reference coordinate system, which is immovable with respect to the user's environment. Body attributes are expressed in the coordinate system affixed to the user's body. Angle attributes are the angles between body parts. The attribute vector from which the classifier inferred the user's activity consisted of ten consecutive snapshots of the user's posture, describing one second of activity.

3.1 Reference attributes

The reference attributes consist of the z coordinates, the velocities and the z components of velocities of all the tags in each of the ten snapshots of the user's posture within the one-second interval to be classified. The x and y coordinates were omitted because the location in the environment where an activity of interest takes place is not important. Additional features are the absolute distances and the distances in the z direction between all pairs of tags.

3.2 Body attributes

Body attributes are expressed in a coordinate system affixed to the user's body. This makes it possible to observe x and y coordinates of the user's body parts, since these coordinates no longer depend on the user's location in the environment.

The body coordinate system is shown in Figure 1. Its origin O is at the mid-point of the line connecting the hip tags (H_R and H_L for the right and left hip respectively). This line also defines the y axis, which points towards the left hip. The z axis is perpendicular to the y axis, touches the line connecting both shoulder tags (S_R and S_L for the right and left shoulder respectively) at point S_z, and points upwards. The x axis is perpendicular to the y and z axes and points forwards.

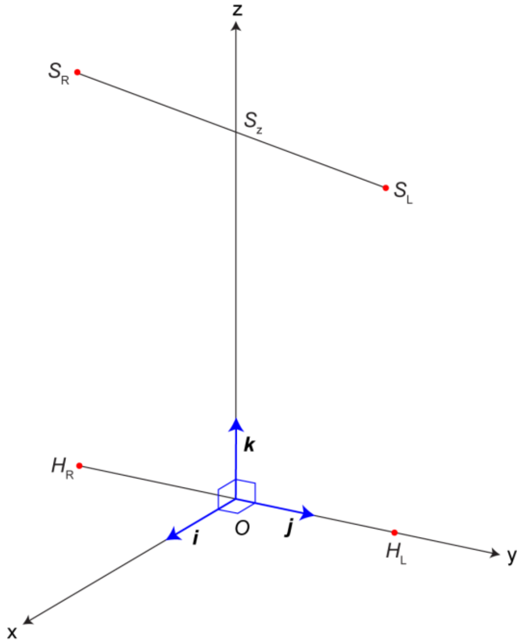

Figure 1: The body coordinate system

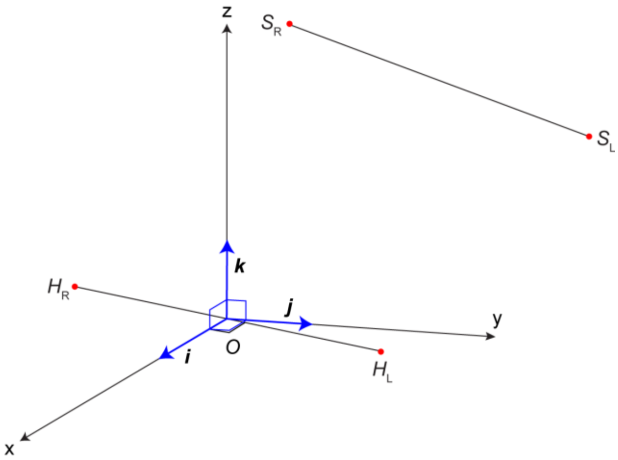

Figure 2: The body coordinate system with the reference z axis

In order to translate reference coordinates into body coordinates, we need to express the origin O and basis ($\boldsymbol{i}, \boldsymbol{j}, \boldsymbol{k}$) of the body coordinate system in the reference coordinate system. Note that bold type denotes vectors and $\boldsymbol{x}$ denotes a vector from the origin to the point X. Equation (1) expresses the origin of the body coordinate system in the reference coordinate system.

$$\boldsymbol{o} = \frac{\boldsymbol{h}_\mathrm{L} + \boldsymbol{h}_\mathrm{R}}{2} \tag{1}$$

Equation (2) gives us the basis vector $\boldsymbol{j}$.

$$\boldsymbol{j} = \frac{\boldsymbol{h}_\mathrm{L} - \boldsymbol{o}}{|\boldsymbol{h}_\mathrm{L} - \boldsymbol{o}|} \tag{2}$$

To obtain $\boldsymbol{k}$, Equation (3) is first used to calculate $\boldsymbol{s}_\mathrm{z}$.

$$\begin{aligned} &\boldsymbol{s}_\mathrm{z} = \boldsymbol{s}_\mathrm{R} + a(\boldsymbol{s}_\mathrm{L} - \boldsymbol{s}_\mathrm{R}) \\ &(\boldsymbol{s}_\mathrm{z} - \boldsymbol{o})(\boldsymbol{h}_\mathrm{L} - \boldsymbol{h}_\mathrm{R}) = 0 \end{aligned} \qquad a = \frac{(\boldsymbol{s}_\mathrm{R} - \boldsymbol{o})(\boldsymbol{h}_\mathrm{L} - \boldsymbol{h}_\mathrm{R})}{(\boldsymbol{s}_\mathrm{L} - \boldsymbol{s}_\mathrm{R})(\boldsymbol{h}_\mathrm{L} - \boldsymbol{h}_\mathrm{R})} \tag{3}$$

Once $\boldsymbol{s}_\mathrm{z}$ is calculated, Equation (4) gives us $\boldsymbol{k}$.

$$\boldsymbol{k} = \frac{\boldsymbol{s}_\mathrm{z} - \boldsymbol{o}}{|\boldsymbol{s}_\mathrm{z} - \boldsymbol{o}|} \tag{4}$$

Finally we obtain $\boldsymbol{i}$ using Equation (5).

$$\boldsymbol{i} = \boldsymbol{j} \times \boldsymbol{k} \tag{5}$$

We also experimented with a variant of body coordinate system with the reference z axis, which is shown in Figure 2. Its origin O is again at the mid-point of the line connecting the hip tags. The z axis is the z axis of the reference coordinate system. The y axis is perpendicular to the z axis, lies on the plane defined by the hip tags and a point on the z axis, and points towards the left hip. The x axis is perpendicular to the y and z axes and points forwards when the user is upright (in general it points in the direction of the cross product of the basis vectors $\boldsymbol{j}$ and $\boldsymbol{k}$). The calculation of the basis vectors for the body coordinate system with the reference z axis is similar to the calculation for the regular body coordinate system.

To finally translate the coordinates in the reference coordinate system into the coordinates in either of the body coordinate systems, Equation (6) is used. The vector $\boldsymbol{p}_\mathrm{R}$ =

$(x_R, y_R, z_R, 1)$ corresponds to the point (x_R, y_R, z_R) in the reference coordinate system and the vector $\boldsymbol{p}_B = (x_B, y_B, z_B, 1)$ to the point (x_B, y_B, z_B) in a body coordinate system. $\boldsymbol{T}_{R\rightarrow B}$ is the transformation matrix from the reference to the body coordinate system. Notation $\boldsymbol{i}_{(B)R}$ refers to the basis vector $\boldsymbol{i}$ belonging to the body coordinate system, expressed in the reference coordinate system.

$$\boldsymbol{p}_B = \boldsymbol{T}_{R\rightarrow B}\boldsymbol{p}_R^T$$

$$\boldsymbol{T}_{R\rightarrow B} = \begin{bmatrix} x_{\boldsymbol{i}(B)R} & y_{\boldsymbol{i}(B)R} & z_{\boldsymbol{i}(B)R} & -\boldsymbol{o}_{(B)R}\boldsymbol{i}_{(B)R} \\ x_{\boldsymbol{j}(B)R} & y_{\boldsymbol{j}(B)R} & z_{\boldsymbol{j}(B)R} & -\boldsymbol{o}_{(B)R}\boldsymbol{j}_{(B)R} \\ x_{\boldsymbol{k}(B)R} & y_{\boldsymbol{k}(B)R} & z_{\boldsymbol{k}(B)R} & -\boldsymbol{o}_{(B)R}\boldsymbol{k}_{(B)R} \\ 0 & 0 & 0 & 1 \end{bmatrix} \quad (6)$$

The body attributes are the x, y and z coordinates, the velocities and the angles of movement of all the tags. Additional attributes describe the relation between the body and reference coordinate systems: the z coordinate, the velocity and the angles of movement of the origin of the body coordinate system expressed in the reference coordinate system, and the orientation of the body coordinate system with respect to the reference one.

So far we expressed body attributes in the body coordinate system of each snapshot of the user's posture. However, the attributes in all ten snapshots within a one-second interval can be expressed in the coordinate system belonging to the first snapshot in the interval. This captures the changes in the x and y coordinates between snapshots within the interval. Most of the first-snapshot body attributes are the same as the body attributes. The differences are in the attributes describing the relation between the body and reference coordinate systems. They appear only once per attribute vector, since there is only one body coordinate system, and the attributes dealing with the movement of the origin of the body coordinate system are omitted.

3.3 Angle attributes

These attributes are the angles between adjacent body parts: the shoulder, elbow, hip and knee angles and the angle between the lower and upper torso. The shoulder, hip and torso have three degrees of freedom, so their angles are represented by quaternions (mathematical constructs often used for describing 3D rotations); the remaining two joints have only one degree of freedom each, so their angles are represented by scalars.

4. Classification of the behavior into activities

We tried various machine learning algorithms to train classifiers for classifying the behavior into the six activities (standing/walking, sitting, lying, sitting down, lying down and falling). To do so, sections of the 135 recordings described in Section 2 were first manually labeled with the activities. Afterwards the recordings were split into one-second intervals and the attributes described in Section 3 extracted from them. This gave us 5,760 attribute vectors consisting of 240–2,700 attributes each (depending on the attribute set). An activity was then assigned to each attribute vector. Finally these vectors were used as training data for eight machine learning algorithms: C4.5 decision trees, RIPPER decision rules, Naive Bayes, 3-Nearest Neighbors, Support Vector Machine, Random Forest, Bagging and Adaboost M1 boosting. The algorithms were implemented in Weka [14], an open-source machine learning suite. Machine learning experiments proceeded in two steps.

In the first step of experiments we compared the classification accuracy of the eight machine learning algorithms and of all single attributes sets described Section 3: reference, body, body with reference z, first-snapshot body, first-snapshot body with reference z and angles. The results are shown in Table 1. The accuracy was computed with ten-fold cross-validation. The accuracy of the best attribute set for each algorithm is in bold type; the accuracy of the best algorithm for each attribute set is on gray background.

Table 1: Classification accuracy for all the algorithms and all single attribute sets

Algorithm \ Attribute set	reference	body	body with reference z	first-snapshot body	first-snapshot body with reference z	angles
	Clean data					
C4.5 decision trees	**94.1**	92.8	93.7	92.9	93.2	91.8
RIPPER decision rules	**93.1**	91.4	92.8	92.0	93.0	90.9
Naive Bayes	89.5	88.7	**90.6**	86.8	88.2	76.7
3-Nearest Neighbor	**97.1**	92.0	82.8	88.1	85.1	96.9
Support Vector Machine	**97.7**	94.4	95.0	94.1	94.3	90.5
Random Forest	**97.0**	96.5	96.8	96.0	96.0	96.8
Bagging	**95.9**	95.3	95.7	95.4	94.9	94.5
Adaboost M1 boosting	**97.7**	94.9	95.3	94.7	94.7	94.4
	Noisy data					
C4.5 decision trees	**90.1**	88.4	89.9	88.9	90.0	80.8
RIPPER decision rules	87.5	84.7	88.1	86.2	**88.6**	80.0
Naive Bayes	83.9	79.1	**84.0**	81.0	82.2	78.2
3-Nearest Neighbor	**95.3**	74.6	79.7	73.4	74.7	93.3
Support Vector Machine	**96.3**	87.2	91.6	89.9	91.1	87.2
Random Forest	**93.9**	90.5	93.4	91.9	93.2	90.5
Bagging	**93.6**	91.8	93.3	92.3	93.5	89.1
Adaboost M1 boosting	**93.2**	92.0	93.1	92.1	92.9	88.4

For the next step of machine learning experiments, we retained the best algorithms and the best attribute sets. To rank them, we compared the classification accuracy of all pairs of algorithms and all pairs of attribute sets. Table 2 shows the number of comparisons in which a given algorithm statistically significantly (p < 0.05) wins over another algorithm, minus the number of comparisons where it loses. Table 3 shows the same for the attribute sets. The accuracies of the algorithms and attribute sets selected for the second step are on grey background; the accuracies of the best algorithms and attribute sets are in bold type. We did not choose attributes for the second step strictly by accuracy, but primarily wanted to discard those that are redundant.

Table 2: The number of wins – losses of every algorithm against the others for clean and noisy data

Algorithm	Wins – losses	
	Clean	Noisy
C4.5 decision trees	–12	–10
RIPPER decision rules	–18	–21
Naive Bayes	–38	–34
3-Nearest Neighbor	–13	–16
Support Vector Machine	13	11
Random Forest	**38**	23
Bagging	17	**25**
Adaboost M1 boosting	13	22

Table 3: The number of wins – losses of every single attribute set against the others for clean and noisy data

Attribute set	Wins – losses	
	Clean	Noisy
reference	**25**	**28**
body	–2	–21
body with ref. z	9	20
1st-sn. body	–11	–9
1st-sn. body with ref. z	–2	12
angles	–19	–30

In the second step of machine learning experiments, we tried combinations of attribute sets. Table 4 shows the classification accuracy for the four algorithms we retained and combinations of the attribute sets we retained. The accuracy of the best combination of attributes for each algorithm is in bold type; the accuracy of the best algorithm for each combination of attributes is on gray background.

Table 4: Classification accuracy for the retained algorithms and combinations of attribute sets

Attribute set combination / Algorithm	reference + body	reference + body with ref. z	reference + angles	body + angles	body with ref. z + angles	all	all (ref. z)
	Clean data						
Support Vector Machine	96.6	96.9	**97.7**	95.3	95.5	96.7	96.9
Random Forest	97.0	97.0	**97.2**	96.7	96.9	97.1	97.0
Bagging	96.1	96.0	96.1	95.6	95.7	**96.3**	96.0
Adaboost M1 boosting	**95.7**	95.6	95.5	95.3	95.3	95.6	95.5
	Noisy data						
Support Vector Machine	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**

5. Conclusion

The paper described the first experiments in WP3 of the CONFIDENCE project. The experiments were carried out in the presence of noise similar to what is expected of the CONFIDENCE equipment. Even with noise, several machine learning methods achieved classification accuracy of over 90% and Support Vector Machine with the best attributes even 96.5%. It should be noted that these measurements were performed for each one-second interval separately. The performance is expected to improve when the continuity of activity is taken into account, i.e., the fact that the activity does not change every one tenth of a second. This means that the basic activities can be recognized quite reliably. If fall recognition takes into account that a fall occurs when several instances of falling are recognized, followed by several instances of lying, it is expected to be even more accurate.

The described approach to reconstruction and interpretation shows advantages and disadvantages. The system learns the behavior of each user and can re-learn in the case of a long-term change in the posture or movement, e.g., a broken leg. This is an advantage because the system adapts to each user. However, it is also a disadvantage because a learning period is needed. The issue can be addressed by including pre-learned properties of postures and movements of a typical person, which can be applied to many users out-of-the-box. However, some elderly do not conform to such typical behavior patterns.

The two main problems encountered during the development of the reconstruction and interpretation methods were the lack of training data and appropriate medical expertise. It is important to work with authentic recordings of the behaviors of the elderly, both healthy and unhealthy, but particularly the latter are difficult to obtain due to ethical concerns. Medical data in a quantitative form suitable for the use in the CONFIDENCE system is not available in the literature, because no such system exists and therefore such data was not needed before. Unfortunately the consortium had not foreseen the full scope of this problem and lacks the personnel with the requisite medical knowledge. We have so far coped with this issue by consulting outside experts, but this solution is not ideal.

In the continuation of the project, the reconstruction methods will be refined and the methods for interpreting the recognized activities as normal or abnormal will be developed on top of them. These methods will be further tested and modified when the prototype of the CONFIDENCE equipment for determining tag coordinates is available. Eventually the whole CONFIDENCE system will be integrated and installed in a test room. This will give us the opportunity to showcase it to potential business partners for the development of a product. We are considering several business models, from selling a stand-alone product to individuals and letting them configure the alarms themselves, to a subscription-based service that includes renting the equipment and provides a call center and medical support. The project will finish in early 2011 and we estimate that the earliest a product based on it could be brought to market is 2013. This should give the software enough time to reach maturity and the price of the hardware, which is at the moment the major barrier to bringing CONFIDENCE to market, should decrease sufficiently. The value of the product might be increased by expanding its functionality, for example by including a personal trainer application capable of monitoring the user's exercise through the body tags.

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