**Preprints of the 19th World Congress
The International Federation of Automatic Control
Cape Town, South Africa. August 24-29, 2014**

RGBD camera monitoring system for Alzheimer's disease assessment using Recurrent Neural Networks with Parametric Bias action recognition

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Abstract: The present paper proposes a computer vision system to diagnose the stage of illness in patients affected by Alzheimer's disease. In the context of Ambient Assisted Living (AAL), the system monitors people in home environment during daily personal care activities. The aim is to evaluate the dementia stage, observing actions listed in the Direct Assessment of Funcional Status (DAFS) index and detecting anomalies during the performance, in order to assign a score explaining if the action is correct or not. In this work brushing teeth and grooming hair by a hairbrush are analysed. The technology consists of the application of a Recurrent Neural Network with Parametric Bias (RNNPB) that is able to learn movements connected with a specific action and recognize human activities by parametric bias that work like mirror neurons. This study has been conducted using Microsoft Kinect to collect data about the actions observed and oversee the user tracking and gesture recognition. Experiments prove that the proposed computer vision system can learn and recognize complex human activities and evaluates DAFS score.

1. INTRODUCTION

Within 2050, demographic changes will become one of the most important aspect for social assistance and healthcare institutions, with a number of elderly that will increase significantly, not only in European Union EU (2013). Among aging people emergencies, dementia, such as Alzheimer's disease, represents a public health challenge, with over 35 million people worldwide who live in this condition Prince et al. (2013) and with consequences as the growth in assistance demand and the adjustment and requirement of sustainability of healthcare systems decreasing workforce. In this contest, AAL aims to support life quality by information and communication technologies (ICT) to guarantee a safe environment, reducing welfare and supporting cost cutting strategies Cardinaux et al. (2011). Particularly, early diagnosis has emerged as a priority target: in fact, only one-third of dementia cases receive a diagnosis of their illness, and without it, addressing their needs and effective intervention is very hard. Dementia is recognised when progressive cognitive decline occurs, having impacts upon abilities to carry out everyday activities. Nowadays clinician diagnosis are supported by careful neuropsychological testing, a history from the patient (subjective impairment in memory and cognitive functions) and from a key informant (objective signs of cognitive decline, and impacts on social and/or occupational functions). These instruments may be able to detect cognitive impairment relative to expected norms, or to that person's previous performance on the same test Prince et al. (2011).

Different works about monitoring systems have been realized in order to assess subject's performances or assist him in accomplishing tasks. In Avgerinakis et al. (2012) a system based on computer vision and Support Vector Machines (SVMs) is proposed. It uses static and wearable camera: motion features are extracted and their trajectories are identified via statistical signal detection. The goal is to estimate the patients' behavioural profile in order to generate reports for doctors to compile an assessment-diagnosis and depicting the progression of the patient's dementia condition. Another approach, proposed in Zhang and Tian (2012), focuses on recognizing activities of daily living by developing skeleton structure-motion using 3D information by RGB-D cameras. This work allows to detect dangerous activities for elderly people like falls under different lighting conditions. In Matic et al. (2012), is proposed a study on monitoring dressing activity as an indicator of both cognitive and motor skills, in people affected by Alzheimer's disease. The action recognition is obtained by using RFID and accelerometers. The system provides a platform to give assistance to patient about dressing difficulties, warning him by voice feedback. It also allows to track, throughout a long period, eventual changes in dressing performance, which can be used as indicators in the evaluation of the cognitive state Klapow et al. (1997).

The proposed vision system has the scope to support clinicians in the identification of emerging Alzheimer symptoms, in a quantitative and objective way and from mild to moderate stages, evaluating DAFS index. DAFS Zanetti et al. (1998) is a standardized observation-based checklist, designed to assess functional capabilities of adults affected by Alzheimer, dementia or schizophrenia. It is used to evaluate the stage of illness and any decline or pharmacological intervention effects on the base of the right actions sequence Datong et al. (Aug.). The idea is that of getting an intelligent instrument, based on the observation of personal care actions, included in the evaluation test, in order to assess a score. In this way it is possible to avoid conditioning patient by the presence of a human tester, who observes him while he is performing different activities. Furthermore, it is tested that the transition of dementia patients into a different environment can be traumatic for them Prince et al. (2013), in this contest the possibility to observe personal care actions directly in patient's bathroom is an important aspect for the test result. Computer vision systems help people to reduce invasivity of body worn sensors and to monitor patients avoiding loss of information and without any interference during the activities Mégret et al. (2010). The employment of video camera is of interest for the users privacy respect; in this context, only some people are allowed to access the information, recorded and processed by the system. It is possible to distinguish two information levels: one more sensitive, represented by the clip recorded, and one less sensitive connected with an information computed from it. Authors use second level access to video information, so only doctors and caregivers can access to the video.

The solution proposed consists of the application of RN-NPB which works as mirroring neurons in the human brain Buscema et al. (2004); Elshaw et al. (2004) in order to learn movements connected with a specific action. In this study, the following personal care actions are analyzed: "brushing teeth" and " grooming by a hairbrush". Authors have supported their work by Microsoft Kinect that allows the data collection about the actions observed and can oversee the "user tracking" and "gesture recognition". This instrument is equipped with an IR emitter and a CMOS sensor that rebuild the depth of the scene Stone and Skubic (2012). Furthermore, autogenerate reports could be monthly provided to doctors and an assessment-diagnosis could be compiled depicting the progression of each patient condition. The paper is organised as follows. Section 2 describes dementia's assessment indexes and specifically the index considered in the work. The neural network used to learn and recognize human activities is described in Section 3. Section 4 describes the developed procedure for the activity recognition. The experimental setup and results are described in Section 5. The paper ends with Section 6 where results, possible future research perspectives and final remarks are given.

2. INDICES FOR DEMENTIA'S ASSESSMENT

Alzheimer's disease and other dementia illnesses include some impairments on patient's life, that arise in social and occupational everyday abilities and show which are the problems in different aspects of the human life. The National Institute of Neurological and Communicative Disorders and the Stroke Alzheimer's disease and Related Disorders association (NINCDS-ADRDA) have assessed which capabilities need to be observed for Alzheimer's disease diagnosis. These are classified into functional and cognitive capabilities and many objective indexes are defined to evaluate them. The DAFS index, which refers to other indexes domain, comprises 7 items that investigate both functional and cognitive aspect in order to maintain an uniform evaluation.

Table 1. PERSONAL CARE

ID	Description	Score	
64	Remove the cap of toothpaste	0	1
65	Put the toothpaste on the toothbrush	0	1
66	Open the faucet	0	1
67	Brush teeth	0	1
68	Wet the sponge	0	1
69	Put the soap on the sponge	0	1
70	Wash face	0	1
71	Close the faucet	0	1
72	Groom hair	0	1
73	Wear a jacket	0	1
74	Button up a jacket	0	1
75	Lace a shoe	0	1
76	Zip up	0	1

A cognitive report of dementia's disease is the Clinical Dementia Rate (CDR)Gelb (2000), which assesses different features as: memory, orientation, judgement, problem solving, community affairs, home and hobbies and personal care. It quantifies the severity of dementia state. The main domain in CDR index is memory, while others are used as correcting factor. A related index, referred to CDR, is the Mini Metal State Examination (MMSE) Zanetti et al. (1998), used to evaluate the cognitive functions. The total score is proportional to cognitive efficiency. It assumes values from 30 (absence of deficit state) to 0 (terminal dementia), and the threshold is 24, that can change in function of age and education. The MMSE evaluates: temporal and spatial orientation, memory, attention and calculation, recall, language, repetition, stage command, reading, writing and copying.

Physical Performance Test (PPT) evaluates functional abilities Zanetti et al. (1998) during activities of daily living. It considers 7 items that are: writing, eating, turning of 360 degrees, wearing and taking off a jacket, raising a book and putting on a shelf, taking a coin from the floor, walking along 15 meters. The score range is $0-28$ and the threshold is 18. Basic Activities of Daily Living (BADL) and Instrumental Action of Daily Living (IADL) are discussed due to their relation to DAFS. BADL evaluates 6 basis activities: bathing, dressing, toilette, moving, urinary continence and eating. Scores assigned are 0 if the action is badly realized or 1 in the other case. IADL assesses the elderly people capacity to make activities necessary to their independence Zanetti et al. (1998).

About the functional activities, DAFS Zanetti et al. (1998) measures behaviours classified into 7 functional domains (items): orientation (time and date), communication abilities, financial skills, shopping skills, transport (optional scale), dressing/grooming skills, feeding abilities. The maximum DAFS score is 86, while a score under 68 denotes the presence of illness at a mild stage. In Tab. 1 are presented actions related to the personal care item and the total score provided by this group is 13. DAFS is defined from the previously discussed indexes. Each domain of the DAFS is previously identified in the literature as an important areas in the assessment of older

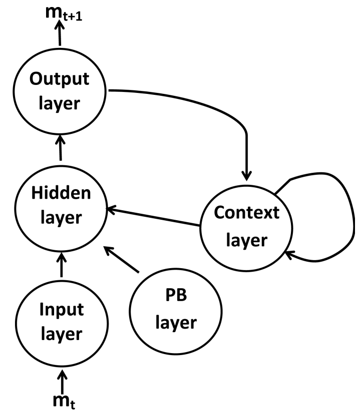

Fig. 1. Recurrent neural network with parametric bias.

individuals. DAFS is able to discriminate clinic patients with Alzheimer's disease from normal elderly subjects on the base of performances realised during the clinical test Loewenstein et al. (1989). Inter-rater reliability is at least 85% agreement between raters on each item of the scale.

If the action is realized correctly the score is 1, otherwise 0. This assessment is not realized on only one observation but the idea of this work, is to evaluate the activity after a set of examinations, to avoid patient conditioning or clustering errors. The approach is to compute the DAFS score of an observation period. Then drifts are evaluated on computed scores related to different measurement periods. Finally automatic report could be generated and transmitted to doctors and caregivers.

3. RECALLED RESULTS

Recurrent Neural Networks with Parametric Bias are introduced in Tani (2003); Tani and Ito (2003) and Tani et al. (2004). The main characteristic of the RNNPB is that chunks of spatio-temporal input data patterns flow can be represented by a small dimension vector, the so called Parametric Bias (PB). This vector plays the role of bifurcation parameters in nonlinear dynamical systems. Thus different PB values make the system able to generate different dynamic patterns. The nonlinear dynamical system considered is a Jordan-type recurrent neural network Jordan (1990), except for the introduction of PB nodes in the hidden layer input. In Fig. 1 the typical scheme of RNNPB is shown. RNNPBs can be used and configured in three different cases: learning, recognition and generation.

3.1 Learning

The learning is referred to the phase where the RNNPB is trained with skeleton-motion features sequences. At this step input data are learned through the forward model of the RNNPB. The connection weight matrices, which are common for all patterns, and the PB vectors, which are assigned differently for each movement pattern in order to let the network predict multiple and sequentially presented time series, are trained by BackPropagation Through Time (BPTT) algorithm Rumelhart et al. (1988); Werbos (1990). The learning algorithm for the parametric bias vectors is a variant of the BPTT algorithm and mainly two different learning algorithms are used in literature Tani (2003); Cuijpers et al. (2009). PB vectors and the internal connection weights are updated at each epoch e, therefore, after that, all time series have been presented. In the proposed approach the internal values of PB vector, related to k^{th} time series ($\rho^{PB}_{k,e}$) are updated according to:

$$\Delta\rho^{PB}_t = \epsilon\delta\rho^{PB}_t + \eta\Delta\rho^{PB}_{t-1}. \tag{1}$$

$$\rho^{PB}_{k,e} = \rho^{PB}_{k,e-1} + \delta\sum_{t=1}^{T}\Delta\rho^{PB}_t \tag{2}$$

$$p^{PB}_{k,e} = sigmoid(\rho^{PB}_{k,e}/\zeta), \tag{3}$$

where ϵ is the learning rate, η is the momentum, T is the duration of each time series, δ is the gain of PBs, and p^{PB} is the parametric bias. The parameter ζ is employed in order to control the value of the parametric bias. If ζ takes small values, the parametric bias tends to have more extreme values that depend from the activation function used, in this case, using a sigmoid activation function, either 0 or 1. On the other hand, if ζ takes large values, the parametric bias tends to take the average value of the output activation function, which in this case is 0.5. In the actual learning process, ζ varies from larger to smaller values as learning proceeds. At the end of learning, one can observe chunks of about 1 or 0 bit representations of the parametric bias during the last epochs.

3.2 Recognition

Recognition refers to the phase where the RNNPB recognizes a given skeleton-motion sequence among those with which the neural network has been previously trained. The recognition phase only differs from the learning phase in that the internal weights of the network are not updated and only the PB vectors are updated. In this phase, the PB values, corresponding to a given sequence, can be obtained by using the update rules for the PB values (Eqs. 1-3) without updating the connection weight values, since the relational structure among training sequences can be acquired in the PB space through the learning process. This enables the RNNPB model to recognize previously unseen sequences without the need of additional learning. In this work, the human action chosen by the RNNPB in the recognition phase, is that which minimizes the euclidean distance between the PB values evaluated by the neural network and those learnt during the training phase.

3.3 Generation

Generation refers to the phase where the RNNPB generates the time series previously learnt by setting the PB vectors to the appropriate values and running the network in closed loop. In this modality, the desired sequence is obtained by carrying out forwarding-forward calculation of the RNNPB; therefore the sensory-motor prediction outputs for the next time step are fed-back into the current step inputs, allowing look-ahead prediction of sensory-motor values for arbitrary future steps without inputs of the actual sensory-motor values. During this phase, no updating takes place.

4. DEVELOPED ALGORITHM

The developed procedure uses Kinect sensor and the Microsoft MSDN Library for Kinect Microsoft (2013) to

Table 2. Sub-Action labels

Labels	Sub-Actions
1	Rest position
2	Take/put away the toothpaste, the toothbrush and the comb
3	Groom hair
4	Open/close the faucet
5	Remove the cap of toothpaste
6	Brush teeth
7	Rinse the mouth and the toothbrush
8	Put the toothpaste on the toothbrush

collect RGBD frames. The RGB-D camera, gives a RGB image as well as depth at each pixel. By this instrument it is possible to recognize the patient, who is performing test actions, during his activity, by looking at his current pose and movement over the time. In order to compute the human pose features, a person is described by a rigid body skeleton with moving joints. This skeleton is extracted using a tracking system provided by Microsoft, and it is represented by the links length and the joint angles. In Microsoft (2013) the considered human skeleton structure and the kinematic chain are described. Due to this representation it is possible to define a joint position and orientation respect its distal joint location in the kinematic body chain, in this way the defined representation is invariant respect to sensor position. Also quaternions are chosen as features, instead of rotation matrices, because they allow to avoid the well known gimbal lock problem Šenk and Chèze (2006), Grood and Suntay (1983). Hence the proposed action recognition system uses the quaternions as input data, considering 20 joints there are $20 \cdot 4$ features for the body pose to be used as input signals.

In this work daily personal care actions are considered. In particular authors focus on 6 actions of the DAFS index, referring to Tab. 1, these are: 64, 65, 66, 67, 71 and 72. The described actions do not consider all possible movements that are performed during their execution. Then in this work a set of so called sub-actions are considered, in order to better perform the classification, and then the sequences of sub-action, classified by the RNNPB, are evaluated and matched with the defined DAFS actions. Thus 8 groups are defined, as described in Tab. 2. It can be noted that some sub-actions are grouped due to their similarities.

In the proposed procedure the RNNPB has the $20 \cdot 4$ joints quaternions samples as inputs and their one-step prediction as output. The classification is performed by the PBs combination while the prediction error is evaluated in order to verify that the RNNPB performance does not degrade.

The procedure training steps consist of:

1. for each patient dataset:
   - acquire Kinect human motion features, extract body joints quaternion signals of each sub-action;
   - train the RNNPB on each sub-action PB configuration;
   - define the sub-action sequences that compose each action in DAFS index formulation.

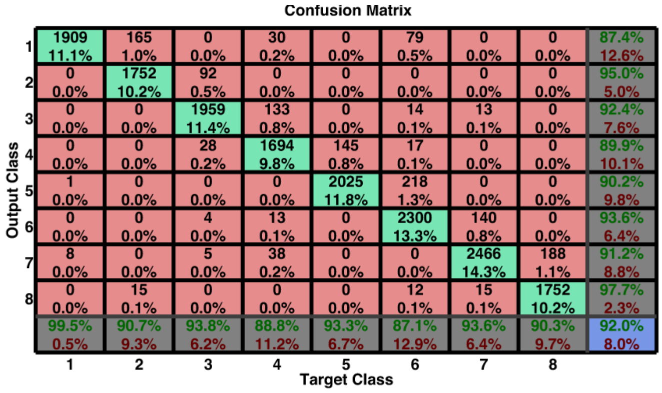

Fig. 2. Confusion matrix of training dataset

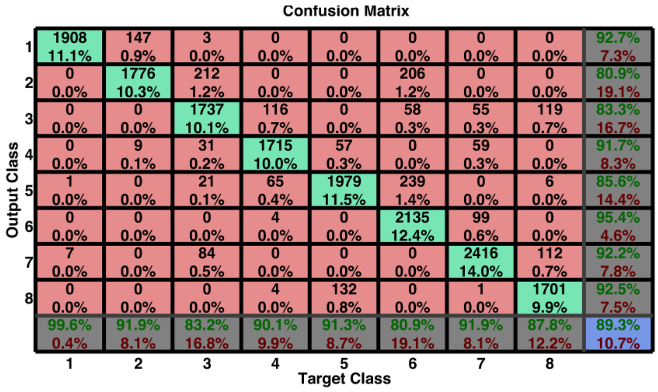

Fig. 3. Confusion matrix of testing dataset

The test steps are then composed by:

1. **if** *the patient is in the bathroom:* **then**
   - acquire Kinect human motion features, extract body joints quaternion signals of each sub-action;
   - recognize the acquired motion sequence and extract PB configuration along time sequence;
   - classify the sequence and assign DAFS score.

   end

5. EXPERIMENTAL SETUP AND RESULTS

The experimentation consists of making actions like "grooming hair" and "washing teeth" by ten actors: people who have realized the actions of DAFS test. For each person, each sub-action runs 5 times for the training phase, and for the testing phase the action is repeated 3 times. A wrong action has been also performed, both for the "grooming hair" and the "washing teeth": in the first case the subject does not groom hair and in the second he does not close the faucet. The errors have been realized once.

The considered RNNPB has 50 neurons for each layer, the number of PBs is 6, the learning rate ϵ is set to 0.1, the momentum η is 0, δ is 10 and ζ varies linearly from 1 to 0.9 as learning proceeded. The RNNPB is trained with 2000 epochs. The performance reached a Mean Square Error (MSE) of $1.9 \cdot 10^{-05}$ at the last epoch.

The classification accuracy is defined as the percentage of frames, respect all frames in dataset, that matches actions correctly. The percentage of classification is explained as the percentage of frames that is correctly classified for each sub-action and for all tests. The confusion matrices of the

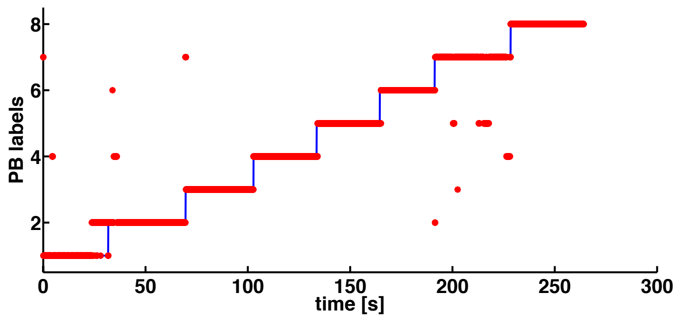

Fig. 4. Sub-Action labels recognized by the RNNPB for testing data

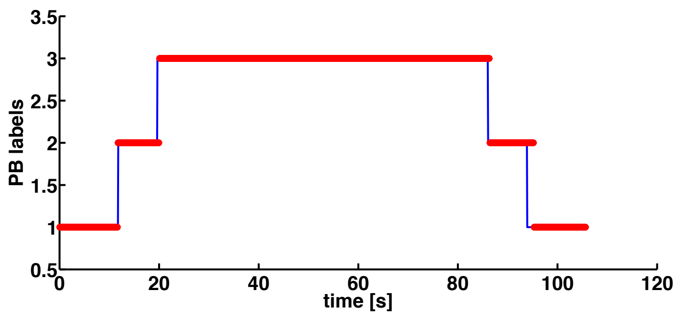

Fig. 5. Sub-Action labels recognized by the RNNPB during the grooming hair action in the case of correct sequence performed by the user

training and testing dataset are shown in Figs. 2 and 3. The percentages are the average of all users and runs.

In Fig. 4 action labels are shown: the RNNPB recognizes the motion of the users for each sub-action. The error is localized during the sub-action change, because the neural network needs some skeleton frames to adapt the PBs and recognize the sub-action. The grooming hair activity is composed by a sequence of five sub-actions: the user is in the rest position, he takes the comb, grooms hair, puts away the comb and lastly comes back in the rest position. Fig. 5 shows the sub-action labels recognized by the RNNPB during the described activity. The classification accuracy for "grooming hair" activity is 97.91%. In this case, as shown in Fig. 5, if the user performs the correct sequence then the DAFS index is set to 1.

In Fig. 6 grooming hair activity is shown, but in this case the user takes the comb and forgets the next sub-action, then puts away the comb and lastly comes back in the rest position. This forgetfulness is recognized by the neural network and the DAFS index is set to 0.

The last test shows the brushing teeth activity that is composed by a sequence of eleven sub-actions: the user is in the rest position, takes the toothpaste, removes the cap of toothpaste, takes the toothbrush, puts the toothpaste on the toothbrush, puts away the toothpaste, opens the faucet, brushes the teeth, rinses the mouth and the toothbrush, closes the faucet, puts away the toothbrush and lastly comes back in the rest position. Fig. 7 shows the action labels recognized by the neural network during the brushing teeth activity, as described above. The classification accuracy for this activity is 95.20%. In this case, as shown in figure, the user performs the correct sequence and the DAFS index is set to 1.

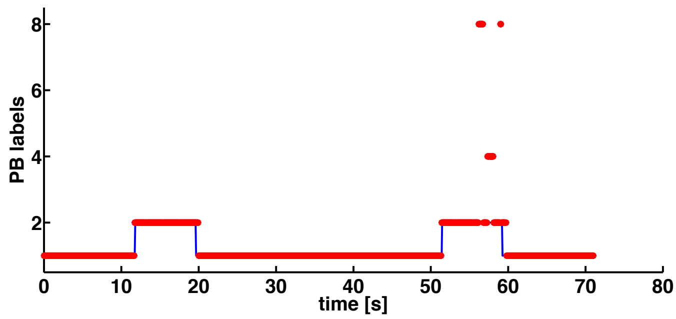

Fig. 6. Sub-Action labels recognized by the RNNPB during the grooming hair action in the case in which the user forgets to comb

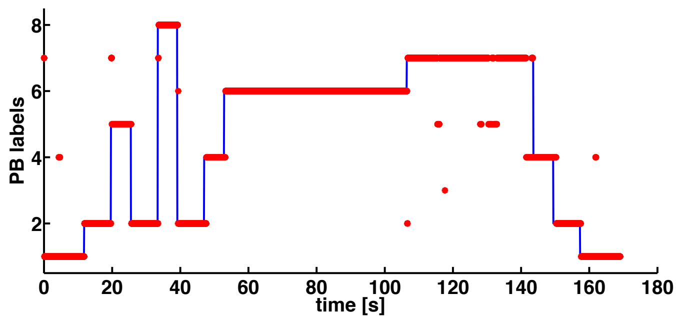

Fig. 7. Sub-Action labels recognized by the RNNPB during the brushing teeth action in the case of correct sequence performed by the user

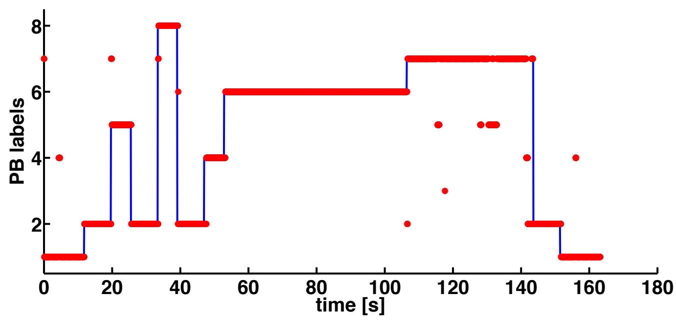

Fig. 8. Sub-Action labels recognized by the RNNPB during the brushing teeth action in the case in which the user forgets to close the faucet

Fig. 8 shows the case in which user forgets to close the faucet. This forgetfulness is recognized by the neural network and the DAFS index is set to 0. The sub-action of closing the faucet is a crucial action, then the system sends a warning signal to the user or caregivers.

6. CONCLUSIONS AND FUTURE WORKS

The contribution of this work proposes an objective technological approach to observe and take note of the Alzheimer's evolution, monitoring patients during personal care actions performance. The results obtained, about the two activities realized, show that classification accuracy is higher than 90%, so it is possible to consider the system able to learn and recognize human activities. This also allows an every day assessment of the particular actions in order to observe possible variations on the total score. The results obtained could be communicated to doctors or caregivers to take note of the deterioration of the patient dementia stage. Authors are currently considering four possible future extensions for the proposed computer vision system. The first is related to the possible increment of the information extracted, so not only skeleton quaternion motion features can be recognized, but also objects used during the activities. In this way, it will be possible to understand if patients make the actions with the right object associated. The second one is related to the testing phase and to obtain more accurate results by increasing the number of actions that the system has to learn and recognize, in order to generalize as much as possible the action recognition. Particularly the goal is to implement also all the other actions present in the item of personal care of DAFS index. The third one is related to the neural networks used, because RNNPB are not the only ones adopted in the literature to learn and recognize activities, so a further investigation will be carried out. The last one concerns the involvement of people with dementia in testing stage and the goal is to verify how this index, which is periodically evaluated, can be used by medical staff and caregivers for dementia's assessment. Finally another improvement that could be investigated in order to realize a system more autonomous, is to introduce an automatic recognition system of the patient by face detection. In this way the technology proposed works only when the patient is identified and his electronic record, with the "actual stage of illness", is associated to him.

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