Learning Human Activities for Assisted Living Robotics

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ABSTRACT
Assistive living has gained increased focus in recent years with the increase in elderly population. This has led to a desire for technical solutions to reduce cost. Learning to perform human activities of daily living through the use of assistive technology (especially assistive robots) becomes more important in areas like elderly care. This paper proposes an approach to learning to perform human activities using a method of activity recognition from information obtained from an RGB-D sensor. Key features obtained from clustering and classification of relevant aspects of an activity will be used for learning. Existing approaches to activity recognition still have limitations preventing them from going mainstream. This is part of a project directed towards transfer learning of human activities to enhance human-robot interaction. For test and validation of our method, the CAD-60 human activity data set is used.

CCS CONCEPTS
•Computing methodologies → Activity recognition and understanding; Supervised learning by classification; Feature selection; Vision for robotics; Image representations;

KEYWORDS
Activity recognition, Assistive robotics, Ambient assisted living, Feature extraction

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1 INTRODUCTION
With the increase in the ageing population in developed societies, Ambient Assisted Living (AAL) technology helps to reduce cost of elderly care. One means of achieving this is by deploying assistive robotics in an AAL environment. This requires the robot to learn tasks that human carers will perform as part of routine duties.

Human Activity Recognition (HAR) has gained a lot of interest in recent years [9][10][11]. In applications involving human-computer interactions (for example, gaming and assisted living environments), HAR enables elaborate explanation/interpretation of activities performed by humans. This is key to understanding how these activities are learned and how one experience relates to another. This improves the collaboration and adaptation of assistive robots.

Prior to assistive robots performing a human activity, they need to learn these activities to effectively perform them. This requires grouping human movements with their descriptive semantics. Observing activities as they are performed through the use of visual or non-visual sensors makes it a lot easier to obtain information of human activities in an environment[4][19][20]. It would be extremely hard to understand and interpret activities using a normal visual sensor such as RGB cameras which provide 2D visual data [6]. These sensors provide limited information for an activity performed in a real world environment. However, recent development in RGB-D sensors show that they are better devices for observing human activities [6]. These sensors provide a means of better observing the world to detect human pose used to build activity recognition systems [4][20]. They also provide a platform for exploiting depth maps, body shape and skeleton joint detection of humans in 3D space which are used in developing sophisticated recognition algorithms.

This paper proposes a supervised learning method to human activities recognition by exploiting 3D human skeleton data provided by an RGB-D sensor. The proposed method shows the observation of activities as they are performed and how features are extracted after a clustering method is applied. Thus, providing a means of classifying different activities. The features extracted simplify the process of learning the activities. The work presented here is part of a research project directed towards improving human-robot or robot-robot interaction through Transfer Learning [12]. This will enable more adaptable robots learn to perform human activities of daily living from transferred knowledge. For example, in Figure
1, two robots are shown performing an activity in which one acts as the teacher while the other acts as a learner using transferred knowledge gained from visual observation as the teacher robot performs the activity. The goal of our research is to develop a state of the art system which will have HAR and learning performance comparable to that of humans.

This paper is organized as follows: In section 2, a review of related work in this area is presented. Section 3 gives details of the method applied to our approach and some initial results are presented in Section 4. Section 5 presents conclusions and future work to be undertaken.

2 RELATED WORK

For an assistive robot to perform an Activity of Daily Living (ADL), an understanding of the activity is required which is the process of learning. An important aspect in the process of learning is the recognition of activities as they are performed by human actors. This creates the need for proper observation of the environment by the robot to rightly interpret the activity.

HAR from information obtained using RGB-D sensors gives very important information relevant for a robot to understand an activity. By exploring human pose detection using RGB-D sensors, activity recognition has seen more advancement in recent times [4][19]. These RGB-D sensors extract 3D skeleton data from depth images and body silhouette for feature generation [1]. In [4], the RGB-D sensor is used to generate human 3D skeleton model with matching of body parts linked by its joints. They extract positions of individual joints from the skeleton in a 3D form x, y, z. Authors in [10] use similar RGB-D sensor to obtain depth silhouette of human activities from which body points information are extracted for the activity recognition system. Another approach is shown in the work in [5] where the RGB-D sensor is used to obtain orientation-based human representation of each joint to the human centroid in 3D space. The data set obtained using RGB-D sensors have to be preprocessed which is an important step in the activity recognition system. This process is carried out to filter the data for better representation of features of an activity.

HAR from video camera sensors can be broken down into two aspects [18]: feature-based and model-based. Feature-based techniques such as Histogram of Oriented Gradients (HOG)[21], subspace clustering based approach (SCAR)[25] are used to extract features for recognizing human activity from data acquired using sensors. Model-based approach has to do with construction of a human model for recognition either as a 2D, 3D or skeletal model. Authors in [1][23] construct models using kinematic approach that extract features from frame sequences for human structure representations. A combination of both feature-based and model-based approaches is seen in [20] where a Maximum Entropy Markov Model (MEMM) for classification of activities using features from skeleton tracking combined HOG. Authors in [3] also used neural network technique to propose an end-to-end hierarchical recurrent neural network (RNN) for representing skeleton based construction. They make use of the raw positions of human joints as input to the RNN.

All methods reported above are using feature extraction techniques to obtain feature vectors which describe the activity performed. HAR approaches which utilize human 3D joint positions information extracted from RGB-D sensors transform joint positions of individual frames into column vectors. A matrix is then formed to encode the sequence of frames at specific time intervals. 14 features obtained from distances between different body parts are used to characterize 12 activities[4]. This was used with a combination of multiple classifiers to form a Dynamic Bayesian Mixture Model (DBMM). Similarly, [8] applied statistical covariance of 3D joints (Cov3DJ) as features to encode the skeleton data of raw joint positions. Another approach seen in [24] used a sequence of joint trajectories and applied wavelets to encode each temporal sequence of joints into features. Since not all joint positions of a person provide substantial information for interpreting an activity performed, different methods are proposed to select key joints which are more descriptive [2][7][14][16] and they will be investigated for an optimal method to be used in this research.

In the next section, the proposed methodology for feature extraction and activity recognition from raw joint positions of skeleton data obtained from an RGB-D sensor will be explained.

3 ACTIVITY RECOGNITION SYSTEM

To recognize activities from RGB-D sensors, the first stage is to recognize skeleton raw joint positions. This is done by obtaining recorded frames of annotated data for activities performed by a human actor. The data captured includes a hierarchical nature of activities, human skeletal features and their transitions over time. The system can be set up in a living environment. An example of RGB and depth image frame extracted from an RGB-D sensor is shown in Figure 2. Once the raw joints positions information is obtained, important features from this data must be extracted before they are classified into different activities. The proposed system architecture is shown in Figure 3. The following key steps are identified:
Figure 2: Frame of RGB and Depth image showing tracked human skeleton.

Figure 3: Overall system architecture of proposed system.

- **Posture feature extraction**: Posture feature vectors representing key human poses that describe an activity are extracted by obtaining centroids of clusters using K-means clustering technique.
- **Activity classification**: Classification of activities from the extracted posture features.

Details of each step is briefly explained in the following sections.

### 3.1 Posture Feature Extraction

Posture feature extraction is a key step in our system for recognizing activities. Features obtained in activity recognition systems can be computed using joint position coordinates extracted from RGB-D sensor skeleton data. This approach is one of the simplest employed by researchers. Two methods can be applied, these are based on raw joint positions and displacement-based representations when considering temporal and spatial data.

The proposed system adopts a method which exploits displacement features from the skeleton joint coordinates. However, temporal information will be excluded to make the system independent of speed of movement. This method was introduced by [2]. For each skeleton frame, a vector $F_N$ is used to represent the posture for joints $j_i$ in 3D where $N$ is the frame (or observation) number for an activity as shown in Figure 4. The Kinect RGB-D sensor considers the skeleton frame of reference to be the sensor. However, in order to compensate the position of the skeleton, the frame of reference will be considered for all joints relative to the torso joint coordinates.

Consider a skeleton which has $i$ joints with $j_x$ representing the torso coordinates. The distance vector $d_i$ between the $i^{th}$ joint and the torso (reference) is given by:

$$d_i = j_i - j_x$$  \hspace{1cm} (1)

After computing the distance $d_i$ for all the joints in a frame of an activity, a vector $V$ representing the set of joints position distance relative to the torso is obtained. Each vector $V$ represents a posture for a skeleton frame. A set of $V_N$ vectors for all frames obtained represent an activity. This process is illustrated in Figure 4.

$$V_N = (d_1, d_2, d_3, ..., d_i)$$  \hspace{1cm} (2)

The proposed approach applies K-means clustering technique for selection of key human pose that represent an activity thereby reducing the complexity in large activity data sets. This technique is used for representation of an activity by a subset of poses, without having to use all observations. $V_N$ vectors representing frames of an activity are grouped in $K$ clusters based on the squared Euclidean distance as a metric.

For an activity consisting of $V_N$ vectors, $K$ clusters are defined to represent key postures for the activity. A cluster $C_K$ is a grouping of closely related joints positions component (joint coordinates) within frames of the activity. After computing, an output of $K$ clusters $[C_1, C_2, C_3, ..., C_K]$ are obtained. Each cluster is a vector containing centroids for all joints that define a key posture within an activity. Once the clusters are formed, they are sorted out following the order the cluster elements occur during the activity. The clustering algorithm provides the ID of the cluster which an observation within the activity belongs. The sequence of the cluster vectors obtained represent the sequence of observations that constitute the performed activity. The centroids of each cluster represent key postures which are the most important features of an activity. These features form the activity features vector $A$. 
For example, considering an activity represented with 10 observations and 3 clusters, one of the outputs after applying $K$-means clustering would be a sequence of cluster IDs representing the activity: $[2, 2, 1, 1, 3, 3, 3, 1]$, this means the first two observations are within cluster 2, the third - sixth observation in cluster 1, seventh - ninth observation in cluster 3 and the tenth observation in cluster 1. Therefore, the activity features vector will be $A = [C_2, C_1, C_3, C_1]$.

One of the challenges of using $K$-means clustering algorithm in the proposed method is obtaining the optimal number of clusters that can effectively represent the posture features of an activity. Considering that, we use different number of clusters $C_K$ for $K = (5, 10, 15, 20, 25, 30)$ and compare the results. The result is evaluated by minimizing the error $Z$ which is the sum of the deviations between the centroids of the clusters and the actual joint positions through the sequence of frames for an activity:

$$ Z = \sum_{i=1}^{n} (C_{k,n} - j_{i,n}) $$

where $i$ is the $i^{th}$ joint, $C_{k,n}$ is the centroid of the cluster $k$ at the $n^{th}$ observation/frame and $j_{i,n}$ is the $i^{th}$ joint at $n$.

### 3.2 Activity Classification

Classification of the activity feature vector is computed to associate each extracted feature vector with the correct activity performed.

To achieve the task of human activity classification, machine learning classification algorithms may be applied. One of such algorithm is an Artificial Neural Network (ANN) trained classifier.

The proposed system employs an ANN algorithm consisting of a hidden layer for classification of human activities. Details of the ANN algorithm for classification which is adopted in this work can be found in [15]. In training the classifier, feature vectors obtained from clustering which describe a performed activity are passed as inputs and the activity labels as targeted outputs of the ANN. An iterative learning process which is a key feature of ANN’s is performed during which the weights of all neurons are adjusted to predict the correct activity label from input activity feature vectors. The structure of the ANN classification is given in Figure 5.
Figure 6: Selected frames of human actor performing activities in a living environment from CAD-60 dataset.

Figure 7: Confusion matrix showing the performance of our system for 6 activities.

4 EXPERIMENTAL RESULTS AND DISCUSSION

The proposed method of learning from activity recognition is tested on a well known human activity data set, CAD-60 data set [22]. The data had been extracted using a Microsoft Kinect RGB-D sensor [13]. It contains RGB frames as well as depth for sequence of human activities performed.

The CAD-60 data set was collected at a frame rate of 15fps which is offered by the sensor and comprises of 12 activities performed by four people. However, for testing the proposed system, 6 activities out of 12 activities are selected which are;

1. Brushing teeth
2. Cooking-chopping
3. Cooking-stirring
4. Open pill container
5. Talk on phone
6. Write on board

This activities are selected based on the type of application of the proposed system for learning using an assistive robot capable of performing these activities. Therefore, only activities which require more participation of the arms when performed are chosen for tests. Selected frames for these activities are shown in Figure 6.

For posture feature extraction, the joint positions are extracted following the process as described in Section 3.1. However, in computing the optimal number of clusters which best represent activity feature vectors different number of clusters ranging from 5 to 30 are tested. The best results are obtained using 25 and 30 clusters. To illustrate this, a plot of cluster centroids and joint positions through a sequence of brushing teeth activity for one joint component (Right hand x-coordinate) is presented in Figure 8. This joint position is selected because it is one of the most significant components in performing the activity.

After clustering, the activity features vectors are associated with their corresponding activity through a sequence of brushing teeth activity for one joint component (Right hand x-coordinate) is presented in Figure 8. This joint position is selected because it is one of the most significant components in performing the activity.

For evaluation of our classifier, we adopt a cross validation method of testing
using a new person data which was not used in training the classifier. Test data from a new person consisting of 1416 observations of different activities is introduced to the trained network and results obtained achieve a recognition accuracy of 85.3% as shown in the confusion matrix plot of Figure 7. The confusion matrix shows the number/percentages of true positives, true negatives, false positives and false negatives of observations from the new person test data set. The axes represent the 6 activities chosen for this test.

After training and validation of the classifier using the extracted activity features vector, each frame of a new person test data is classified to the closest posture feature within the activity features vector. The features vector which represent centroids of closely related joint components for a pose and therefore an input frame vector of joints positions can be associated to a corresponding feature vector for the activity. The system does not have to wait for a complete sequence of a new person activity before classifying the activity performed. Considering that, the proposed system should be capable of fulfilling real-time performance which will be explored in subsequent research work.

Figure 8: Result of different number of clusters in an activity for one of the key joints in performing an activity of brushing teeth from CAD-60 dataset.
5 CONCLUSION AND FUTURE WORK

The work in this paper presented a method of learning human activities via computing activity features vector by clustering raw joint positions extracted from human skeleton representation from an RGB-D sensor. The method can be applied to a human assistive robot which would be capable of performing these activities whenever the activity is detected. The robot could perform the activity via coordinate mapping of its joints to the human skeleton joints. However, this is beyond the scope of this paper.

The classification of activities result show that some observations from the test data are classified wrongly. This could be as a result of a feature vector representing a particular pose in the activity similar to that of another activity. Therefore, part of the future work is to investigate the degree of membership to which a feature vector belongs to different activities in order to distinctly classify the activity using more sophisticated computational intelligence method.

Another aspect not considered in this work is temporal information of performed human activities which could be very useful in differentiating similar joint coordinates position of differing activities. Also, in selection of the best amount of clusters K given a specific activity, other approaches could be explored for example Bayesian Information Criterion (BIC) [17] as a way to score and select an optimal value for K. This will be considered in further research.

This method can be used in assisted living/elderly care to have assistive robots used in performing most ADLs for elderly or people incapable of performing activities within a living environment effectively. The results show a very promising outcome in the area of assistive robots’ coexistence in human living environments.

REFERENCES


