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Building a Framework For Recognition of Activities of Daily Living from Depth Images Using Fuzzy Logic

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***Abstract*—Complex activities such as instrumental activities of daily living (IADLs) can be identified by creating a hierarchical model of fuzzy rules. In this work, we present a framework to model a specific IADL – "making the bed". For this activity recognition, the need for a three level Fuzzy Inference System (FIS) model is shown. Simple features such as bounding box parameters were extracted from the foreground images and combined with 3D features extracted from the Kinect depth data. This was then fed as input to the three layered FIS for further analysis. Data collected from several participants were tested and evaluated. Such a framework can be used to model several other IADLS as well as basic activities of daily living (ADLs). Analysis of ADLs can be used to compare daily patterns in older adults to measure changes in behavior. This can then be used to predict health changes to assist older adults in leading independent lifestyles for longer time periods.**

Keywords*—*activities of daily living; fuzzy rules; depth image; machine learning

I. Introduction

FALL risk measurement in an in-home setting using non-intrusive, non-wearable, passive sensors has been the focus of our ongoing research at TigerPlace, an independent living facility in Columbia, Missouri [1]. Activities of daily living (ADL), when measured over an extended period of time, can show deviations in health for older adults. Clark et al. [11] showed improvement in functional, mental and physical health status, life satisfaction, social functioning, body pain and emotional problems following a routine activity enhancement group among older adults. In that study, older adults were divided into groups for intervention or control. The intervention group participated in group discussions, exercises, and practiced techniques which had significant positive effects on quality of life, functional status, and life satisfaction after intervention. Zisberg et al. [12] developed a new instrument called SOAR to evaluate routine in the lives of older adults. These subjects were sampled from independently dwelling residents in four retirement communities in United States. The items were measured by a set of survey questions related to their behavior on a typical day. Then participants reported the time of waking and the time of going to sleep. They were then asked for detailed information regarding activities like eating main meals, eating snacks, meal preparation, going out for meals, watching television, bathing, showering, light housework, etc. For each of the mentioned activities, participants are asked to report the number of times the activity was performed within the relevant time frame (day or week); the time taken to perform the activity (duration); and the time of day at which the activity was performed. The general results pattern indicated that older adults with lower functional indicators tended to have more rigid or stricter routines in basic and rest activities. Hence, this study indicated that any deviation in the routine of frail older adults could indicate a change in health and function.

Studies described in [11], [12] indicate the importance of longitudinal studies analyzing the routine behavior of older adults to study anomalies or deviations in their regular patterns in an automated, non-intrusive manner. In order to do so, the activities need to be ordered in a methodical way for day-to-day behavior comparison. One approach is based on ontological activity modeling. The idea for representing ADLs using ontology is not new. In [13], Chen et al. proposed an ontological method to recognize activities. A theoretical foundation was set up to fuse different sensor data and build a context in the framework of ADLs. In particular, the activity ontologies were defined for housework, kitchen work, manage money, medicine intake, use phone, and recreational ADL activities. Sensor data from contact sensors, motion sensors, tilt sensors and pressure sensors were used for the activity analysis. Experiments were conducted under laboratory settings and activity recognition was tested on a subset of the ADL activities including making tea, brushing teeth, have a bath, watch television. An accuracy of 94% was achieved on a small subset of 3 subjects performing each activity thrice but using different objects each time. In another study, Latfi et al. [14] described an ontological approach to specifically describe the medical history of older adults in an assisted living facility using a system called Telehealth Smart Home system (TSH). In this framework, they created a PersonAndMedicalHistory ontology which comprised two parts: the person and his/ her medical history. The first part contained not only the profile of the person himself but also the interactions with different "actors" namely the medical staff, the management staff, and all individuals who interact on a social level with the individual. The medical history part comprised three main components: deficiencies (physical, sensorial), diseases, and risk factors. Each of these classes had their individual attributes to describe their respective properties. A theoretical framework was proposed in this work, so there were no validation results.

In another approach, Rodriguez et al. [15] proposed an ontological framework called Care to describe ADLs in a nursing home scenario. For all the activities, such as taking medication, the following attributes were used for description: the Person who executes the activity, the StartTime and FinishTime of the activity and the Location where the activity is being executed. The implementation details or the activity subset was not described in this study. Instead, a simulated example was provided to describe the proposed future work. While there are several studies which describe work on ADLs, the goal in this study is to observe the activities of the person from the point of view of his or her interactions with surfaces (such as counter top, tables, chairs) and other moving objects.

In this paper we propose a unique method to learn complex activities of daily living. Specifically, we discuss the framework to recognize the "making the bed" IADL using fuzzy logic. IADLs are different from the basic ADLs because they are not considered the fundamental activities for self-care. However, they are of key interest for evaluation of independent living. Some common IADLS are housework, taking medication, managing money, etc. Our study on "making the bed" can then be used to create models for several other ADLs to learn the behavior patterns of monitored individuals. The idea of using fuzzy logic in activity analysis was employed by Anderson et al. [6] who generated linguistic summaries of activity analysis. The rule based system was then effectively utilized for fall detection. One of the main advantages of applying a FIS is its interpretability [10]. The rule based system is easy to interpret for researchers from different disciplines, which is beneficial for an interdisciplinary group of clinicians, physical therapists, social workers, and engineers. The other great advantage is its flexible structure: rules can be added or removed without disturbing the existing system.

For our system, image features extracted from the depth sensor acquired using the Microsoft Kinect system were computed and given as input to a three stage FIS system. Our system is unique since it uses contextual information to glean more information about the activity. For example, knowing that the room is the bedroom and having identified the bed region, it is much easier to identify activities related to the bed. This not only makes the activity recognition much simpler, but also more accurate.

The rest of the paper is divided into the following sections. Section II describes the preprocessing involved to extract the foreground before the features are computed. Section III describes initial region segmentation to determine the surfaces in the scene. Section IV describes the features used as input to the FIS. Section V describes the rules and the reasoning behind the multi-staged process. Section VI discusses the experiments and the ground truth extraction. Section VII concludes the paper and discusses the future work.

II. Preprocessing - Silhouette Extraction

Foreground was extracted on the raw depth images from a single Microsoft Kinect sensor using a standard background subtraction algorithm. The minimum and maximum depth value of each individual pixel was obtained from an initial set of background only images. Any depth value outside this range was recognized as a foreground pixel [2]. We utilized the dynamic background update algorithm to account for the constant changes in the environment in real world setting in the apartments at TigerPlace. Once the 2D silhouettes were extracted from the 3D depth images of a single Kinect, features were computed. The basic block diagram is shown in Figure 1.

Silhouette features and 3D features were extracted and fed to the first level in the FIS. This provided the activity states of the individual image frames. These activity states were then combined to form activity summaries and then fed to the second level of the FIS. Again, the activities were summarized and fed to a third level to make the final decision about the overall activity.

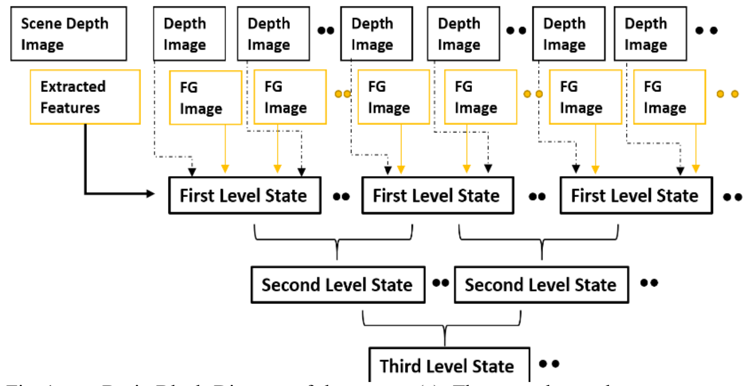

Fig. 1. Basic Block Diagram of the system (a). The second row shows an example of a depth image of a person walking (b) and the corresponding foreground is shown in (c).

III. Intial Scene Segmentation

Figure 2(a) shows the depth image of the scene after inpainting it [17]. The process is described further in [18]. The ground plane is extracted during the sensor set up by manually selecting ground points. Using this information as well as some more image features, the horizontal surfaces are automatically extracted from the scene. Figure 2 (a) shows an inpainted depth image of our motion capture set up containing a long table and the lower left corner, a chair, a bed and a small table. Figure 2 (b) shows the automatically extracted horizontal surfaces excluding the ground plane. For now, we have manually labeled the surface corresponding to the bed. Eventually we plan on automatically identifying the bed surface using contextual information based on its location and size and shape.

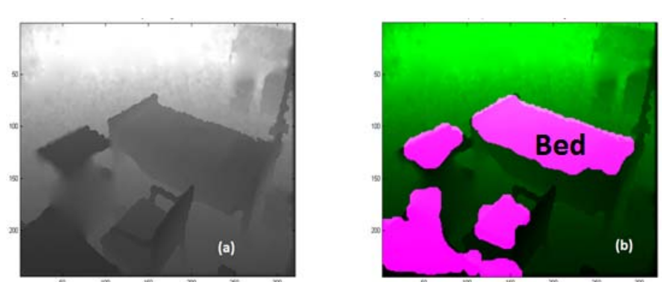

Fig. 2. Inpainted depth image (a) and the corresponding horizontal surfaces extracted highlighted in pink (b). Here, the bed surface has been manually labeled for activity recognition.

IV. INPUTS AND OUTPUTS TO THE FIS SYSTEM

Once the areas of interest are extracted, features are computed for activity recognition. For a given sequence, these eleven simple features are calculated only if a moving foreground object is detected. This helps to speed up processing so that only sequences with noticeable movement (number of moving pixels above a certain threshold) are further considered for activity analysis. The following features are extracted for inputs to the first stage FIS level. For these experiments, the rules and membership values were developed heuristically using a small training sequence. Rules were added in an iterative manner and those which did not affect the error significantly were removed.

A. Bounding box features

These are the parameters of the minimum dimension rectangle that can be fit to the foreground objects. The three features are the width (BBX) and height (BBY) of this bounding box as well as the area (BBA) of the rectangle. The temporal differences of these features are also considered and termed DBBA and DBBX, respectively.

B. Centroid Position

This is the (x, y, z) location of the moving foreground object. For input to the FIS system, the difference in these values in consecutive frames is computed (temporal differencing). These are called DXY (difference in XY location) and DH (difference in height), respectively. Apart from that, the height of the foreground object (H) was also an input to the first level FIS.

C. Distance from the Bed

This is used to detect the proximity to the bed surface. For input to the first level FIS, the smallest distance between the foreground object and the bed surface (DB) is considered.

D. Distance from the Sensor

This is used to detect the proximity to the Kinect sensor. We consider this input since the depth values are inaccurate when the detected foreground is too close or too far to the sensor. For input to the first level FIS, the distance between the centroid of the foreground object and the sensor (DS) is considered.

E. Number of Points on the Boundary

This parameter is important to determine the confidence of the person exiting/entering the field of view. The number of points on the boundary (NB) is measured by the number of points of the object present on the boundary of field of view.

V. FUZZY RULES TO THE FIS

A. First Level Rules

This section describes the rules which determine the confidence for activity states of near bed, at field of view, downward motion near bed (down bed), upward motion near bed (up bed), lift mattress, lie on bed, walk and previous state.

By previous state, we mean that the same activity state as the previous frame is continuing in the current frame. For our current experiments, 31 rules were used. In the interest of computational efficiency, we kept the rule base as small as possible.

We categorized the rules into seven groups. For the first group, the five parameters used are NB, DB, DS, H and DH. For each of these inputs, we use trapezoidal or triangular membership functions. The trapezoidal membership function parameters are [a b c d], where parameters a, d are the "feet" of the trapezoid and b, c are the "shoulders". The triangular membership functions have parameters [a, b, c] where a, c are the base of the triangle with the peak at b. Two rules have been implemented using these variables (Table 1). The parameters for NB are Low (L) = [0 0 7], High (H) = [10 60 100] with the upper bound set at 60. DB values were bounded between 0 and 100 with membership functions: Very Low (VL) = [0 0 6], Low (L) = [0 0 10], and High (H) = [11 100 140]. DS values were bounded between 0 and 8000 with membership functions: Low (L) = [0 50 100], Medium (M) = [250 1500 3000], and High (H) = [2500 5000 10000]. For the height, there are five membership functions for Very Low (VL) = [0 20 40], Low (L) = [40 45 48], Medium (M) = [48 50 53], High (H) = [55 58 68], Very High (VH) = [68 72 75]. DH has membership functions Negative (N) = [-3 -1 0], Zero (Z) = [-1 0 1], Positive (P) = [0 1 3]. The membership functions for all the output variables are Low (L) = [0 0 0.4], Medium (M) = [0.1 0.5 0.9], and High (H) = [0.6 1 1]. All the antecedents are joined using the AND operator as a connective for the rule generation.

TABLE I. FIRST SET OF FUZZY RULES FOR LEVEL 1

	NB	DB	DS	H	DH	NEAR BED
1	H					L
2	L	L	M	H	Z	H

Table II generates the confidence of the person being at the edge of the field of view from the depth sensor. This can be used for further filtering of the data since height information as well as other features tend to be less reliable when the person is at the edge of the field of view.

TABLE II. RULE FOR FIELD OF VIEW ACTIVITY STATE

	NB	FIELD OF VIEW
3	H	H

The membership functions for DXY are Low (L) = [0 0 1] and High (H) = [3 5 7] and BBX are Low (L) = [0 0 7], High = [40 80 100], Very High (VH) = [155 170 200 250].

TABLE III. THIRD SET OF FUZZY RULES FOR LEVEL 1

	DB	DXY	DS	BBX	H	DH	DOWN BED
4	L	L	M			N	H
5	L		M	NVH	M	N	H
6	H						L
7	L		M	NVH	M	N	H
8	L	VL	M			N	H
9	VL	L	M			N	H
10	VL		M	NVH	M	N	H
					VH		L
11	VL		M	NVH	M	N	H
12	VL	VL	M			N	H

The membership functions for BBA are Low (L) = [0 0 70] and Medium (M) = [50 100 150], High (H) = [500 750 1000] and Very High (VH) = [5000 1000 15000 20000]. The membership functions for DBBA and DBBX are Low (L) = [0 10 20] and High (H) = [60 90 120] and Very High (VH) = [150 200 250 300].

TABLE IV. FOURTH SET OF FUZZY RULES FOR LEVEL 1

	DB	DXY	DS	BBX	H	DH	UP BED
13	L	L	M			P	H
14	L		M	NVH	M	P	H
15	H						L
16	L		M	NVH	M	P	H
17	L	VL	M			P	H
18	VL	L	M			P	H
19	VL		M	NVH	M	P	H
20	VL		M	NVH	M	P	H
21					VH		L
22	VL	VL	M			P	H

Table V gives the rules for lying on the bed activity state.

TABLE V. FIFTH SET OF FUZZY RULES FOR LEVEL 1

	DB	DXY	DS	H	DH	LIE ON BED
23	L	L	M	VL	N	H
24	L	L	M	VL	N	H
25	L	L	M	VL	Z	H

Table VI gives the rules for evaluating the confidence for lifting mattress. Here, lifting the mattress is identified by a sudden increase in the area and the width of the bounding box features while the person is near the bed. The linguistic interpretation of the Rule 26 is

IF the Distance from Bed (DB) is ***Low*** and the Difference in Bounding Box width (DBBX) is ***High*** and the Distance from Sensor (DS) is ***Medium*** and the Height (H) is ***High*** and the Difference in Bounding Box Area (DBBA) is ***Very High***, ***THEN*** the membership for **Lift Mattress** is ***High***.

TABLE VI. SIXTH SET OF FUZZY RULES FOR LEVEL 1

	DB	DBBX	DS	H	DBBA	LIFT MATRESS
26	L	H	M	H	VH	H
27	L	H	M	VH	VH	H
28	L	VH	M	H	VH	H
29	L	VH	M	VH	VH	H

Table VII gives the rule to evaluate previous state. This just informs us that not much has happened since the previous frame.

TABLE VII. SEVENTH SET OF FUZZY RULES FOR LEVEL 1

	DH	DXY	PREVIOUS STATE
30	VL	VL	H

Table VIII gives the simple rule to detect walking. Here, the idea is that if the height of the moving object is high and the change in the x-y coordinates from the previous frame is high, then there is a strong confidence of the activity state being a walk.

TABLE VIII. EIGHTH SET OF FUZZY RULES FOR LEVEL 1

	H	DXY	WALK
31	H	H	H

Using the above set of rules, we can obtain the confidence of the activity state for the individual frames. Individual states were identified only when the confidence values exceeded 0.5. This also take care of the condition when there are no rules fired since in that case, the default value for the states is 0.5. Summaries are then generated for each of these activity states after temporal filtering using a window size of three frames (or equivalently about 0.5 seconds). This is then converted to an activity summary which stores the beginning and end time of that state. These states are then used for the activity segmentation in the second level. While this is not a complete set of rules by any means, the rule set was able to identify the states of the training dataset. If we were to evaluate a complete set, there would be at least 11^5 rules as compared to the 31 rules currently implemented. This would not only increase the computation time exponentially but also make the system difficult to adapt if we tried to learn all the parameters using artificial intelligence techniques.

B. Second Level Rules

For the second stage, we are primarily focusing on the activity states related to making the bed, so in this case, we look for the activity "Arrange Bed". This activity implies that there is some interaction with the bed and there is some bending and upward motion taking place near the bed surface. From the summaries generated by the previous stage, the upward motion frequency, the upward motion duration, the downward motion frequency, the downward motion duration is computed for every minute with a window size of five minutes. This is then fed as input to the second level of the FIS. A sample of the state memberships for a small segment of the arranging bed activity is shown in Figure 3. The red line represents Up Bed, the blue line Down Bed, the green line Near Bed and the dotted black line Previous State. We see that there is a high confidence for downward motion near the bed initially and then a high confidence in upward motion near the bed. During this entire time period, the near bed confidence is high as well. Also, there are several frames during this duration where the previous state confidence is high.

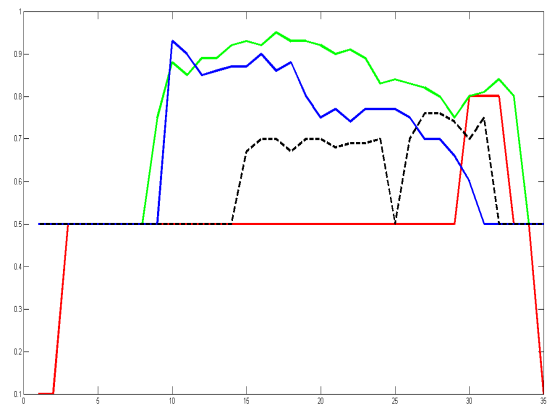

Fig. 3. State Membership Plot for a part of the Arrange Bed activity. The duration of the plot is around 4 seconds. Here, the X axis is the frame number and the Y Axis is the confidence value for the activity states ranging from 0 to 1.

The rules for the second stage are given in Table IX. The membership parameters for Down Duration (DD) and Up Duration (UD) are Medium (M) = [1 5 6 10], High (H) = [5 9 14 20], and Very High (VH) = [15 40 100 120] where the upper bound is set at 100. These values are in seconds. The parameters for Up Frequency (UF) and Down Frequency (DF) are Medium (M) = [1 2 3 4], High (H) = [3 4 6 7], and Very High (VH) = [5 10 15 20]. The upper bound is set to 15.]. The membership functions for Arrange Bed output confidence are Low (L) = [0 0 0.4], Medium (M) = [0.1 0.5 0.9], and High (H) = [0.6 1 1].

Once the Arrange Bed times are extracted, summaries are created by merging two or more events which take place within a 5 minute interval. Again, this is intuitive since it is unlikely that a person will make the bed twice within a short time interval.

TABLE IX.

TABLE X. SET OF FUZZY RULES FOR LEVEL 2

	DD	DF	UD	UF	ARRANGE BED
1	H		H		H
2	VH		H		H
3	H		VH		H
4		H		H	H
5		VH		H	H
6		H		VH	H
7	H	H			H
8	VH	H			H
9	H	VH			H
10			H	H	H
11			VH	H	H
12			H	VH	H
13	M	M	M	M	H
14	M		M	M	H
15	M	M	M		H
16		M	M	M	H

These summaries are then fed to the third level for the final analysis.

C. Third Level Rules

The third stage was included to eliminate certain false alarms at the second level. One of the scenarios for this was when the participant took the sheets off or "unmade the bed" before lying on the bed. Here also there is bending and upward movement near the bed. To distinguish this and other similar activities, the third stage needs to be included to take into account what happened after the "arrange bed" activity over a window of 3 minutes. An example of this activity is shown in Figure 5. For this stage, there are two inputs Arrange Bed Duration (ABD) and Lie Bed Duration (LBD). The membership functions for both the inputs are Very Low (VL) = [0 0 1], Low (L) = [5 6 8], High (H) = [8 10 12 20] and Very High (VH) = [12 40 120 350]. The membership functions for Make Bed output confidence are Low (L) = [0 0 0.4], Medium (M) = [0.1 0.5 0.9], and High (H) = [0.6 1 1].

TABLE XI. FUZZY RULE FOR LEVEL 3

	ABD	LBD	Make bed
1	H	VL	H
2	H	L	H
3	VH	VL	H
4	VH	L	H
5	VH	H	L
6	VH	M	L
7	VH	VH	L
8	H	H	L
9	H	M	L
10	H	VL	L

To generate the final make bed activity summaries, the time stamp of the beginning of the first activity segment with a membership of over 0.5 was chosen. Correspondingly, the end of the segment was taken as the end of the activity. Segments with similar activities within one minute were combined to make a single instance of the make bed activity. The maximum confidence during this interval was chosen to be the overall confidence of this detected activity.

In the future, we plan to create an automated way to generate an optimal set of rules. Once all the rules are evaluated, the final confidence measures are computed using centroid defuzzification on the aggregate fuzzy responses corresponding to the fuzzy rules described above. We observed that simple image features prove to be the most robust to noise, especially in dynamic environments. We used the above rules and tested them on our experimental dataset. This is described in the next section.

VI. EXPERIMENTAL RESULTS

Depth data were recorded using the Microsoft Kinect sensors at a frame rate of approx. 6.5 frames per second for a duration of ten days continuously i.e. for a period of approximately 240 hours. The training data was not a part of the test sequences. Here, 24 instances of making the bed from six participants were part of the study. Apart from making the bed, several instances of the following activities were also part of the dataset- walking, sitting on a chair, moving furniture, lying on the bed, bending to pick up an object, sitting on the bed, placing objects on the table, etc. The time stamps of the making bed activity were recorded and taken as the ground truth.

Figure 4 shows sample foreground images of a person making the bed. The blue region indicates the identified ground region and the orange region shows the moving foreground. In Figure 4 (a), the foreground comprises the person as well as the sheet while the bed is being made. Figure 4 (b) and (c) show the bending movement near the bed.

The large black object in the center of the image is the bed and we can see the parts of the bed getting identified as foreground in Figures 4 (a) and (c) as they get moved and rearranged.

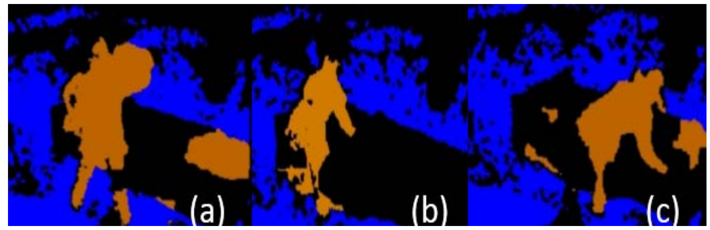

Fig. 4. Sample foreground images of a person making the bed.

Figure 5 shows an example of an activity sample of a person getting ready for bed. As can be seen, Figure 5 (a) and (b) are very similar to the foreground images of a person making the bed as shown in Figure 4. However, the latter images (Figure 5 (c) and (d)) show the person getting into bed and lying on the bed. Using the rules from level 3, this activity gets a low confidence for "making the bed".

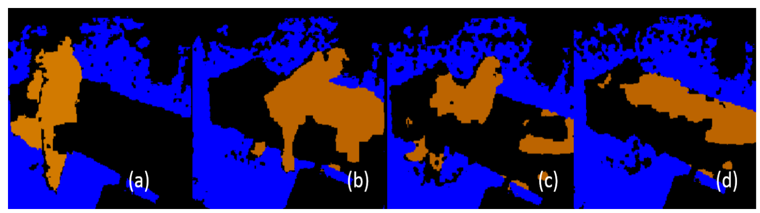

Fig. 5. Sample foreground images of a person "unmaking" the bed and lying on it.

Figure 6 shows a combination of first, second and third level activities to show the overall activity summary for the making bed example shown in Figure 4. In this activity example, the person walked into the scene, made the bed and then walked out of the scene. In the graph, the red line gives the confidences for being at the boundary of field of view or near boundary (NB). The green line gives the confidence for the walking activity state (W). The blue line gives the Arrange Bed (AB) activity confidence. The confidence values are plotted every 15 seconds i.e. at a frame rate of 4 frames/second. We can see that there are more spikes in the confidence measures for NB and W since these are first level states and were evaluated at every frame. Also, there are high confidences for W for the entire time since all the activities involve the walk movement. Even during the AB activity, the person has to move around the bed so there are frames with high W confidence. The AB graph is less noisy since it is evaluated every minute so the confidence value remains the same over the minute interval. The make bed is evaluated every three minutes so its duration is the longest. Hence, we can get an accurate and complete picture of the entire activity summary using this combination of the different level activity states.

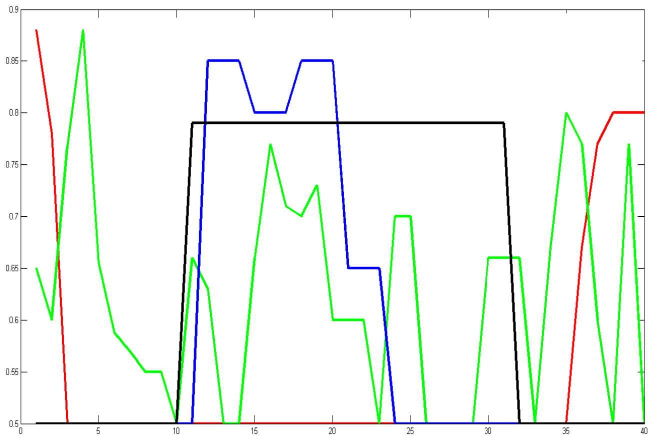

Fig. 6. The confidence measures for two of the first level activity states: Walk (green) and Near Boundary (red), second level activity Arrange Bed (blue) and the final complex activity Making Bed (black) for a period of ten minutes. Here the X axis is the frame number at a frame rate of 4 per second. The Y axis is the confidence value over [0.5 1].

All 24 instances of the making bed were correctly identified using our algorithm and there were no false alarms. We plan to conduct a more rigorous testing of the algorithm as is described in the concluding section.

VII. CONCLUSION

We present a technique to build a framework for learning IADLs in this paper using a fuzzy rule based system. Specifically, a complex IADL "making the bed" was successfully analyzed using a three level hierarchical FIS and the results evaluated on depth data collected in laboratory settings. We are currently building a larger dataset to include many more instances of IADLs and ADLs. We will build a similar framework for these ADLs and run these algorithms simultaneously on the entire dataset to test the robustness of the overall system.

Many of the quantities used in this work are based on empirical observations. To address this, automated tuning of rules and membership functions using evolutionary computation techniques will also be considered. Currently, we have manually labeled the horizontal surface as the bed surface. In the future, we hope to automatically identify the regions by using their contexts. For example, if we know that we are monitoring the bedroom, then we can assume that the largest horizontal surface is the bed. We can further validate our assumption if we can learn that the person is detected to lie on that surface.

We also plan to incorporate some more contextual information into understanding the activity. For example, after making the bed, the bed should have a more uniform surface after the sheets are straightened than before it was made. Was the bed "unmade" before? Is it more "made" now? Once we are able to quantify this, it will further strengthen our confidence that the activity is making the bed instead of more complicated activities like dressing near the bed while putting the clothes on the bed.

ADLs have a strong interaction with the scene and the objects present in it. If we can exploit and quantify these interactions, they can be easily recognized. This knowledge can then be used to build activity summaries of the combined ADLs of individuals over extended time periods. Analysis of these ontologies can then help evaluate the physical functionality of the individuals and provide valuable information on fall risk for the older population. This in turn can enable interventions when necessary and help them lead an independent lifestyle for a longer time.

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