Identifying Important Action Primitives for High Level Activity Recognition

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Abstract. Smart homes have a user centered design that makes human activity as the most important type of context to facilitate people by adapting the environment according to their needs. Sensor systems that include a variety of ambient, vision based, and wearable sensors are used to collect and transmit data to reasoning algorithms to recognize human activities at different levels of abstraction. Despite various types of action primitives are extracted from sensor data and used with state of the art classification algorithms there is little understanding of how these action primitives affect high level activity recognition. In this paper we utilized action primitives that can be extracted from data collected by sensors worn on human body and embedded in different objects and in the environment to identify how various types of action primitives influence the performance of high level activity recognition systems. Our experiments showed that wearable sensors in combination with object sensors clearly play a crucial role recognizing high level activities and it is indispensable to use wearable sensors in smart homes to improve the performance of activity recognition systems.

1 Introduction

Smart homes aim to facilitate people by adapting to their requirements to accomplish their goals and objectives in dynamically changing and continuously emerging situations. Human activity is the fundamental type of context to build many applications in these environments. Consequently, activity recognition has become an active research field to design dependable systems to recognize human activity. Different sensor modalities including ambient sensors [6, 13],vision based sensors [5, 7], and wearable sensors [14] are used with reasoning algorithms to extract information from the environment to detect activities at different levels of detail, ranging from the basic short time human action primitive to human activities that span over comparatively longer period of time, such as activities of daily living (ADL). In spite of all these sensing modalities that are used to detect human activities, one of the key challenges in building effective and reliable activity recognition systems is to identify an optimal set of primitives that contains enough information to accurately recognize human acuities and decrease the overheads in terms of sensor cost, human effort, and computing resources, that have been used to extract the primitives of less importance. But still these is a lack of research efforts that have been undertaken to identify the significance of various types of action primitives in recognizing ADL. Most of the works have been limited to use action primitives from a single sensing modality to recognize ADL.

In this paper we identify the importance of the different types of action primitives, such as specific hand movements, object or environment usage, to recognize ADL. Distinguishing the role of such primitives will be crucial for two reasons. First, it will help in designing an ambient intelligent environment to indicate where to place sensors, such as on body, in objects, or in the environment. Second, it will also indicate which action primitive are worthwhile to invest additional effort in designing action primitive spotting algorithms to recognize those action primitives. ,e.g., "hand cutting the bread movement" action primitive is worthwhile to invest additional effort in designing an algorithm to spot this primitive as it is giving a clear indication that subject is preparing a sandwich. We used the annotations of the EU project OPPORTUNITY data set [11] that are based on the recordings of the proceedings of data collection activity as action primitives. These annotations include body movement primitives like walk, sit, and stand, arm movement primitives like reach, release, and cut, and object or environment usage primitives. Our study shows that although object and environmental usage primitives are quite fundamental in recognizing ADL, human body movement primitives also showed significant performance in some cases even when those primitives have been used alone. Human body movement action primitives used in combination with object and environmental usage primitives showed best performance in recognizing ADLs that make using wearable sensors an indispensable choice to recognize ADL.

The rest of the paper is organized as follows. Section 2 gives an overview of the existing work in literature. Section 3 briefly describes the process of activity recognition and classification algorithms that have been used in this work. Section 4 presents the detail of the data set that has been used in the experiments. Section 5 exhibits and discusses the result. Finally we present the conclusion of this research effort in Section 6.

2 Related Work

Research efforts that had been undertaken to recognize ADL are mainly dominated by environmental change or the object motion primitives. Kasteren et al. [13] had recognized ADL by collecting and using environmental sensor data in a smart home. Sensors were embedded in doors, cupboards, and refrigerator. Mckeever et al. [8] had also used the Van Kasteren data set [13]. Tapia et al. [12] used environmental change sensors that had been installed on doors, windows, cabinets, drawers etc. Lepri et al. [5] recognized the ongoing activities by using the visual sensors. They equipped the living room and kitchen of a flat with tree web cameras where different subjects performed activities of daily living. They processed the video streams to get the primitives about the location and posture of the subject to recognize high level activities. But these primitives had not proved to be enough to recognize activities like eating, drinking, cleaning. Mostly aforementioned works have used sensor systems that can provide primitives about the environmental state change. Lepri et al. [5] has used human body posture primitives with their location to detect the ADL. Neither of these works have used action primitives related to human body movements like walk, run, reach.

Logan et al. [6] used the place lab, an instrumented home environment [4], to collect their data set. They used environment built-in sensors, object motion sensors, and RFID tags. Two 3-axis accelerometer sensors were also worn by subject on his limbs to show his motion. In their experiments they provided a comparison of accuracy that was achieved by environmental and object motion sensors. Their experiments showed that a combination of environmental and object motion sensors provided better results. But they only showed their results for all the activities collectively. They did not provide any information if any type of primitives provide better performance for a particular activity. As compared to their work we have also included action primitives extracted from wearable sensor data in our experiments. In our results we have also showed our results for each activity separately so we can distinguish which category of action primitives show better performance for a specific activity. Maekawa et al. [7] used a customized sensor embedded with a camera, microphone, accelerometer, and a digital compass. That sensor set was worn as a wrist band and collect data while subject was busy in performing different activities. Although they compared the performance these sensors by using the data sets by including and excluding each type of sensor, they did not provide any comparison on the basis of different type of action primitives. As compared to these works we not only used the object motion and environmental change action primitives but also included action primitives about human body motion, such as walk, sit, stand, and catch, to detect ADL. Our experiments also showed a comparison of the performance to recognize ADL that have been achieved by using these action primitives individually and in combination with each other.

3 Activity recognition from action primitives

Common systems that recognize high level activities from different sensing modalities collect data from the sensors embedded in the environment, objects, and worn by the human as shown in the Figure 1. State of the art machine learning algorithms are used to interpret action primitives from sensor data. These algorithms are first trained with sensor data to extract primitives of interest. Primitives that are extracted from sensor data give information about different current events in the environment, e.g., "subject is walking" is a primitive about human body motion. Set of such primitives are provided to trained machine learning algorithms to recognize activities that spread over a longer period of time. Many machine learning algorithms are available in WEKA [3] that provides researchers an easy access to state-of-the-art techniques in machine learning and had been used for activity recognition in different works such as [2, 6, 10].

We have used J48, Hidden naive Bayes (HNB), and IBK for the purpose of classification of high level activities. J48 is the WEKA implementation of C4.5 decision tree [9] that have also been used for activity recognition in different works, such as [2,6,10]. At each node decision tree chooses one attribute of the data that most effectively splits its set of samples based on the criterion of normalized information gain (difference in entropy). The attribute with the highest normalized information gain is chosen to make decision. A Bayes classifier is a simple probabilistic classifier based on applying Bayes theorem with strong feature independence assumptions and has been commonly used for activity recognition in various works, such as [2, 6, 10]. In this work we have used

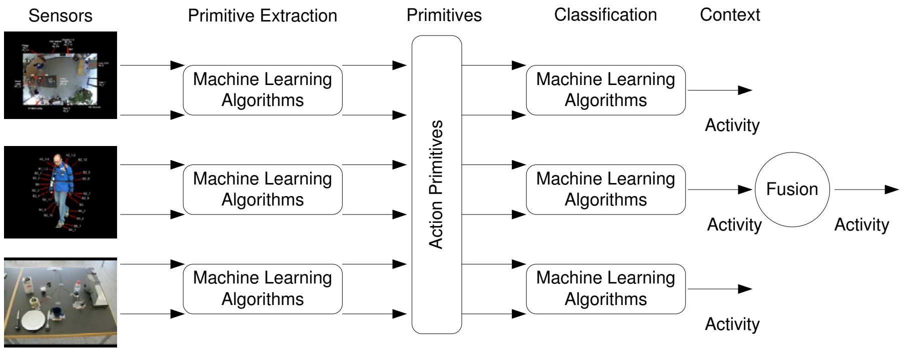

Fig. 1. Activity recognition process using different sensing modalities

Hidden naive Bayes [15] that is an extended form of naive Bayes and accommodates the attribute dependencies. HNB creates a hidden parent for each attribute using the average of weighted one-dependence estimators. IBK [1] implements *k*-nearest neighbor, an instance-based learning algorithm that generates classification prediction using only specific instances. *k*-nearest neighbor has also been used in [2, 10] for activity recognition. We have chosen these commonly used classification algorithms considering different learning strategies, such as decision tree, probability based learning, and instance based, used in these algorithms. We have used the sample by sample classification strategies with these algorithms. Reason for these choices was to put more emphasis on the study of the influence of primitive actions on activity recognition rather than on the powers of more advanced classification algorithms or strategies.

Activities	*Description*	*Duration (s)*
Idle	Not performing any activity	583
Relaxing	Go outside and have a walk	157
Early morning	Move around in the room and casually check the objects	276
Coffee time	Prepare coffee with milk and sugar using coffee machine and drink it	129
Sandwich time	Prepare sandwich with bread, cheese, and salami using bread cutter, various knives, and plates and eat it	375
Clean up	Put objects used to original place or dish washer and cleanup the table	183

Table 1. Different activities and duration for single run (in seconds)

Human performs different activities in different parts of house. She may be busy in kitchen while preparing breakfast or she may be relaxing in the lounge. Different nature of these activities apply that these activities are composed by different set of primitives. Different composition of these activities demand to look at each activity individually that will not only give us the opportunity to observe that which type of sensors should be used to recognize which activity but it will also indicate which type of sensors should be used in which part of house. Considering these requirement first we look at the influence of each activity individually. Later we also study the influence of different kind of action primitives collectively.

4 Data Description

We have used the data sets that have been collected in the EU project OPPORTUNITY [11]. Data set about the naturalistic human activities is collected in a sensor rich environment: a room simulating a studio flat with kitchen, deckchair, and outdoor access where subjects performed daily morning activities. 15 networked sensor systems with 72 sensors of 10 modalities were deployed integrated in the environment, objects, on the body. Deployment of the large number of networked sensor systems of different modality make this data set ideal to study the impact of different sensing modalities in activity recognition. Table 1 shows the short description of those activities and their duration for a single run. Twelve subjects executed activities of daily living in this environment, yielding as average of 2 hours of effective data per subject, for a total twenty five hours of sensor data. According to estimations over 11000 interactions primitives with objects and over 17000 interactions primitives with environment have been recorded. This makes data set highly rich in gesture primitives and largest for the purpose of multimodal activity recognition.

Action primitive category	*Description*	*Primitive Values*
Locomotion	basic human movements	walk, run, stand, lie, sit, stairs up, stairs down
Left arm locomotion	left arm movements	reach, move, release, lock, unlock, open, close, stir, sip, bite, clean, cut, spread
Right arm locomotion	right arm movements	
Left arm object	left hand interaction with objects	fridge, dishwasher, drawer1 (top), drawer2 (middle), drawer3 (lower), door1, door2, switch, table, cup, chair, glass, spoon, sugar, knife salami, knife cheese,salami, bottle, plate, cheese, bread, milk, lazy chair
Right arm object	right hand interaction with objects	

Table 2. Brief description and values of action primitive categories

Table 2 shows the different action primitives that are used in the experiments. These action primitives are extracted from the annotations of the data sets. These annotations are performed by experts using the videos of all the proceedings during data collection process and identified all the actions performed by the subject during his activities. Table 3 shows all the sensors that have been deployed in the environment and which type of action primitives can be extracted from these sensors. Locomotion primitives are extracted from data collected by the sensors worn the subject body. Locomotion include action primitives such as walking, sitting, lying. Arm locomotion data is extracted from data collected by the sensors worn on the arms of the subject and include the action primitives such as cut, spread, release. Object data is collected from the interaction of sensors embedded in the arms and objets. Primitives extracted from this data present whether a particular object is used or not at a specific instance. Multiple sensors of different modalities collecting information about the activities performed in the environment made this data set ideal to perform activity recognition in an opportunistic environment and observe the effectiveness of different sensing modalities. We have used five runs of single subject of this data set.

Sensor System	*Location and observation*
Commercial wireless microphone	Chest and dominant wrist. Senses user activity
Custom wireless Bluetooth acceleration sensors	12 locations on the body. Senses limb movement
Custom motion jacket	Jacket including 5 commercial RS485-networked XSense inertial measurement units
Custom magnetic relative positioning sensor	Emitter on shoulder, receiver on dominant wrist. Senses distance of hand to body
Commercial InertiaCube3 inertial sensor system	One per foot, on the shoe toe box. Senses modes of locomotion
Commercial Sun SPOT acceleration sensors	One per foot, right below the outer ankle. Senses modes of locomotion
Custom wireless Bluetooth acceleration and rate of turn sensors	On 12 objects used in the scenario. Senses object use
Commercial wired microphone array	4 at one room side. Senses ambient sound
Commercial Ubisense localization system	Corners of the room. Senses user location
Axis network cameras	3 locations, for localization, documentation and visual annotation
XSense inertial sensor	On the table and chair. Senses vibration and use
USB networked acceleration sensors	USB networked acceleration sensors
Reed switches	13, on doors, drawers, shelves. Sense usage, provides ground truth
Custom power sensors	Connected to coffee machine and bread cutter. Senses usage
Custom pressure sensors	3 on the table, user placed plates and cups on them. Senses usage

Table 3. Sensor systems locations and observations

5 Experiments

In our experiments we analyzed the impact of different combinations of action primitives on high level activity prediction. For this purpose we divided the different type of action primitives in seven different combinations. First, we have done experiments for every individual activity will all primitive sets. Later, we have also observed the impact of primitive sets considering all activities collectively. In this section we will discuss the different primitive sets, impact of those sets on each activity, impact of the sets on all activities, and finally we will discuss the results and present our recommendations.

5.1 Primitive Sets

Table 4 shows the action primitive sets and the categories of action primitives that have been used in those sets. In the first set we used all the action primitive categories described in Table 2. In the second set we excluded the left arm object movement action primitives and the right arm object movement action primitives. In the second set we depended upon the action primitives extracted from wearable sensors like arm motion, e.g., moving, reaching, releasing an object. In the third set we also excluded all the wearable sensors that give us information about the locomotion of human limbs. In this set we are left only with action primitives that have values about human actions like walk, sit, stand. In S4 we used action primitives with both arms locomotion. In S5 and

S6 we used left and right arm locomotion respectively. In S7 we used only object sensors, i.e., we will only have information about the use of a specific object and we did not have any information that whether concerned person was sitting, standing, lying, or walking. Similarly we did not have any information that which hand is used to handle an object. We used these different combination of sensors with classification algorithms explained in Section 3. Table 1 present the detail of the values of these primitives.

Action primitive set	*Categories of action primitives*
S_1	locomotion, left arm movements, right arm movements, left arm object, right arm object
S_2	locomotion, left arm movement, right arm movement
S_3	locomotion
S_4	left arm movement, right arm movement
S_5	right arm movement
S_6	left arm movement
S_7	object movement

Table 4. Different sets of action primitives

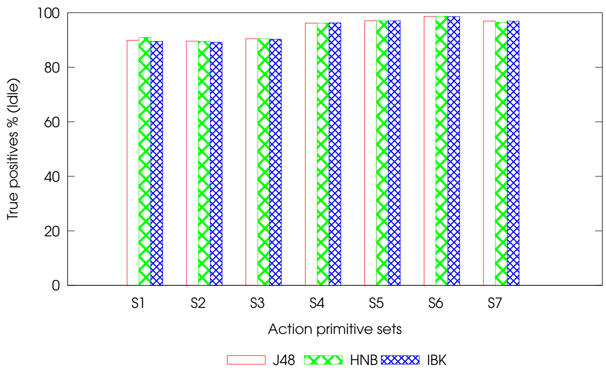

Fig. 2. True positive percentage of activity Idle

5.2 Action primitive impact in recognizing activities separately

Here we will look at the impact of these primitive sets on each activity separately. Figure 2 shows the true positive rate of all primitive sets for activity *Idle* that have been used with classification algorithms J48, HNB, and IBK as discussed in Section 3. Action primitive sets S4, S5, S6, and S7 have shown partially better performance in recognizing this activity. These sets present the action primitives extracted from the wearable sensors worn on the limbs. These primitives include information whether the subject has used an object or not. S7 consists of the object sensor. This action primitive set also provides information about the usage of object available in the environment. Although primitive sets involving the object sensors showed relatively better performance, sensors that have been used to extract other locomotion activities are also not much away from them. This result was not surprising as when the subject is idle, she is neither interacting with any of the objects nor making much movements. So any primitives from wearable sensor or the objet sensors are not particularly crucial for recognizing this activity. Sensor from any modality can easily detect that whether the subject is idle or not.

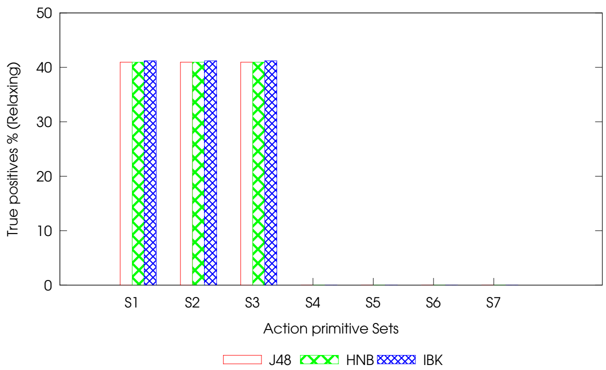

Fig. 3. True positive percentage of activity Relaxing

Figure 3 shows the true positive rate of all action primitive sets for activity *Relaxing* that had been used with classification algorithms J48, HNB, and IBK. This activity proved to be most difficult one to recognize. During this activity subject was either taking rest or casually moving around the building. She has not been particularly involved in any activity. She has not also been interacting with any object in the environment. Looking at the true positive rate of this activity it can clearly be seen that action primitive sets S4, S5, S6, and S7 completely failed to recognize this activity. The Main reason was that during this activity the subject was neither interacting nor making a lot of physical movements. Classifiers get almost the same feature for this activity as the *Idle* activity. Comparatively high number of idle activity overwhelmed the classifiers decision and classifiers got completely confused to make distinction between *Idle* and *Relaxing*. Classifier detected almost all of the *Relaxing* activities as the *Idle* activity. This is also evident from the high false positive rate of primitive sets S4, S5, S6, S7 as shown in Figure 8. Figure 8 that shows the weighted average of different evaluation metrics for J48, HNB, and IBK respectively. Primitive sets S1, S2, and S3 showed better performance in recognizing this activity as subject was comparatively more dynamic than being completely *Idle*. But when primitive sets exclude primitives extracted from wearable locomotion sensors recognizing *Relaxing* activity becomes impossible. Consequently wearable sensors giving information about human locomotion primitives proved vital for recognizing this activity.

Figure 4 shows the true positive rate of all action primitive sets for activity *Early_morning* that had been used with classification algorithms J48, HNB, and IBK. During this activ-

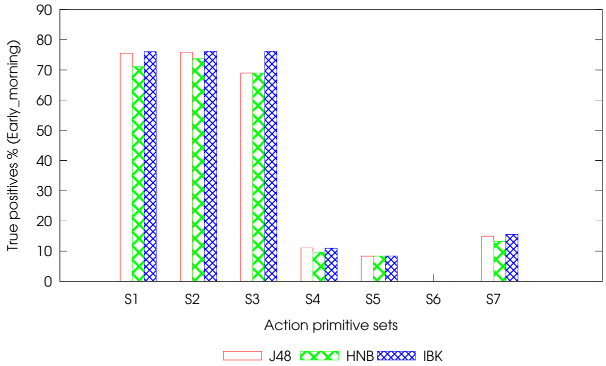

Fig. 4. True positive percentage of activity Early_morning

ity subject moved in the room, and randomly checked some objects in the drawers and on the shelf. Although primitive sets S4, S5, and S7 showed better performance in recognizing this activity as compared to recognizing *Relaxing* activity, wearable sensors providing locomotion primitives won in this case too. The reason for their better performance was that during this activity the subject spends a lot of time in physical activities. Again in this case she has not interacted with object available in the environment for much time. Object sensors had been able to recognize this activity when subject had not interacted with some of the objects. Wearable sensors that had been used to extract action primitives about left hand locomotion were completely failed when those primitives had been used alone. The main reason for their failure is that user had been casually interacting with different objects and had not been performing any serious activities, so subject had only used dominant right hand for this purpose. Wearable sensor providing human locomotion primitives again proved vital in this case.

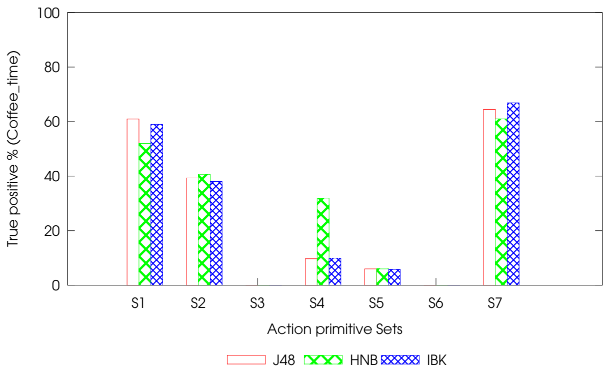

Fig. 5. True positive percentage of activity Coffee_time

Figure 5 shows the true positive rate of all primitive set for activity *Coffee_time* that had been used with classification algorithms J48, HNB, and IBK. During coffee_time the subject prepared coffee with milk and sugar by using a machine, took sips of coffee and also interacted with different objects in the environment. As evident from the activity description this activity is more distinctive on the basis of objects that have been used during this activity as compared to human action primitives. Subsequently object usage primitives also performed comparatively better than human body motion primitives in recognizing this activity.

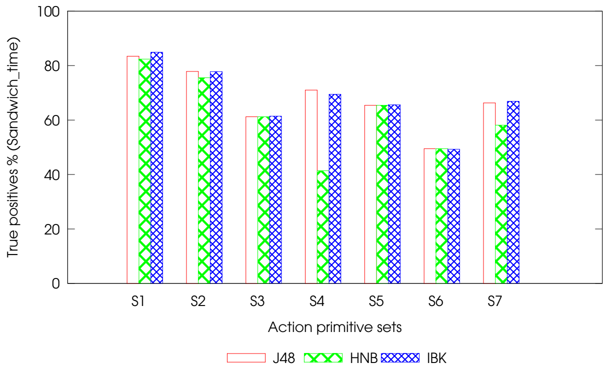

Fig. 6. True positive percentage of activity Sandwich_time

Figure 6 shows the true positive rate of all primitive sets for activity *Sandwich_time* that had been used with classification algorithms J48, HNB, and IBK. During this activity the subject interacted with different objects in the environment like bread, cheese, and salami, and had also used bread cutters, various kind of knives, and plates to prepare the sandwich. Later the subject ate that sandwich. Contrasting to *Idle* activity when subject was motionless most of the time and have interacted with few objects, in this activity subject has not only performed many low level physical activities like cutting the bread but has also interacted with various objects in the environment. As a result all primitive sets had also performed good in case of this activity as compared with other activities. Human body action primitives that can be extracted from wearable sensors data provide better rate of true positives as compared to object usage primitives. But in case of this activity clear winner is the primitive set that used combination of all action primitives extracted from wearable sensors and object sensors. Combining the action primitives from wearable sensors with primitives about the usage of objects available in the environment provided a clear evidence about *Sandwich_time* activity as indicated by the high true positive rate of algorithms using sensor set S1 in Figure 6.

Figure 7 shows the true positive rate of all primitive sets for activity *Cleanup* that had been used with classification algorithms J48, HNB, and IBK. *Cleanup* was the final activity in the drill run for data collection. During this activity subject put all objects used to original places or dish washer and cleanup the table. Classification al-

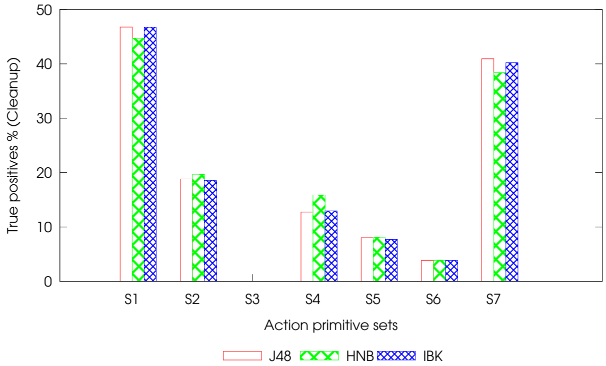

Fig. 7. True positive percentage of activity Cleanup

gorithms could not show good accuracy for this activity. Body locomotion primitives, such as walk, sit, and stand, failed when these primitives have been used alone to detect *Cleanup* activity. However, limbs locomotion primitives, such as reach, move, and release, showed good performance. If we compare the performance of all the action primitive sets when these action primitive sets have been used alone, object usage primitive set showed the best performance as shown in Figure 7. Overall primitive set that used combination of human locomotion primitives, limbs locomotion primitives, and object usage primitives showed the best performance to detect *Cleanup* activity.

5.3 Sensing modalities impact in recognizing all activities

Figure 8 shows the weighted average of true positive rate, false positive rate, precision, recall, f-measure, and roc area of all accuracies using J48 classification algorithms. Sensor set S1 that includes all the sensing modalities available in the data set showed the best true positive rate with comparatively low value of false positives. Subsequently we also have good values of other metrics for primitive set S1. Although use of wearable sensors to recognize high level activities is very rare they have also showed comparatively good performance as depicted by the evaluation metrics of primitive set S2 that contain only primitives extracted from wearable sensor data. The reasons for their good performance is the comprehensive nature of the action primitives that were extracted from those sensors. These sensors not only provide information about the action primitives like walk, sit, and stand but also indicate that one of the objects available in the environment is used. These primitives also proved very helpful in recognizing activities like idle, when subject is not performing any activity, early_morning, when subject is walking around and handling different objects, and relaxing when subject is siting or lying. However, classifiers get confused when they have to detect a single activity among ones that used same objects as these have not been any information about which object is used as shown by the high value of false positive rate and low value of precision as compared with sensor set S1 where we used all the sensors.

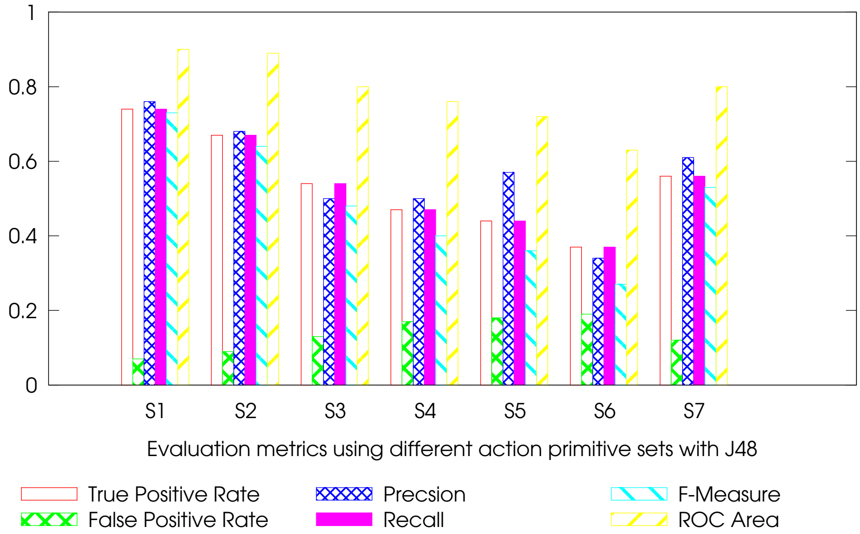

Fig. 8. Evaluation metrics for different primitive sets using decision tree

Primitive set S3 consists of only locomotion action primitives that inform about low level human actions. This sensor set had shown comparative performance with sensor set S7 that consists of primitives from object sensors. Weighted average of these sensors are almost equal to each other. The main reason is that locomotion primitives are better in recognizing activities like relaxing and early_morning while object sensors were proved good in detecting activities in which subject have higher number of interaction with different objects such as *Sanwich_time*. These sensor sets got confused in recognizing other activities as evident by their high false positive rate and low value of precision. Primitive set S4 used primitives extracted from both arms. This set has not performed as good as the locomotion primitive sets or the object usage primitive set. Primitive set S5 used only action primitives extracted from right arm and primitive set S6 used only primitives extracted from left arm. Although both of these primitive sets showed good quality for some of the activities, they could not show good overall accuracy when they are used alone. Primitive set S7 showed better performance comparatively. Clearly primitive set S1 that used combination of object sensors with wearable sensors proved best to recognize human activities in smart home environment.

5.4 Discussion and recommendations

Considering the results of our experiments we had observed that wearable sensors that have been ignored in recognizing human activities in smart home played a significant part in improving the performance of human activity recognition systems. Although when different type of action primitives have been used alone, object or environment usage action primitives gave better results, human body locomotion and limbs locomotion primitives also proved vital in recognizing some of human activities, such as relaxing, idle, and sleeping. Object and environmental usage primitives completely failed in recognizing these activities. Limbs locomotion primitives, like reach, cut, and touch, also proved significant in recognizing those activities that include not only using but also performing actions on different objects. Examples of the actions performed on objects include cutting bread, applying bread spreads. Wearable sensors that can be used to extract action primitives like sip or bite are also important in correctly distinguishing activities like drinking coffee or eating a sandwich. Object or environmental usage sensors are very important to install in areas, such as kitchen, where human are expected to have greater interaction with those objects to recognize human activities. Wearable sensors are significant in recognizing activities during which human does not interact much with environment, such as *Relaxing*. Sensors used with dominant limbs are more reliable in recognizing human activities than sensors used with other limbs. As wearable sensors in combination of object sensors clearly outperformed only object sensors in recognition of all activities, it is indispensable to use wearable sensors in smart environments to improve their performance.

6 Conclusion

In this paper we have compared different sets of action primitives in terms of their influence in recognizing the activities of daily living. We included the human locomotion and limbs locomotion primitives, that can be extracted from the wearable sensors data, in our experiments that have so far been ignored in the research efforts undertaken to build systems to recognize high level human activities. When different locomotion action primitive sets and object usage primitive set have been used alone we had not find any clear winner. The weighted average of true positive rate for all the activities that have been recognized using locomotion action primitives, such as sit, stand, walk, run is comparable with true positive rate of all the activities that have been recognized using object usage action primitives. But when we consider the activities that have been detected with those action primitives they are completely different for each type of action primitives. Locomotion action primitives out performed object usage primitives in recognizing those activities where there have been less interaction of subject with objects available in the environment. Object usage primitives completely failed in recognizing such type of activities. Usually these are the activities that have not been performed in the kitchen area. These activities include *Idle*, *Relaxing* and *early_morning* activities. Object usage sensors performed better in recognizing other activities. Limbs locomotion primitives related to dominant arm also performed better than locomotion primitives from other arm. We will highly recommend to place wearable sensors in the dominant limbs to extract their locomotion primitives. We find that object usage and movement primitives are quite fundamental in recognizing the activities that have been performed the kitchen area. Limbs locomotion primitives are also helpful with object usage primitives in recognizing kitchen area activities. Human locomotion primitives outperformed object usage primitives in recognizing activities that have been performed in areas other than kitchen. Overall combination of object usage and locomotion primitives showed best performance in recognizing ADLs that make using wearable sensors an indispensable choice to recognize ADLs in smart homes.

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