Detecting Unusual Inactivity by Introducing Activity Histogram Comparisons

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Abstract: Unusual inactivity at elderly's homes is an evidence that help is needed. Hence, the automatic detection of abnormal behaviour with a low number of false positives is desired. The aim of this work is to improve the accuracy of inactivity detection by introducing a new approach based on histogram comparison in order to reliably detect abnormal behaviour in elderly's homes. The proposed approach compares activity histograms with a pre-trained reference histogram and detects deviations from normal behavior. Evaluation is performed on a dataset containing 103 days of activity, where six days were reported as containing "unusual" inactivity (i.e., longer absence from home) by an elderly couple.

1 INTRODUCTION

Ambient Assisted Living (AAL) solutions are developed to assist elderly and enable them to stay in their own homes longer. Due to the demographic change in Europe, assistive technologies are needed to fulfill the raising demand of taking care. A focus in the development of AAL technologies is to detect critical events and provide help as soon as possible since this reduces the mortality rate (Noury et al., 2008). Fall detection focuses on the critical event of falling down and being not able to get up on your own and approaches to detect falls are proposed (e.g., (Lee and Chung, 2012; Anderson et al., 2006; Nait-Charif and McKenna, 2004; Planinc and Kampel, 2012)). These approaches use computer vision to detect falls in home environments and thus provide unobtrusive AAL solutions. However, not only falls are critical events to be detected, but also changes in the daily routine of the elderly indicate situations where help is needed (e.g., due to illness). Human action recognition (Ballin et al., 2013) can be used to detect and model actions which are performed during the daily routine, but focus on the pre-defined actions.

Since the type of actions elderly perform during the day is not relevant for the detection of unusual inactivity, the authors of this work focus on a more generic approach. Similar work is performed by Floeck & Litz (Floeck and Litz, 2008) and Cuddihy et al. (Cuddihy et al., 2007). They introduced an approach to model inactivity and to detect unusual inactivity by only considering motion data, independently from the source of data (e.g., motion data is obtained by motion sensors, door sensors).

The aim of this paper is the introduction of a histogram based activity modeling approach and the detection of unusual (in)activity while reducing the number of false alarms. Activity data is obtained by using tracking information from the OpenNI tracker NITE and an Asus Xtion pro, but can be obtained by any arbitrarily tracking algorithm or sensor type (e.g., motion sensor). Tracking information consists of the center of mass of a person and the timestamp when motion (activity) is detected. If more than one person is present, only tracking information of one person is stored, since this indicates activity and the number of people being present is not relevant for this approach.

The rest of this paper is structured as follows: Section 2 presents the state of the art in the field of unusual inactivity detection whereas Section 3 introduces the proposed approach. An evaluation in Section 4 demonstrates the feasibility of our approach and finally a conclusion is drawn in Section 5.

2 STATE-OF-THE-ART

Nait-Charif & McKenna (Nait-Charif and McKenna, 2004) use tracking information from an overhead camera to summarize activity in home environments. The movement of the person is tracked and the room

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is divided into entry/exit zones, inactivity zones and transition areas. A typical use of the room is modeled as follows: a person enters the room via an entry zone, moves to one or more inactivity zones and finally leaves the room via an exit zone. Transition areas are defined to be areas where the transition from an entry/exit zone to an inactivity zone or between inactivity zones take place. Inactivity zones are learned automatically using the approach introduced in (McKenna and Nait-Charif, 2004). The person's speed is analyzed to define whether the person is active or inactive. Depending on the location of the person during the inactivity, the system detects whether the inactivity occurs in an already pre-defined inactivity area or outside such areas. This allows to detect unusual inactivity which can be caused by a fall. Furthermore, activity patterns (i.e., sequence of visiting different zones) are analyzed and deviations of patterns are detected. However, the work of Nait-Charif & McKenna (Nait-Charif and McKenna, 2004) focus on spatial aspects of inactivity, but temporal aspects are not taken into consideration since only the sequence of visiting zones is analyzed but not associated with the time of the day (e.g., the sequence of visiting different zones may change depending on the time).

In contrast, Floeck & Litz (Floeck and Litz, 2008) and Cuddihy et al. (Cuddihy et al., 2007) focus on temporal aspects of inactivity. Activity data is collected using 30 sensors (i.e., motion detectors, door and window sensors) resulting in an activity profile (Floeck and Litz, 2008). However, due to the diversity of sensors used, inactivity profiles are introduced to combine the data from different sensors to one profile. An inactivity profile is constructed by analyzing the duration of inactivity over time, where inactivity is defined as no activity from any sensor. As long as no activity is detected, the duration of inactivity raises over time, shown in Figure 1. If any kind of activity is detected, the inactivity duration is set to zero (e.g., between 7 and 8 AM). Afterwards, the inactivity duration raises since no activity is detected between 8 and 9 AM. Due to the combination of motion and door sensors, the approach proposed in (Floeck and Litz, 2008) is able to differentiate between inactivity due to absence of the person (data obtained by door sensors) and inactivity when the person is present. Figure 2 depicts an inactivity diagram, distinguishing whether a person is present or absent when inactivity is detected.

In order to detect abnormal inactivity, the inactivity profile is compared to a pre-trained reference profile (e.g., average inactivity profile of one month). Therefore, the profiles are divided into n different time slots. Floeck & Litz (Floeck and Litz, 2008) calculate the integral of inactivity of each time slot and

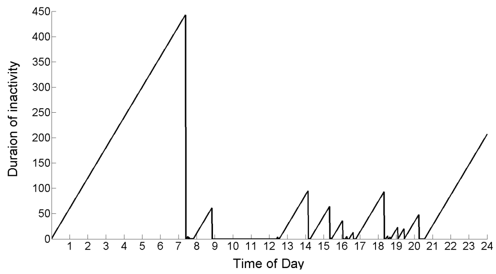

Figure 1: Inactivity profile.

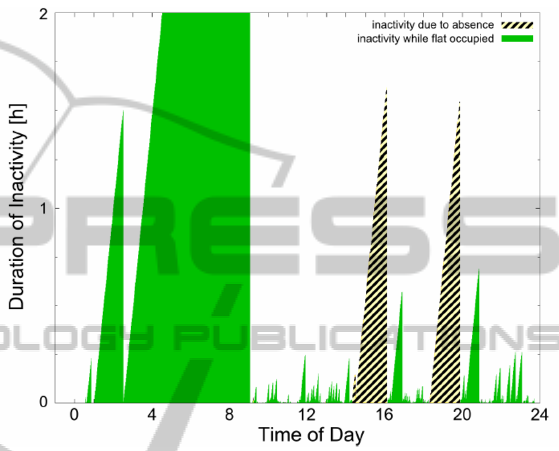

Figure 2: Inactivity profile considering data different sensor types (Floeck and Litz, 2008).

combine all n time slots to one feature vector per day, which is compared to the reference vector using the Dice coefficient (Dice, 1945). By introducing a tolerance value and a convolution with a weighting vector, small temporal and numerical deviations are compensated (e.g., sleeping 5 minutes longer than usual). Since the inactivity profiles are compared on a one-day vector basis, deviations are detected at the end of the day. However, extensive evaluation of this approach is missing and thus no performance measures when being applied to real world scenarios can be obtained.

Cuddihy et al. (Cuddihy et al., 2007) use door sensors to detect if a person leaves the flat in order to minimize false positives when no person is present. Similar to (Floeck and Litz, 2008), the authors use inactivity profiles and each day is divided into n time slots. A reference alert line is learned over the duration of 45 days by analyzing the maximal inactivity duration at each time slot and adding buffers to allow small deviations. The uniform and variable buffer act as vertical tolerance and ensure, that the sensitivity of the algorithm is adopted according to the amount of inactivity (i.e., the algorithm is more sensitive during active times and less sensitive during inactive times). Furthermore, time shifts are compensated by applying a weighting function to the inactivity data and thus considering also adjacent intervals providing a temporal buffer. Each time interval is compared to the corresponding time interval of the alert line immediately, hence alarms are raised at the end of each time interval. The alert line is adopted based an a 45 days rolling window approach, hence the alert line is learned from the last 45 days and adopts to behavioral changes automatically.

3 METHODOLOGY

Floeck & Litz (Floeck and Litz, 2008) and Cuddihy et al. (Cuddihy et al., 2007) use inactivity profiles since they argue that it is difficult to combine different signals (start/stop signals and discrete events) to one common profile. This work focus on discrete events (i.e., motion detected / no motion detected), hence no inactivity profiles need to be calculated to fuse the sensor data. Instead, activity histograms are used to detect unusual inactivity. Since histogram comparison is widely used in the area of image processing (e.g., image retrieval), activity histograms are introduced in this work in order to detect unusual inactivity. Activity data is aggregated in histograms of 24 bins representing one day, resulting in one bin per hour. The number of bins was choosen to achieve a trade-off regarding the granularity of the approach, i.e. the activity is not analyzed in detail (e.g., per minute) and not per day, but on an hourly basis. Figure 3 depicts an example of an activity histogram (top) and the corresponding inactivity profile (bottom). Since motion (activity) was detected during the night between one and two AM, the inactivity dropped to zero. The inactivity between 8:30 and 9:30 AM is better reflected in the inactivity profile, since only a smaller amount of activity is depicted in the activity histogram. But since a temporal buffer need to be added to detect abnormal inactivity, both representations are feasible.

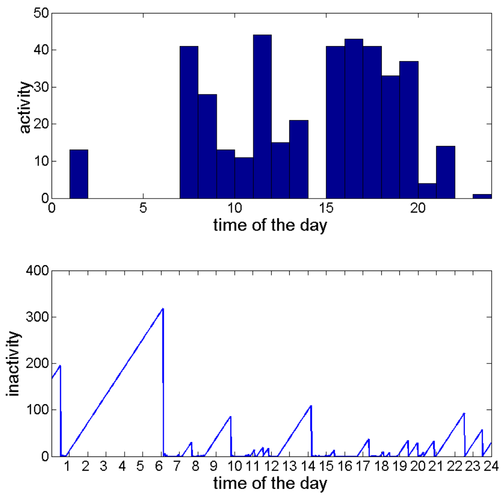

Figure 3: Example of an activity and corresponding inactivity profile.

During the training phase, the histograms H_n for all n training days are calculated. The average histogram H_{ref} of all histograms H_n is calculated and used as a reference for "normal" behavior. In order to model the variability of the training data, the distances d_n between the nth histogram and the reference H_{ref} are calculated.

The distance matrix D_n represents the distances between all bins and the distance d_n is the sum of all distances D_{ij}, shown in Equation 1.

$$d_n = \sum_{i,j=1}^{24} D_{ij} \tag{1}$$

The average distance $\overline{d}$ and standard deviation σ are calculated from the training set and used as decision criteria during the test phase. A deviation from a normal daily routine is detected if

$$|d_t| \geq \overline{d} + \sigma \tag{2}$$

where d_t denotes the histogram distance of the day to be analyzed to the reference histogram H_{ref}.

For the calculation of the distances, the euclidean, chi-square (Cha, 2008), earth mover's distance (Rubner et al., 2000), bhattacharyya distance (Comaniciu et al., 2000; Bhattacharyya, 1943) as well as intersection (Swain and Ballard, 1991) and the Pearson Product-Moment Correlation Coefficient (Rodgers and Nicewander, 1988) are analyzed during the evaluation.

The chi-square distance is defined as

$$d(H_1, H_2) = \frac{1}{2} \sum_i \frac{(H_1(i) - H_2(i))^2}{H_1(i) + H_2(i)} \tag{3}$$

The earth mover's distance is calculated by computing the optimal flow f_{ij} and the ground distance d_{ij} and is defined as

$$d(H_1, H_2) = \frac{\sum_i \sum_j d_{ij} f_{ij}}{\sum_i \sum_j f_{ij}} \tag{4}$$

The bhattacharyya distance for histograms is based on the bhattacharyya coefficient and is defined as

$$d(H_1, H_2) = \sqrt{1 - \sum_i \frac{\sqrt{H_1(i) \cdot H_2(i)}}{\sqrt{\sum_j H_1(j) \cdot \sum_j H_2(j)}}} \tag{5}$$

The intersection of histograms is defined as

$$d(H_1,H_2) = 1 - \sum_i min(H_1(i), H_2(i)) \quad (6)$$

The Pearson Product-Moment Correlation Coefficient is defined as

$$d(H_1,H_2) = \frac{\sum_i (H_1(i) - \overline{H}_1) \cdot (H_2(i) - \overline{H}_2)}{\sqrt{\sum_i (H_1(i) - \overline{H}_1)^2 \cdot \sum_i (H_2(i) - \overline{H}_2)^2}} \quad (7)$$

where

$$\overline{H}_k = \sum_i \frac{H_k(i)}{n} \quad (8)$$

In order to provide a lateral buffer, the histograms are compared on a daily basis resulting in a delay of an alarm in comparison to the approach introduced by Floeck & Litz (Floeck and Litz, 2008), but reducing the number of false positives dramatically.

Figure 4: Part of the living room being monitored.

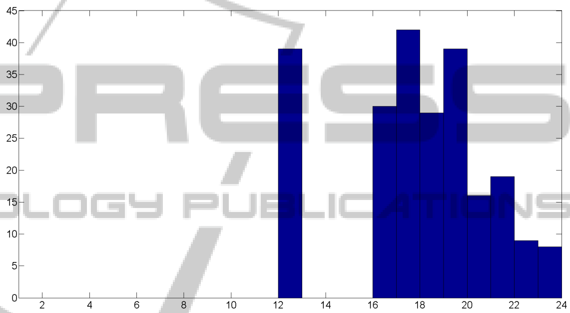

Figure 5: Example of a normal day 1 - activity in the morning is missing, but this day is considered as normal activity.

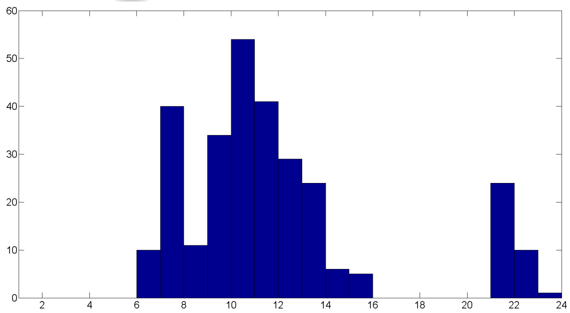

Figure 6: Example of a normal day 2 - activity is present throughout the day, except the afternoon.

4 EVALUATION

The evaluation is based on activity data obtained by the observation of the living room of an elderly couple over the duration of 103 days. The monitored field of view is shown in Figure 4 and covers the area of the living room, where a table is used for food intake. Six of the monitored days were reported as ”unusual” by the couple, i.e., consist longer absence from home or dramatically changed daily routines. Hence, 97 days are considered as normal days where no alarm should be raised. Since this dataset is not artificially altered but acquired from a real scenario, it might be unbalanced with respect to the ratio of alarms and days not containing an alarm.

Nevertheless, the recorded dataset is challenging, since it represents the daily activities of real persons, not considering the change of daily activities during the week or on the weekend. Only the six days reported by the elderly where marked as alarms and thus being absent for half a day (Figure 5) is not reported as ”unusual”, since this is not unusual for the couple. However, a typical histogram of activities is depicted in Figure 6: getting up in the morning between 6 and 7 AM followed by a peak of activities due to preparing and eating breakfast. Moreover, around noon, activity is increased due to typical activities performed during the morning and early afternoon (e.g., eating, playing cards, reading the newspaper). In the afternoon, no activity is detected due to watching TV in another part of the living room followed by activity due to preparing and eating dinner. Figure 7 depicts a similar histogram of activity, although the shape is different compared to Figure 6 due to a changed intensity of performing activities. Figure 8 shows an ”unusual” behavior due to enhanced activity in the morning but decreased activity during the day (the amount of activity is significantly lower than ”normal”). An abnormal shape of activity is depicted in Figure 9 and thus results in being categorized as ”unusual” activity. Absence for almost the whole day is also reported as ”unusual” since usually at least one person of the elderly couple is at home during the day (e.g., around noon), depicted in Figure 10.

Evaluation results are obtained by varying the number n of randomly choosen training days from

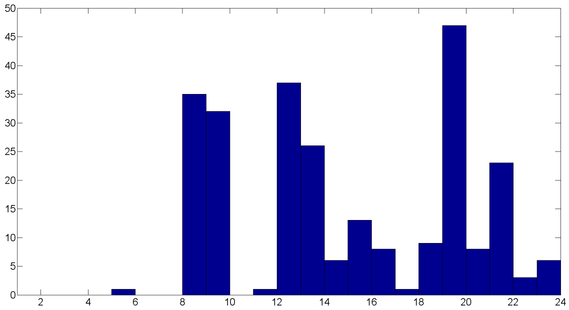

Figure 7: Example of a normal day 3 - activity and inactivity are present throughout the day.

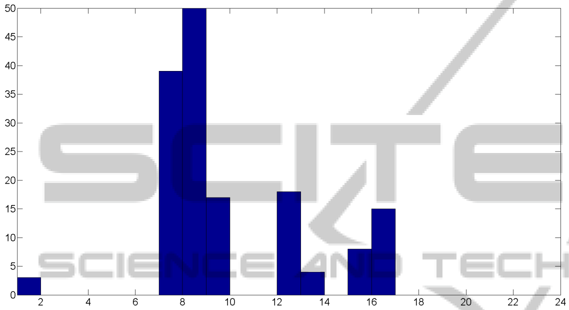

Figure 8: Example of unusual activity 1 - activity is reduced in the afternoon/evening.

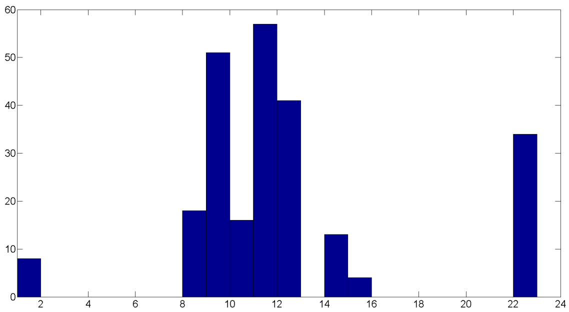

Figure 9: Example of unusual activity 2 - no activity in the afternoon/evening.

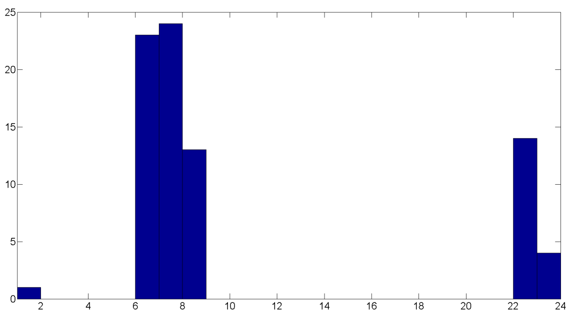

Figure 10: Example of unusual activity 3 - absence during the day.

two up to 97 training days. The six days reported as abnormal behavior were not included in the trainingset, but in the testset. Thus, the size of the testset is 101 to six test samples, depending on the training set.

Since inactivity detection often results in false alarms, the goal is to reduce the number of false positives while detecting true positives. The proposed approach is evaluated using the toolbox provided by (Dollár, 2012) and compared to the approach using an alert line introduced by Cuddihy et al. (Cuddihy et al., 2007). Evaluation results, depicted in Figure 11, visualize the number of alarms depending on the number of training days. As can be clearly seen, the number of false alarms using the alert line approach is high, especially with only few trainingdata (over 500 alarms when using 2 days of training data). In comparison, using the proposed approach, the number of false alarms when using few training data is reduced to less than 100 false alarms. Please note that 100 resp. 500 false alarms on a testset including 101 test days results in one resp. five false alarms per day in average. Figure 12 shows a detailed view of Figure 11, where the maximum number of alarms is cut off at 100 in order to enhance the comparability between the approaches.

In order to improve the accuracy of the system, more training data is needed . However, even when increasing the trainingset to the size of 45 days, which is proposed by Cuddihy et al. (Cuddihy et al., 2007), the proposed approach still reduces the number of alarms from 35 when using the alert line approach to less than 16 alarms using the proposed approach. Since six alarms are included in the testset, the number of false positives is even lower.

In order to evaluate the accuracy of the system, the f-score (C. J. van Rijsbergen, 1979) is calculated and plotted depending on the size of the trainingset. The f-score is defined as

$$F = 2 \cdot \frac{precision \cdot recall}{precision + recall} \tag{9}$$

with

$$precision = \frac{TP}{TP + FP} \tag{10}$$

and

$$recall = \frac{TP}{TP + FN} \tag{11}$$

where TP is the number of true positives, FP the number of false positives and FN the number of false negatives. Figure 13 depicts the f-scores of the introduced approach using different distance measures and the f-score of the alert line approach. All distances except the earth mover's distance and the correlation clearly outperform the alert line method (Cuddihy et al., 2007), not only in terms of less alarms but also in terms of better f-score values. The histogram

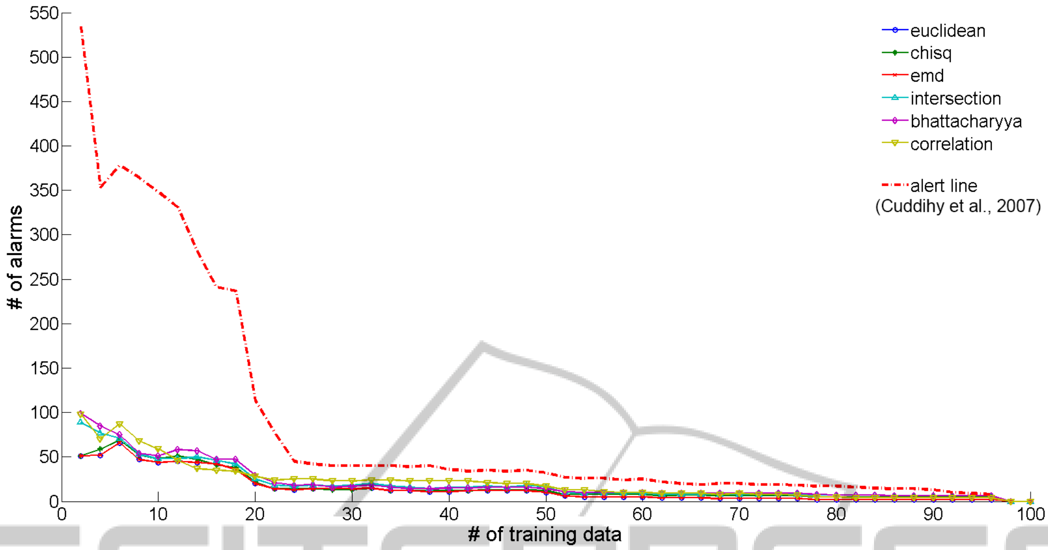

Figure 11: Alarm rate depending on the size of the training sample.

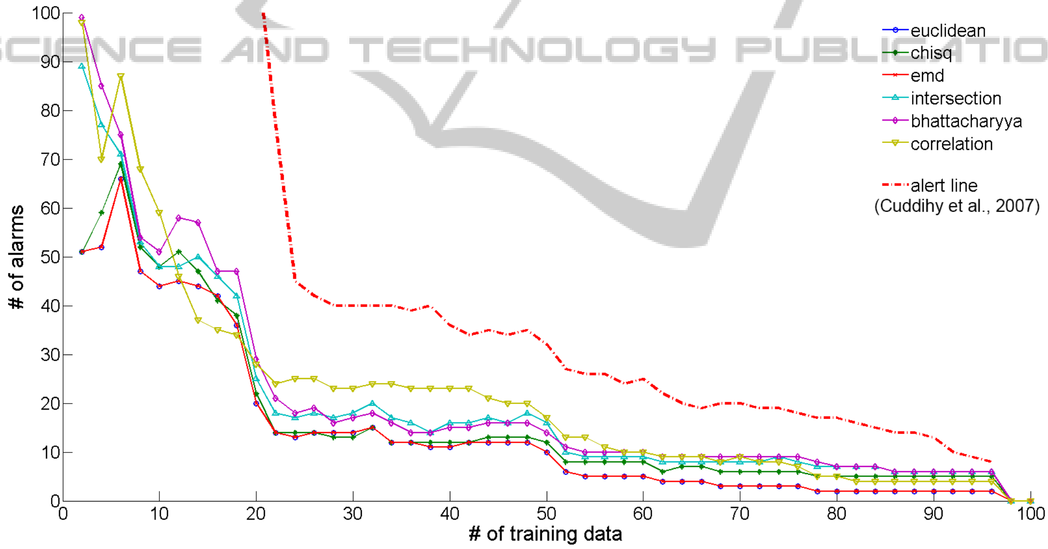

Figure 12: Detailed view of alarm rate (number of alarms $\leq$ 100) depending on the size of the training sample.

correlation performs similar to the alert line approach, whereas the earth mover's distance results in a lower f-score than the alert line approach.

Table 1 depicts the number of alarms depending on the size of the training data. All histogram comparisons perform better in comparison to the alert line approach in terms of less false positives. However, the number of alarms do not indicate whether the alarm is a true or false positive and thus the f-score is calculated and used for comparison of these approaches, e.g., the number of alarms using the euclidean distance and the earth mover's distance result in the same number of alarms, but in different f-scores due to consideration of true and false positives when calculating the f-score.

Table 2 illustrates the accuracy of the proposed approach using different distance measures and compares the results to the alert line method introduced in (Cuddihy et al., 2007). The highest f-score values are marked bold and thus can be seen that the chi-square distance performs best and increases the accuracy compared to the alert line approach.

5 CONCLUSIONS

This work introduced the comparison of activity his-

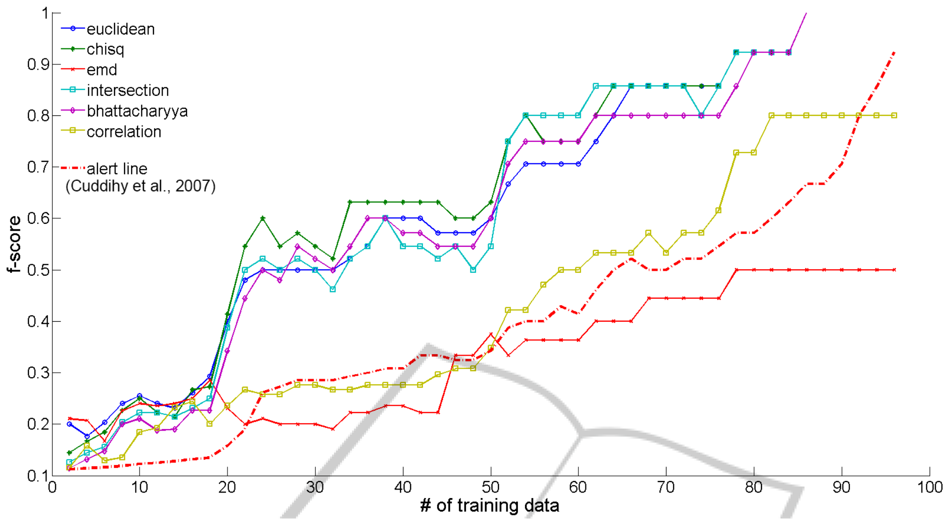

Figure 13: f-score depending on the size of the training sample.

Table 1: Number of alarms.

training size	euclidean	chisq	emd	intersection	bhattacharyya	correlation	alert line (Cuddihy et al., 2007)
10	44	48	44	48	51	59	348
20	20	22	20	25	29	28	113
30	14	13	14	18	17	23	40
40	11	12	11	16	15	23	36
50	10	12	10	16	14	17	32
60	5	8	5	9	10	10	25
70	3	6	3	8	9	9	20
80	2	5	2	7	7	5	17
90	2	5	2	6	6	4	13

Table 2: F-score.

training size	euclidean	chisq	emd	intersection	bhattacharyya	correlation	alert line (Cuddihy et al., 2007)
10	**0,255**	0,250	0,240	0,222	0,211	0,185	0,122
20	0,400	**0,414**	0,231	0,387	0,343	0,235	0,158
30	0,500	**0,545**	0,200	0,500	0,522	0,276	0,286
40	0,600	**0,632**	0,235	0,545	0,571	0,276	0,308
50	0,600	**0,632**	0,375	0,545	0,600	0,348	0,343
60	0,706	0,750	0,364	**0,800**	0,750	0,500	0,414
70	**0,857**	**0,857**	0,444	**0,857**	0,800	0,533	0,500
80	**0,923**	**0,923**	0,500	**0,923**	0,923	0,727	0,571
90	**1,000**	**1,000**	0,500	**1,000**	**1,000**	0,800	0,706

tograms to detect unusual inactivity. In contrast to state-of-the-art methods, activity histograms are used without constructing inactivity profiles. A reference activity histogram is learned over time and the decision if an abnormal long inactivity occurred is based on histogram comparison. This approach was evaluated on a dataset containing 103 days of tracking data obtained from an elderly couple and results showed, that the proposed approach outperforms the alert line approach, when using appropriate distance measures (e.g., the chi-square distance).

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