Combining Spatial and Temporal Information for Inactivity Modeling

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***Abstract*—Unusual inactivity is caused by events, where elderly need help (e.g., falls, illness). In order to detect unusual behavior, modeling of activity results in inactivity profiles. State-of-the-Art approaches focus on temporal aspects of inactivity by only considering deviations of inactivity over time. This work proposes the use of spatial information in combination with temporal aspects to enhance the robustness and reduce the number of false alarms. The proposed approach is evaluated on two different datasets containing 100 days resp. 50 days of activity data of elderly people and results are compared to the State-of-the-Art.**

***Keywords*-inactivity modeling; unusual behavior detection; spatio-temporal analysis;**

I. Introduction

Due to the demographic change, Europe's population is growing older and thus automated systems to assist elderly are needed. Ambient assisted living (AAL) solutions aim to provide assistance and help for elderly, hence the detection of critical events and unusual behavior is crucial. Furthermore, getting help quickly after a fall reduces the risk of death by over 80% [1] and thus AAL does not only assist elderly, but is also able to save their lives. However, research mainly focus on the detection of events (e.g., detection of falls [2], [3], [4], [5]). In order to detect events, two different approaches are used: first, the specific event itself is detected directly (e.g., falls [2], [3], [6]) or second, events are detected indirectly on a more abstract level by detecting abnormal inactivity (e.g., [7], [8], [9]). The latter approach offer the advantage to be able to detect different critical events at the same time, but is not able to distinguish the cause of inactivity (e.g., inactivity due to fall, illness, vacation).

However, more attention is drawn to the detection of (short-term) events than to the detection of (long-term) unusual behavior. Behavior in the context of AAL can be modeled using activity patterns and generating inactivity profiles to detect abnormal long periods of inactivity ([7], [8]). Since Cuddihy et al. [7] as well as Floeck & Litz [8] only focus on temporal aspects of inactivity, the novelty of this paper is the introduction of a spatio-temporal approach to model inactivity depending on spatial information and to detect unusual inactivity locally.

The rest of this work is structured as follows: Section 2 describes the State-of-the-Art methods to model and monitor inactivity, whereas our region-based approach is introduced in Section 3. Section 4 presents an evaluation and results of the proposed algorithm and finally a conclusion is drawn in Section 5.

II. State-of-the-Art

Monekosso and Remagnino [10] equipped a home-lab with different sensors (e.g., motion detector, temperature sensor, lighting status) and developed a model for behavioral trends. This model is based on a hidden markov model. After a training phase without any atypical behavior, the model is tested in order to detect atypical behavior. However, detected deviations from typical behavior not only result from the person, but also from the sensor itself since noise disturbs the sensor data.

Temporal aspects of activity patterns and trends are analyzed by Virone and Sixsmith [11]. Again, the motivation is the detection of deviations during the performance of activities of daily living (ADL), where the following ADLs are defined: sleeping, dressing, eating, bathroom, meal preparation, hygiene, cleaning, phoning, washing, walking and sitting. Deviations are detected on each activity separately by using an unsupervised approach [12] in order to estimate the behavior of the person and detect deviations from a normal behavior. Evaluation is based on motion sensor data combined with a stove-top temperature sensor and a bed-based vital sign monitor, gathered by 22 residents in an assisted living setting and software simulations. Spatial aspects are modeled by the placement of one motion sensor per room, hence only information about the occupancy in a room can be retrieved, but not the exact location within the room.

Activity detection based on tracking information is introduced by Nguyen et al. [13]. The environment is split into a grid of different areas and landmarks are identified. Activity detection is based on the visit of a person to specific landmarks and thus considers spatial information in order to detect the activity. As an example, the landmarks door, cupboard, fridge and dining chair are visited during the behavior "short meal". A set of primitive behaviors (i.e., transitions between landmarks) are defined and activities are recognized using a hierarchical hidden markov model. This approach considers spatial aspects, but temporal aspects (time of the day) are not considered, hence only activities are detected but abnormal behavior can not be detected.

The work of Nait-Charif & McKenna [9] uses tracking information from an overhead camera to summarize activity in home environments. The movement of the person is tracked and the room is divided into entry/exit zones, inactivity zones and transition areas. A typical use of the room is modeled as entering the room via an entry zone, moving to one or more inactivity zones and finally leaving 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 [14]. The person's speed is analyzed to define whether the person is active or inactive. Depending on the position 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 outside pre-defined areas 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 [9] 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, Cuddihy et al. [7] and Floeck & Litz [8] do not focus on spatial but on temporal aspects of inactivity. Activity data is collected using 30 sensors (i.e., motion detectors, door and window sensors) resulting in activity data [8]. 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). In order to detect unusual inactivity, the inactivity profile is compared to a reference profile (i.e., average inactivity profile of one month). Therefore, the profiles are divided into n different time slots. Floeck & Litz [8] calculate the integral of inactivity of each time slot and combine all n time slots to one feature vector per day, being compared to the reference vector using the Dice coefficient [15]. By introducing a tolerance value and a convolution with a weighting vector, small temporal and numerical deviations are compensated (e.g., sleeping five minutes longer than usual). Since the inactivity profiles are compared on a one-day basis, deviations are detected at the end of the day. However, extensive evaluation of this approach is missing and thus no results when being applied to real world scenarios are provided.

Cuddihy et al. [7] use additional door sensors to detect if a person left the flat in order to minimize false positives when no person is present. Similar to [8], 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 of each time slot and adding buffers to allow small deviations. The uniform and variable buffer act as vertical tolerance and ensure, that the sensitivity

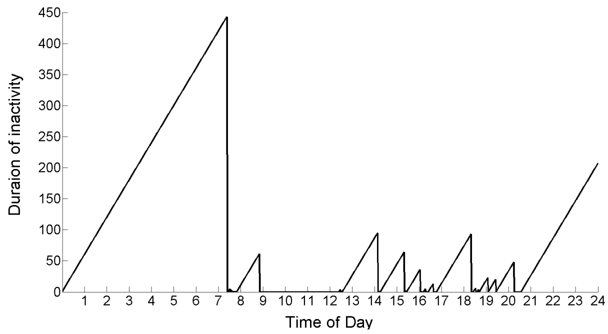

Figure 1. Example of an inactivity profile

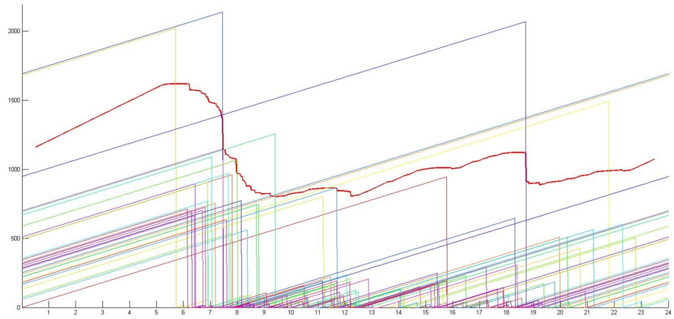

Figure 2. Example of an alert line

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 if the inactivity duration exceeds the threshold defined by the alert line. An example of an trained alert line is shown in Figure 2: the alert line is shown as bold red line, together with the inactivity profiles of different days. All inactivity profiles exceeding the threshold result in an alarm, since an unusual amount of inactivity is detected.

The alert line is adopted based an a 45 day rolling window approach, hence it is learned from the last 45 days and adopts to behavioral changes automatically. The algorithm analyzes temporal aspects of inactivity considering the time of the day, but on a global level. Hence, all sensor data is aggregated and taken into consideration, thus spatial information is lost.

III. Methodology

The proposed approach introduces the use of spatial information in combination with temporal aspects in order to enhance the accuracy of inactivity detection and to reduce the number of false positives. In contrast to the State-of-the-Art, a depth sensor together with a tracking algorithm provided by the OpenNI SDK is used to collect tracking data.

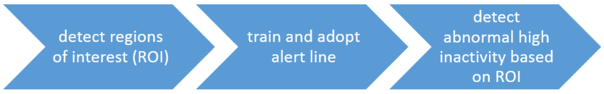

Figure 3. Workflow

The use of a depth sensor is motivated by the potential to combine the proposed approach together with other approaches (e.g., fall detection systems [3], [4]) without the need for additional sensors. In contrast to Cuddihy et al. [7], no door sensors are used. Thus, no information about the absence of a person due to vacation, shopping, etc. is available. Since these times of absences are incorporated in the overall inactivity model, longer periods of inactivity (i.e., higher amount of inactivity) are calculated. Moreover, alarms are triggered after a longer period of time since the trained inactivity model already consists of high inactivity values due to the absence of a person. However, the information from door sensors can be integrated into the system easily, in order to improve the accuracy.

The proposed workflow of our approach is illustrated in Figure 3: in the first step, regions of interest (ROI) R_i are detected by the algorithm. In the second step, alert lines are calculated based on the approach of Cuddihy et al. [7], but for each spatial region R_i individually.

A. *Region of Interest Detection*

Tracking data is captured in world coordinates relative to the sensor and is distorted. In order to obtain accurate results, the tilt of the depth sensor is calculated and used to rectify the motion data. Pixelwise accumulation of motion data indicates ROIs and thus the pixels (and their surroundings) with the highest count of motion data are defined as ROI. This is achieved by using a grid-based approach, calculating a 75x75 histogram of the motion data. In order to retrieve interesting regions of the scene, all bins with motion data higher than 60% of the maximal motion are pre-filtered as regions of interest. This initial regions are refined by using a non-maxima suppression, where similar region centers are eliminated. As a result, the center of i regions R_i containing a high amount of motion are obtained and are thus used as region of interests. Figure 4 depicts the top view of the scene including the motion data. Moreover, regions with a high amount of motion are detecting by applying a threshold and are marked as circles. After applying the non-maxima suppression, only relevant ROIs are extracted, marked as X. These relevant regions are then used in the second step in order to calculate regional alert lines.

An example of the ROIs is shown in Figure 5: although it seems that the two detected ROIs are close together, the 3D representation in Figure 6 illustrates that different distances are taken into account and thus, distinct ROIs are identified.

Using the proposed region based approach allows to focus on specific regions being from high interest and eliminates a high amount of motion data from other areas. This information

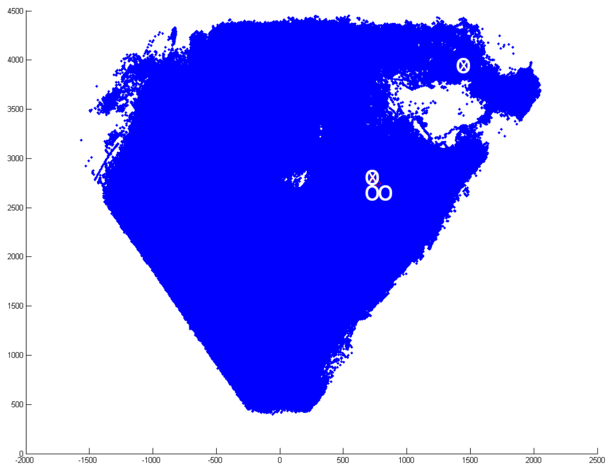

Figure 4. Top view of motion data and detected regions of interest (dataset 1): circles represent the initially calculated ROIs by threshholding whereas crosses mark the final ROI centers after using non-maxima suppression

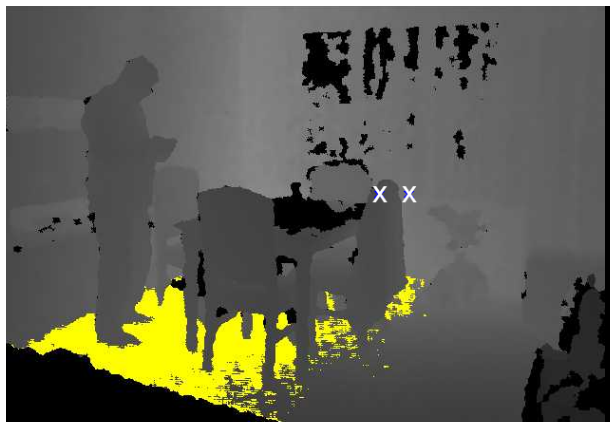

Figure 5. Region of Interest (dataset 1): depth image (ground floor marked yellow)

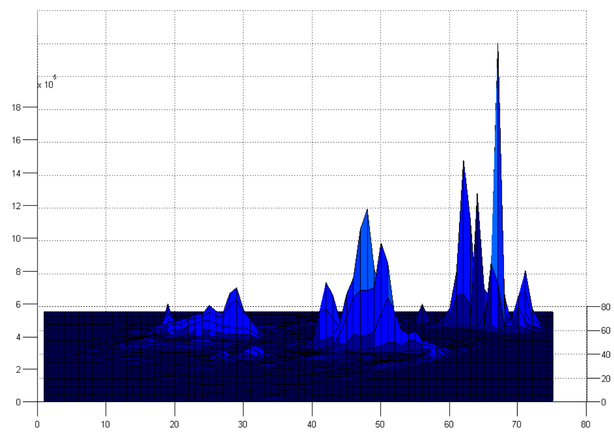

Figure 6. Region of Interest (dataset 1): 3D visualization of the 75x75 histogram

about the interesting areas of a scene can be either used to refine the modeling of inactivity and detect unusual inactivity, or can be used to detect time depending actions. Regions with high activity contain typical, regular actions (e.g., eating) since those actions are performed at the same place (e.g., at a table).

An example is shown in Figure 6: one ROI with the highest activity is located in the back right corner, where the window is located. The second significant ROI is detected at the chair at the right side of the table. Another possible, but not significant and thus not detected ROI is located at the opposite of the table where another chair is placed. All ROIs can be explained and interpreted very easily: ROI 1 at the window indicates regular ventilation of the flat, whereas ROI 2 at the table reflects regular meal consumption. Since data is obtained from a flat where an elderly couple live in, the possible ROI at the opposite of the table indicate the area of the second person during food consumption. This indicates that the proposed approach is able - in combination with further knowledge of the scene - to not only monitor activity in general, but to model specific actions (e.g., food consumption) and the behavior of different persons individually (i.e., it is assumed that person A sits on the right side of the table whereas person B usually sits on the left side of the table).

B. Alert Line Calculation

The inactivity profile (i.e., alert line) is calculated for each region R_i during the training phase, using the method of Cuddihy et al. [7]. Only activity within this region and their surrounding, defined by a maximum tolerance radius r (e.g., r =25cm), is taken into consideration. In comparison to the approach introduced by Cuddihy et al. [7], regional alert lines contains a higher amount of inactivity since motion information is only analyzed in a small area of the scene, defined by the ROI.

After the training of the alert line, activity is analyzed in each region R_i individually and compared with the corresponding alert line A_i. The comparison is done per time interval and an alarm is triggered if the duration of inactivity is above the threshold of the alert line for this interval. Hence, unusual inactivity (i.e., deviation from the trained inactivity profile) is detected already at the end of the time interval allowing to provide immediate alarms. Unusual inactivity is defined as reduced movement at time intervals, where usually a high amount of movement is present (calculated during the training phase). This unusual inactivity can be caused due to illness or other physical impairments (not being present during the training phase) or the absence of the person.

IV. Results

The evaluation is performed on two different datasets containing motion data obtained by a Asus Xtion in combination with the tracker provided by OpenNI. Depth data is available up to ten meters and thus the use of the Asus is feasible for most rooms in practice. For the analysis, an elderly couple was monitored over the duration of more than 100 days and motion data was captured (dataset 1). For dataset 2, activity

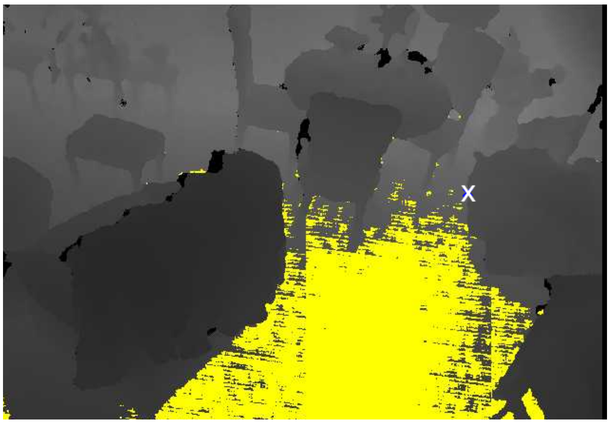

Figure 7. Region of Interest (dataset 2): depth image (ground floor marked yellow)

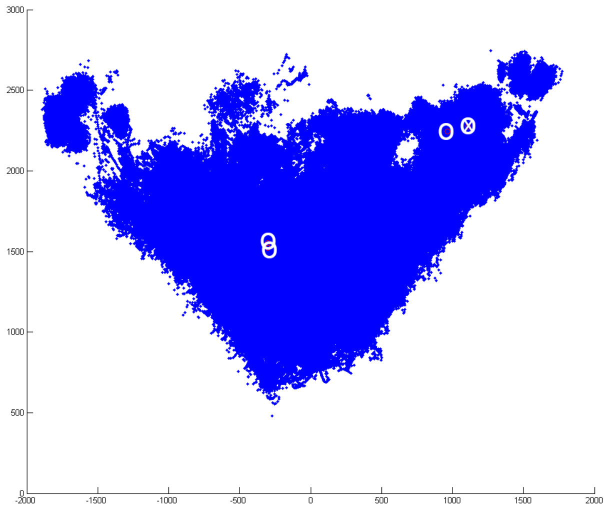

Figure 8. Top view of motion data and detected ROIs (dataset 2): circles represent the initially calculated ROIs by threshholding, crosses mark the final ROI centers after using non-maxima suppression

data of an elderly man was recorded over the duration of more than 50 days. Days without activity are removed in a first step in order to remove outliers, resulting in a dataset of 100 resp. 50 days. The depth image of the scene in dataset 1 is visualized in Figure 5. Figure 7 illustrates the depth image of the scene of dataset 2. The only region of interest is detected at a table, indicate a high amount of motion close to the table (i.e., sitting down and getting up). Candidate regions of interest are illustrated in Figure 8, where only one region of interest was detected to be significant.

Two regions of interest are detected in dataset 1 and the alert lines obtained by training over a duration of 46 days are shown in Figure 9: (a) shows the global alert line, whereas (b)-(c) show the alert lines to their corresponding regions 1 and 2. Since all alert lines use the same scale (but different offsets), the alert line in region 1 shown in (b) is similar to the global alert line shown in (a), but provides a more distinctive

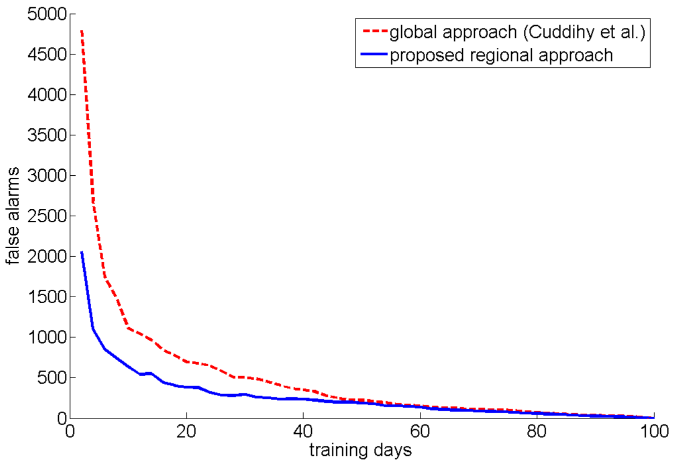

Figure 10. Comparison of global and regional false alarm rate depending on the duration of the training (dataset 1)

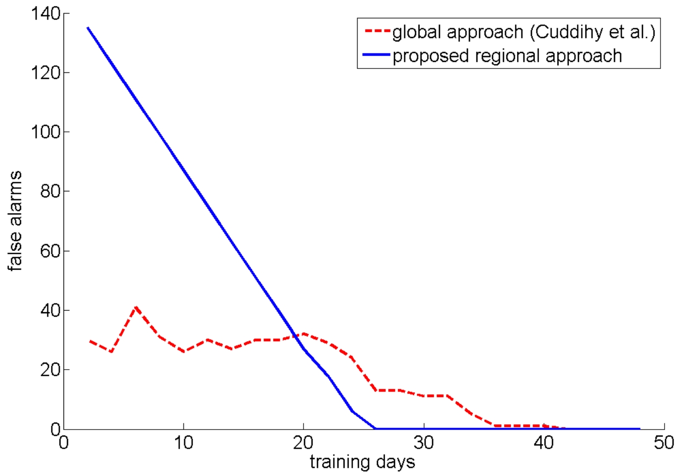

Figure 11. Comparison of global and regional false alarm rate depending on the duration of the training (dataset 2)

change of inactivity, i.e., the difference from the maximal to the minimal value is larger. Furthermore, the alert line from region 2, depicted in (c) resp., indicate activity between 9 and 11 AM. This information is completely lost in the global alert line and thus illustrates an advantage of the proposed region based approach, where each region is analyzed individually and thus spatial information is preserved.

Since the global alert line is formed due to the high activity in region 1, further evaluation is performed to compare the performance of the global alert approach with the proposed region based approach in region 1. Evaluation is performed by calculating the number of alarms in region 1 and on a global level using cross validation. For dataset 1, nine rounds of cross validation were performed, for dataset 2 three rounds. For each round of cross-validation, the dataset is split into a training and test data set randomly and the number of training data is varied from two days of training up to a training of 98 days. The rest of the data set is used as test set, hence resulting in a number of 98 test cases resp. a test set of two days. The results of all rounds are averaged and shown in Figure 10 (dataset 1) and Figure 11 (dataset 2). Multiple rounds of cross-validation are performed in order to avoid overfitting of data since the training data is randomly chosen multiple times.

Figure 10 compares the proposed region based approach with the global approach introduced in [7] based on dataset 1: our approach clearly outperforms the global approach since the number of false alarms is always lower. Please note that during the recording of the activity data no unusual event was reported by the elderly couple, hence the number of false alarms should be zero. Thus, the number of false alarms indicates the performance of the algorithms.

To verify the results, the region based and global algorithm are evaluated on a smaller dataset containing 50 days of activity data of an elderly man. The results, depicted in Figure 11, again shows that the proposed algorithm outperforms the global approach introduced by Cuddihy et al. [7], when using more than 20 training days. The false alarm rate drops to zero when using more than 25 days of training due to the small dataset available and possible overfitting (half of the data set is used for training).

V. Conclusion

Detecting unusual inactivity in comparison to a reference profile provides information about events where elderly need help. The proposed approach introduces the use of spatial information to enhance the accuracy of temporal inactivity monitoring. An evaluation on two datasets of elderly people showed that due to the combination of temporal and spatial information, the proposed algorithm reduces the number of false alarms. Future work will enhance the detection of regions of interest, since the correct detection of regions of interest is crucial. Moreover, semantically interesting regions of interest can be retrieved by this approach and combination with temporal aspects can be used to obtain information about different activities, depending on the time of execution. Finally, more extensive evaluation on additional datasets will be performed.

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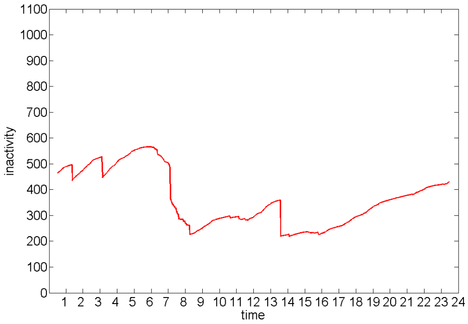
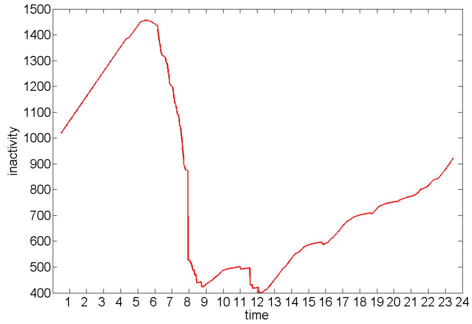
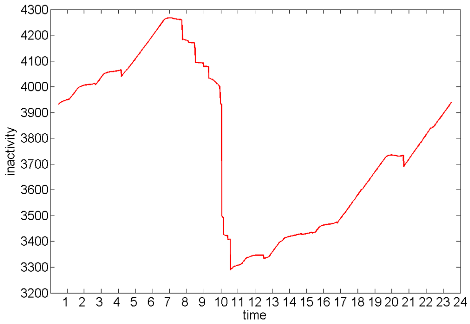


(a) global alert line without spatial information [7]



(b) alert line of region 1 (using the proposed approach)



(c) alert line of region 2 (using the proposed approach)

Figure 9. Comparison of global and regional alert lines

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