

An intelligent emergency response system: Preliminary development and testing of a functional health monitoring system

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T. Tam, A. Dolan, J. Boger, A. Mihailidis, An intelligent emergency response system: Preliminary development and testing of a functional health monitoring system, Gerontechnology 2005; 4(4):209-222. Changes in a person's routine of daily activities can signal a change in health. To support the growing elderly population who want to age-in-place, techniques and algorithms have been developed to build a system that monitors functional health in the home environment. This health monitoring system has been developed with machine vision and pattern analysis components to track the occupant, learn his/her pattern of activity, and detect significant deviations that could indicate a change in health status. The effectiveness of the health monitoring system was investigated with a pilot study capturing video footage of a 28-day simulation including 21 days of normal activity and seven days of abnormal scenarios. The system was effective in learning an occupant's pattern of activity and detecting deviations that were indicative of changes in the occupant's functional health status. Overall, the results indicate that a health monitoring system could be developed that uses machine vision and basic artificial intelligence with promising potential to support aging-in-place.

Keywords: emergency, health monitoring, aging-in-place, computer vision

Providing support to older adults who want to continue to live independently in their own homes is a growing social concern, especially for those who live

alone, perhaps in rural locations where immediate assistance is not readily available^{1,2}.

To support aging-in-place, a variety of alarm systems have been developed to provide a means of signalling for help when a person is in a situation where his/her safety is compromised. These devices usually have a panic button and are typically worn on the wrist or around the neck as a necklace. The main problem with this approach is that as much as 27 to 40% of users do not wear the alarm on a daily basis, which renders the system ineffective in the event of an emergency. Many users may be hesitant to use the system and may not recognise a situation where s/he is in danger³. Additionally, users may be unable to push the button if they have lost consciousness or somehow become injured. Finally, these systems can only provide alerts for acute events such as a fall or an injury. They cannot detect gradual declines in overall health status, both physical and cognitive, which would place the independence and well-being of an older adult at risk.

Studies have shown that a decline in an older adult's ability to complete activities of daily living (ADL) such as self-care tasks, is a strong indicator of declining health and may also indicate an increased likelihood of an emergency situation occurring⁴. Changes in sleep patterns, frequency of toilet use, and medication use can be used as indicators of physical and mental health disorders. Declines may present as a reduction in the number of ADL completed and/or an increase in the duration of time it takes to complete ADL^{5,6}. In response to these and other similar findings, there has started to be more research and health monitoring/emergency response systems being developed that use these types of health indicators.

In order to interpret the collected data and determine the status of the user, research in this area has focussed on two

primary areas: measuring and tracking activity levels and pattern analysis. Previous work in the area of measuring activity has included the use of force-sensitive load tiles^{7,8}, touch sensors on furniture and magnetic switches on doors⁹, the use of Radio Frequency Identification (RFID) tags¹⁰, and motion sensors¹¹. The use of more sophisticated sensing systems, such as computer vision, has been far more limited. The CAREMedia group investigated the use of machine vision in a nursing facility to automatically assess patient progress traditionally documented by staff observation reports of patient activity¹². Investigations in pattern analysis include Honeywell's ILSA project, which analyzed sequential patterns of motion sensor firings¹³, the SmartHouse project¹⁴, which considered behavioural patterns based on the time interval that events occurred, and the MavHome project¹⁵, which looked for deviation from patterns with missing events, extra events, or changes in regularity.

This paper describes preliminary work on a computer vision-based health monitoring system to support older adults who wish to remain independent in their own homes, while at the same time providing a means to monitor for signs of unusual activity that might indicate a decline in health. It is thought that computer vision is a more effective means of measuring and tracking activity, as it can provide a much richer data set than other typically used sensors (e.g. motion sensors). This paper will also present a simple pattern analysis algorithm that aims to provide caregivers with 'scores' of how much a person's pattern of activity (and thus level of health) is changing in comparison with normal patterns. Finally an overview will be presented of an initial pilot study that was conducted with the new prototype.

OVERVIEW OF THE HEALTH MONITORING SYSTEM

This health monitoring system uses levels of mobility and activity completion as its primary measures. As previously described, these measures have shown to be indicative of overall health in older adults and are less obtrusive than other indicators such as physiological measurements. Furthermore, levels of activity can be more easily captured using our proposed machine vision and pattern analysis algorithms than other measures, which in fact, may be impossible to collect using these techniques. This system has two primary components: machine vision and pattern analysis. The machine vision component tracks the location of an occupant and creates a log entry when an occupant is present in one of the pre-defined areas of activity. The pattern analysis component uses these event data to model the occupant's activity and to calculate a 'score of conformance' to previously observed patterns. The score is based on two criteria in each activity zone: the time of day that events have occurred, and the frequency of an event.

Figure 1 illustrates the process used to capture and analyze the data required to determine the status of the user. The System Interface is used to configure the system by defining the location of the activity zones in the environment and setting thresholds (i.e. the acceptable amount of deviation from normal patterns) for notifying the caregiver. In future prototypes, these thresholds would be initially determined using empirical data and then be automatically adjusted by the system according to the needs of each individual user. Image-processing algorithms are then applied in the Image Extraction and Image Analysis stages to track the occupant's location. When the occupant enters a defined activity zone, the event information is stored in the Event Log of the database for subsequent analysis. In the Health Assessment stage, probability models are developed for each of the activity zones and are automatically calculated and stored as Event Probabilities. Specifically, two data sets are created using these data for each day of the week—one that describes the fre-

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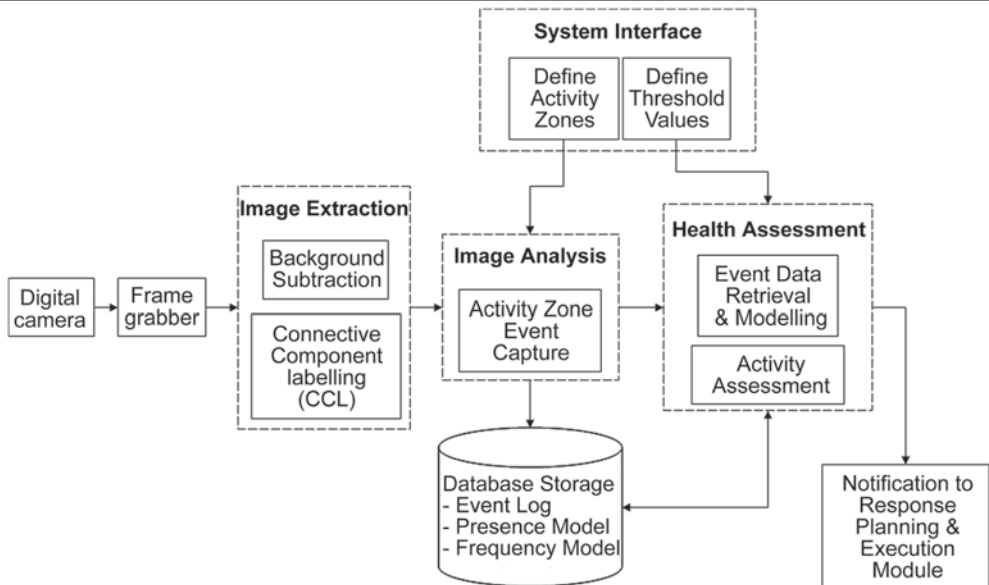


Figure 1. Diagram showing the process of acquiring the image using a video camera, identifying the object to track, and storing and analysing data for adverse events¹⁸

quency with which events typically occur in a particular zone over the course of the day (Frequency Probability) and one that describes the time of day different events typically occur (Presence Probability). Taken together, these two measures may be able to characterize an occupant's conformance to his/her normal pattern of activity. Normal user performance would be determined by a training set of data that would be automatically collected for each individual user at system start-up. The required length of these training periods for each person is currently unknown, however, it is expected that three weeks of data would suffice. Every 24 hours a score of this conformance is calculated based on the collected data and the person's typical performance of the same activities over that time period. A caregiver can then be notified if the user's activity deviates significantly from the normal pattern of activity discovered during the system's training period.

MACHINE VISION

The machine vision component, including the parameters that will be described, is built upon the automated fall detection system designed by Lee and Mihailidis¹⁶. A charge coupled device (CCD) digital video camera is used to capture images from the environment. It should be noted that while a colour camera is used, this prototype only uses grey-scale images during its image processing. The colour components will be used in future versions to improve the robustness of the system, for example by using skin colour as an additional marker for tracking the location of a person. A Matrox Meteor II™ frame grabber card is used to capture individual video frames, and the Active Matrox Imaging Library (ActiveMIL) software is used for image processing. To identify and track the occupant, the machine vision component uses an adaptive background subtraction algorithm (BGS) to

separate the background (extraneous environment) from the foreground (region or object of interest), similar to the Pfunder algorithm¹⁷. Image segmentation is achieved by comparing the grey-scale value of each pixel in the initial image of the environment with the current image. Differences between pixel greyscale values that are above a set threshold are identified as part of the object of interest and extracted. The resulting extracted image is then processed using a connective-component labelling technique¹⁸ with the end product being a 'blob' or silhouette of the occupant. Figure 2 shows how the application of successive algorithms is applied. The greyscale pixel values (ranging from a value of 0 to 255) of the captured image (B) are subtracted from pixels of the background image (A). Pixels exceeding the threshold are replaced by white pixels, resulting in image (C). A threshold value difference of 60 pixels was found to be optimal for the common fluorescent lighting conditions under which the current system was tested. The connected-component-labelling algorithm is also applied in (C) to group pixels adjacent to each other. A low-pass filter is applied to remove Gaussian noise, and also remove blobs with areas less than a minimum blob size to produce the image (D). The minimum blob size used was 300 pixels, which was determined empirically using subjects of various heights and sizes during prototype development.

The co-ordinates of the geometrical centre of this blob are calculated and tracked as the occupant moves throughout the environment. During system initialization, the System Interface is used to define regions in the camera's field of view as activity zones, such as the bed and the toilet. Figure 3 shows a snapshot of a System Interface with activity zones defined.

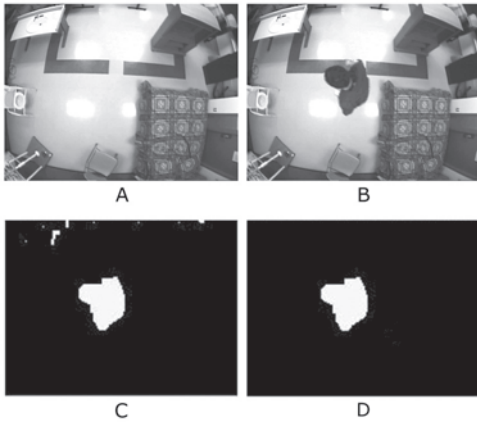


Figure 2. Application of background subtraction, connected component labelling, and filters to captured video frames; A: Original background image, B: Captured image with the occupant, C: Application of background subtraction, D: Application of low-pass Gaussian noise filter, and blob-area filters

When an occupant enters a zone, corresponding events are logged to a Microsoft Access™ database, as described in detail in the section 'Pattern Modelling and Analysis'. For this prototype, events that occurred with duration of one second or less were ignored as it was assumed that the person was just walking through the zone. If the occupant is detected in another activity zone outside of the currently active activity zone, the previous event information is logged to the database, and the timer and event information is reset for the current event.

Pattern modelling and analysis

Two sets of probabilities are calculated by processing the event information captured by the machine vision component and stored in the database: the probability of the person entering a specific zone a certain number of times on a given day of the week (frequency probability), and the probabilities that a person is present in a specific zone, at a

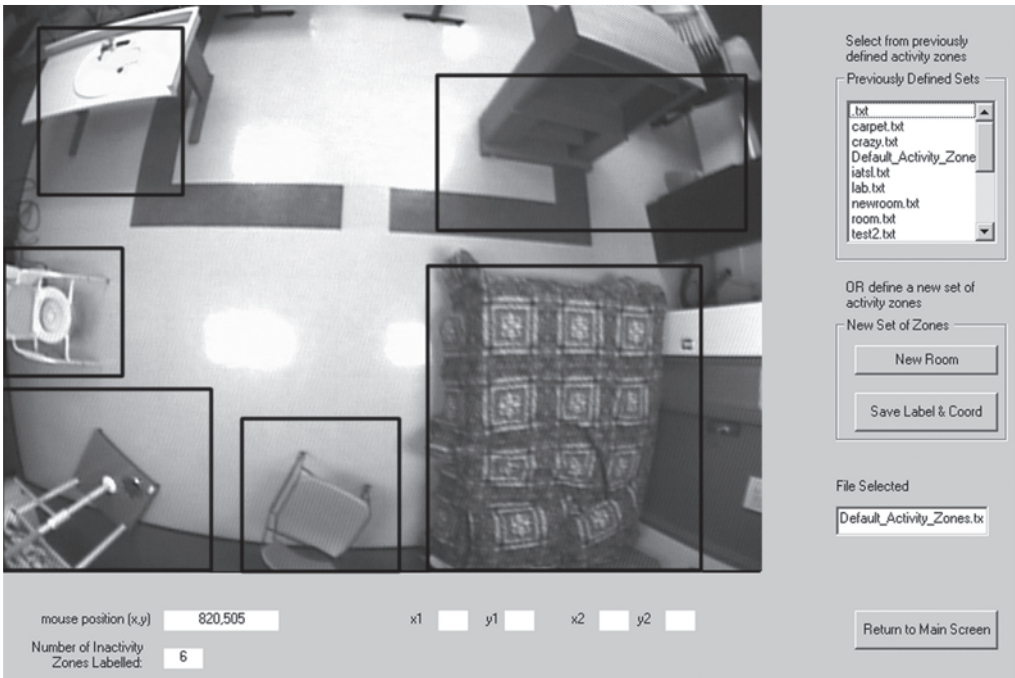


Figure 3. System Interface showing the digital camera's field of view and defined activity zones

specific time interval of the day, on a given day of the week (presence probability).

The frequency probability is currently calculated every 24 hours. This interval can be modified as is appropriate. The Frequency Probability (FP) is calculated using the following data: Zone Number, Day of the Week, Events in Zone, and Number of Cases. The Zone Number is the number assigned by the machine vision component for a defined activity zone, the Day of the Week has a numeric value from Sunday(0) through Saturday(6), and the Events in Zone is a count of how many times the person entered a specific zone over a 24-hour interval. Number of Cases represents the number of times the Events in Zone value has occurred for the same day of the week for a specific zone. To calculate the Frequency Probability, the system first calculates the sum of all the Number of Cases values for a specific day of the week. This sum represents the total number of times the system has observation data for this zone on this day to give the Total Number of Cases. The Number of Cases for each zone for the same day of the week are then divided by the Total Number of Cases to give the Frequency Probability (FP), as shown in Equation 1:

$$FP = \frac{\text{Number of Cases}}{\text{Total Number of Cases}} \quad (1)$$

The Presence Probability (PP) is calculated from the following data: Zone Number, Day of the Week, Number of Cases, and Time Interval. Zone Number, Day of the Week, and Number of Cases correspond to the same values used to calculate FP, as described above. Time Interval currently has a value of 0 to 23 representing each hour interval in the day, however, this interval can be modified as needed. The Presence Probability is calculated by dividing the number of

times the occupant has been present in a particular zone on a specific day of the week during the same Time Interval by the Number of Cases (representing the number of times this time interval on this day of the week has been recorded). The following is performed every time an event is recorded. The data are queried for the Number of Cases for the corresponding Zone Number and day of the week for the event. The Presence Probability (PP_n) is calculated using Equation 2:

$$PP_n = \frac{[(PP_{n-1} * \text{Number of Cases}) + 1]}{\text{Number of Cases} + 1} \quad (2)$$

The current Presence Probability (PP_n) is calculated by multiplying the previous Presence Probability (PP_{n-1}) by the Number of Cases (giving the total recorded number of events in this zone and on day of the week until today), plus one (for the current event in this zone). This is divided by all of the days the system has recorded (whether the occupant was in the zone or not) including the current day. The presence probability is also updated for each of the subsequent time intervals that span the event duration.

The activity zone score represents the likelihood of both the presence and frequency patterns occurring together over the observed 24-hour period and is calculated by Equation 3:

$$P(A \cap B) = P(A) * P(B) \quad (3)$$

P(A) is the product of the Presence Probabilities of all the time intervals (t₀, t₁, ..., t_n) for the zone of interest on a specific day of the week. This calculation can be represented by Equation 4:

$$P(A) = P(t_0 \cap t_1 \cap \dots \cap t_n) = PP_0 * PP_1 * \dots * PP_n \quad (4)$$

P(B) is the Frequency Probability value for the zone of interest on the same day of the week; namely P(B) = FP. It should

be noted that at this stage of work Equation 3 assumes that events A and B are mutually exclusive, which may not be valid at all times. However, it is felt that this assumption is valid at this time in order to begin to explore one potential method for looking at conformance in activity levels. Future work will focus on a more valid calculation.

The current model does not take into account standard deviation in the collected data. For this prototype acceptable variability in data is dealt with through an interpolation calculation performed on the data. Specifically, the Piecewise Cubic Hermite Interpolating Polynomial (PCHIP) interpolation MatLab function¹⁹ is used to estimate new probabilities.

This interpolation only occurs on initially calculated probabilities that are below 50 percent (an arbitrary threshold used for this initial investigation). This is necessary as there are cases, especially during the initial training period of the system, where the calculated probabilities are very low because an unobserved 'normal' event has occurred. For example, if an occupant always sleeps in the 23:00-23:59 time interval, but on one occasion sleeps at 22:58, the system has not observed a bed event in the 22:00-22:59 time interval previously and will report a low probability. It is planned to include standard deviation in addition to the interpolation in the next version of the system.

Table 1. Normal and Abnormal Activity for Sample Calculation of Day 3 (Wednesday); The abnormal activity consists of an increased frequency of toileting throughout the day

Normal Activity			Abnormal Activity		
Start Time	Activity Zone	Activity Duration (hours)	Start Time	Activity Zone	Activity Duration (hours)
0:00	Bed	Sleeping (7:05)	0:00	Bed	Sleeping (7:01)
7:05	Toilet	Morning grooming (0:10)	7:01	Toilet	Morning grooming (0:14)
7:15	Sink	(0:15)	7:15	Sink	(0:15)
7:30	Shower	(0:30)	7:30	Shower	(0:30)
8:00	Closet	Dress (0:15)	8:00	Closet	Dress (0:15)
		Breakfast and leave home (4:22)			Breakfast and leave home (3:53)
8:15	ABSENT		8:15	ABSENT	
12:37	Toilet, Sink	Come home for lunch (0:08)	12:08	Toilet, Sink	Come home for lunch (0:07)
12:45	ABSENT	Lunch and out of home (1:15)	12:15	ABSENT	Lunch and out of home (1:45)
14:00	Bed	Afternoon nap (1:02)	14:00	Bed	Afternoon nap (1:20)
			15:20	Chair	Watch TV (0:25)
15:02	Toilet, Sink	(0:13)	15:45	Toilet	Abnormal #1 (0:20)
15:15	Chair	Watch TV (2:05)	16:05	Chair	Watch TV (1:07)
17:20	Toilet, Sink	Prepare for dinner (0:15)	17:12	Toilet, Sink	Prepare for dinner (0:03)
17:35	ABSENT	Prepare and eat dinner (2:25)	17:15	ABSENT	Prepare and eat dinner (2:45)
20:00	Chair	Watch TV (2:17)	20:00	Chair	Watch TV (0:30)
			20:30	Toilet, Sink	Abnormal #2 (0:15)
			20:45	Chair	Watch TV (0:45)
			21:15	Toilet, Sink	Abnormal #3 (0:30)
			21:45	Chair	Watch TV (0:21)
22:17	Toilet, Sink	Prepare for sleep (0:13)	22:06	Toilet, Sink	Prepare for sleep (0:24)
22:30	Closet	Change (0:10)	22:30	Closet	Change (0:10)
22:40	Bed	Sleep (7:00)	22:40	Bed	Sleep (0:21)
			23:01	Toilet, Sink	Abnormal #4 (0:14)
			23:15	Bed	Sleep (7:00)

Table 2. Presence Table for Sample Calculation; Zone name = Toilet; Zone number = 4; Day of the Week = 3

Time Interval	Presence Probability
0	0
1	0
2	0
3	0
4	0
5	0
6	0.5
7	0.95
8	0
9	0
10	0
11	0
12	1
13	0
14	0
15	0.8
16	0.43
17	1.0
18	0
19	0
20	0.25
21	0.25
22	1
23	0.25

Table 3. Frequency Table for Sample Calculation; Zone name = Toilet; Zone number = 4; Day of the Week = 3

Number of Events	Number of Cases	Frequency Probability
0	0	0
1	0	0
2	0	0
3	0	0
4	0	0
5	3	0.75
6	0	0
7	0	0
8	0	0
9	1	0.25
10	0	0
11	0	0
12	0	0
13	0	0
14	0	0
15	0	0

The following examples illustrate how the scoring is used to indicate conformance or deviation from an occupant's normal pattern of activity. Table 1 shows a sample of a normal and an abnormal activity day. Assume the Pattern Analysis component has included the events of the day and updated the presence and frequency tables for the Toilet activity zone for this day of the week as shown in Tables 2 and 3, respectively.

On the normal day, the occupant entered the toilet zone during the following times: 7:05, 12:37, 15:02, 17:20, and 22:17. The corresponding time intervals and probabilities (shown in brackets) taken from the presence table are the following: 7:00 (0.95), 12:00 (1.0), 15:00 (0.8), 17:00 (1.0), and 22:00 (1.0). The 1.0 value (100%) at 12:00 and 17:00 indicates that the occupant has been observed in the toilet activity zone in those time intervals every Wednesday in the previously observed history. The product of the presence probability P(A) for the toilet activity zones is calculated from Equation 4 as follows:

$$\begin{aligned}
 P(A) &= P(t_1 \cap t_2 \cap t_3 \cap \dots \cap t_n) \\
 &= P(t_1) * P(t_2) * P(t_3) * \dots * P(t_n) \\
 &= P(7:00) * P(12:00) * P(15:00) * \\
 &\quad P(17:00) * P(22:00) \\
 &= (0.95) * (1.0) * (0.8) * (1.0) * (1.0) \\
 &= 0.76
 \end{aligned}$$

From Table 3, the Frequency Probability of five events occurring in the toilet activity zone on a Wednesday is 0.75. The Activity Zone Score for the toilet activity zone is calculated from Equation 3 as follows:

$$\begin{aligned}
 P(A \cap B) &= P(A) * P(B) \\
 &= 0.76 * 0.75 \\
 &= 0.57
 \end{aligned}$$

From the data captured during the pilot study, significant deviations from an occupant's normal pattern of activity were shown to drop the activity zone score below 0.10, namely activity zone scores

below this threshold would be a cause for concern. Therefore, in this study the 0.57 score is well above 0.10 and the occupant's patterns of activity in the toilet zone are considered to be 'normal'.

On the day of abnormal activity, the occupant entered the toilet zone at the following times: 7:01, 12:08, 15:45, 16:35, 17:12, 20:30, 21:15, 22:06, and 23:01. The corresponding time intervals and probabilities (shown in brackets) taken from the presence table are the following: 7:00 (0.95), 12:00 (1.0), 15:00 (0.8), 16:00 (0.43), 17:00 (1.0), 20:00 (0.25), 21:00 (0.25), 22:00 (1.0) and 23:00 (0.25). If an event had a duration that stretched into subsequent time intervals, each subsequent time interval's presence probability would also be included in the calculation. The toilet event at 15:45 stretched to 16:05, therefore it was logged in both the 15:00 and 16:00 time intervals.

The product of the presence probability $P(A)$ for the toilet activity zones is as follows:

$$\begin{aligned}
 P(A) &= P(t_1 \cap t_2 \cap t_3 \cap \dots \cap t_n) \\
 &= P(t_1) * P(t_2) * P(t_3) * \dots * P(t_n) \\
 &= P(7:00) * P(12:00) * P(15:00) * \\
 &P(16:00) * P(17:00) * P(20:00) * \\
 &P(21:00) * P(22:00) * P(23:00) \\
 &= (0.95) * (1.0) * (0.8) * (0.43) * \\
 &(1.0) * (0.25) * (0.25) * (1.0) * (0.25) \\
 &= 0.0051
 \end{aligned}$$

Again, the activity zone score is calculated as the product of the presence probabilities $P(A)$ multiplied by the frequency probability $P(B)$. In this case $P(B)$, the probability of 9 events occurring in the toilet activity zone on a Wednesday taken from the frequency table is 0.25. The Activity Zone Score for the toilet activity zone is calculated as follows:

$$\begin{aligned}
 P(A \cap B) &= P(A) * P(B) \\
 &= 0.0051 * 0.25 \\
 &= 0.0013
 \end{aligned}$$

The low activity zone score of 0.0013

was the result of both the low presence probabilities and a low frequency probability. This score is well below the 0.10 threshold for concern and indicates a deviation from the occupant's activity pattern in the toilet activity zone.

PILOT STUDY

A small pilot study was conducted to test both the machine vision and the pattern analysis components of the system. A bedroom and bathroom were constructed for simulation and the researcher, acting as the occupant, simulated 21-days of normal activity and seven days of abnormal activity. For the study, the following activity zones were monitored: bed, closet, toilet, sink, shower, and a chair.

Study set-up

An overhead Sony Exwave HAD SSC-DC-393 colour video camera, with a Cosmicar/Pentax 3.5-8mm wide 'fish-eye' lens was used to record video of the pilot study to a VCR. Figure 4 shows the camera view of the pilot study scene. Video of the pilot study was used to compare and validate the results of the health monitoring system's analysis.

A script containing time-specific events was created to simulate both normal and abnormal occupant activity. For the

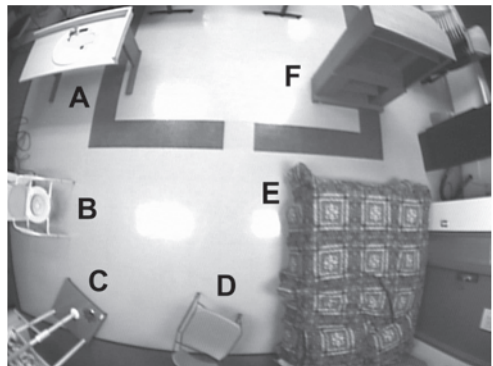


Figure 4. Camera view of pilot study scene. The following activity zones were used in this study; A: Sink, B: Toilet, C: Shower, D: Chair, E: Bed, F: Closet

training period of normal activity, a script representing each of the seven days of the week was repeated three times, with slight variations in timing to simulate the normal variation in an occupant's activity. Simulated activities on abnormal days included getting out of bed in the middle of the night and pacing, going to the bathroom several times throughout the night, and decreases in general activity. Sample scripts for both normal and abnormal activity are similar to the data presented in Table 1. Five-hundred events were simulated for the pilot study (369 normal and 131 abnormal events).

During the recording of the scenarios, the duration of activity that would normally take place over an hour was compressed into one minute intervals. This enabled the activity of a 24-hour day to be simulated in 24 minutes and allowed the researcher to simulate 28 days of data over the space of two days. A research assistant (RA) was positioned outside of the camera scene. He was equipped with the scripts, a stopwatch, the VCR, and a computer monitor to observe the video feed. The RA was given instructions to tell the researcher when and where to move in the scene. Although the RA was asked to use the script as a guideline, he was also encouraged to vary the times to simulate the normal variability of an occupant's living pattern on a typical day.

Pilot Study Results

The data obtained during the pilot study were used to assess the efficacy of the machine vision and the pattern analysis components, as well as to assess limitations and find opportunities for future work.

After the video was processed and the timestamps translated, the events logged by the machine vision component were verified against the video,

which acted as the ground truth. A research assistant, who was not involved in the recoding of the trial, compared the logged data to the video of the trial. At this stage of work only a single rater was used. Of the 500 simulated events, the machine vision component accurately identified 476 events (95.2%), capturing 348 (94.3%) of the normal events and 128 (97.7%) of the abnormal events. Errors during this event included 24 false negatives (the system did not capture events that were recorded on video), six false positives (the system logged events that did not correspond to the video), and four false extras (the system recorded several consecutive events in a zone that should have been represented with a single event). The Pattern Analysis component analyzed the data captured from the machine vision component and generated individual activity zone scores and an overall score for each day.

Individual activity zone scores were averaged over each week and presented graphically in Figure 5. The first week showed 100% conformance in each zone. This is to be expected as the model generated for the first week is based on a single set of data. Weeks two and three showed reductions in conformance because of normal variations

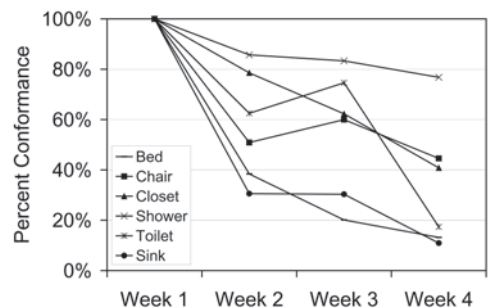


Figure 5. Graphical representation of the pattern analysis component pilot study results. The first three weeks show training data, and the fourth week shows scores from abnormal activity (weekly averages)

in the occupant's activity. Week four showed a greater decrease in conformance in each activity zone, indicating significant deviations from the occupant's pattern of activity.

DISCUSSION

Overall, the machine vision's high capture rate of events (95.2%) and its ability to generate scores that distinguished between normal and abnormal activity in the pilot study are positive outcomes. While the number of false positives, false negatives, and false extras were greater than anticipated, the machine vision system still performed well.

Some of the capture problems can be attributed to an unusual flicker of one of the fluorescent lights in the pilot study environment. The vision system was designed to track the largest foreground object and the occasional momentary flicker would create a blob (from the reflection of the light on the shiny surface of the floor) that was larger than the occupant, which was then tracked in error. False extras were sometimes created when the activity zone was too small. In these cases, the centre of the occupant's blob appeared on the border or just outside the defined activity zone and was misinterpreted by the system as the occupant leaving and re-entering the zone. Some of the false negatives were due to the unique properties of the bed and the blanket. For example, when the occupant awoke and pushed the blanket aside, the difference in grey-scale values between the blanket and the bed sheet created a blob with an area greater than the size of the occupant. In real-time simulations the adaptive background subtraction algorithms would blend the non-moving bed sheet into the background. However, the accelerated pace at which the trial took place did not leave enough time.

This work has helped to identify some

of the advantages and limitations of using machine vision in this application as opposed to other sensing methods such as motion sensors and environmental switches. In particular, some of the primary strengths of using computer vision are that it provides a richer data set that can be used in other applications, it requires less hardware to be used and installed within a home, it can be more easily adapted to changes within the environment (e.g. change in furniture configuration), and it can be used for increased security features, such as identifying users. Some of the primary limitations include that it has potential privacy issues, especially if images need to be recorded and transmitted (which is currently not the case in our system), the lead time is greater since more advanced and sophisticated algorithms need to be developed, and, at least at this stage of our work, it only gives information about the completion of activities at a gross level—i.e. not tracking the finer details of task completion.

In the graphical representation of the pattern analysis results (*Figure 5*), week one shows 100% conformance to the occupant's pattern of activity. This is expected, as the event data set logged during that week is the only set of data of the pattern analysis component that has to generate a model. The second and third week of the training period show more variance as events from week to week may have occurred in different time intervals (for instance, if an event occurred at 09:59 in the first week, and 10:02 in the second week, the presence probability would be 50% in both the 09:00 and 10:00 time intervals for that zone on that day). Low probabilities in the second and third week may also be attributed to errors in the pattern analysis models created by incorrect machine vision event captures (false positives, false negatives, and

false extras) as mentioned in the machine vision results above. With a longer training period and a greater number of observations (i.e. logged events), the model would more accurately represent the occupant's pattern of activity and be more robust.

The fourth week, which simulated abnormal activity, showed greater deviations from the occupant's normal patterns of living in the form of dramatic drops in activity zone scores. After reviewing the data, and analyzing the causes behind low scores, significant deviations from normal patterns of activity that were noted as cause for concern were those with activity zone scores below 0.01, and overall scores of less than 0.0001. Again, it should be noted that these threshold scores were based solely on observations and data collected during these trials, and thus, may need to be adjusted during future trials. It is probable that the magnitude of scores that are identified as possible cause for concern will vary depending on the regularity of the individual's normal activity routine, his/her health needs, and possibly even specific activities. Overall, the pattern analysis component performed well in learning the patterns of activity of the occupant in the trial, building probability tables to describe his activity, and detecting significant deviations in patterns during the abnormal activity scenarios of the trial. However, these preliminary data also show that more training data (i.e. more than 21 days) are required to build a more functional model. A method for identifying when enough training data has been gathered for an individual needs to be determined through more in-depth trials.

The goal at this stage of work was to determine the initial efficacy of the machine vision and pattern analysis components developed for the health monitoring system. With this in mind,

conditions were optimal for these trials. For example, only one subject was in the room throughout the study, no other moving objects such as pets or mobility aids were introduced, and no furniture was moved outside of its associated activity zone. The mock-up bedroom/bathroom had no outside windows, therefore effects of outdoor lighting or other environmental factors were not tested. The system must eventually be able to identify and track multiple moving objects, as well as being able to automatically redefine activity zones when items such as furniture are moved. Incorporating colour-based tracking is one method that could solve many of these problems, as colour data can be used to identify and track objects much more easily. The system was only tested so far with one camera, however, the system can be expanded by implementing camera tracking algorithms to switch between room cameras, or have machine vision systems in each room feed data to a common database for the pattern analysis component to process.

The simulated declines in health for the pilot study were based on estimates of expected possible associated behaviours. Much work will have to be done into areas such as identifying how specific activities are affected by changes in health, how much variance there is between different individuals, and if certain activities are more indicative of a change in health and therefore more important to monitor than others. As different health problems will likely correspond to the same changes in activity patterns (for instance, drinking more water at the onset of diabetes), it is possible that the system could be used to help recognise specific medical conditions at an earlier stage than they may otherwise have been detected.

Other limitations of the pilot study in-

cluded that the simulation was scripted and not a live clinical trial and was executed in an accelerated time frame. However, at this stage of development this type of pilot testing is needed before performing trials with actual users. While the occupant's activity was simulated in a shorter period of time in the study, his movements were not similarly accelerated – he did not move faster. The study also did not simulate night time conditions when no lights were illuminated or occasions when the occupant left on vacation. Finally, the researcher was the occupant in the pilot study and this may have also introduced bias.

The activity zone scores and overall scores generated by the pattern analysis component may provide a compact set of indicators that can help a caregiver determine if an occupant's pattern of activity is normal or whether there is a cause for concern. However, this concept still needs to be proven through more in-depth clinical trials with input from professional caregivers.

CONCLUSION

The SmartHouse project¹⁴ considered behavioural patterns based on the time interval that events occurred (presence probabilities), while the MavHome project¹⁵ looked for deviation from patterns with missing events, extra events, or changes in regularity (frequency probabilities). By including both these aspects in the calculation of activity zone scores, the health monitoring system presented here has the ability to give a more holistic representation of an occupant's ongoing state of well-being.

Some of the main items identified for future work include the following: (i) Improve reliability and robustness of the vision system in identifying the occupant under varying light conditions; (ii) Extend the pattern analysis compon-

ent's capability to also be able to analyze trends over a longer period of time to detect a more gradual decline in activity over several weeks or months; (iii) Incorporate the ability to automatically learn the value of the threshold (distinguishing normal from abnormal activity) that is required for each individual through the use of decision-theoretic planning algorithms (e.g. partially observable Markov decision processes—POMDPs); and (iv) Identify how declines in health effect patterns in ADL.

Once the system is considered robust, clinical in-field trials need to be undertaken to determine the training period necessary to characterize an occupant's normal pattern of activity. To reduce the training period, approximate values can be used to initialize the system based on the individual's living pattern characteristics. These values would need to be determined from future work in clinical trials with real occupants.

Furthermore, it is believed that the scores generated by the health monitoring system can be correlated to clinical tests as a measure of functional health. As part of the system validation process, the scores generated by the system should be compared to timed performance tests done in clinics. Functional health trends identified by the system during clinical trials should also be compared with models of functional decline to see if they correlate with the Death, Terminal Illness, Frailty, Organ Failure models identified by Lunney et al.²⁰.

The indicators developed in this study could help to identify changes in the health of an occupant early, hence improving the likelihood of a successful intervention. This could give the occupant a better sense of autonomy and independence, while still providing a greater

measure of safety. An accurate machine vision and pattern analysis system that can automatically capture and analyze data about an occupant's pattern of activity, in combination with an appropriate response system, could provide an invaluable tool to support aging-in-place for older adults.

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