A Smart Sensor to Detect the Falls of the Elderly

To detect falls, the SIMBAD system uses a low-cost array of infrared detectors. A field trial and user research indicate that SIMBAD could significantly enhance the functionality and effectiveness of existing monitoring systems and community alarm systems.

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Falls are a major health hazard for the elderly[1,2] and a major obstacle to independent living.[3,4] The estimated incidence of falls for both institutionalized and independent persons aged over 75 is at least 30 percent per year.[5] As you'd expect, the frequency of falling is considerably higher among the more dependent elderly, such as those living in nursing homes. Researchers have estimated that up to 50 percent of nursing-home residents fall each year, and more than 40 percent of these might fall more than once.[6]

Falls also have important social and service dimensions. Increasingly, the elderly are living alone with only limited support from formal and informal sources of assistance. Nursing homes have also experienced a considerable drive toward single-occupancy rooms. Although we must respect privacy, we must also recognize that this increases the risk of being alone when a fall occurs.

Technological solutions to the problem of falls and other emergencies have been around for many years. With *community alarm systems*, someone in difficulty can raise an alarm in a control center by pushing a button on a special telephone or on a pendant device he or she is wearing. However, this has little value if the person is unable or unwilling to raise the alarm—for example, if he or she is unconscious.[7] Recent R&D has addressed this problem by developing intelligent monitoring systems that trigger an alarm and appropriate response, even when the person is incapacitated.[7–11]

In the SIMBAD (*S*mart *I*nactivity *M*onitor using Array-*Ba*sed *D*etectors) project, we've developed an intelligent fall detector based on a low-cost array of infrared detectors. The SIMBAD system ultimately aims to enhance the quality of life of the elderly, afford them a greater sense of security, and facilitate independent living.

Justification for our approach

A considerable potential market exists for automatic fall detection; in a recent UK survey, 79 percent of respondents aged 75 and over expressed some level of interest.[12] However, the current and emerging technologies have key limitations:

- Simple sensors, such as single- or dual-element PIR (passive infrared) sensors, provide fairly crude data that's difficult to interpret.[8]
- Wearable devices such as wrist communicators and motion detectors have potential but rely on a person's ability and willingness to wear them.
- Cameras might appear intrusive and require considerable human resources to monitor activity. Machine interpretation of camera images is complex and might be difficult in this application area.

IRISYS (InfraRed Integrated Systems) thermal-imaging sensors can help overcome these limitations. The sensor is wall mounted, and users don't

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Figure 1. IRISYS sensor output: (a) test subject and (b) corresponding 16 × 16 thermal-array data. (The poor picture quality is due to the low resolution of the data-logging software.)

(a) (b)

have to wear a device. Detailed analysis of a subject's motion can occur locally, within the detector, using only a modest processor. This is due to the relative ease with which data from the sensor can be interpreted, compared to the data from alternative sensors such as video devices. Besides this solution's cost-effectiveness, we felt that because the low-level data lacks detail and there's no need to transmit data outside the detector, the system will seem less intrusive to users. We explored this issue in focus groups as part of the project.

Previous research on intelligent monitoring suggests that this technology's main benefits would be for the elderly who spend time alone in unsupervised environments.[8] This would include people living alone in ordinary housing or sheltered accommodation (apartment complexes for the elderly with a local warden) and people in noncommunal areas in nursing-home environments (for example, bedrooms and en suite bathrooms and toilets).

A starting point for SIMBAD was to obtain information that would let us assess the proposed sensor optics' suitability. The basic information required at this stage was the type and typical size of room in which the sensor is likely to be installed. A small survey of sheltered schemes (81 rooms in four facilities) suggested that most rooms have a regular shape (rectangular) and size equivalent to normal domestic housing (the median was 3.85 m × 2.9 m, and the largest was 4.95 m × 2.9 m). This was well within the sensor's performance range, letting us monitor most of a room at a spatial resolution sufficient to detect relatively small subject movements. To accommodate larger spaces and irregular shapes, we could use multiple sensors.

SIMBAD's technical development

The IRISYS sensor's low-element-count infrared array technology can reliably locate and track a thermal target in the sensor's field of view, providing size, location, and velocity information. Figure 1 illustrates the low-level thermal data that an IRISYS sensor typically generates. So, the sensor provides a much richer source of data than current home-monitoring systems that rely on sensors such as door switches and conventional PIR movement detectors.

To achieve intelligent activity monitoring and fall detection, SIMBAD considers two distinct characteristics of observed behavior. First, it analyzes target motion to detect falls' characteristic dynamics. Second, it monitors target inactivity and compares it with a map of acceptable periods of inactivity in different locations in the field of view. The combined fall detection and inactivity monitoring is potentially powerful, avoiding many false alarms by observing the activity after what looks like a fall. In addition, this lets the system still raise an alarm even if it doesn't actually observe a fall. So, SIMBAD is basically an activity-monitoring system that can raise an alarm more rapidly if it observes clear evidence of a fall.

We implemented the SIMBAD prototype as an embedded system that executes on the processor in the detector unit. The system communicates with a host PC to report alarm conditions, upload system parameters, and output debugging information. This allows limited adjustment of the system during laboratory and field trials.

Perhaps the most significant uploaded system parameter is a user-defined risk map that segments the field of view according to the extent of acceptable inactivity. This risk map is fundamental to inactivity monitoring. For example, it might specify that the system can expect long periods of inactivity in a doorway (because the subject is in another room) but only brief periods of inactivity in a room's open areas. This information must be expressed accurately for the system to raise alarms in the absence of a fall detection, while having a very low false-alarm rate. So, in the future, the system might learn this empirical knowledge from extended observation.

Figure 2 illustrates the prototype system architecture, which has five major components.

Tracker

This subsystem is based on an elliptical-contour gradient-tracking system that identifies and tracks an elliptical target using data from the IRISYS sensor. The tracker can track moving targets that are either hotter or colder than the background, and provides real-time estimates of target position, velocity, shape, and size.

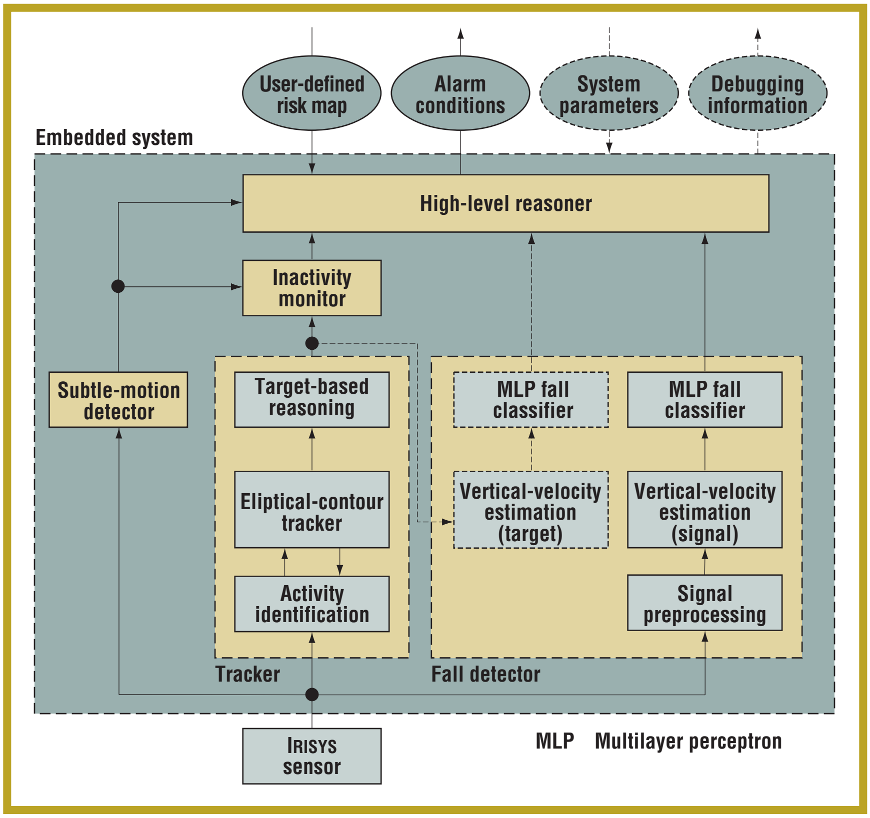

Figure 2. The prototype architecture for the SIMBAD (*S*mart *I*nactivity *M*onitor using Array-*B*ased *D*etectors) system. Dashed boxes indicate subsystems; dotted boxes, ovals, and arrows indicate optional or debugging components and data flow.

Fall detector

This subsystem employs a neural network to classify falls using vertical-velocity estimates derived either directly from IRISYS sensor data or from the tracker. We trained the multilayer perceptron neural network using data from predefined fall scenarios performed by an actress. We generated this data set specifically for classifier training, covering a variety of fall types, viewpoints, and degrees of obscuration. In total, we used 108 scenarios that produced approximately 10,000 sample vectors for network training, each vector classified as either a fall or nonfall. To provide an efficient embedded solution, we implemented the resulting classifier as an optimized sequence of arithmetic operations.

Subtle-motion detector

This relatively simple signal-based mechanism identifies small movements in the sensor's field of view. Because such movements generate insufficient responses to activate the tracker, the system would otherwise ignore them.

Inactivity monitor

This uses output from the tracker and subtle-motion detector to monitor periods of inactivity in the sensor's field of view. Once a target is no longer visible, this subsystem monitors two distinct types of inactivity in the neighborhood of the last known position. *Coarse-scale inactivity* identifies the period of time since the tracker last tracked the object. *Fine-scale inactivity* identifies the period of time since the system detected subtle motion in some neighborhood of the object's last known position.

Figure 3. A typical fall scenario. (The poor picture quality is due to the low resolution of the data-logging software.)

High-level reasoner

This subsystem performs the reasoning required to monitor the output of the fall detector, inactivity monitor, and subtle-motion detector and to generate alarm signals if required. The system generates two classes of alarm—those triggered by excessive periods of inactivity (according to the risk map) and those triggered by the detection of a fall.

Evaluating SIMBAD's performance

We evaluated the prototype SIMBAD system's performance using laboratory trials and a field trial. The laboratory trials primarily evaluated the fall detector's effectiveness. The field trials primarily evaluated the full system's false-alarm rate in a real-life environment.

Laboratory trials

We performed these trials at Liverpool University using SIMBAD to monitor a specialist actor who performed predefined fall and nonfall scenarios. The 20 fall scenarios comprised a variety of fall types (for example, slips and trips), movement dynamics (for example, twisting and arm movement), viewpoints, and degrees of obscuration. Some of these scenarios involved subsequent activity and thus weren't intended to trigger alarms. Figure 3 shows a typical fall scenario. We also monitored 10 nonfall scenarios involving activities that could generate false alarms (such as jumping up and down or sitting abruptly).

TABLE 1
How SIMBAD classified falls and nonfalls in laboratory trials.

Event		Classification results: Alarm	Nonalarm
Fall	Alarm	35.7%	64.3%
	Nonalarm	3.3%	96.7%
Nonfall	Alarm	—	—
	Nonalarm	0%	100%

Preliminary fall-classification results (Table 1 gives a summary) were, at first sight, not encouraging, indicating that an alarm wasn't triggered in almost two-thirds of the fall scenarios that required one (that is, falls followed by inactivity). In addition, the detailed results indicate that the fall detector identified only 30 percent of the actual falls, well below expectation. However, only one of the fall scenarios followed by subsequent activity incorrectly caused an alarm (owing to obscured postfall activity).

Clearly, the fall detector's classifier performed poorly. We had hoped that the training data was both sufficiently varied and viewpoint invariant to yield a classifier that would exhibit good generalization. During the laboratory trials, detector mounting constraints led us to use a different mounting position than we used in training, and the fall types were more varied. Thus, the resulting poor performance might indicate an inadequate training set. However, we also observed that the vertical velocity estimates that served as inputs to the classifier were sometimes rather unstable. Good fall detector performance might also require more information than just vertical velocity.

The classification results for nonfall scenarios were, however, more encouraging: no nonfall scenario resulted in an alarm (see Table 1). The detailed results indicate that this is partly because the classifier is often able to differentiate a fall's dynamics from those of many nonfall scenarios, while the inactivity monitor removes any remaining potential alarms.

These preliminary results provide evidence of the effectiveness of postfall activity monitoring while indicating that the fall detector requires significant further development. In particular, we must address the system's failure to detect certain types of fall, and velocity estimation must be more accurate and more robust. We might also need to consider a more elaborate representation of a fall's dynamics than that provided by a sequence of vertical velocity estimates. In addition, we need to retrain the classifier using a more extensive population of scenarios covering a wider range of viewpoints and behaviors.

In hindsight, performance might have been better if the classifier had greater sensitivity. Although we might expect that the false-positive rate would increase along with the true-positive rate, postfall activity monitoring should ensure that many potential false positives are negated. However, it's important to recognize that if the fall detector fails, the inactivity monitor will, given sufficient time, actuate an alarm due to the cessation of activity. In such cases, the system's robustness and effectiveness depends on the accuracy and validity of the knowledge encoded in the risk map.

Field trial

We conducted the field trial over a two-month period in a single-occupancy apartment in a sheltered-accommodation facility in Merseyside, UK. We mounted the detector close to a corner of the room and positioned it to view as much of the room as possible (see Figure 4).

In addition to using the host PC to set system parameters and gather data from the detector, the field trial required a mechanism for notifying an external party about alarm conditions. This mechanism

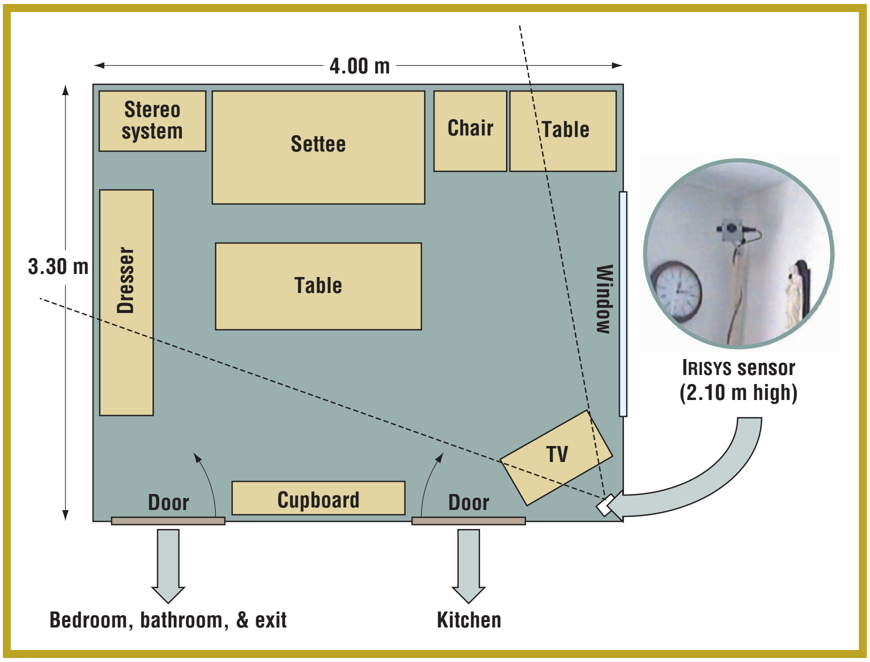

Figure 4. The setup for the field trial of the SIMBAD prototype. The dotted lines illustrate the sensor's approximate field of view.

had two purposes. First, it let us contact the resident to determine whether the alarm corresponded to a real fall. (Because the laboratory trials showed that the fall detector had a low false-detection rate, we assumed that most alerts would be false positives triggered by excessive inactivity.) Second, it let us obtain feedback from the resident about the alarm's possible cause. To allow for remote parameter adjustment, system monitoring, and alarm notification, we installed a GSM (Global System for Mobile Communications) modem in the host PC.

During the field trial, the host PC recorded three types of information. First, it recorded rudimentary debugging information from SIMBAD on every processed data frame during the trial. This data, which we would analyze later, contained time stamps, target centroid data, and a number of status flags indicating major events.

It also recorded detailed debugging information for a short time before and after each alarm notification, thus letting us diagnose the precise cause of fall-actuated alarms.

In addition, it maintained a simple text-based alarm log containing a single line for each alarm event. This line indicated the time stamp, the alarm's cause, the location, and the parameter most relevant to the issuing of the alarm (that is, fall probability or period of inactivity). This file's small size allowed easy transmission via the GSM link.

SIMBAD ran successfully throughout the trial period, outputting data and alarm notifications as required. For the trial's first two weeks, we configured SIMBAD to notify IRISYS researchers if an alarm occurred during office hours. This let us monitor the false-alarm rate and modify the system parameters accordingly. During this configuration stage, we regularly downloaded the alarm log file and used the information to update the system parameters. Analysis of the alarm log suggested that the system parameters were reasonable, so the only changes we made were iterative refinements of the risk map.

For the rest of the trial, we configured the system to notify a field researcher if alarms occurred during office hours. We used this period to demonstrate a caregiver-response mechanism and to let us query the resident about the causes of remaining false alarms. During this period, observation of the alarm log indicated that further refinement of the risk map might have been beneficial.

During the field trial, the system logged only one alarm event caused by the fall detector. Examination of this event's debugging data indicated that the alarm was triggered as the resident exited the room. The generation of the alert appeared to be due to a failure of the velocity estimation mechanism, resulting in a false fall classification, as the resident left the field of view. The subsequent inactivity due to the resident's absence prevented the negation of this false alarm.

Of primary importance to SIMBAD's stability is the segmentation of the field of view into appropriate inactivity risk regions. During the field trial, we employed four different realizations of the risk map; we based the initial map on a brief walk-through during installation and subsequently refined it as misclassified regions became apparent. Each successive refinement reduced the false-alarm rate, giving a final rate of approximately one alarm every three days.

The risk map's final realization excluded the exit regions corresponding to doorways while dividing the remainder of the field of view between low- and high- risk areas. In low-risk areas (seating), the system allowed up to 30 minutes of fine-scale inactivity or one hour of coarse-scale inactivity. In high-risk areas (open floor), it allowed up to five minutes of fine-scale inactivity or 10 minutes of coarse-scale inactivity. We based these periods of inactivity on the results of a previous trial that considered the resident's activity patterns.

These results indicate that the inactivity monitor has an unacceptably high false-alarm rate. Introducing a statistically based learning scheme for risk map acquisition and adaptation might help reduce this rate while simplifying system setup and configuration. Such a system will, however, require significant testing to determine whether it's effective in raising alarms due to inactivity while maintaining a very low false-alarm rate.

User issues

The SIMBAD project has focused primarily on hardware and software development at the technical level, with the scope of field trials in "real life" situations limited to one installation. However, we carried out some limited research to explore potential user benefits and problems with the SIMBAD system. We based this research on three focus groups comprising 28 people aged 65 to 82. One focus group involved residents in sheltered housing; the other two involved people living in ordinary housing. We began the focus groups with an introductory presentation on SIMBAD. We then held a semistructured discussion covering issues including problems facing the elderly, personal experiences relating to falls, general views about SIMBAD, and its positive and negative aspects.

Overall, the participants viewed SIMBAD positively. They generally saw it as a significant improvement over existing community alarm systems, and they felt that a considerable market would exist for this type of device.

Some participants expressed concerns about cost, intrusiveness, reliability, and replacement of human services by technology. These concerns reflected the results of previous studies of assistive technology.[9,13]

We noticed a lack of understanding of how the technology works. This will inevitably shape people's perceptions of the sensor. For example, someone might consider the "blob" images an invasion of privacy, even though the system doesn't reconstruct an image for viewing. However, the participants generally viewed thermal imaging more positively than cameras.

From the participants' responses, we conclude that getting the message across to potential users is important to user acceptability. Whatever the practical benefits might be, users might not accept the technology if they believe it impinges on their privacy and lifestyle.

The ethical aspects of implementing such technology are also important. In particular, these technologies should be used only where end users or their caregivers understand the technology and can provide informed consent. Technology solutions should be one of a range of care options available to people. Ensuring that implementation doesn't lead to a technological "fix" for all the problems facing the elderly should be central to good practice.

This research indicates that systems such as SIMBAD could significantly enhance the functionality and effectiveness of monitoring and community alarm systems. However, SIMBAD's current limitations and performance level show that it's still very much at the prototype stage. The system requires additional R&D to improve the fall detector and increase the inactivity monitor's effectiveness. To refine SIMBAD and extend its capabilities, we're

- Improving the fall detection algorithms, which, as we mentioned before, might involve developing a more elaborate representation of a fall's dynamics
- Creating algorithms to track, locate, multiple individuals in a multiroom environment
- Developing a sensor subsystem that lets a group of sensors monitor the activity of one or more individuals throughout a building's living spaces and discriminate between real and false alerts
- Developing infrared optics that provide the necessary coverage patterns to suit most living spaces—that is, a 90-degree field of view
- Integrating the sensor in a host telecare system—for example, a community alarm system or smart-home environment
- Conducting further field trials to assess SIMBAD's usefulness in supporting the elderly living in the community

Moreover, SIMBAD's ability to accurately track individuals in their homes has potential for applications other than fall detection. As well as monitoring general activity, SIMBAD could help automatically control in-home devices to respond to the user's position in the home or to detect intruders.

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