



Mobile Medical Alert to Improve Fall Detection Models

¹P.Jayalakshmi, ²E.Maria Monica, ³S.Nivetha, ⁴T.Jayapriya

^{1,2,3} Student, ⁴ Assistant Professor, Department of Electrical and Electronics Engineering
IECW, Chinnasalem, ¹lakshmi3595@gmail.com, ²mariamonica96eee@gmail.com, ³selvamnivetha22@gmail.com,
⁴jayapriyat.92@gmail.com

Abstract— The oldest people are not feeling well or the old people have unconscious fell down or incase accident happen suddenly press the chip in our neck by using satellite signal moving to nearer hospital then ambulance is coming and then the signal is also given to our relations also. In this paper we describe a decision theoretic approach to classification and alerting that incorporates context, such as location and activities, to improve probability and utility estimates for new classes, including near falls and known confounding events. We describe how to use monitored context to provide real-time assessment of true patient state to improve training data sets, as well as the use of context in improving classification, detection and alerting.

Keywords— alerting algorithms, sensor

I. INTRODUCTION

Deficits associated with cognitive decline or brain injury due to trauma or pathology not only increase a patient's risk for falls, they increase vulnerability for trauma from a fall. A few factors that increase fall risk include impaired balance, agitation, confusion, elimination issues, visual impairments, and medications. Patients with compromised brain function frequently suffer from many or all of these challenges. It is therefore important to develop reliable approaches to automatic monitoring for detection of falls and also for predicting increased propensity of falls. Within the last ten years there has been a great deal of research in automated fall detection.

In addition to the actual trauma of a fall, fear of falling in itself has been shown to be associated with negative consequences, such as avoidance of activities, less physical activity, falling, depression, decreased social contact and lower quality of life. The potential benefit of being able to detect falls and communicate alerts to provide help has been shown to reduce fear of falling. At the end of the study, those who wore the fall detector reported that they felt more confident and independent, and considered that the detector improved their safety. One of the conclusions of the study was that the fear of falling is likely to be substantially affected by user perception of the reliability and accuracy of the fall detector.

II. CURRENT APPROACHES TO RARE FALL DETECTION

Before we used pace meter angiogram used the connection between the patients and doctors and hospital also, but patient out of the house, walking or jacking that time will happen some incidence in that situation information only reach to the doctor, not given to relation. In general, automatic fall monitoring approaches can be categorized as wearable-sensor-based, ambient-sensor-based or combined-sensor-based approaches. The vast majority of wearable fall detectors are in the form of accelerometer devices. Some of them also incorporate other sensors such as gyroscopes to obtain information about the patient's orientation and barometers to assess vertical position. Wearable sensors are typically built into wrist-worn bands or watches, attached to clothing or worn as a pendant. More recently fall detection algorithms have been incorporated into mobile phones using the built-in accelerometers and gyroscopes as data sources.

Alternative ambient approaches to fall detection include the use cameras (video or gaming cameras such as the Kinect camera) and pressure sensitive floor mats or carpets. Although they may have greater specificity, error rates are also a problem with these devices, but the larger issues identified by recent review articles have to do with the limited area being monitored and privacy issues associated with the camera approaches. [4] discussed about an eye blinking sensor. Nowadays heart attack patients are increasing day by day. "Though it is tough to save the heart attack patients, we can increase the statistics of saving the life of patients & the life of others whom they are responsible for.



III. CHALLENGES

One approach to augmenting the number of “true” falls is to record simulated falls. Researchers sometimes train on simulated events with healthy volunteers (often graduate students) performing falls onto a cushioned flooring. Even if the simulated falls are performed by talented actors, it is not clear that they represent true patient falls.

Additionally, without camera-based techniques, we do not have information on what might have precipitated the fall event, making classification much more difficult. For example, a fall due to tripping on an irregularity in the ground surface is likely to look much different from a collapse when fainting. Additionally, with frail older adults falls are sometimes precipitated by weak bones fracturing prior to the fall and actually causing the fall. Fall detection algorithms need to cover classifications of the varying types of falls. It is our premise that in addition we need classifications of the varying types of near falls and confounding activities that produce false positives to substantially improve the specificity of fall detectors. One of the primary barriers to advances in the field of fall detection has been in finding representative training data that includes a sufficient number of real falls. True fall events are rare, and a great deal of monitoring must be acquired on many individuals to build valid models based on statistical or machine learning methods. One approach to augmenting the number of “true” falls is to record simulated falls. Researchers sometimes train on simulated events with healthy volunteers (often graduate students) performing falls onto a cushioned flooring. Even if the simulated falls are performed by talented actors, it is not clear that they represent true patient falls.

IV. ROLE OF CONTEXT IN ALERTING ALGORITHM

- Location – In the case of medication alerting, knowing if the person is near the medication dispenser makes the alerting more successful and perceived to be more appropriate.
- Activities (Do not remind if) - sleeping, using the phone, videoconferencing, etc.
- Activities (Do remind if) – preparing to leave house and within time window of target medication time. Activities (Weighted influence) – visitors, watching TV etc.

In our previous work we have found context to be an important factor in providing

meaningful home monitoring activity inference and tailored timely feedback. The notion of context depends on the classification task being performed. As an example, for our work on intelligent medication alerting we used a decision theoretic approach to determining when and with what strength to alert a user to take his or her medication. The medication adherence algorithm triggered an alert at any point in time if the expected utility of the alert at a given strength (loudness/media) was greater than the expected utility (cost) of an inappropriate or unneeded alert. The expected utility for alerting or not alerting was calculated based on the probability that the individual would remember to take the medication independent of the alert multiplied by the utility of alerting or not. Utilities included the importance of the drugs (e.g., vitamins versus critical medications), precision needed for the timing of taking the drug, and also the costs of over alerting (“nagging” and alert fatigue). For this medication alerting application the types of context used in modifying the probabilities and utilities included: With inexpensive and unobtrusive sensors we have been able to monitor context in the homes of older adults. In previous studies we used X10 passive IR sensors place in each room of interest to measure and individual’s location and provide input to the activity classification. Figure 1 shows a sample apartment of an older adult with the pink triangles showing the range of the motion sensor. The three sensors in the hallway with reduced field-of-view are used to detect walking speed.

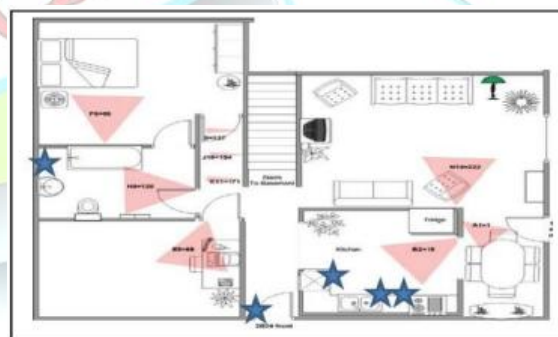


Figure 1. Diagram of a representative home where we could use motion sensors and contact sensors to provide location and activity inference. The pink triangles indicate the field-of-view of the motion sensors and the blue stars show the location of contact sensors.

For the application of fall detection, very similar classifications of location and activity are relevant. Again, a decision theoretic framework is important in having a principled approach to deciding when to send an alert about a fall (possible fall) at a particular strength. For the fall detection application alert strength is encoded in the text of the message and in



the intended receiver of the alert, i.e., the informal caregiver, neighbor, home health aide, nurse, or ambulance.

V. APPROACH TO USING CONTEXT IN FALL DETECTION.

Our approach to incorporating the previously described types of context into algorithms on classifying falls consists of three categories:

- Improving the estimates of probabilities and utilities in the classification / detection / alerting algorithms.
- Providing fall risk assessments via informed prior probabilities of falls given the patient state and context.
- Augmenting traditional training data sets with just-in-time patient self-report on true events when prompted via mobile phone assessment as confounding classification events occur.

The fall detection and fall risk prediction algorithms similarly will evolve and require metadata representations to facilitate data harmonization over time as well as guidance for sensor fusion algorithms, where we are able to take information from several sources to better predict clinical classifications such as a fall event. Monitoring and incorporating context is important for sensor fusion, in that some sensor data is likely to be more robust under some contexts than others. A simple average is usually not optimal. In our work we focus on augmenting existing best practice algorithms for wrist-worn accelerometer and gyroscope sensor data. Given the rapid development of sensors, where nearly weekly new devices appear on the market becoming smaller, more accurate, more comfortable, more integrated with other functionality and longer battery

life, it is important to have sensor agnostic algorithms. New devices must not only transmit accelerometer and gyroscope data, but must also record the metadata needed to harmonize the data with previous versions, sensors in other studies, and with sensors yet to come. The metadata needs to include a representation of the sampling, filtering, accuracy, reliability, potential bias and summary metric definitions.

Best practice fall detection algorithms, such as Kotsiopoulos' fall detector using residual movement analysis, can serve as a basis for creating a hierarchical classification of detected events where confounders as well as true falls are intently described and classified, using monitored context (location and activities) as an input vector in addition to the accelerometer and gyroscope-based classifiers. However, training for classifying confounding events

has been problematic. Our approach to augmenting training data incorporates real-time patient input. We use a novel approach to augment our inference and activity classification algorithms by collecting real-time feedback using ecological momentary assessments. Using this approach, an inferred event classification, such as "somewhat probable fall" triggers an automated brief assessment via mobile phone text message to the patient. For example, in the case of a somewhat probable fall, a triggered text message would query if a true event occurred (e.g., answer "fall", "trip", "other"), the activity and context (e.g., "walking on stairs"), and provide the opportunity for further comment. This real-world feedback is valuable in improving the specificity of falls detection (notably reducing false positives) by providing actual real world outcomes an contextual information for sensory data patterns that identify confounds in inferred fall events or provide evidence to make true classifications of "near-fall" or confounding events".

Finally, our decision-theoretic approach to classifying and alerting for falls using context information to better specify the dynamic probabilities of a fall and utilities for alerting provides a framework for graded alerts. The gradation of severity of the alert allows us to specify the level of the recipient from family members, informal caregivers, and neighbors to nurse care managers or emergency services. In each of these aspects of fall management, context serves a key role

CONCLUSION

The use of monitored context variables relating to location and patient activities can serve to enhance estimates of prior probabilities and utilities for decision theoretic fall alerting algorithms. The necessary improvement in the specificity of fall detection alerting systems requires a more complete understanding of confounding events that trigger alerts. Context measurements can be used to make the prior probability of a fall given the context more accurate for the classifier. In addition, these dynamic priors are useful in ongoing risk assessment for fall prevention protocols. Finally, we can improve our training data for classifying confounders and fall events through the use of ecological momentary assessment techniques by using rapid mobile phone



assessments from the user when potential fall events or confounders are detected. The “true” self-reported activity is used to annotate the training data and improve classifier performance. Thus, the monitoring of context using inexpensive and unobtrusive sensors, in addition to the accelerometer / gyroscope data from wearable wrist devices, can improve the care and safety of patients in the home through augmented training data, predictive algorithms, and a principled decision theoretic system for graded alerts.

VI. REFERENCES

- [1] Holly B. Jimison, *Member, IEEE* and Misha Pavel, *Senior IEEE Life Member* “Real-Time Measures of Context to Improve Fall-Detection Models” 978-1-4577-0220-4/16 ©2016 IEEE
- [2] SizeWise.Net. (2015, March 14). *Fall Risk Toolkit, Understanding Fall Risk, Prevention, & Protection*. Available:<http://www.sizeWISE.net/getattachment/2d5c6915-509c-4d99-a653-bef8bcc56fdc/SW-Fall-Risk-Toolkit.aspx>
- [3] J. A. Langlois, W. Rutland-Brown, and M. M. Wald, “The epidemiology and impact of traumatic brain injury: a brief overview,” *The Journal of head trauma rehabilitation*, vol. 21, pp. 375-378, 2006.
- [4] Christo Ananth, S. Shafiq Shalaysa, M. Vaishnavi, J. Sasi Rabiya Sabena, A. P. L. Sangeetha, M. Santhi, “Realtime Monitoring Of Cardiac Patients At Distance Using Tarang Communication”, *International Journal of Innovative Research in Engineering & Science (IJIRES)*, Volume 9, Issue 3, September 2014, pp. 15-20
- [5] N. Noury, A. Fleury, P. Rumeau, A. Bourke, G. Laighin, V. Rialle, *et al.*, “Fall detection-principles and methods,” in *Engineering in Medicine and Biology Society, 2007. EMBS 2007. 29th Annual International Conference of the IEEE*, 2007, pp. 1663-1666.
- [6] F. Bagalà, C. Becker, A. Cappello, L. Chiari, K. Aminian, J. M. Hausdorff, *et al.*, “Evaluation of accelerometer-based fall detection algorithms on real-world falls,” *PloS one*, vol. 7, p. e37062, 2012
- [7] T. Perry, S. Kellogg, S. M. Vaidya, J.-H. Youn, H. Ali, and H. Sharif, “Survey and evaluation of real-time fall detection approaches,” in *High-Capacity Optical Networks and Enabling Technologies (HONET), 2009 6th International Symposium on*, 2009, pp. 158-164.
- [8] N. Pannurat, S. Thiemjarus, and E. Nantajeewarawat, “Automatic fall monitoring: a review,” *Sensors*, vol. 14, pp. 12900-12936, 2014.
- [9] R. Igual, C. Medrano, and I. Plaza, “Challenges, issues and trends in fall detection systems,” *Biomed. Eng. Online*, vol. 12, pp. 1-66, 2013.
- [10] A. C. Scheffer, M. J. Schuurmans, N. Van Dijk, T. Van Der Hooft, and S. E. De Rooij, “Fear of falling: measurement strategy, prevalence, risk factors and consequences among older persons,” *Age and ageing*, vol. 37, pp. 19-24, 2008.