Privacy Preserving Fall Detection System using LIDAR-Lite

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December 8, 2015

I. INTRODUCTION

Current market available fall detection sensors are limited to wearables and context-aware systems that lack privacy preservation. Wearables tend to be accessories the user can have with them comfortably at all times: watches, necklaces, phone apps, etc. Personal Emergency Response Systems (PERS) are wearable fall alert systems, where the user has to manually indicate if a fall has occurred and if help is needed. Many of these devices are also waterproofed so the user does not have to remove it to shower. Wearable devices have the same problem: users must remember to keep it with them at all times. If a user falls and becomes unconscious, then manually activated fall alert systems are not sufficient.[1]

Context-aware systems range from one sensor to multiple-sensors installed in a specific room or throughout the house. They often include cameras that can accurately detect the user's movements. This becomes an issue in settings where privacy is important, such as the bathroom and bedroom. Research reveals that most falls happen in the bathroom, especially for adults over the age of 65.[2] Our focus was to create a privacy preserving context-aware system using multiple sensors in the bathroom, limiting our scope to the bathtub area. In theory, the system can be extrapolated to function in any setting as long as the software is given ample data to learn its environment.[1]

I. Previous Work and Sensors

A wide range of sensors have been used in fall detection systems. One particularly successful study detected falls for users getting in and out of the bathtub based on sudden changes in the distance read by the ultrasound sensor. The study customized the expected height to each user and could differentiate between intentional behaviors, such as sitting or bending, and accidental behaviors like falls. This background research is one of the reasons why we decided to include an ultrasound in our multiple sensor system. [3]

LIDAR, a topology sensor, has been used to detect human movements for security purposes. In prior studies, it has shown promise in differentiating people from background.[4]

II. CONCEPT, NOVEL CONTRIBUTIONS, AND APPROACH

Our prototype implementation operated under the assumption that combining data from multiple sensors would produce a more accurate depiction of the context. Thus we measured distance data using both static ultrasonic and rotating LIDAR-lite sensors. Our project is the first instance of using any form of LIDAR for fall detection. Linear distance data expresses the distance between the sensor and the nearest object without identifying that object in any way. This property allowed our system to detect the presence and height of a person with-

*Thanks to Professor HT Kung and Marcus Comiter for making this project possible.

out being able to recreate their image, which allowed us to preserve user privacy in their bathtub. As we collected the data, we applied support vector machines (SVM), a type of machine learning, to contiguous sections of data in real time in order to determine if a fall has occurred.

III. System Description and Implementation

We placed the sensors in distinct configurations in order to maximize their combined field of view. The ultrasound, located approximately at the top-center of the bathtub, faced directly down and measured the height of anything within its 30° field of view (FOV). The LIDAR-Lite was placed opposite the shower head atop a servo motor with 180° rotation. Due to the user-specific nature of the system, the prototype was set up to work with the height of the test subject. The LIDAR-lite was angled down across such that when the subject stood in the middle of the bathtub, the LIDAR's laser would hit the subject's mid chest area. Figure 1 shows this general setup while Figure 2 depicts our exact implementation.

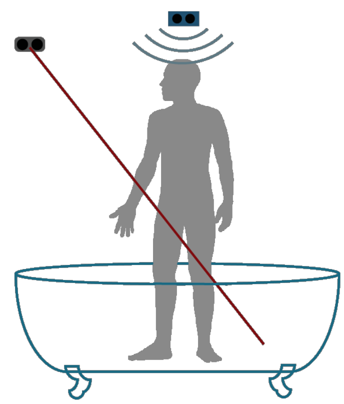

Figure 1: *General layout of the multiple sensor system.*

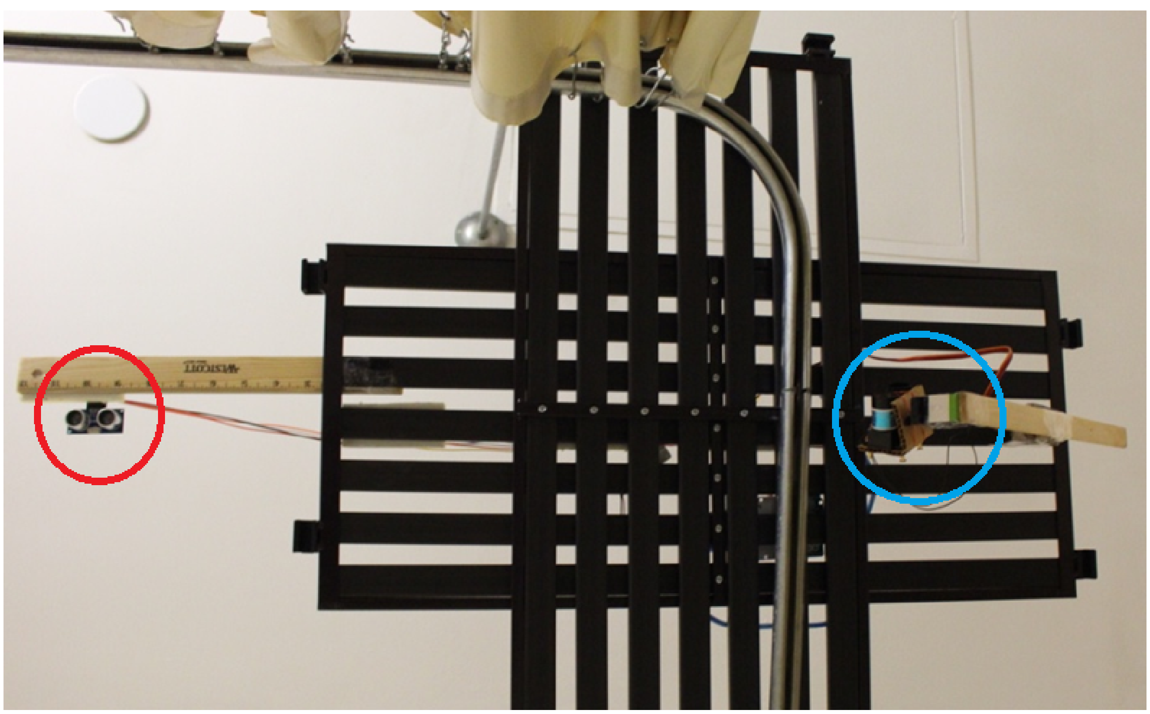

Figure 2: *Photograph of prototype multisensor system, ultrasound circled in red, LIDAR-lite in blue.*

Data was collected near-simultaneously from both sensors. After each 180° servo motor rotation, a WiFi shield sent that rotation's data to a local IP address over a mobile hotspot. This ensured that the data received at any point would include a full image of the bathtub scene. We retrieved the data using continuous HTTP requests and preprocessed it into groups of two and three consecutive rotations. We then applied variants of SVM with four distinct kernel functions: linear, polynomial, radial basis function (RBF), and sigmoid separately to both the pairs and triples of consecutive rotational data. Our training data included examples of falling, bending over, standing in the tub, stepping out of the tub, and an empty tub.

IV. Evaluation and Lessons Learned

I. System Evaluation

We performed 30 trials wherein each trial encapsulated a series of plausible bathtub movements that included at most one fall. We evaluated each trial in real time using each of the eight combinations of SVM kernel type and number of rotations in order to compare their performance. In each case, we calculated the true positive rate (TPR), false positive rate (FPR), true negative rate (TNR), and the false negative rate (FNR). Due to the importance of identifying falls, we determined that an FNR at or above 0.5 was unacceptably high because that would mean that our system failed to alert for at least half of the falls. Such results could endanger the lives of future users. This criterion eliminated RBF and Sigmoid kernels for both two and three rotations. [Table 3, Table 4, Table 7, Table 8] Among the remaining four combinations, we looked to maximize the receiver operator characteristic (ROC) value, which is calculated by taking the ratio of the TPR to the FPR.[5] ROC measures the usefulness of a measured positive result by calculating the likelihood of its being an actual positive result. Of the four combinations, two rotations evaluated on a Polynomial kernel had the highest ROC at 1.83. [Table 2] Two rotations evaluated on a Linear kernel was next closest at 1.5, [Table 1] while both of the three rotation options had high FPRs, translating to low specificity. [Table 5, Table 6] Overall, given small scope of the training and test data, as well as the relatively brief duration of the project, our system performed reasonably well.

Table 1: *Linear, 2 rotations*

Measured \ Actual	Fall	No Fall	Total
Fall	6	11	16
No Fall	2	11	14
Total	8	22	30

TPR	FPR	TNR	FNR
0.75	0.5	0.5	0.25

ROC: 1.5

Table 2: *Polynomial, 2 rotations*

Measured \ Actual	Fall	No Fall	Total
Fall	6	9	15
No Fall	2	13	15
Total	8	22	30

TPR	FPR	TNR	FNR
0.75	0.41	0.59	0.25

ROC: 1.83

Table 3: *RBF, 2 rotations*

		Actual		
		Fall	No Fall	Total
Measured	Fall	2	1	3
	No Fall	6	21	27
	Total	8	22	30

TPR	FPR	TNR	FNR
0.25	0.05	0.95	0.75

ROC: 5.5

Table 4: *Sigmoid, 2 rotations*

		Actual		
		Fall	No Fall	Total
Measured	Fall	0	0	0
	No Fall	8	22	30
	Total	8	22	30

TPR	FPR	TNR	FNR
0	0	1	1

ROC: Undefined

Table 5: *Linear, 3 rotations*

		Actual		
		Fall	No Fall	Total
Measured	Fall	7	13	
	No Fall	1	9	
	Total	8	22	30

TPR	FPR	TNR	FNR
0.88	0.59	0.41	0.13

ROC: 1.48

Table 6: *Polynomial, 3 rotations*

		Actual		
		Fall	No Fall	Total
Measured	Fall	7	14	21
	No Fall	1	8	9
	Total	8	22	30

TPR	FPR	TNR	FNR
0.88	0.64	0.36	0.13

ROC: 1.38

Table 7: *RBF, 3 rotations*

		Actual		
		Fall	No Fall	Total
Measured	Fall	2	3	5
	No Fall	6	19	25
	Total	8	22	30

TPR	FPR	TNR	FNR
0.25	0.14	0.86	0.75

ROC: 1.83

Table 8: *Sigmoid, 3 rotations*

		Actual		
		Fall	No Fall	Total
Measured	Fall	0	0	0
	No Fall	8	22	30
	Total	8	22	30

TPR	FPR	TNR	FNR
0	0	1	1

ROC: Undefined

II. Hardware Lessons

We began this project with the assumption that all hardware would be easy to use and work consistently. Initially, we believed that our sensors could plug directly into the Arduino. Fortunately, we realized our mistake prior to purchase and bought necessary breadboards and male-to-male wires. However, even with these supplies we could not use the passive infrared (PIR) sensors because their prongs were physically blocked from plugging into the breadboard. [Figure 3]

Figure 3: *The PIR sensor cannot directly plug into a breadboard*

II.1 Inferior Hardware

Our HC-SR04 ultrasonic sensors contained a bug: once no object was in the sensor's range, the sensor failed to register objects reintroduced into range. We researched potential workarounds, but we constructed our final setup such that the bottom of the tub remained in range of the sensor. Therefore, the bug never appeared. However, the ultrasound occasionally output invalid values, particularly at the beginning of a rotation. This may have influenced our results.

Additionally, the Sparkfun WiFi shield proved difficult to keep connected. After passing wires through corresponding holes in the shield and the Arduino, we had to physically hold the device in precise alignment in order to keep the connection alive long enough to be useful. We attempted to solve this problem with the purchase of recommended shield headers, but they also seemed to be misaligned. Eventually, we discovered that plugging the WiFi shield into a breadboard successfully stabilized it. However, we needed the breadboards elsewhere, so we had to find a new solution. Soldering the headers in place fixed the problem.

Unfortunately, we learned the hard way to research potential issues before using devices. We broke the bootloader of one IEIK Uno when we ran code for the servo motor while powering the system via USB. We then discovered that the servo motor uses more power than the USB connection can provide and must be used with a stronger power source, such as a battery.[6] The USB port on a second IEIK Uno broke, though the reason for this malfunction was not clear. We purchased additional Unos after these incidents, including an Arduino brand device. The Arduino Uno generally performed better than the IEIK Unos and experienced fewer issues.

While many hardware components proved problematic, we never had difficulty using a breadboard or the LIDAR-Lite. The LIDAR-Lite worked to specification with no difficulties whereas breadboards helped us solve many other problems. The LIDAR-Lite cost over $100 and we bought higher end breadboards because we thought that we might need some of the features. These experiences led us to conclude that the old adage is true: you get what you pay for.

II.2 Positioning

Both of the sensors used had a limited field of view in which they can detect objects. While we did our best to position both sensors so that the test subject was always in view, this was not always possible. In particular, since the ultrasound pointed straight down at the middle of the tub, the test subject standing at either end of the tub was out of range. We suspect that such circumstances were responsible for some of the false negative results that we collected.

Additionally, while the placements of the ultrasound and the LIDAR-Lite were fixed relative to each other, the system was not in a fixed position relative to the bathtub. Slight shifts in system position may have reduced the consistency of measurements and by extension, the quality of predictions.

III. Machine Learning Lessons

While machine learning-based classification led to more sophisticated and individualized results than a manually generated algorithm, it was not without its difficulties. Gathering training and testing data required the test subject to fall repeatedly in the bathtub. The sole test subject, who provided all the test data, complained of soreness and risked injury with every round of data collection. As such, we compromised the quality of our algorithm by collecting relatively little data. Additionally, we had difficulty with manual fall identification in the training data because the height difference sometimes appeared in multiple rotations or only for some LIDAR-Lite angles. Any misidentification could have resulted in poorer classification. On the other hand, varying parameters from their default, especially the kernel type (default RBF), vastly improved the quality of our predictions.

V. Conclusion

Our prototype of a privacy-preserving multi-sensor bathtub fall detection system showed great promise in improving quality of life for the elderly. The next step would be to improve data collection and more rigorously test our system. However, collecting more data in the same manner is not only dangerous to the user but also insufficient for full testing. Using data from real elderly bathtub usage would be ideal, but there is currently no system in place for acquiring such data. As a result, very few fall detection systems have been tested outside of laboratory settings.[1]

We could also test other combinations of sensors to see if different types of sensors provide different results. As noted in the previous section, more expensive versions of sensors may also produce more reliable results. Additionally, we need to consider what resources would be in place to handle fall alerts generated by such a system.

Once we have shown that our system works with real world data, there are several logical extensions that can be made. These include acquiring more LIDAR-Lite and ultrasonic sensors to increase coverage of the bathtub, adding a cancellation mechanism for false positives, using a PIR sensor to save energy by turning the system on and off when someone enters the tub, and potentially adding sensors to detect other health concerns such as heart attacks. Hopefully one day, such systems will be present in all bathrooms in case of emergency.

We affirm our awareness of the standards of the Harvard College Honor Code.

References

[1] "Challenges, issues and trends in fall detection systems"

[2] Important Facts about Falls

[3] "Fall Detection System for Bather Using Ultrasound Sensors"

[4] "Tracking People with a 360-Degree Lidar"

[5] "Plotting and Intrepretating an ROC Curve"

[6] "Servo motor: power supply from Arduino vs external power supply"