Signal Processing of Geospatial and Biometric Data from Wearable Devices for Fall Detection

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Abstract. In this paper, we present a detection algorithm that accurately differentiates the event of a person falling from normal activities of daily living (ADL). Our algorithm processes signals recorded from accelerometers built into wearable activity monitoring devices such as a Fitbit or Apple Watch that is worn on an individual's wrist. Given the potential danger of injury resulting from a fall, especially for the elderly population whom are more susceptible, an accurate fall detection algorithm could be the precursor to an autonomous emergency alert system that pages paramedics. Immediate medical intervention is critical for survival in urgent situations such as a stroke, cardiac event, or TBI; unfortunately, in many of these cases the individual may be unconscious and unable to intervene on their own behalf. With the advancement of geospatial technology, an algorithm that can distinctly detect the event of a fatal fall can automatically trigger a call for emergency medical services to the exact GPS coordinates of a mobile device or the wearable wrist device itself. We will explore the use of a combination of threshold-based and machine learning-based approaches to develop a refined fall-detection algorithm that builds upon previous research.

Keywords: fall detection · activities of daily living (ADL) · signal processing

1 Introduction

In 2016, approximately 30,000 adults aged 65 years and older died as the result of fatal falls in the United States, the leading cause of injury-related fatalities within this age range. The adjusted-age death rates for this senior population have steadily increased 31% from 2007 to 2016, with an estimated 43,000 deaths due to fatal falls in 2030 if these current rates remain stable. [1] These higher death rates are consistent with risk factors of advanced age as well as other associated predispositions such as: 1) reduced activity; 2) chronic conditions, including arthritis, neurological disease, and incontinence; 3) increased use of prescription medications, which act synergistically on the central nervous system; and 4) age-related changes in gait and balance.

[1] https://www.cdc.gov/mmwr/volumes/67/wr/mm6718a1.htm?s_cid=mm6718a1_w

Globally, the World Health Organization (WHO) reports an estimated 37.3 million falls annually, the second leading cause of accidental injury-related deaths worldwide, that require medical attention and potentially hospitalization with an estimated 646,000 fatalities. [2] Their findings are consistent with the fact that adults older than 65 experience the greatest incidents of fatalities from a fall, but report a wider range of risk factors that include: 1) occupations with hazardous working conditions, 2) substance abuse, 3) socioeconomic factors, 4) underlying medical conditions, 5) side effects of medication, and 6) physical depreciation.

The dangers of a fall are not life-threatening itself, but may be associated with potential complications that the elderly are especially susceptible to such as a traumatic brain injury (TBI). The critical danger of a fall is being in a prolonged supine state, in which the person remains on the ground for an extended period unable to help themselves after a fall. (Bagala et al. 2012). This can result in severe loss of self-confidence psychologically and depending on injury, become susceptible to dehydration and internal bleeding. The first fall detection system proposed was a personal alarm system (PAS), in which a user-activated device could be worn as a wrist band or necklace. It required the user to be conscious when a fall had occurred to press a button in order to alert emergency personnel (De Backere et al. 2015; Garripoli et al. 2015; Ozcan et al. 2017). [3] Novel fall detection systems have since been developed to account for the possibility of unconsciousness. These systems can be categorized into camera-based systems, ambient environment sensors, and wearable sensors. This study will focus on fall detection systems using wearable sensors. We aim to develop an autonomous fall-detection algorithm that is trained on accelerometer and gyroscope data extracted from wearable activity monitors on an individual's wrist. With the detection of a fall in cases where an individual is unable to assist themselves, the wrist device would be programmed to alert paramedics and dispatch them to the exact GPS location of the device for immediate medical intervention.

Sensor placements are recommended to be placed at the head and waist position on the body for efficiency purposes when developing algorithms. While the waist intuitively makes sense as the optimal placement being the site closest to the human anatomy's center of gravity, placement at the head has shown to produce superior impact detection sensitivity. Triaxial accelerometer data from both sites produced efficient fall detection algorithms with a sensitivity around 97% and specificity of 100%, even with simple threshold-based algorithms. [4] Due to the limitations with comfortability and daily use of sensor placements at the head and waist, we will primarily focus on wrist sensors for its minimal invasiveness and potential for daily application. Additionally, wrist sensors expands this application beyond the targeted elderly population because wrist-worn devices can be accessorized by individuals in any age group and offer a safety buffer in the event of an accident.

[2] `https://www.who.int/news-room/fact-sheets/detail/falls`

[3] `https://link.springer.com/article/10.1007/s12652-017-0592-3`

[4] `https://www-sciencedirect-com.proxy.libraries.smu.edu/science/article/pii/S096663620800026X`

We will analyze how competing algorithms perform when combining a threshold-based model with different machine learning-based models. We are specifically interested in seeing how linear discriminant analysis (LDA), support vector machines (SVM), naïve Bayesian (NB), decision trees (DT), and random forests (RF) compare on a binary-classification task that differentiates between a fall and an ADL. We will compare competing models based on the classification accuracy, specificity, sensitivity, and precision using ROC-AUC curve to visualize the results.

Detecting falls presents a myriad of technical, logistical, and practical challenges that we will need to address. From a modeling standpoint, an ADL-based dataset will have a very unbalanced response. This will also include a number of false flag activities, such as sitting or laying down. Additionally, falls can occur from multiple positions, such as standing, sitting, or many positions in between. This creates potential for both Type 1 and Type 2 error, and our model will need to be robust to both.

ADLs encompass a wide variety of activities, categorized into six different areas: bathing, ambulatory, transferring, toileting, eating, and dressing. These types of activity will inform our majority response and will be highly dominant in the data. Right away we can tell several of these pose a risk for falls, such as ambulatory or transferring. Transferring is defined as transitory periods from one activity to another, such as getting out of bed, sitting down to eat, getting in and out of chairs or vehicles, or going to sleep at night. Our model would need to know the difference between a transferal and a fall. This could be done by testing accelerometer data against the position in space, and check if the transition was the appropriate speed.

This solution would not encompass all falls, and could ignore some important fall patterns. One common fall behavior, particularly in senior populations, is fainting during toileting. This can present an unexpected challenge - falls from a variety of different positions. If our model were only to expect falls to present a certain change in position at a certain rate, it would be unable to detect the aforementioned fall during toileting. The idea that not all falls are created equal will inform our model so that it can handle a variety of scenarios.

As mentioned before, this data will have a heavily unbalanced response, so appropriate measures will need to be taken to address this, such as downsampling and stratified cross validation. One possible method of addressing many of the previous challenges as well as dealing with the unbalanced response would be training the model for anomaly detection. This would require normalizing the variance across all ADLs, then treating that variance as the positive class of a binary response. The amount of data we have to train a positive response will be more than enough for an anomaly detection architecture.

The first question is defining a fall itself. Fortunately, science defines this for us fairly succinctly in Newtonian physics, where any object upon which gravity is the only actor is said to be in free fall. A fall could be analyzed in much the same way - a person is said to be falling when gravity has more control of their movement than they or another person or device may have at that moment.

The question then becomes how we define a fall in the context of the algorithm. We already mentioned sensors and accelerometers as our tools of measurings a person's ADL and current state. Principle components or quadratic discriminants could be a simple method of measuring changes in state. Since we are not interested in the exact measurements in space - only types of changes - PCA or QDA could be a simple and efficient way of detecting changes. The challenge then becomes finding the range of the minority response.

Since there will be multiple types of falls, as well as falls that appear similar to other ADLs, establishing a threshold for falls - anomalies in this context - will be critical to this algorithm being successful. It is not reasonable to expect a small amount of anomalies to be sufficient in detecting any type of fall, nor all types. Therefore, we plan to leverage methods such as reinforcement learning to solve this problem.

At the crux of fall detection is striking a balance between exploiting the known (leaning on the knowledge of past falls) and exploring the unknown (discerning new falls and types of falls). Reinforcement learning is best suited to this task, as it will be key for this algorithm to seek to learn from past errors, both Type I and Type II, and reduce error going forward.

This has proven to be effective in past experiments with movement. Although there have been no uses in fall detection that we could find, researchers at the University of Porto have tested reinforcement learning in teaching robots to move in quicker, more efficient ways. By using a policy reuse algorithm, they were able to significantly improve the robot's gait when compared to other gait-improvement algorithms.[5]

Policy reuse could be particularly useful in our case. By maximizing the reward of our decision process, we can ensure our algorithm is more accurate with the more decision points we create. The challenge with this, again, is the unbalanced response. Without a handful of falls to train on, we still might not maximize this function. One way to counteract this is to introduce Monte Carlo methods. Even if our algorithm were to go into long periods of majority state, a Monte Carlo method would ensure continuous evaluation to make sure policies are improved.

All that said about falls, we need to give considerable thought to our majority response - ADLs. As described above, ADLs in their simplest form are motions of day-to-day life. While most movement scientists describe them in the 6 categories mentioned previously, there is some disagreement on that point. Many scientists do not feel that those 6 categories encompass the range of activities that should be included in the ADL catgory.

Researchers in Switzerland have proposed creating 3 very broad subcategories of ADLs based on their own fall detection research: basic movements, standard movements requiring some mobility, and sporting movements[6]. These ranges capture a broader population of ADLs and could serve us better in identifying

[5] `https://www-sciencedirect-com.proxy.libraries.smu.edu/science/article/pii/S0952197619302921`

[6] `placeholderforCasilaricitation`

our majority response. Additionally, since their work was based on more able-bodied adults, it would help us in crafting a more practically applicable model for wearable devices.

Speaking of practical significance, our choice to focus on wrist-based sensors was driven by a desire to match commonly preferred products on the market today, like Fitbit, Garmin, and Apple Watch. This choice brings its own set of benefits and challenges. Clear benefits include developing an algorithm that is more beneficial to a broader population. Most individuals concerned with falls will not want to wear sensors on their hips or heads, or multiple sensors, so a product that works only on the wrist will do the most good for the most people.

Unfortunately, some research has shown wrist sensors to be unreliable. Researchers testing fall detection reliability have found that false positive rates are high when using a single wrist sensor[7]. Generally, torso and head based sensors have proven to be more effective in detecting falls, but in this study, wrist-based sensors were still able to detect faster falls with some accuracy.

Fortunately, methods have been developed to account for this accuracy issue with wrist-based sensors. Researchers tested four different hand-based ADLs - waving, knocking, clapping, and exercise - that frequently are mistaken for falls. Using ensemble stacked autoencoders and one-class classification based on the convex hull (ESAEs-OCCCH), the researchers were able to generate a novel form of fall detection. This technique could be incorporated into our model to produce a more reliable metric from our sensors[8].

2 Related Work

3 Materials and Methods

4 Results and Discussion

5 Conclusion

[7] `https://search-proquest-com.proxy.libraries.smu.edu/docview/1796351719/70A85E3E925D40F5PQ/3?accountid=6667`

[8] `placeholderforChenpapercitation`