Recognizing Seatbelt-Fastening Behavior with Wearable Technology and Machine Learning

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ABSTRACT

Nearly 1.35 million people are killed in automobile accidents every year, and nearly half of all individuals involved in these accidents were not wearing their seatbelt at the time of the crash. This lack of safety precaution occurs in spite of the numerous safety sensors and warning indicators embedded within modern vehicles. This presents a clear need for more effective methods of encouraging consistent seatbelt use. To that end, this work leverages wearable technology and activity recognition techniques to detect when individuals have buckled their seatbelt. To develop such a system, we collected smartwatch data from 26 different users. From this data, we identified trends which inspired the development of novel features. Using these features, we trained models to identify the motion of fastening a seatbelt in real-time. This model serves as the basis for future work in which systems can provide personalized and effective interventions to ensure seatbelt use.

CCS CONCEPTS

• **Computing methodologies** → **Machine learning algorithms**; • **Human-centered computing** → *Smartphones*; *Mobile devices*; **Mobile computing**.

KEYWORDS

Human Activity Recognition, Wearable Technology, Automobile Safety, Seatbelt Use

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1 INTRODUCTION

Automobile accidents remain one of the leading causes of death in the United States, especially for Americans under 60 [7, 9]. Nearly half of Americans who died in car crashes in 2014 were not wearing a seatbelt at the time of the crash [1]. This statistic exists despite research that has shown that seatbelt use reduces the risk of fatal and serious injuries from car crashes by approximately 45% and 50% respectively [2] and widespread detection and warning systems designed specifically to enforce seatbelt use in cars. According to statistics published by the Centers for Disease Control and Prevention (CDC), young adults are the least likely age group to wear a seatbelt [8, 31], and men are less likely to wear their seatbelt than women [31]. Clearly, existing seatbelt warning systems leave room for improvement in their encouragement of safe user behavior.

Commonly, automotive safety systems vie for the driver's attention using an audible tone or visual indicator on the dashboard [36]. These warnings are triggered by sensors integrated within the vehicle [37] (often within the buckle [3] itself). However, the effectiveness and coverage of these safety systems is limited. The standard design has these systems centered around the driver with sensors only in the front seats and warning indicators only visible to the driver. Furthermore, these systems can be circumvented fairly easily. For example, drivers or passengers may leave their seatbelts always buckled across their seats, sitting on top of the belt while riding in the car. In other words, these safety systems are vehicle-centric and ironically require cooperative behavior from a user who refuses to cooperate with safety guidelines.

This work explores a human-centered paradigm for seatbelt monitoring. Current interventions are broad and static, operating with a standard procedure regardless of the identity of the passenger. There is no precedent for altering interventions based on the behavior of individual passengers. A human-centered seatbelt safety system would function independently of the vehicle as it is built around specific users. Notably, such a system would always remain in effect, regardless of what vehicle the user may be riding in or what seat they may be sitting in. Furthermore, a user's record would not be contaminated by other people driving their vehicle. This system would also allow for personalized intervention tactics to ensure greater seatbelt compliance. For instance, knowledge of a user's tendencies could inform a plan for improvement, and the system could intervene in ways that the user has historically been more receptive to.

In this work, we develop the groundwork for a personalized, context-aware seatbelt monitoring system, proposing a human-centric activity recognition methodology for detecting whether a user has buckled their seatbelt. Activity recognition, or the recognition of physical activities from sensor data, has achieved considerable success in promoting healthy user behavior. For example, many health-related applications which monitor self-care activities (such as eating habits) [20, 21, 33] and intervene to correct undesirable behaviors [5, 10] depend on activity recognition. These systems commonly rely on wearable sensors, e.g., accelerometers [10], and machine learning classifiers [12]. Building upon this body of work, we found that the motion of buckling a seatbelt can be distinguished from other common activities with similar motions using algorithms built on features commonly found in activity recognition literature and based on patterns observable in the raw data.

2 RELATED WORK

Activity recognition systems generally fall into two categories: vision-based recognition and wearable inertial sensor-based recognition. In this work we follow the latter approach as it better suits the nature of the problem.

A number of studies have utilized wearable inertial sensor data to achieve human activity recognition. Early work explored the use of a variety of different sensors attached to various locations on the body [21, 22, 25, 27, 32]. These other types of sensors included barometers, gyroscopes, heart rate sensors, humidity sensors, light sensors, microphones, and thermometers. Lester et al. [21] noted that not all of these sensors were necessary to successfully classify user activities and demonstrated similar precision and recall using a sensor subset of accelerometers, microphones, and barometers. In each of these experiments, sensors were arranged in custom-built arrays which were intrusive and impractical for widespread use. Two notable exceptions were Maurer et al. [22] and Győrbíró et al. [15] who used senors built into early versions of smartwatches to recognize common human activities.

Further research has demonstrated that collecting data from only a few biaxial or triaxial accelerometers is sufficient to recognize many activities [10, 13, 15, 29, 30, 32, 34]. One notable study was done by Bao & Intille [4] who placed biaxial accelerometers on the upper arm, wrist, hip, thigh, and ankle to recognize 20 common activities. From this study they found that accelerometers placed on the thigh, hip, and ankle were the best indicators for activities that had some form of ambulation or posture, while accelerometers placed on the wrist and arm were the best indicators for activities that involved mostly the upper body.

Recent work has focused on off-the-shelf products such as smartphones [6, 19] and smartwatches [14, 33, 35], building off of these conclusions that accelerometers placed at the locus of the activity's movement provides the best basis for recognizing these activities. Furthermore, commercially available devices are more practical for daily wear, are more likely to be worn by eventual users as they offer other functionality, and do not have the social stigma that may be associated with the use of a prototype system [21]. These studies have focused on recognizing a wide range of mostly health-related activities [10, 18, 27] such as meal tracking [25, 33, 35], monitoring cleanliness (e.g., brushing teeth, showering) [11, 14, 21, 30], and exercise encouragement [5, 23, 24, 28]. This work builds upon this body of work and uses smartwatch accelerometer data and machine learning techniques to detect the action of putting on a seatbelt, an activity which, to our knowledge, has not yet been recognized in literature.

3 METHODOLOGY

3.1 System Implementation

In this work we collected accelerometer data from a wrist-worn smartwatch. Using accelerometer data from the wrist is well established in the literature, especially for activities concentrated in the upper body and arms [4, 14, 18, 33]. We specifically used a Pebble smartwatch, which possesses a 4G 3-axis accelerometer [26]. Accelerometer data was sampled at a rate of 25 Hz. The Pebble smartwatch is no longer commercially available; however, this study is not dependent specifically on this particular smartwatch, rather it simply requires a wrist-worn device containing an accelerometer. It has been used in a number of other activity recognition studies [11, 33].

3.2 Data Collection

The motion of buckling a seatbelt generally consists of an arm-raising motion (wherein the user reaches up and grabs the seatbelt) followed by an arm-lowering motion (wherein the user brings the seatbelt back down and buckles it in). More specifically there are generally three different ways in which individuals buckle their seatbelt:

(1) Reaching up with their *left* hand and bringing the seatbelt all the way down to buckle it.
(2) Reaching up with their *right* hand and bringing the seatbelt all the way down to buckle it.
(3) Reaching up with their left hand, *transferring* the seatbelt from their left hand to their right hand, and fastening the buckle with their right hand.

This realization added a degree of complexity to our study, especially considering that only one wrist is being monitored by sensors. To provide data samples as uniform as possible, the user was directed to wear the Pebble watch on whichever arm they used to perform the initial upward reach, as this arm is most important in performing the characteristic arm-raising/arm-lowering motion. Furthermore, it was important that our algorithm was tested against a number of "control" activities, or activities whose motions are similar to that of buckling a seatbelt, as those are the activities most likely to generate false positives in a real-world system. These other activities consisted of:

- Removing something from a shirt pocket.
- Putting a phone in a pants pocket after sending a text.
- Putting a phone in a pants pocket after ending a phone call.
- Putting on a backpack.
- Taking off glasses/sunglasses.
- Putting on a jacket.
- Reaching up and touching one's face or adjusting hair.

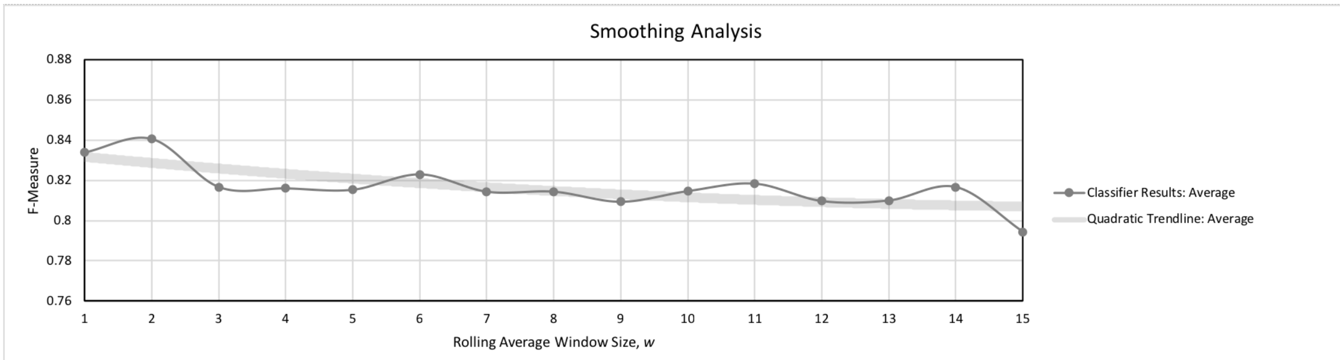

Figure 1: The average F-measure of IBk, Multilayer Perceptron, and Random Forest when trained on data with rolling average window sizes $w = 1 \dots 15$.

We conducted three separate data collection sessions, collecting accelerometer data from a total of 26 unique participants over the course of these sessions.

3.2.1 Controlled Study. We conducted a controlled study first to obtain an initial understanding of the activity. Users buckled their seatbelt ten times, then performed each of the seven control actions five times. Data was collected from twelve participants during this portion of the study.

3.2.2 In-the-wild Study. Following this study, we conducted a second study in which participants wore the watch for an hour and half. This session provided "ambient" data, ensuring that a deployed version of this system would not classify every action a user performed as one of the six labeled activities done during the controlled study. Participants were asked to buckle their seatbelts at least ten times during the period, but were otherwise free to go about their day. Common activities participants performed included walking, standing, opening doors, and getting in and out of a vehicle. Fourteen participants participated in this study, six of whom had participated in the first study.

3.2.3 Test Data. Activity data from an six additional individuals served as test data for our algorithms. These individuals were not a part of either the controlled or in-the-wild studies. These individuals received the same instructions as those who participated in the in-the-wild study.

3.3 Data Processing

Raw accelerometer data was filtered using a rolling average function shown in Equation 1 where i is a particular data point on axis p that is centered in a window of size w. We trained three classifiers—IBk, Multilayer Perceptron, and Random Forest—on each of the different values of w; the average performance of the three classifiers for each value of w can be seen in Figure 1. From this analysis we used a rolling average filter with a window size of 2.

$$p'_i = \frac{1}{w} \sum_{j=i-\lceil \frac{w-1}{2} \rceil}^{i+\lfloor \frac{w-1}{2} \rfloor} p_j \tag{1}$$

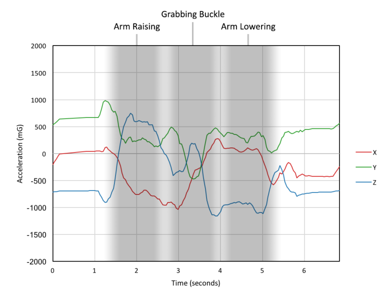

Figure 2: A plot of filtered accelerometer data for one instance of buckling. The first "third" of the data corresponds to the period where the user lifts their arm to grab the buckle. The second "third" corresponds to the period where the user searches and grabs the buckle. The third "third" corresponds to the period where the user lowers their arm to fasten the buckle.

Data was segmented into 6 second windows with a 4 second overlap. This window size was determined empirically to ensure that the entire activity is captured within a single window. Within each of these windows we extracted features to detect the three actions that compose the activity of buckling a seatbelt: raising the arm, grabbing the buckle, and lowering the arm. A depiction of this pattern can be seen in Figure 2. It's important to note that because the user wore the watch on the arm that they used to grab the seatbelt, this general structure holds regardless of how the user buckled their seatbelt.

3.4 Features

The features we extracted from this processed data are shown in Table 1. Features A–H have been used extensively in previous activity recognition studies [12]. Features I–L were derived based on patterns observed in the raw data.

Features I and J were derived based on the observation that certain axes appear very close in value during certain sections of the window. Features K and L were derived based on the observations that when individuals raised their hand there was a large difference

Table 1: Features extracted from filtered accelerometer data. In the feature equations A represents an axis.

#	Feature Name	Equation	Symbol
(A)	Average	$\frac{1}{n}\sum_{i=1}^{n} a_i$	μ_X, μ_Y, μ_Z
(B)	Standard Deviation	$\sqrt{\sigma_A^2}$	$\sigma_X, \sigma_Y, \sigma_Z$
(C)	Minimum	$min(A)$	$x_{\min}, y_{\min}, z_{\min}$
(D)	Maximum	$max(A)$	$x_{\max}, y_{\max}, z_{\max}$
(E)	Product	$\frac{1}{n}\sum_{i=1}^{n} a_{1i}a_{2i}$	$X \times Y, X \times Z, Y \times Z$
(F)	Correlation	$\frac{\sigma_{A_1 A_2}}{\sigma_{A1}\sigma_{A2}}$	$\rho_{XY}, \rho_{XZ}, \rho_{YZ}$
(G)	Variance	$\frac{1}{n}\sum_{i=1}^{N}(a_i - \mu_A)^2$	$\sigma_X^2, \sigma_Y^2, \sigma_Z^2$
(H)	Covariance	$\frac{1}{n}\sum_{i=1}^{N}(a_{1i} - \mu_{A1})(a_{2i} - \mu_{A2})$	$\sigma_{XY}, \sigma_{XZ}, \sigma_{YZ}$
(I)	Average Difference between Axes	$\frac{1}{n}\sum_{i=1}^{n} a_{1i} - a_{2i}$	$X - Y, X - Z, Y - Z$
(J)	Average Absolute difference between Axes	$\frac{1}{n}\sum_{i=1}^{n} \lvert a_{1i} - a_{2i}\rvert$	$\lvert X - Y\rvert, \lvert X - Z\rvert, \lvert Y - Z\rvert$
(K)	Difference between X-Y absolute difference and the Y-Z absolute difference	$\frac{1}{n}\sum_{i=1}^{n} \lvert x_i - y_i\rvert - \lvert y_i - z_i\rvert$	$\lvert X - Y\rvert - \lvert Y - Z\rvert$
(L)	Absolute Difference between X-Y absolute difference and the Y-Z absolute difference	$\frac{1}{n}\sum_{i=1}^{n} \lvert\lvert x_i - y_i\rvert - \lvert y_i - z_i\rvert\rvert$	$\lvert\lvert X - Y\rvert - \lvert Y - Z\rvert\rvert$

between the X and Y axes and a small difference between the Y and Z axes and when individuals lowered their hand there was a small difference between the X and Y axes and a large difference between the Y and Z axes. Each feature was extracted four times: once over the first third of the window, once over the second third of the window, once over the third third of the window, and once over the whole window. Features A–J were extracted for each axis or for each pair of axes. In total 128 features were extracted from the filtered, windowed sensor data.

Table 2: Subset of features extracted from filtered accelerometer data

Window Region	Features
Arm Raising	σ_X^2, ρ_{XY}
Grabbing Buckle	$x_{\min}, y_{\min}, z_{\min}, x_{\max}, y_{\max}, X-Y, \lvert Y - Z\rvert, \sigma_X^2, \sigma_Y^2, \sigma_Z^2, \sigma_X, \rho_{YZ}$
Lowering Arm	$Y \times Z, \sigma_{XY}$
Full Window	$z_{\min}, \lvert X - Y\rvert, \lvert Y - Z\rvert, \sigma_X^2, \sigma_Y^2, \sigma_Z^2, \sigma_Z, \rho_{XY}, \rho_{XZ}, \rho_{YZ}$

To improve the generalization and classification performance of classifying buckling vs. not buckling activities, we performed feature subset selection using the data from both the controlled and in-the-wild studies. We choose to use the Correlation-based Feature Selection (CFS) subset evaluation tool in the WEKA Data Mining Tool Kit [16]. This tool evaluates each feature in our set on the basis of their ability to predict the class as well as on the basis of redundancy with other features. This evaluation technique will generate a smaller subset of features that have a high correlation with the class but low inter-correlation [17]. Of our 128 features, CFS Subset Evaluation selected 26. These features are shown in Table 2.

4 RESULTS

To establish an upper bound on the expected performance, we trained classifiers using the data from the controlled and in-the-wild studies. This was done in WEKA using stratified cross validation. The selected algorithms include representatives from commonly used classes of machine learning algorithms: probabilistic classifiers (Naive Bayes), tree-based classifiers (J48), neural networks (Multilayer Perceptron), support vector machines (SMO), k-nearest neighbor classifiers (IBk), and ensemble methods (Random Forest). We used the ZeroR (Zero Rule) classifier to obtain the baseline performance. If the system cannot outperform a model that only selects the most probable label, then this performance indicates an issue with the architecture design and/or feature set. The performance of these algorithms was evaluated using the F1-score metric

Table 3: Classifier F1-scores for Phase II advanced testing with CFS feature reduction.

Classifier	Activity	F1-score
IBk	Buckling	0.755
	Not Buckling	0.931
J48	Buckling	0.673
	Not Buckling	0.920
Multilayer Perceptron	Buckling	0.789
	Not Buckling	0.947
Naive Bayes	Buckling	0.725
	Not Buckling	0.911
Random Forest	**Buckling**	**0.795**
	Not Buckling	0.950
SMO	Buckling	0.681
	Not Buckling	0.928
ZeroR	Buckling	0.000
	Not Buckling	0.889

to avoid the accuracy paradox. As the activity of not-buckling was significantly more common than buckling one's seatbelt both in our dataset and real-world , the accuracy metric would be inflated and be a poor representation of the model's actual performance. The formula for the F1-score is given in Equation 2.

$$\text{F1-score} = 2\left(\frac{\text{Precision} \cdot \text{Recall}}{\text{Precision} + \text{Recall}}\right) \tag{2}$$

The results on the training data can be seen in Table 3. The best performing classifier was Random Forest with the highest individual F1-scores on both the buckling and not buckling activities. The precision of this classifier is relatively high as evidenced by the 0.95 F1-score on the not-buckling activity, indicating that the model is not mistaking other daily activities from the in-the-wild study as buckling. However, the recall of the buckling activity could be improved based on the 0.795 F1-score.

Finally we trained a model on the entirety of the training data and evaluated it on the testing data. These results can be seen in Table 4. In contrast to the performance on the training data, the best performing model was SMO. Notably when applying our methodology to unseen data there were only small decreases to the individual F1-scores for both the buckling and not buckling activities.

5 DISCUSSION AND FUTURE WORK

In this work we demonstrated that it is possible to recognize when individuals buckle their seatbelt using smartwatch accelerometer data, a simple set of features from prior literature and based on observable patterns in the data, and standard machine learning algorithms. It is worth noting that although we collected "ambient" data through our in-the-wild study design, these studies were not representative of "real-life" usage patterns. In the future, we plan on evaluating and retraining our algorithms on data representative of participants natural driving habits. To further improve upon the performance of the algorithms developed in this work, algorithms trained on this data could also ostensibly take advantage of contextual information such as the time of day and the user's calendar (e.g., putting on a seatbelt might look different if an individual is running late to a meeting) as well as other sensors such as the GPS in the user's phone.

Table 4: Classifier F1-scores for Phase II verification testing.

Classifier	Activity	F1-score
IBk	Buckling	0.707
	Not Buckling	0.900
J48	Buckling	0.690
	Not Buckling	0.899
Multilayer Perceptron	Buckling	0.756
	Not Buckling	0.927
Naive Bayes	Buckling	0.583
	Not Buckling	0.788
Random Forest	Buckling	0.722
	Not Buckling	0.919
SMO	**Buckling**	**0.781**
	Not Buckling	0.939
ZeroR	Buckling	0.000
	Not Buckling	0.889

One key limitation of our study was the requirement of having participants wear the smartwatch on the hand they buckled their seatbelt with. This requirement likely made participants especially aware of being studied during data collection and is not ultimately practical for real-world deployment of the system. Future work can address this limitation in a couple ways. First, studies could look at the movement of the other hand during seatbelt buckling (e.g., finding and holding the buckle) and add this to the overall classifier to ensure that it is robust enough to recognize the activity regardless of which wrist the smartwatch is worn on. Second, future studies could look at hardware solutions. If interfaces leveraging algorithms to recognize this and other activities were designed for non-wearable devices such as tablets or smartphones, a simple, lightweight band or bracelet functioning primarily as a wearable sensor (similar to several commercially available fitness trackers) could be practically worn on either wrist.

Future studies should explore how to track seatbelt safety over time and the design of interfaces to present this data to users. This information could be used as an indicator of how safe a driver is, e.g., a rate of whether or not the individual wore their seatbelt while in a vehicle. Such data could be used by insurance companies to reward drivers who practice proper driving safety, although future studies should examine the privacy concerns associated with this use case before widespread adoption of this idea occurs. Beyond that, encouraging higher rates of seatbelt-compliance among individuals will likely require the development of novel interfaces and intervention techniques to make the individual aware of their habits. Such interfaces would need to be evaluated in a long-term user study to determine if the interventions improve the user's seatbelt safety practices. The interface should ideally increase the rate of how often the user wears a seatbelt and not serve as a potential source of distraction if they are driving the vehicle. That said, the algorithm presented in this work serves as the first step towards designing effective human-centric, lifestyle-compatible seatbelt safety systems.

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