Near-Miss Accident Detection for Ironworkers Using Inertial Measurement Unit Sensors

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Abstract -

In the construction industry, fall accidents are the leading cause of construction-related fatalities; in particular, ironworkers have the highest risk of fatal accidents. Detecting near-miss accidents for ironworkers provides crucial information for interrupting and preventing the precursors of fall accidents while simultaneously addressing the problem of sparse accident data for ironworkers' fall-risk assessments. However, current methods for detecting near-miss accidents are based upon workers' self-reporting, which introduces variability to the collected data. This paper aims to present a method that uses Inertial Measurement Unit (IMU) sensor data to automatically detect near-miss accidents during ironworkers' walking motion. Then, using a Primal Laplacian Support Vector Machine, a developed semi-supervised algorithm trains a system to predict near-miss incidents using this data. The accuracy of this semi-supervised algorithm was measured with different metrics to assess the impact of the automated near-miss incident detection in construction worksites. The experimental validation of the algorithm indicates that near-miss incidents may be estimated and classified with considerable accuracy—above 98 percent. Then the computational burden of the proposed algorithm was compared with a One-Class Support Vector Machine (OC-SVM). Based upon the proposed detection approach, high-risk actions in the construction site can be detected efficiently, and steps towards reducing or eliminating them may be taken.

Keywords: Sensing and Communication, worker safety, near-misss, Inertial Measurement Unit sensor.

1 Introduction

The construction industry is still dangerous, accounting for about 21% of fatal injuries in the United States[1]. Among these fatal injuries, falls to a lower level have been ranked as the foremost fatal accident type in the construction industry, representing 33% of all fatal accidents [2]. In order to reduce the number of fatal fall accidents, the Occupational Safety and Health Administration began regulating the use of accident-prevention measures (e.g. personal fall arrest systems); however, the administration cannot address certain types of accidents that occur due to dangerous circumstances [3]. Among construction trades, ironworkers have been exposed to the highest lifetime fatal accident risks [4]. However, estimating the fall risk of an ironworker is still very challenging due to the sparse amount of detailed information on actual fall accidents. Thus, there is insufficient knowledge to give forewarning to potential subjects of fall accidents.

For this reason, the identification of near-miss accidents has been brought forward as a consideration that could help prevent future accidents in the construction industry [5], [6]. According to Phimister [7], a near-miss accident is defined as an event that did not cause any harm but that had the potential to become an accident under slightly different conditions. The logic runs that behind one major accident there are numerous near-miss accidents and a few minor accidents [8]. Thus, data about the number of near-miss accidents could be used as a harbinger of an upcoming major accident in general cases.

In this context, this research proposes a method for detecting the near-miss accidents of ironworkers that uses wearable inertial measurement unit (IMU) sensors containing accelerometers, gyroscopes and magnetometers. As discussed in previous publications, laboratory experiments were conducted on two unskilled ironwork subjects. In order to detect near miss-fall accidents, this research classified the condition of the workers' postures during a movement and proceeded to detect the near-miss incidents observed while the subjects walked. Machine learning algorithms were then applied (i.e., Support Vector Machine (SVM) and OC-SVM) to increase accuracy of predicting of near-miss accidents while decreasing computational burdens.

2 Background

In order to increase the safety of construction workers, diverse technologies (e.g., vision, sensors) have been applied to the construction industry. Vision-based methods utilize single or multiple video- or vision-cameras to track a worker or piece of equipment to prevent exposure to dangerous situations [9]–[12]. These methods investigated appropriate algorithms to observe workers and equipment on construction sites using individual or multiple vision apparatuses. However, in construction sites there are many obstacles that can interrupt devices' vision. In addition, near-miss accidents are normally subtle incidents that are challenging to detect using vision-based methodologies.

With regards to monitoring a construction worker, different types of sensors have been applied to acquire informative data to classify workers' activities and behaviours. Joshua [13] applied accelerometers to classify workers' masonry activities in order to investigate workers' productivity. Taneja [14] investigated inertial measurement unit (IMU) sensors for location-tracking in a building site as compared to other sensors that used established local area networks (WLAN) and radio frequency identification (RFID). Various types of sensor have been used for workers' activity classification and behaviour monitoring in research; however, this research is one of the initial attempts to use sensors for near-miss accident detection in the construction area.

Our previous study [15] applied IMU sensors to classify workers' postures and motions and to detect near-miss accidents for ironworkers. Data was obtained from one test subject. Due to scarcity of near-miss incidents, we faced limitations in training the best classifying function. We preferred an OC-SVM in the previous research because it was mostly successful in training a classifying function. In order to increase the feasibility of this near-miss detection approach, this research utilized a different algorithm and compared its accuracy with previous research results. This work is based upon the detection of ironworker's fall incidents using IMU sensors, which have high sensitivity to capture the subtle difference between normal and near-miss accidents. This research conducted a preliminary laboratory experiment and used worker's motion data to implement the near-miss accident detection approach.

3 Research Objectives & Methodology

Extensive growth in the construction field has resulted in an increasing demand for improving the safety of construction workers. This call for safety improvement in turn gives rise to the application of state-of-the-art machine learning algorithms on data. A class of promising algorithms for classification purposes is semi-supervised learning. Semi-supervised learning algorithms estimate a target classification from a few labelled examples alongside a large collection of unlabelled data. In this research, we aim to use a semi-supervised learning algorithm and IMU sensor data to develop a system for detecting ironworkers' near-miss incidents. This objective is achieved through five phases: (1) setting up the test bed, (2) collecting data from IMU sensors and videotaping the data collection period for generating labels, (3) analysing data to get the desired frequency and extracting features, (4) training the classifier and, finally, (5) evaluating the performance of the classifier function. Figure 1 illustrates the overall research steps.

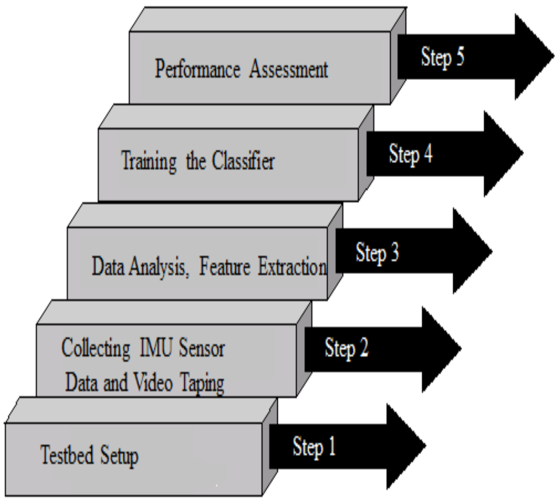


Figure 1: Near-miss-incidents detection research phases

During the data collection phase, an IMU sensor was attached to the subjects' waists and collected data on the workers' motions. Motions included walking and unintended near-miss activities on a steel frame. Subjects were walking on the frame for a few minutes with a steady speed. This rectangular frame was comprised of two four-inch flange I-beams and another two two-inch width steel beams. The dimensions of this frame were 12 feet 1 inch by 6 feet 6 inches (see Figure 2-b). Videotaping the data collection period aided with the assignation of appropriate labels for deciding whether the ironworker was in a safe condition or was experiencing a near-miss incident.

The type of IMU sensor used to collect the ironworkers' motion data was a SHIMMER 9DoF with three axes each for the accelerometer, gyroscope and magnetometer (See Figure 2-a). IMU sensors recorded motion data at a frequency of 51.2 Hz and transferred the data to a laptop computer via Bluetooth. Concurrently, a video recorder filmed the experiment to create reference data labels to assist in training the classifier. To keep track of the beginning and end of the data collection process and to synchronize collected motion data with video recording, an impact was given to the sensor at both the start and end of data collection. Figure 2 illustrates the experiment equipment and layout.

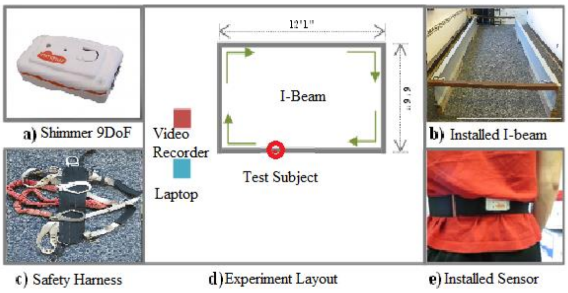


Figure 2: Laboratory experiment layout and equipment

From raw data received from IMU sensor, we observed a frequency of 51.2 Hz. However recorded video of the experiment didn't have this frequency since objective labelling cannot reach the same sampling speed of IMU sensor. In order to match the frequency of the data received from the IMU sensors and the labels produced with the monitoring video recordings, we reconstructed both raw data and video labels by a sampling rate of 32 Hz with 50% data overlap. Within each sample window, data was sampled using the features for both the accelerometer- and the gyroscope-measured data points present in that window. The accelerometer and gyroscope each have *x*, y and *z* axis, hence there were six values for each sampling technique per each data point. In each sampling window, we measured mean, standard deviation and peak values per *x*, *y* and *z* axis, for both the accelerometer and gyroscope. This makes up 18 features. Another 20 features are extracted by using correlation, spectral entropy, and spectral centroid functions. Considering all of these features, 38 features were extracted.

Considering that workers' near-miss incidents will create irregular patterns in IMU sensor data, the detection of near-miss incidents can be formulated by training a classifier function, which differentiates signal patterns that do not conform to expected signal patterns—in this case, those signals that are departures from workers' stable postures during a movement. A near-miss is a motion in which the subject loses balance slightly. Finding near-miss incidents therefore depends on subjective labels assigned by reviewing recorded video from the data collection period. However, subjective labelling is not feasible in all circumstances and is computationally expensive. Additionally, due to the rare and dynamic nature of near-miss incidents, it is difficult to record labelled data that includes all sorts of conditions leading to a near-miss incident. Therefore, we favoured a semi-supervised classifier function that can benefit from both labelled and unlabelled data. In order to evaluate the performance of the classifier function, data was divided into 60% training data and 40% test data. Accuracy in predicting near-miss incidents against the total number of data points and the computational time elapsed to achieve this accuracy were measures to assess the performance of the classifier.

4 Identification of near-miss incidents

Recently, many algorithms have been proposed to enhance the quality of a semi-supervised classifier function [16], [17]. The premise of semi-supervised learning is that a marginal distribution of a decision boundary can be estimated based upon labelled data, and that each point of a cluster can be distinguished from data points belonging to other clusters by a curve that separates a dense area of a cluster from a non-dense boundary area. The boundary between different classes is not as dense as the area in each class. This characteristic of the semi-supervised learning algorithms is called the Cluster Assumption. Another assumption in this algorithm is the Manifold Assumption, which states that the boundary lies on or near low-dimensional manifold and that the classifier function moves smoothly along this boundary. The Manifold Assumption produces low-dimensional space using key class features, and therefore is effective in the applications where data has noise.

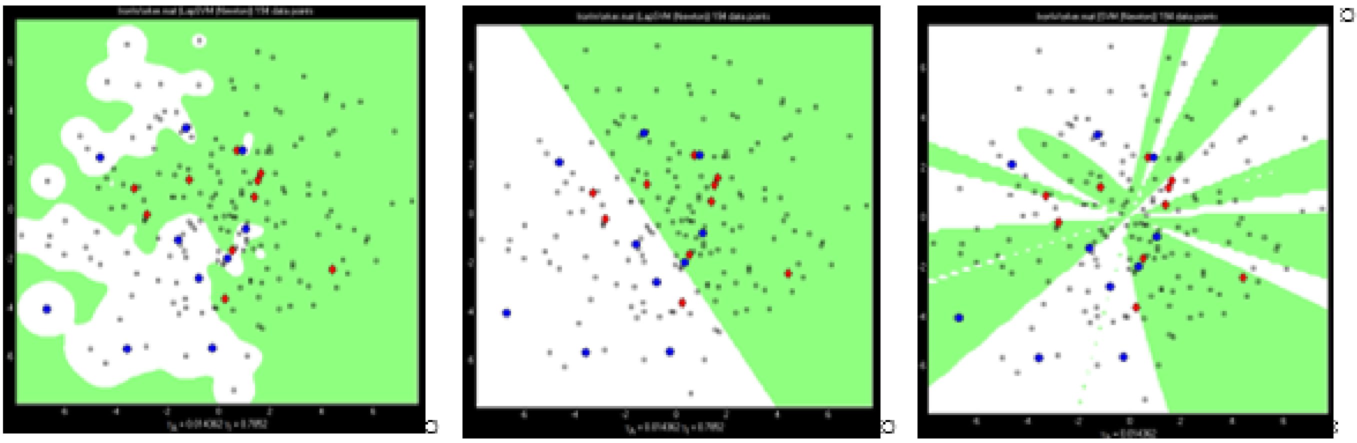
In this paper we focus on a Primal Laplacian Support Vector Machine (LapSVM) approach. The original Laplacian Support Vector Machine (LapSVM) was proposed by Belkin et al [18]. The original algorithm of LapSVM had a dual formation, which was defined by a number of dual variables equal to l, the number of labelled points. In LapSVM, if the number of labelled data points is l and the number of unlabeled data points is n (where usually $n \gg l$), then the relationship between data points is found by a linear system of n equations and variables. Belkin et al. [15] also proposed the Manifold Regularization method, which is based on the geometry of marginal distribution: Assuming that the probability of the distribution of data has a Riemannian manifold (say, M), labels of two points that are close to one another in the intrinsic geometry of P_x will be similar or the same sense the conditional probability distribution $P(y|x)$ should change little between two such points. LapSVM follows the principals behind manifold regularization with hinge loss function [19]. Hinge loss function forgives noise introduced to the training data.

In recent years there has been a major focus on employing a primal approach to solve nonlinear LapSVM problems rather than the dual approach that was being used in the original LapSVM. The original—or dual—LapSVM requires two steps in training, but using the primal form allows us to collapse training to a single step. This is done by setting a maximum number of iteration and checking the stability of the classifier after every few iterations of training. The classifier function is finalized when a maximum number of iterations or stability is reached. The advantages of the primal approach over the dual approach are the use of the greedy technique in building the classifier, an efficient solution to the original problem with no need for variable switching, and the faster computation of the approximate solution

with an unseen pattern in it in combination with a priori-specified probabilities. For better evaluation of classifying boundaries shaped by a trained classifier, the test set has to include data points from both normal and near-miss incidents. Therefore, test data was picked from a data set that includes both types of data points.

5 Results

In our experiment, training and test data was selected from both labelled and unlabelled data. Each data set included 973 data points after sampling raw data points. Labelled validation data provides more information to compare than stable condition data. If a classifier function is trained using only stable condition data, it results in a non-informative decision system. However, validation data introduces more information to the decision system. The solution for the Primal LapSVM efficiency problem was generated by employing the Preconditioned Conjugate Gradient (PCG) [18]. PCG is an iterative algorithm that finds the numerical solution for a linear system containing many variables. A LapSVM is an example of such a system, and the decision boundary is an efficiency problem that we



a) b) c)

Figure 3: decision boundary between near-miss incidents (blue) and stable working condition (red) for a) Radial Basis Function Kernel b) Linear Kernel and c) Polynomial kernel

Since the mathematics of this topic are outside of the scope of this paper, we will not be dealing with them here. However, the future of LapSVM classifiers seems to be in the primal approach due to its promising performance accuracy, low memory consumption, and easier computation.

To detect near-miss incidents, we redefined data labels such that '-1' was a normal and stable working condition, and '1' was an anomaly or near-miss incident. Assuming that data was collected from an unknown probability distribution function, we needed to find a set

solved using PCG. We set the maximum number of iterations to 1000 iterations and set the classifier function to keep checking the stability of the classifier every three steps to determine whether the classifier was precise enough to quit the training process. Whether the classifier is precise enough or not depends upon measuring the error rate and stopping the training once the error rate is less than the user-defined value. In this experiment, the boundary value was set to 0.3.

Results show that for both subjects, the classifier could successfully detect all stable conditions. For a sampler size of data, a Radial Basis Function (RBF) kernel showed a better decision boundary when compared to Linear or Polynomial kernels (See Figure 3). RBF in nature usually acts as a low-band pass filter, it acts by smoothing decision boundaries formed by hyper plane defined by support vector machine. This smoothing is at the cost of some loss estimated by loss function, meaning we would allow some outliers in the decision boundary for sake of keeping hyper planes as smooth as they can be. Whether we can use it for different fall-related studies depends on many factors. We can try different kernels and based on "out of sample" results from cross validation we can choose the best kernel. Another factor would be computational complexity. Linear kernels usually compute much faster than radial or poly kernels. Data received from each test subject was processed using an RBF Kernel to train the classifier function while the distance between data points were measured by Euclidian distance. In our previous research [13] we used an OC-SVM in which the classifier was trained only on the positive class; however, in this research, the training and test sets were used without pre-processing in the sense of normalization. In both studies, the data set was divided to 60% training set and 40% test set. We used the PCG method to solve the LapSVM optimization problem rather than Newton's method to prevent unnecessary iterations [18]. We can see that for both test subjects, Primal LapSVM using PCG optimization produced a classifier in a shorter amount of time compared to the dual approach used in the OC-SVM. Also, the experiments showed that Primal LapSVM using the PCG method achieved the same accuracy as before, if not better. While the error rate for both test subjects was satisfactory, the algorithm also resulted in a faster training process (See Table 1 and 2). A more in-depth look at the accuracy of the Primal LapSVM is presented in table 3. Comparison between Primal LapSVM and OC-SVM is based on previous research [17] and was performed only on subject 1. For this comparison we measured Precision and Recall.

Table 1 Comparing Primal LapSVM and OC-SVM

	Primal LapSVM	OC-SVM
Time Elapsed for training (sec) Subject 1	5.99	9.42
Time Elapsed for training (sec) Subject 2	5.61	8.79

Table 2 Negative Predictive Value for Primal LapSVM and OC-SVM

	Primal LapSVM	OC-SVM
Negative Predictive Value Subject 1	93.4	91.2
Negative Predictive Value Subject 2	93.8	92.7

Since we aimed to detect near-miss incidents—which are rare—we need a metric that would compare the number of detected incidents against the total number of incidents in the data set. The Negative Predictive Value compared the total number of true near-miss incidents in the data set to the total number of data points classified as near-misss by the classifying function. (As this value gets closer to 100%, fewer near-miss incidents are wrongly classified as stable by the classifier function.) The error rate was counted as the count of incidents where the prediction of the classifier function didn't agree with real-world data.

Table 3 Performance of Primal LapSVM on Two Test Subjects

	Subject 1	Subject 2
Precision	100%	100%
Recall	99%	99%
Negative Predictive Value	93.4%	93.8%
Error Rate	0.5%	0.1%
Training Duration (Sec)	5.99	5.61

6 Conclusion and Future Work

In this research, we improved previous methods of automatic detection of near-miss incidents [17] by both enhancing the level of accuracy of the trained classifier and decreasing the computational complexity involved in the training. Using a Primal LapSVM, the solving optimization problem for the classifier function was reduced from cost of $O(n^3)$ to $O(kn^2)$. Significant improvements in memory consumption and the time spent on generating an approximate classifier raises hope for applying greedy techniques for incremental classifier building in future. This study focused on near-miss accidents during walking motion as an advocate for measuring the success of the proposed algorithm. Study showed very promising near-miss accidents detection. When used with different movements, a two level classification is required. The first level of classification aims at detecting each action. Second level of classification will detect near-miss accidents specifically trained for that motion, which is left for the future work. However, this new model proposed in this research does provide the construction industry with an opportunity to improve safety and identify fall accidents before they actually happen.

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