ICCEPM 2022
The 9th International Conference on Construction Engineering and Project Management
Jun. 20-23, 2022, Las Vegas, NV, USA

Automated Phase Identification in Shingle Installation Operation Using Machine Learning

Amrita Dutta[1]*, Scott P. Breloff[2], Fei Dai[1], Erik W. Sinsel[2], Christopher M. Warren[2], John Z. Wu[2]

[1] *Department of Civil and Environmental Engineering, West Virginia University, P.O. Box 6103, Morgantown, WV 26506; Email: {amdutta@mix, fei.dai@mail}.wvu.edu*
[2] *National Institute for Occupational Safety and Health, 1095 Willowdale Road, Morgantown, WV 26505; Email: {sbreloff, ESinsel, cpw4, ozw8}@cdc.gov*

Abstract: Roofers get exposed to increased risk of knee musculoskeletal disorders (MSDs) at different phases of a sloped shingle installation task. As different phases are associated with different risk levels, this study explored the application of machine learning for automated classification of seven phases in a shingle installation task using knee kinematics and roof slope information. An optical motion capture system was used to collect knee kinematics data from nine subjects who mimicked shingle installation on a slope-adjustable wooden platform. Four features were used in building a phase classification model. They were three knee joint rotation angles (i.e., flexion, abduction-adduction, and internal-external rotation) of the subjects, and the roof slope at which they operated. Three ensemble machine learning algorithms (i.e., random forests, decision trees, and k-nearest neighbors) were used for training and prediction. The simulations indicate that the k-nearest neighbor classifier provided the best performance, with an overall accuracy of 92.62%, demonstrating the considerable potential of machine learning methods in detecting shingle installation phases from workers knee joint rotation and roof slope information. This knowledge, with further investigation, may facilitate knee MSD risk identification among roofers and intervention development.

Key words: machine learning based methods, knee musculoskeletal disorders, roofer safety

1. INTRODUCTION

Residential roofers spend more than 75% of their working time in awkward kneeling postures while performing shingling activities on sloped rooftops [1]. Due to prolonged and repeated awkward kneeling, roofers frequently encounter significant amount of rotation in their knee joints. Roof slope and awkward kneeling postures have been identified as contributing risk factors of work-related knee musculoskeletal disorders (MSDs) in the roofing community [2]. The authors' prior work demonstrated that roofers get exposed to increased risk of knee MSDs at different phases of a sloped shingle installation task [3]. Some of the phases are relatively riskier than others in terms of awkward knee joint rotation. For example, roofers get exposed to the highest amount of awkward knee joint rotation during placing and nailing shingles; hence these are potentially the two riskiest phases of shingle installation that may lead to development of knee MSDs. To avoid potential injuries or disorders, it is crucial to identify if a roofer is spending an unusual amount of time in a particular phase, especially in relatively riskier phases, such as placing and nailing shingles, with greater awkward rotation and repetition. This requires automated and accurate categorization of each knee joint rotation angle by understanding the postural differences among different shingling phases, based on the activities roofers perform at residential roofing task. However, knowing if knee joint rotation angles are able to accurately identify the activities of the phases of shingle installation has not been identified in the literature. This study focuses on investigation of the application of machine learning for automated identification of seven phases of a shingle installation task, namely: 1) reaching for shingles (P1), 2) placing shingles (P2), 3) grasping the nail gun (P3), 4) moving to the first nailing position (P4), 5) nailing shingles (P5), 6) replacing the nail gun (P6), and 7) returning to upright position (P7), using knee kinematics data and roof slope information. A simulated laboratory experiment was conducted to examine these phases. Three supervised machine learning classifiers were trained to classify the seven phases using knee kinematics variables and roof setting data. The findings may help understand if machine learning application can be extended to develop effective interventions, such as, an automated activity monitoring system that uses knee joint rotations and roof slope observations as informative sources to facilitate knee MSDs risk identification among roofers in roofing jobsites.

2. BACKGROUND

There has been an increasing number of studies that utilize machine learning to classify human activities and its associated postures in occupational tasks. For example, in the construction industry, supervised machine learning methods were used to identify different awkward postures of construction workers [4,5], to detect inadequate posture of workers at work [6], calculate ergonomic risks in occupational tasks associated with overexertion [7], for awkward posture recognition [8], to analyze the handler's foot placement strategies during lifting load [9], to identify safe and productive pose of mason workers [10] and to predict injury type, energy type, and body part during construction task [11]. In the area of biomechanics and gait research, machine learning has been used to detect lying postures [12], sitting posture [13], surface- and age-related differences in walking [14] and changes in gait parameters [15]. Among multiple machine learning algorithms utilized in these works, random forests, decision trees, k-nearest neighbors, and support vector machines are most widely used for awkward posture recognition and activity classification which have proved promising in classification and detection, with an accuracy ranging from 83% to 98%. However, it remains unknown if these machine learning algorithms can contribute to the activity recognition in construction roofing tasks. To the best of the authors' knowledge, there is no study that has analyzed the postural differences involved at different phases of a roofing shingle installation task by means of classifying the phases using knee kinematics and roof setting information. Therefore, there is a lack of knowledge about the possibility of automated recognition of roofers' activity during shingle installation and identification of the risky phases with the application of machine learning.

3. RESEARCH OBJECTIVE

The objective of this study was to analyze the effectiveness of machine learning methods to classify different phases of a residential shingle installation roofing task, specifically, to determine if knee kinematics (knee joint rotations) of roofers and roof setting information (roof slope) at which they operated, can be used to distinguish among different phases of shingle installation.

4. METHODOLOGY

A schematic overview of the research methodology is displayed in Figure 1. A laboratory-based experiment was conducted where nine participants simulated a roofing shingle installation task on a sloped platform, mimicking the roof surface. Trajectory data of the participants were collected during simulation using an optical motion capture system equipped with retroreflective markers. The markers' coordinates were further processed to compute the knee joint rotation angles along sagittal (flexion), coronal (abduction-adduction), and transverse plane (internal-external rotation). These rotation angles together with roof slope angle were used as features for classifying the phases. Then, feature data were divided into separate training, validation and testing sets. The training and validation sets were used to build three supervised and non-parametric machine learning classification models - random forest (RF), decision tree (DT), k-nearest neighbors (KNN); the testing set was used as a hold-out set that represented the data that had never been used in training, to evaluate the performance of the built models. Finally, the performances of the three classification models were compared to decide the single best classifier that could provide the most accurate results.

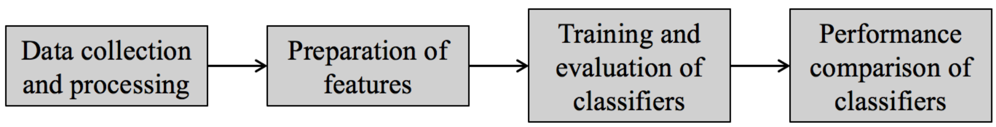

Figure 1. Overview of the research methodology

5. EXPERIMENT AND IMPLEMENTATION

5.1. Participants

This study included nine male participants [26.1 years (mean) ±5.6 years (standard deviation), 180.2 cm (mean) ±6.1 cm (standard deviation), and 99.7 kg (mean) ±27.6 kg (standard deviation)] without any prior roofing experience in the experiment. No participant was suffering from any known MSD or neurological diseases. The research protocol was approved by both the Institutional Review Boards (IRBs) of the National Institute for Occupational Safety and Health (NIOSH) and West Virginia University.

5.2. Instruments and data collection procedure

A VICON optical motion capture system equipped with 14 MX Vicon cameras (Oxford, UK) was used to collect the segment endpoint data of the participants. Forty-two (42) retroreflective markers for motion capture were placed bilaterally on the lower extremities of the participants including feet, heels, toes, ankles, shanks, knee joints, thighs, and hip joints (Figure 2).

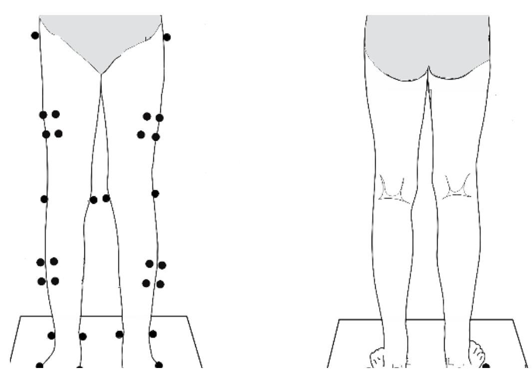

Figure 2. Roofing marker setup [3]

Three-dimensional (3D) coordinates of these markers (trajectory data) were provided by the VICON optical motion capture system which were subsequently used to calculate the knee joint rotation angles. A 1.2 ×1.6 m custom-made adjustable wood platform was used to mimic the roof surface for shingle installation. A battery powered lift would raise the roof platform which could be adjusted to a slope angle ranging from 0° to over 30° by two sets of wooden legs. More details on the data collection procedure are available in reference [2].

The experiment was conducted in the NIOSH Biomechanics Laboratory. The participants were fitted with motion markers for kinematic calibration and data collection. For data collection, subjects would first assume a deep kneeling posture on the residential roof. When subjects were instructed to start, they first reached for and placed two shingles in front of them. Then they picked up the nail gun from their right side and mimicked affixing six nails (three in each) into the two shingles side by side on the roof simulator, starting on the left and moving to the right of the shingle. Once finished, the participants replaced the nail gun and returned to their resting/starting position. Similar to a previous study done by the authors, the entire shingle installation could be divided into seven phases, as depicted in Figure 3 [3]. Each participant performed the simulated shingle installation task on the roof simulator at three slope angles — 0°, 15°, and 30°. At each slope angle, the requested task was repeated five times. This resulted in a total of 45 trials data (5 trials × 9 participants) at each of the slope angles. All data were recorded at a sampling rate of 100 Hz.

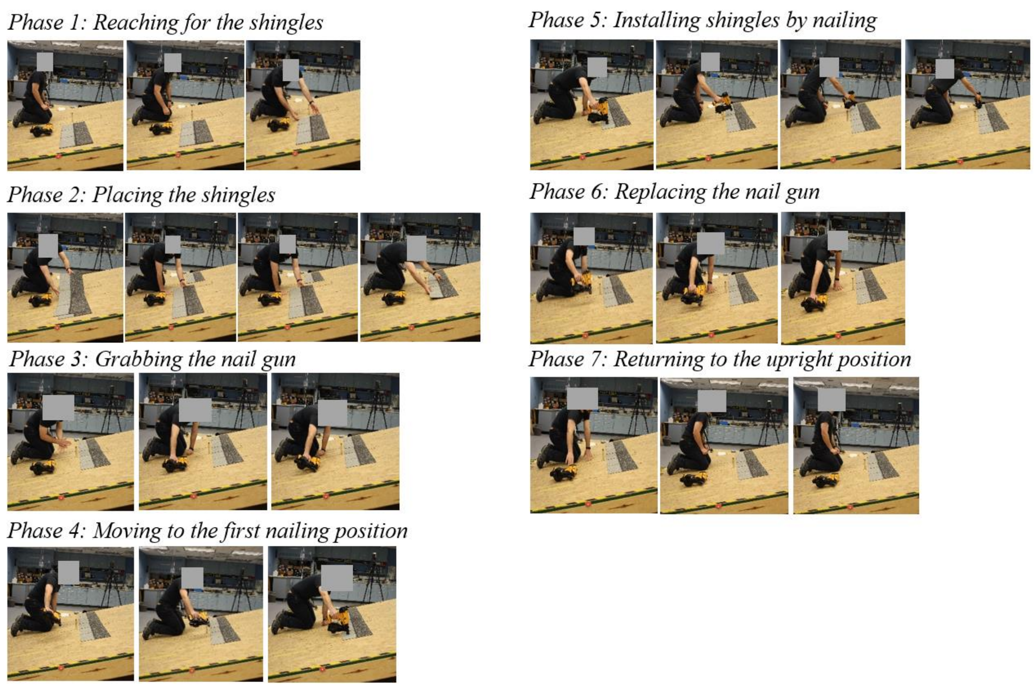

Figure 3. Seven phases of shingle installation process

5.3. Data processing

Trajectory data (coordinates of the markers) captured by VICON were filtered in Visual 3D (C-Motion, Germantown, Maryland), using a 4th order Butterworth filter with a 6Hz cut off. Using these trajectory data, knee joint flexion, abduction-adduction and internal-external rotation were computed using the method provided by [16]. These knee joint rotations and roof slope angles were used as input feature set as summarized in Table 1.

Table 1. Collected variables (features)

Features	Unit	Variable type	Range/value
Flexion (FL)	Degree (deg)	Numerical	77° to 163°
Abduction-adduction (AB_AD)	Degree (deg)	Numerical	-18° to 18°
Internal-external rotation (IN_EX)	Degree (deg)	Numerical	-22° to 32°
Roof slope (S)	Degree (deg)	Categorical	0°, 15° and 30°

5.4. Training and evaluation of classifiers

A total of 148,574 time-series data points of knee joint rotation angles were collected from 45 trials data for three roof slope angles. Ninety percent of the feature data were used for training and validation, and the remaining ten percent (hold-out) were used for testing. For building the classification models with minimized bias, variance, and overfitting, a 10-fold cross validation was conducted for each classification approach where all observations in the training and validation set were randomly assigned to 10 separate folds (10% each). Then the classifier was trained using 9 of the folds and validated using the remaining fold. The accuracies obtained from the 10 resulting folds were thus averaged to provide the mean cross validation accuracy for the input feature set. During the building process of each classification model, the classifier's specific parameters were tuned to obtain the optimal performance from the classifiers according to the procedures described in [17–19]. For each classifier, after parameter tuning, the best performing model was determined by the highest mean cross-validation accuracy.

The testing dataset (hold-out) was used to evaluate the prediction performance of each classifier on untrained data. Specifically, the predicted values were compared with the ground truth by applying three performance metrics: (a) overall accuracy (ratio of correctly predicted observations to the total observations), (b) Precision score (number of observations correctly predicted over the number of observations predicted), (c) Recall score (number of observations correctly predicted over the actual number of observations that should have been returned correctly), (d) F1 score (harmonic mean of precision and recall), and (e) Kappa index (weighted average of Precision and Recall that indicates agreement between predicted observations and ground truth observations). The training and evaluation process was carried out for each of the three classifiers. After computing the mean cross-validation accuracy, overall accuracy, precision, recall, F1 score and Kappa index for each classifier, the values of these performance metrics computed for all the three classifiers were compared. The classifier with the highest mean cross-validation accuracy, overall accuracy, precision, recall, F1 score, and Kappa index values were deemed to provide the best phase classification results and hence finally selected as the best performing phase classification model. Each classification algorithm was applied using the standalone Python programming language (version 3.6.4).

6. RESULTS

Mean cross-validation accuracy along with standard deviations and the lowest cross-validation accuracy obtained from different classifiers are shown in Table 2.

Table 2: Mean cross-validation accuracy of phase classification

Classifier	Mean Cross-validation accuracy ± standard deviation	Lowest cross-validation accuracy (%)
DT	87.00 ± 0.0058	86.63
RF	90.87 ± 0.0041	90.55
KNN	**92.16 ± 0.0041**	**91.79**

For different classifiers, overall accuracy, F1 score, precision score, recall score and Kappa index are provided in Table 3.

Table 3: Performance metrics of three classification approaches

Classifier	Overall accuracy (%)	F1 score	Precision score	Recall score	Kappa index
DT	87.29	0.8729	0.8730	0.8729	0.8407

RF	91.12	0.9106	0.9107	0.9112	0.8880
KNN	**92.62**	**0.9260**	**0.9220**	**0.9262**	**0.9020**

Tables 2 and 3 show the KNN classifier was the most accurate in differentiating among the seven phases. An overall classification accuracy of 92.62% and mean cross-validation accuracy of 92.16% was achieved by this classifier. The highest precision, recall and F1 scores (0.9220, 0.9262, and 0.9260 respectively) were also obtained from this classifier. High precision relates to low false positive rates, while high recall relates to a low false negative rate in the prediction. F1-score indicating the harmonic mean of precision and recall with a value close to 1 gives a better indication of the KNN classifier's ability to correctly identify the phases that standard classification accuracy alone. Kappa index value of 0.902 indicates an excellent agreement between the test data and the predicted data as a range of 0.81 to 1.00 indicates almost a perfect agreement.

Table 4: Confusion matrix by KNN (k=1) classifier using four features

	Class	**Actual**							**Total**	$\boldsymbol{Precision_i}$
		P1	P2	P3	P4	P5	P6	P7		
Predicted	P1	1534	25	1	5	9	10	43	1627	0.943
	P2	35	4878	79	79	49	30	32	5182	0.941
	P3	3	63	661	34	9	3	4	777	0.851
	P4	4	51	35	1153	38	23	11	1315	0.877
	P5	12	59	9	46	2933	49	20	3128	0.938
	P6	9	24	3	15	40	1054	26	1171	0.900
	P7	52	20	7	5	8	17	1549	1658	0.934
	Total	1649	5120	795	1337	3086	1186	1685	14858	
	$\boldsymbol{Recall_i}$	0.930	0.953	0.831	0.862	0.950	0.889	0.919		

Table 4 represents the confusion matrices by KNN classifier, where per-class classification accuracies in terms of precision and recall have been provided. The diagonal elements of the confusion matrices represent the number of observations for which the predicted class is the same as the actual class, while off-diagonal elements are those that are not predicted correctly by the classifier. The higher the diagonal values of the confusion matrix the better, indicating that the classifier could make many correct predictions. For example, in Table 4, $Precision_1$ 0.943 of class P1 indicates that, out of the total number of observations classified as P1, 94.3% were correct. A Recall value of 0.930 indicates that out of all the observations that actually belong to class P1, 93% were classified as P1.

7. DISCUSSION AND CONCLUSION

The purpose of the current study was to investigate the application of machine learning to classify roofers' activities in shingle installation process using knee joint rotation and roof slope information. Three classification methods - decision tree, random forest, and k-nearest neighbors - were tested in this study. The performance of the classifiers was assessed using 10-fold cross-validation technique to avoid overfitting. The classifiers were evaluated by using an untrained test dataset, which assessed whether including new data collected in future observations to existing data would result in acceptable detection and classification of the shingle installation phases. The classification result suggested that the highest testing accuracy of 92.62% was obtained by the KNN classifier. Although several studies have focused on awkward posture recognition, there is limited information on its identification in a work context. As roofers encounter both awkward postures and repetitive motions during shingle installation,, which are considered to be major contributing factors of MSDs, knee MSDs incident rate is also the highest among roofers. Proper identification of these two factors and the duration roofers are spending in awkward posture and repetitive motions can minimize the exposures of the roofers and alleviate the chances of knee MSDs. This study has demonstrated the discriminant ability of machine learning to recognize the shingling phases based on roofers' knee joint rotation angles and residential roof setting information where they operate. The current study has implications to both researchers and practitioners in the field of occupational safety and health and in the construction industry. There is great potential for the implementation of machine learning, along with any non-invasive biomechanical device or inertial measurement units (IMUs) capable of measuring knee rotational kinematics in dynamic movement, which can help develop automated activity monitoring system as an intervention for the roofers. In this way, roofers' postures can be continuously monitored and evaluated throughout the entire sloped shingle installation task. It can also be observed if a worker is spending an unusual amount of time in a particular phase, especially a risky one with greater awkward rotation and repetition, such as placing and nailing.

This study has several limitations. First, only knee kinematics and roof slope information were used as features in this study. Activation of the knee postural muscles were not considered. Awkward postures can result in higher muscle activation and muscle overloading, which can cause knee MSDs. Second, the participants were not real roofers, and the experiment was conducted in a laboratory setting. It is possible that novices and expert roofers may have different installation strategies in real world roofing setting. Future studies will explore effects of knee postural muscle activation on shingle installation phase classification to examine if muscle activation can yield useful discriminative features for in-depth understanding of postural differences among the phases. In addition, application of deep neural network learning models will be further investigated to get more insights on the underlying classification mechanisms. Finally, applications of models from the present study will be extended to real world roofing settings, to examine the feasibility of automated recognition with the participation of professional roofers.

ACKNOWLEGEMENTS

The authors acknowledge the support of NIOSH, who funded this research. The findings and conclusions in this report are those of the authors and do not necessarily represent the official position of the National Institute for Occupational Safety and Health, Centers for Disease Control and Prevention.

REFERENCES

[1] D. Wang, F. Dai, X. Ning, Risk assessment of work-related musculoskeletal disorders in construction: State-of-the-art review, J. Constr. Eng. Manag. 141 (2015) 4015008.

[2] S.P. Breloff, A. Dutta, F. Dai, E.W. Sinsel, C.M. Warren, X. Ning, J.Z. Wu, Assessing work-related risk factors for musculoskeletal knee disorders in construction roofing tasks, Appl. Ergon. 81 (2019). https://doi.org/10.1016/j.apergo.2019.102901.

[3] A. Dutta, S.P. Breloff, F. Dai, E.W. Sinsel, C.M. Warren, J.Z. Wu, Identifying Potentially Risky Phases Leading to Knee Musculoskeletal Disorders during Shingle Installation Operations, J. Constr. Eng. Manag. 146 (2020). https://doi.org/10.1061/(ASCE)CO.1943-7862.0001783.

[4] M.F. Antwi-Afari, H. Li, Y. Yu, L. Kong, Wearable insole pressure system for automated detection and classification of awkward working postures in construction workers, Autom. Constr. 96 (2018) 433–441.

[5] J. Chen, J. Qiu, C. Ahn, Construction worker's awkward posture recognition through supervised motion tensor decomposition, Autom. Constr. 77 (2017) 67–81.

[6] E. Barkallah, J. Freulard, M.J.-D. Otis, S. Ngomo, J.C. Ayena, C. Desrosiers, Wearable devices for classification of inadequate posture at work using neural networks, Sensors. 17 (2017) 2003.

[7] N.D. Nath, T. Chaspari, A.H. Behzadan, Automated ergonomic risk monitoring using body-mounted sensors and machine learning, Adv. Eng. Informatics. 38 (2018) 514–526.

[8] I. Conforti, I. Mileti, Z. Del Prete, E. Palermo, Measuring biomechanical risk in lifting load tasks through wearable system and machine-learning approach, Sensors. 20 (2020) 1557.

[9] A. Muller, J. Vallée-Marcotte, X. Robert-Lachaine, H. Mecheri, C. Larue, P. Corbeil, A. Plamondon, A machine-learning method for classifying and analyzing foot placement: Application to manual material handling, J. Biomech. 97 (2019) 109410.

[10] A. Alwasel, A. Sabet, M. Nahangi, C.T. Haas, E. Abdel-Rahman, Identifying poses of safe and productive masons using machine learning, Autom. Constr. 84 (2017) 345–355.

[11] A.J.-P. Tixier, M.R. Hallowell, B. Rajagopalan, D. Bowman, Application of machine learning to construction injury prediction, Autom. Constr. 69 (2016) 102–114.

[12] S. Caggiari, P.R. Worsley, Y. Payan, M. Bucki, D.L. Bader, Biomechanical monitoring and machine learning for the detection of lying postures, Clin. Biomech. 80 (2020) 105181.

[13] R. Zemp, M. Tanadini, S. Plüss, K. Schnüriger, N.B. Singh, W.R. Taylor, S. Lorenzetti, Application of machine learning approaches for classifying sitting posture based on force and acceleration sensors, Biomed Res. Int. 2016 (2016).

[14] B. Hu, P.C. Dixon, J. V Jacobs, J.T. Dennerlein, J.M. Schiffman, Machine learning algorithms based on signals from a single wearable inertial sensor can detect surface-and age-related differences in walking, J. Biomech. 71 (2018) 37–42.

[15] A. Baghdadi, F.M. Megahed, E.T. Esfahani, L.A. Cavuoto, A machine learning approach to detect changes in gait parameters following a fatiguing occupational task, Ergonomics. 61 (2018) 1116–1129.

[16] D.G.E. Robertson, G.E. Caldwell, J. Hamill, G. Kamen, S. Whittlesey, Research methods in biomechanics, Human kinetics, 2013.

[17] J.L. Grabmeier, L.A. Lambe, Decision trees for binary classification variables grow equally with the Gini impurity measure and Pearson's chi-square test, Int. J. Bus. Intell. Data Min. 2 (2007) 213–226.

[18] L. Breiman, Random Forests, Mach. Learn. 45 (2001) 5–32. https://doi.org/10.1023/A:1010933404324.

[19] N. Roussopoulos, S. Kelley, F. Vincent, Nearest neighbor queries, in: Proc. 1995 ACM SIGMOD Int. Conf. Manag. Data, 1995: pp. 71–79.