Human Activity Recognition Using Wearable Sensors on Silvicultural Workers

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Pamela Matute, Researcher, Fibre Supply

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REVIEWERS

Olivier Tsui, Researcher,
Remote Sensing, Supply Chain Analytics

CONTACT

Pamela Matute, FIT
Researcher, Fibre Supply
604-222-5698
Pamela.Matute@fpinnovations.ca

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1. INTRODUCTION

Recent advances in ubiquitous sensing, such as accessible, wearable sensing technology and the emerging field of big data analytics have sparked the current wave of interest in self-tracking by means of personal wearable devices that quantify everyday activities and improve behaviours and processes. This trend is quickly extending into the workplace: It is estimated that by 2020, over 75 million wearable devices will be used in the workplace (Kaul and Wheelock, 2016). In this context, knowledge extracted from pervasive sensor data can lead to improvements in the health and productivity of workers and to gains in data-driven operational efficiency across a wide spectrum of sectors.

Most wearable sensing systems used for activity tracking make use of human activity recognition (HAR) technology linked to a variety of sensors for measuring acceleration, environmental attributes, location, physiological signals, etc. HAR is a detection, recognition and classification problem and as such it is best handled by machine learning tools that are able to analyze, recognize and predict patterns in large data sets. In particular, classifier algorithms are used in activity recognition to analyze data sets and predict to which category (i.e., activity, in this case) a new instance (i.e., time unit) belongs to. Classifier algorithms commonly used in activity recognition applications include decision trees (e.g., ID3, C4.5, CHAID), Bayesian methods (e.g., Bayesian networks, Naïve Bayes), neural networks and instance-based learning, among others. Of these algorithms, decision trees produce the most intuitive models, have the lowest computation costs and tend to be the most accurate tools for activity-recognition problems (Lara & Labrador, 2013).

This study explores HAR with wearable sensors in the context of manual silvicultural operations. The objective of this study was to develop an activity predictive model capable of recognizing specific activities performed by silvicultural workers. Data were collected from a variety of sensors located on silvicultural workers' bodies for two operational scenarios: Manual tree planting work and manual pre-commercial thinning work. The C4.5 and CHAID (chi-square automatic interaction detector) decision tree algorithms were used to develop both models. This work will provide the basis for the development of a wearable sensor system that can track a worker's physical motions and physiological signals and provide activity and productivity information to the worker.

Applications for such a tool range from enabling cost-effective time and productivity studies, to providing a tool that helps tree planters become more aware of their work habits, regulate their performance and prevent injuries by monitoring the planter's biometric data linked to specific work duties. On a larger scale, the concept could also be further developed to streamline reforestation operations by providing information about the spatial location of individual seedlings. This info would help in estimating actual planting density and in identifying missed (unplanted) areas or tree-stashing problems in a timely manner.

2. METHODOLOGY

Data collection

Data were collected from silvicultural workers in two operational scenarios: Tree planting and pre--commercial thinning.

For the tree planting scenario, heart rate (bpm), speed (m/min) and motion (g) were measured for eleven tree planters over the course of three days in naturalistic conditions and without researcher intervention. Heart rate and location data were collected every 1 sec with a Garmin GPSMAP 62s unit connected to a Garmin heart rate monitor chest band (Figure 1). Each planter's resting heart rate was measured to establish a baseline and provide a measure of fitness and to allow comparisons between planters. Speed and distance were calculated from the GPS data.

Figure 1. Instruments used for data collection Accelerometer, heart rate chest band, GPS unit and sound level meter

Motion was measured with a GDC X16-1D ±16g triaxial accelerometer positioned on each tree-planter's back, secured to the back strap of the planting bag. While wrist-worn devices would improve ease of use and length of wear time, the back was chosen in this study since activity recognition from wrist-worn sensors presents challenges due to the high variability of movement of the limbs (Zhang, et al., 2012, Mannini, et al., 2013). This is particularly the case with tree planters because many of them are ambidextrous when using planting shovels. The accelerometer collected data at a sampling rate of 25 Hz or 25 records per second. The accelerometer sampling rate was based on work by Maurer et al. (2006) who found that no significant gains in accuracy are obtained with frequencies over 20 Hz.

The activity at each instance or time point was labelled manually. Three main physical activities associated with tree planting were identified and used in model training: Preparation work, walking and planting. Preparation work is an umbrella term that includes light work (e.g., preparing gear prior to planting), refilling planting bags at the tree cache and resting.

For the pre-commercial thinning scenario, heart rate, speed, distance (m) and sound intensity (dB) were measured for five workers. Data collection for pre-commercial thinning operations was conducted in a different way due to the nature of the work duties: A data-logging sound-level meter from Reed Instruments (model IA799) was used instead of an accelerometer in order to capture the sound of working brush saws. Sound intensity, heart rate and GPS location were measured every 10 sec. Two of the workers lacked sound intensity measurements and were excluded from the data set during model development. Speed and distance were calculated from the GPS data. The physical activities observed and included in the model and in the training data set were: Thinning, moving, resting, performing maintenance tasks (e.g., fuelling) and preparing to work. However, due to the poor differentiation in heart rate and speed between these activities, they were simplified into productive (thinning) time and non-productive (not thinning) time.

Data Processing and Feature Extraction

Accelerometer data required further pre-processing before it could be used as input for model training and development. Figure 2 shows raw acceleration data and the different acceleration patterns for each of the three physical activities in the tree planting scenario. To extract pattern information from the raw data, several statistical features were calculated from 1-sec non-overlapping time windows (equivalent to 25 acceleration records). A variety of window lengths, ranging from 1 to 30 sec (Lara & Labrador, 2013), have been used successfully in activity recognition problems, but Banos et al. (2014) recommend a window length of 1 to 2 sec for recognition speed and accuracy of whole-body activities, such as walking or planting.

The following 13 features were extracted from the acceleration signals:

- Mean acceleration in each axis (e.g., x, y and z)
- Standard deviation of acceleration in each axis (e.g., x, y and z)
- Average absolute difference between individual acceleration signals and time window average for each axis
- Average resultant acceleration, measured as the time window average of the root sum squared of all axis
- MinMax value for each axis, defined as the difference between maximum and minimum acceleration signals on each time window

These features were used as independent variables in the development of the tree planting model. Other variables used to build the model were: Speed, heart rate, heart rate at rest and effort as measured by the difference between heart rate and heart rate at rest for each tree planter. For the pre-commercial thinning model, the only independent variables used were sound intensity, heart rate, speed and distance covered.

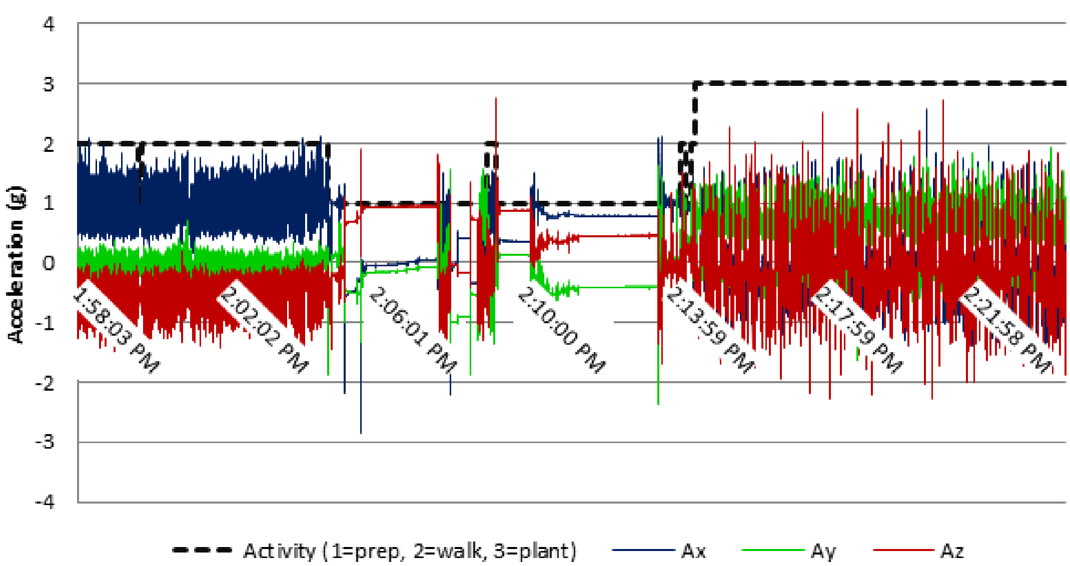

Figure 2. Sample acceleration signals show differences in signal structure during the three physical activities in the tree planting scenario: preparation work, walking, and planting

Classification Algorithm

The C4.5 and CHAID decision tree algorithms were used to build an exploratory decision tree to predict which activity a worker was undertaking (i.e., preparation work, walking or planting) given a set of independent variables (i.e., heart rate, speed, etc.).

In order to classify an instance into the most likely activity class, a decision tree identifies the most significant independent variable and the best way to split it. In a decision tree, each node denotes a test on a variable and each leaf holds a homogeneous set of the population with an assigned predicted category. C4.5 remains the most popular decision tree algorithm in HAR classification problems and while CHAID is not often used in the context of activity recognition, it can use the same type of data and produce similar outputs (Arentze, et al., 2000). CHAID studies the relationship between a dependent variable and independent or predictor variables and uses a chi-square independence test for splitting nodes. By contrast, C4.5 uses information gain, or decrease in entropy, as the splitting criterion. The data-mining software called Sipina Research (version 3.12) was used to create the decision trees.

The performances of the decision trees were then evaluated in terms of overall accuracy when predicting activities and F-measure for each activity class. F-measure is a classifier evaluation metric ranging from 0 to 1, where 1 means perfect activity prediction. It combines precision (ratio of correctly classified positive instances to the total number of instances classified as positive) and recall (ratio of correctly classified positive instances to the total number of positive instances) in a single value:

$$F - measure = 2 \times \left(\frac{precision \times recall}{precision + recall}\right)$$

3. RESULTS

The tables in Appendix 1 summarize the data used in the model after data processing. Five planters chose to wear the planting bag without using the shoulder straps and so, these planters were excluded from the analysis. Similarly, all records with missing heart rate, sound or location data were deleted from both data sets. The data for each subject was then aggregated for model construction.

A five-fold cross-validation method was applied to train and test both algorithms for both data sets independently. In this method the data set is divided into five equal-sized subsamples. The classifier then runs for five iterations, using each of the subsamples for model testing at a time, while the remaining subsamples are used for training. The resulting prediction accuracy is then averaged and a confusion matrix is constructed.

The tables in Appendix 2 show the performance of the two decision tree algorithms for both scenarios (i.e., tree planting and pre-commercial thinning), and they show the confusion matrix that resulted from the cross validation exercise. The confusion matrix shows, for the total number of instances (i.e., seconds), what the actual activity was during those seconds vs. what the model predicted the activity to be. Appendix 3 provides a visual example of a C4.5 decision tree for pre-commercial thinning.

4. DISCUSSION

The best accuracy when predicting tree planting activities was achieved using the C4.5 classifier: The model could predict tree planter activity with 91.51% accuracy (i.e., only 4.22 h of the total 49.69 h were misclassified) (Appendix 2). But while C4.5 was better at predicting the activity, it had a much more complex tree architecture (Table 1) than the CHAID tree due to the latter's ability to control maximum tree depth. The tree planting confusion matrix shows that most of the error in both algorithms stemmed from a high proportion of walking instances being misclassified as planting, possibly due to uneven terrain and/or because the exercise effort level and ground speed for walking are similar to that of planting.

Table 1. Decision tree architecture

Architecture [a]	Algorithm	
	C4.5	CHAID
Nodes (no.)	1793	333
Leaves (no.)	897	167
Min. leaf size (no. instances)	10	10
Tree depth	36	10
Accuracy (%)	91.53	90.09

[a] For a single sample tree, using 80% of data as training data and 20% as testing data.

Prediction accuracies were higher in the pre-commercial thinning scenario for both classification algorithms (93.82% using CHAID and 94.15% using C4.5), thanks to the use of sound intensity as a variable. Sound intensity was significantly higher when brush saws were working than during unproductive time. A sound-level meter is therefore a key sensor to be included in the development of a wearable system for pre-commercial thinning workers.

Further exploration of feature sets, window lengths and machine learning algorithms could result in better prediction accuracies. Acceleration features used successfully in previous work that could be explored with our data set include energy, correlation and kurtosis, among others (Bao & Intille, 2004; Ravi et al., 2005). Similarly, a host of different algorithms other than decision trees and combinations of algorithms have proven to have high success rates in activity recognition problems (Ravi et al., 2005; Bayat, et al., 2014; Lu, et al. 2016). Future work in feature and algorithm selection should focus on differentiating between planting and walking activities.

One study weakness to note is the lack of diversity in research subjects, particularly in the tree planting scenario. Data were collected for subjects of different ages and sexes but some subjects had to be dropped during the analysis because they wore the straps of their planting bag off their shoulders and on their hip instead of in the required position of across the back. Further model refinement could still be possible by obtaining more data from a wider range of subjects in both scenarios.

5. CONCLUSION

This study proved that automatic activity recognition with wearable sensors is possible in tree planting and pre-commercial thinning operations. The data obtained during this project could be used as a starting point to develop an activity recognition system with 91.51% recognition accuracy for tree planting and 94.15% recognition accuracy for pre-commercial thinning operations. Further research could help refine the concept and achieve higher accuracies by testing different feature sets and algorithms. Such refinement would give way to more detailed outputs, such as providing the exact time planters spend bending over to plant, which in turn would allow for more detailed time studies and better performance tracking.

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7. APPENDICES

APPENDIX 1. SUMMARY OF DATA USED FOR MODEL CONSTRUCTION: TREE PLANTING AND PRECOMMERCIAL THINNING SCENARIOS

Tree planting data set

Tree planter	Total time (h)	Breakdown of time spent in each activity		
		Preparation (%)	Walking (%)	Planting (%)
TPS1	7.94	19.2	8.7	72.1
TPL1	7.91	35.0	7.8	57.2
TPM2	7.97	32.4	12.4	55.2
TPJ1	6.48	40.3	9.1	50.6
TPG1	10.82	25.0	13.1	61.9
TPM1	8.57	13.6	3.4	83.0
Total	**49.69**			

Pre-commercial thinning data set

Thinning worker	Total time (h)	Breakdown of time spent in each activity	
		Unproductive (%)	Productive (%)
PCTM1	3.39	29.5	70.5
PCTS1	5.15	28.3	71.7
PCTS2	5.12	35.0	65.0
Total	**13.66**		

APPENDIX 2. CONFUSION MATRIX AND EVALUATION METRICS FOR TWO CLASSIFICATION ALGORITHMS PREDICTING TREEPLANTING AND PRECOMMERCIAL THINNING ACTIVITIES

Tree planting data set [a]

Decision tree algorithm		Predicted activity: Preparation	Predicted activity: Walk	Predicted activity: Plant	F-measure	Total prediction accuracy (%)
C4.5						
Actual activity	Preparation	**6189**	93.6	469.8	0.92	91.51
	Walk	160.0	**1286.4**	804.4	0.66	
	Plant	316.4	278.4	**15411.2**	0.94	
CHAID						
Actual activity	Preparation	**7059.8**	90.8	566.6	0.92	91.37
	Walk	211.2	**1300.2**	1061.0	0.62	
	Plant	336.6	199.4	**17756.6**	0.94	

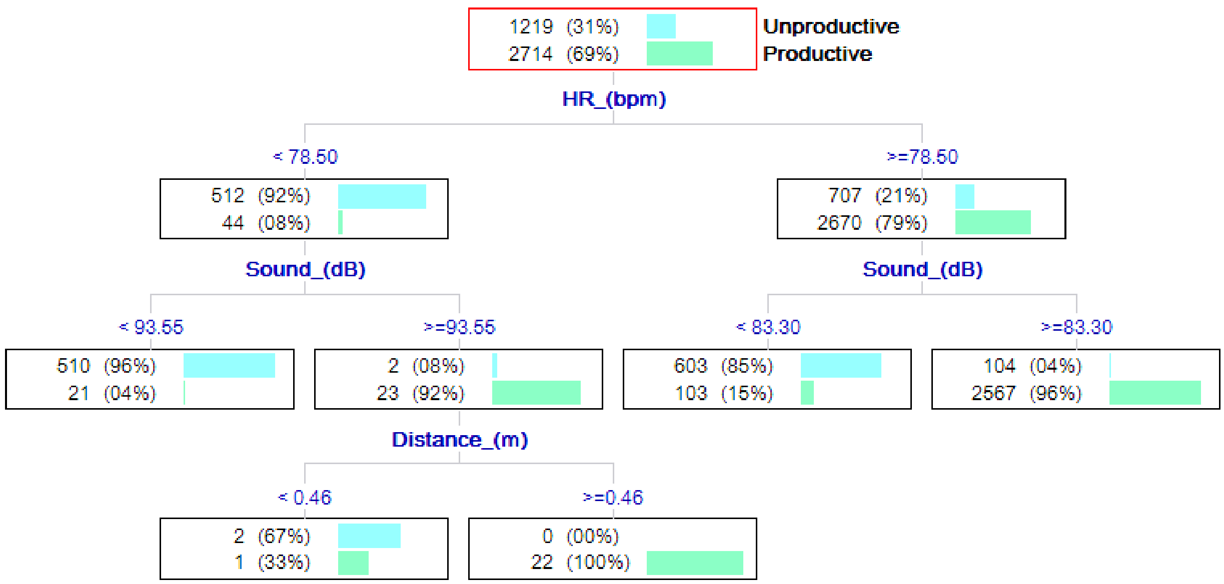
[a] White boxes: Number of instances (seconds) that were correctly classified. Grey boxes: Instances (seconds) that were incorrectly classified.

Pre-commercial thinning data set [b]

Decision tree algorithm		Predicted activity: Unproductive	Predicted activity: Productive	F-measure	Total prediction accuracy (%)
C4.5					
Actual activity	Unproductive	**222**	21.8	0.90	93.82
	Productive	26.8	**516**	0.95	
CHAID					
Actual activity	Unproductive	**221.4**	22.4	0.91	94.15
	Productive	23.6	**519.2**	0.96	

[b] White boxes: Number of instances (seconds) that were correctly classified. Grey boxes: Instances (seconds) that were incorrectly classified.

APPENDIX 3. EXAMPLE OF A C4.5 DECISION TREE FOR CLASSIFICATION OF PRECOMMERCIAL THINNING PRODUCTIVITY



FPInnovations®

Head Office

Pointe-Claire

570, Saint-Jean Blvd

Pointe-Claire, QC

Canada H9R 3J9

T 514 630-4100

Vancouver

2665 East Mall

Vancouver, BC

Canada V6T 1Z4

T 604 224-3221

Québec

319, rue Franquet

Québec, QC

Canada G1P 4R4

T 418 659-2647

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