Snow Depth Classification using MultiSensory Ubiquitous Platform and Machine Learning

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Abstract—**In the drastic period of climate change the continuous data monitoring of snow characteristic is required.The immensely impact of snow on hydro production, water resource management and its inhabitants, drive to the need for the importance of snow information such as its extent, dynamics and water it holds at global and local scale. At present, there are various approaches such as traditional ground-based approach, optical satellite imaging and the radio, which are available for snow monitoring at global scale. However, the use of these approaches incurs from large labor and high monitoring cost. Since, the advance in sensor technologies and Internet of Things (Iot), provides an appealing possibility to develop a framework for monitoring snow parameters at enormously low cost. In this study. we implemented two machine learning classifiers model based on the input acquired from the low-cost wearable sensor platform. The results of Random forest classifier showed the accuracy of 88.8%, indicate a promising alternative in snow depth measurements with in-situ validation, when data or wireless sensor network are not available or affordable.**

I. Introduction

Various studies have established and determined the relevance of snow to the climate system. Comprehending the snow occurrence and dynamic is essential to understand the phenomena like global warming, which primarily causes drastic change in climate condition. It also plays a key role in understanding ecological processes, climate feedback and frost penetration [1], [2], [3]. The need to monitor snow conditions in northern regions is very important for hydropower [4], domestic and industrial extraction, due to the seasonal runoff changes occurring at the period of spring flood, whereas, it is also considered important for prediction and prevention of flood [4], [5], [6]. Furthermore, snow accumulation and ablation are mass balance for glaciers and polar ices [7]. Ice layers in snow play a significant role for the timing of the snow melt release, for the potentials of quest for reindeers, small mammals, birds of prey and for avalanche risk assessment [8], [9]. Among factors often associated with snow information, one distinguishes snow depth, snow water equivalent (SWE), snow density, which provide handful information about the snow characteristics. Snow depth provides important information regarding soil process, water resources, surface energy and ecological system for snow cover studies. Similarly, it provides insights in identification of other relevant properties of snow such as SWE and snow density. Knowing these properties, allows the researchers to understand the structure and formation of snow pack as well as snow drift model [10].

Traditionally, manual investigations were used to measure the snow depth and snow density. The foremost benefits of such snow survey manual are the direct measurements and in situ validation of the snow depth and SWE data. Though, they are highly demanding in terms of time and labor and, sometimes become unfeasible in remote, complex or hazardous terrain [11], [12]. On the contrary, remote sensing instruments on airborne and space platforms are an alternative to groundbased measurements of snow properties. The advance in remote sensing technologies provided new ways of modalities and data with enhanced spatial and spectral resolution [13]. For instance, airborne laser scanning (ALS) is a remote sensing tool with the ability to retrieve surface elevations at high spatial resolutions in rough terrain and in heavily forested region [14]. Recently, the continuous adoption of this technology in measuring and mapping the snow surface characteristics are rapidly emerging as a new standard. To date, the methodology to calculate snow depth from airborne. Lidar data requires two datasets, one during the time when the surface is snow free and another when it is covered with snow and computed the difference of snow surface and bare ground using point to point, point to grid and grid to grid algorithm to estimate the snow depth [15], [16].

Both terrestrial [17] and airborne [18] Light Detection and Ranging (Lidar) technologies provided high resolution in estimating the spatial distribution of snow depth. Nevertheless, these technologies encounter some limitations as well. The key limitations for Terrestrial Laser Scanning were restricted only to easily observable and accessible areas. On the other hand, Airborne Laser Scanning requires a proper planning and repetitive flights which incur to long time and excessive expenses [19]. Though, the current techniques used are highly reliable. They are limited to provide spatial coverage at larger extent and demands operational costs time and labor, which calls for future research on the issue.

This study aims to overcome the above challenges (operational costs, time and labor experience in remote sensing technologies and WSN deployment challenges) by utilizing the low-cost sensor in the form of wearable device. The goal is to introduce a new perspective in data acquisition and analysis from a handed low-cost sensor in terms of wearable platform, for estimating and classifying the snow depth measurements.

II. Wearable platform

The wearable platform was developed by utilizing the synergy of three sensors, namely, flexi force sensitive resistor, temperature and humidity sensor and Bluetooth sensor,

Fig. 1. Bluetooth sensor is employed solely for transmission purpose. An android application was also developed to store the readings obtained from the sensors on a mobile application and send it over to a cloud platform for further processing.

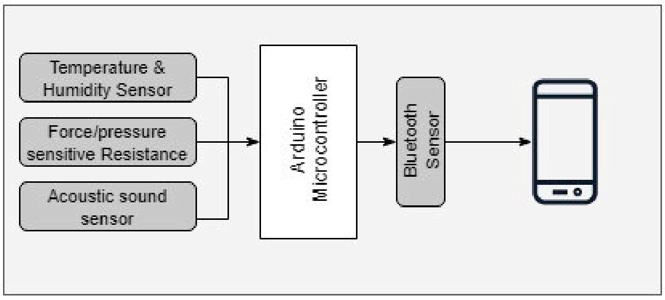

Fig. 1. Wearable platform: sensor and microcontroller communication

We have chosen DHT 22 temperature and humidity sensor, due to its high reliability, good stability and compatibility with Arduino platform. The DHT22 sensor consists of two parts: a capacitive humidity sensor, which is responsible for measuring the humidity, and a thermistor that measures the temperature of its surroundings. The sensor has the capacity to measure the temperature in the ranges from -40 to +125 degrees Celsius with +-0.5 degrees accuracy, offering excellent quality, fast response, anti-interference ability and cost-effectiveness. It can be easily interfaced with Arduino board, which enables us to read the temperature from the sensor and display it in the serial monitor. Flexi force sensor, also referred as the force sensitive resistor, is used for calculating the pressure value. It operates by changing its resistance when the external force, pressure or stress is applied. Here, Tekscan flexi force A 201 was employed. A fixed value resistor of 1Mohm is connected in a series with the FSR resistance. The connection of FSR with Arduino is established. In order to determine the force of unknown loads, a set of input-output voltage measurements were carried out, and the best linear fit is identified. For sensor-mobile communication purpose, the HC-05 Bluetooth sensor was selected because of its simplicity and capability of transferring the data over a short distance. The module can easily be interfaced with Arduino board. The logic voltage level of data pin of HC-05 is 3.3V. Therefore, the connection of data line between Arduino TX and RX needs to connect through a voltage divider in order to not burn the module. An android mobile application is developed using Android Studio for the purpose of recording the readings from the developed multi-sensor platform. The application uses the Bluetooth communication for acquiring the real time sensor data from the HC-05 Bluetooth module and further, stores the data information. The acoustic sound sensor was added in later stage of the study, the rationale behind the idea is to investigate how sound measurements deviate during the process of experiment, when interacts with different depths of snow. The sound sensor is attached to the right end of the platform. Electret Microphone Amplifier MAX9814 with Auto gain, have chosen to conduct the testing. The Microphone consists of four pin VDD, GND, OUT and GAIN. It can be easily interfaced with Arduino board via connecting the VCC pin to 5v, GND to GND pin and OUT to any of the analogue pin of the Arduino board.

III. Snow depth data measurements

A. Study area

The study for this investigation were conducted in 45 different locations points in Oulu region, Finland, see Fig. 2. Oulu resides in the Middle of Finland and experiences healthy snow fall during winter season. According to Finnish meteorological statistics https://en.ilmatieteenlaitos.fi/snowstatistics, the maximum snow depth is usually found around March period and the ground is almost kept covered with snow throughout the month. Therefore, we have carried out our experiments during this month. For simplicity purpose, the experiments were conducted in the fresh snow fall condition to avoid any external environmental constraints.

Fig. 2. Study area: snow depth and platform data acquisition were performed

We have collected 90 samples observations and the division of area wise experiments is as follow: 25 experiments in Area 1, 25 experiments in Area 2, 20 experiments in Area 3, and finally, 20 experiments in Area 4. The intuition behind is to perform the experiment covered with different level of snow depth.

B. Experiment setup and procedures

To evaluate the platform, the experiments were designed, keeping in consideration the objectives of the various study parameters. In total 90 experiments were conducted to generate the datasets. In each experiment, the interest was in collecting the parameters associated with pressure attributes, acoustic sound measurements, and temperature and humidity sensor via foot wearable platform. For this purpose, the sensors data are obtained automatically through the attached platform. Whereas other parameters of interest such as snow depth, snow weight and snow density are only indirectly inferred from the observation / sensor measurement as detailed later. Armed with the developed footwear platform, the user performs normal walking task at each site. The attached platform contains straps that helps to attach it with the foot and further, the masking tape is used to assure a firm grip with the foot. The pressure sensor is placed inside the shoe to record the applied pressure of the toe on the sensor as shown. The wearable platform is very light weight, around 100 grams, whereby, causing no trouble in movement when attached to the foot. The strap was tightened comfortably around the ankle position ensuring that the pressure of the strap would not restrict the subjects movement during the experiments. On average 30 sec of walk was performed, covering the surface distance of 10 meter and 35 steps.

C. *Field measurements of snow parameters*

The measurement of snow depth is carried out on the same area where the data acquisition platform was enabled. Initially, we marked the start point and the end point covering 10 meters of distance to perform the experiment and measured the snow depth at four different points at 2.5 meters interval. Due to irregular spread of snow over the surface, we took four measurements d_i of snow depth as pointed out earlier, which are then averaged to yield the marked snow depth at the prescribed site, see Fig. 3, and expression (1) for details.

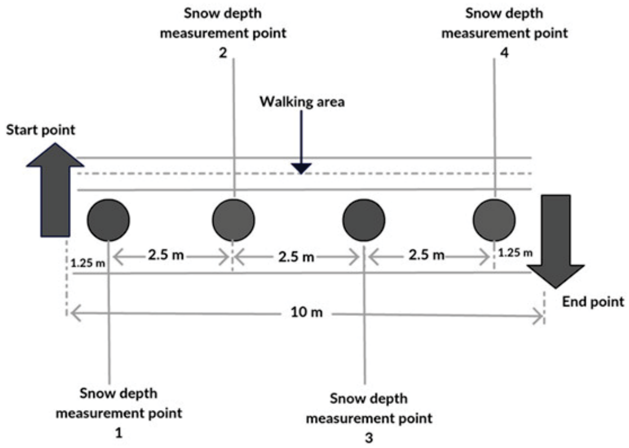

Fig. 3. Snow depth data and measurement points

$$d = \sum_{i=1,4} \frac{d_n}{4} \tag{1}$$

where d_i stands for the snow-depth at given site.

Another important parameter employed in the study was the snow density. The density is computed using a simple mass volume equation. For this purpose, we have also gathered samples of snow along the process of snow-depth measurement where a predefined volume of snow is collected and then weighted in order to determine the corresponding density.

D. *Platform data acquisition*

During each test, the measurement of applied force (kilogram-force kgf) is enumerated using the embedded flexi force resistance sensor. More specifically, the heel force or pressure of steps is measured and communicated via Bluetooth sensors to Android application, where it is logged. Fig. 4, exemplifies the pressure measurements at one of the experiment locations, while acoustic measurements are shown in Fig. 5.

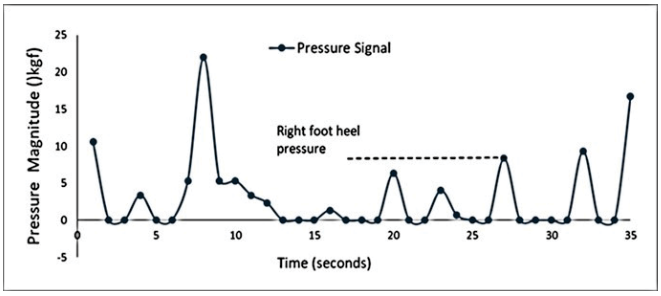

Fig. 4. Pressure sensor measurements points

On average 30 sec of walk was performed by the user covering a 10 meter and 34 steps surface (combining right and left footsteps), where at each foot movement, pressure reading at the subsequent time periods were collected and shown in Fig. 4. In latter, the zero value indicates the swing phase of the walk, occurring when the left foot is in contact with the surface. Whereas, values greater than zero indicate some stance phase where the right foot (device attached to) is in contact with ground surface.

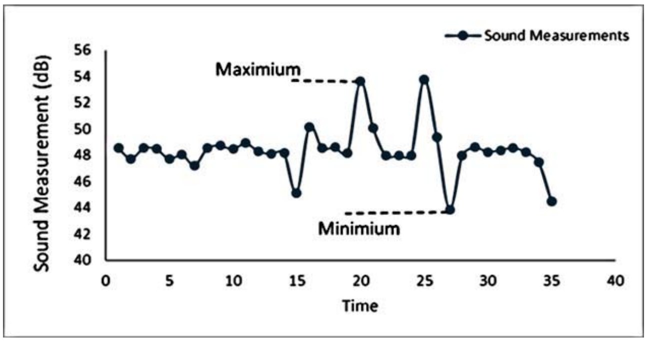

Fig. 5. Sound sensor measurement points

Similarly, the acoustic signal, temperature and humidity were also recorded via sensory platform. Before training, during the data preprocessing stage, the pressure magnitude at zero scale were eliminated. Further, all the data points obtained via pressure and sound sensors were normalized using the maximum and minimum values according to equation (2).

$$x' = (x - min(x))/(max(x) - min(x)) \tag{2}$$

E. *Variable extraction for classification of snow depth*

A machine-learning based approach was devised in order to classify the snow depth measurements. Two classification algorithms were considered for classification of snow depth. This boils down to using pressure sensor and/or sound sensor for deriving attributes for the machine learning model. On the other hand, ground truth measurements of snow depth, snow weight and density were carried out using field measurement, which then serve as a basis for training database of our learning model. Initially, as the attributes of our classification model, seven attributes or features were considered: maximum pressure, minimum-pressure, average-pressure values, maximum-sound, minimum-sound, and average-sound and snow density. Table I summarizes the set of attributes related to pressure measurements and found relevant in this study. The temperature and humidity were left out in the subsequent analysis and training of the classifier, due to lack of enough variation in the readings of both parameters, due to short span of time of experiment.

TABLE I. LIST OF ATTRIBUTES CONSIDERED BY THE CLASSIFIER SYSTEM

Measurement	Attributes	Mode of Collection	Relevance
Pressure	Max, Min and Mean	Automatic via Sensory platform	Predictor independent
Sound	Max, Min and Mean	Automatic via Sensory platform	Predictor independent
Temperature	Temperature observed	Automatic via Sensory platform	Not included in subsequent analysis
Humidity	Humidity observed	Automatic via Sensory platform	Not included in subsequent analysis
Snow Para.	Snow Density	Computed	Predictor dependent
Snow Para.	Snow Volume	Computed	dependent variable
Snow Para.	Snow Weight	Field measurement	Dependent variable
Snow Para.	Snow Depth	Field measurement	Target variable

TABLE II. LABEL ENCODING OF SNOW DEPTH

Categorizing SD measurement	Class label
10-15 cm	1
15-20 cm	2
20-25 cm	3
25-30 cm	4
30-35 cm	5
35-40 cm	6

To convert our problem into a classification problem, we have associated a class label to each range of snow depth. During the evaluation phase, the maximum and the minimum snow depth were recorded between 40cm to 10cm. Therefore, we divide the snow depth classes in the range of 5cm as summarized in Table II.

IV. DATA ANALYSIS & RESULTS

A. Correlation analysis

To better understand the relationships between variables, we first computed Pearson correlation (r) between the attributes and the target variables. Table III indicates very weak or no linear relation between mean pressure, max sound, min sound and snow depth, as their Pearsons correlation is close to zero. In contrary, very weak significant correlation relationship exist between the mean pressure and snow depth r(89) = 0.15, n = 90. However, a strongly significant inverse relationship observed between the maximum pressure and minimum pressure with SD r (89) = -0.84, n = 90.

TABLE III. PEARSON CORRELATION WITH TARGET VARIABLE

Independent Variable	Pearson correlation
Max pressure	-0.84
Min pressure	-0.68
Mean pressure	0.021
Max sound	0.025
Min sound	0.098
Mean Amplitude	0.15
Snow Density	0.034

B. RF and SVM accuracies predicting snow depth

Random Forest (RF) and Support Vector classifiers (SVC) were used to predict the target variable after being trained on the training dataset using the underlined attributes or features. The results showed that the accuracies of RF dominated SVC in all cases, with subset of one best feature, and when using either the two best feature or three best features. RF has the built-in capability of calculating the importance of attributes. Thus, using the above functionality we have selected the best attributes for training individual training. Similarly for SVC, the correlation matrix results of Table III were used to select the best attributes. Fig. 6 shows the attributes performance, ranked by importance, a relative measure ranging from 0 to 1.

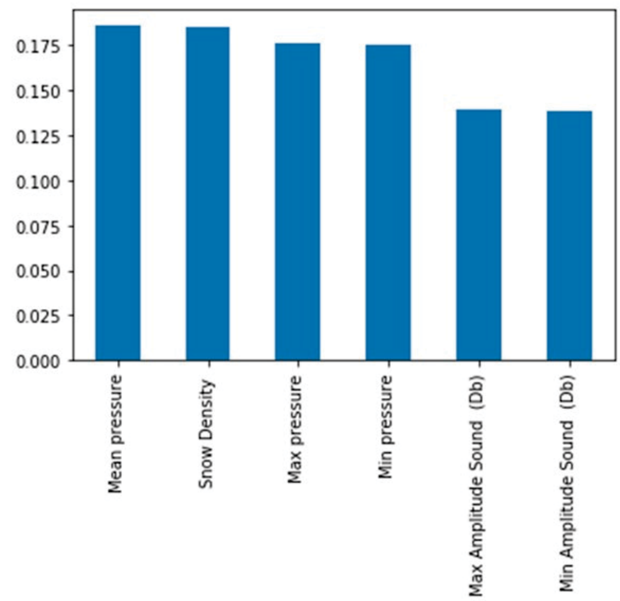

Fig. 6. Attributes importance for random forest training algorithm

Random Forest without hyper-parameter tuning showed moderate accuracy of 0.71 in predicting the snow depth. Subsequently, the model is improved with hypermeter tuning using the validation curve technique, to find the optimal n_estimators and max_depth see Fig. 7.

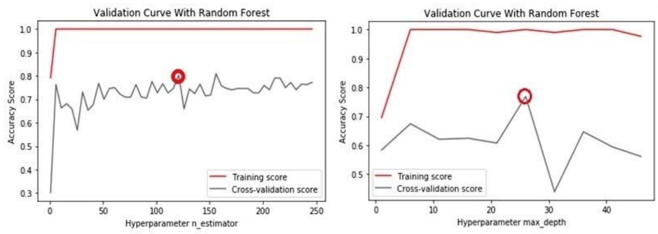

Fig. 7. Validation curve of (a) n_estimator and (b) max_depth

The results indicate the important improvement of the model after adjusting the hyper-parameters. The improvements reflect only for the cases when the model was trained considering all predictors and one best predictors. In contrary, the SVC results were lower in terms of accuracy, even, when tested with the best selected feature, two and three attributes. A decreasing accuracy level was also observed as well, see Table IV.

TABLE IV. ACCURACY'S OF ALL CASES WITH RF & SVC

Attributes Matrix	Accuracy of Classifiers in %			
	RF		SVC	
	w/o-HPtuning	HPtuning	w/o-HPtuning	HPtuning
All Attributes	71.40	72.80	61.1	66
1st best	83.3	88.8	33	33
2nd best	88.8	88.8	22.7	16
3rd best	88.8	88.8	27	27

V. DISCUSSION

The findings indicate the possibility of classifying the snow depth by utilizing a low-cost foot wearable platform. The classifiers trained on the acquired data revealed that the maximum and the mean pressure are significantly more correlating with the snow depth. This is because the higher snow depth causes difficulty for adjusting the body balance and stepping which eventually affects the application of heel pressure. In contrast, low amount of snow depth over ground causes less difficulty in stepping patterns. Thus, based on the above findings and results, we implemented and trained two classifiers. Random Forest classifier showed good accuracy in classifying the labelled ranges of snow depth measurements, when trained on all the incorporated attributes with tuned hyper-parameter.

However, one should also point out some limitations and uncertainly pervading the above approach. First, the experiments were mainly conducted with one single user wearing the ubiquitous sensor foot-based platform. This trivially makes the result pervaded by several uncertainty that are worth considering in future work. For instance, users body weight straightforwardly influences the numerical values of the pressure and acoustic sensor. Nevertheless, we believe that the influence of such phenomenon is limited, as the interest is on the correlation of the pressure /acoustic values with the snow depth not on the exact value of the pressure /acoustic values. Second, the walking patterns of the individual might also affect the pressure sensor readings. Although a full investigation of such effect would require a proper ergonomic analysis, the short interval between two measurements makes the impact of such factor likely limited as well. Third, other sensor placed in the ubiquitous platform, mainly, temperature and humidity, could not exhibit much variations. The foremost reason behind this result is the short time span of recording the sensor measurement, which in turn, resulted in less variability in these measurements. However, the measurement can be considered in the condition, when the experiment is conducted for longer time period, for instance. In future consideration, we will involve sensor input from temperature and humidity sensor, which can be utilized in training the model for more efficient result.

VI. CONCLUSION

In this paper, a new foot wearable platform that integrates pressure, sound and humidity/temperature sensors were proposed and implemented for the purpose of estimating snow-depth. We have successfully implemented two machine learning classifiers, trained on the attributes associated with pressure, sound and snow density that can be used to classify different measurement of snow depth. The idea is based on finding the key variation from the sensor measurement at different level of snow depth. The approach uses Random forest and Support vector classifier that involves pressure (minimum-pressure, maximum-pressure and mean-pressure) and sound related attributes (minimum-sound, maximum-sound and mean-sound). The correlation analysis showed that maximum-pressure and mean-pressure are more significant and, are important feature for classifying the snow depth. Although, this is a pilot approach and much work is still needed in order to construct more efficient machine learning model, considering users various modalities and possibly of integrating other soil related sensors. In addition, our approach provides the feasibility for estimating minimalistic characteristic of snow coverage nearly at very low cost and, with less labor demand.

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