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Development of a wood damage monitoring system for mechanized harvesting

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Abstract. Cut-to-length harvesting is a cost-efficient method of the wood supply chain. However, it risks causing stem damage in the mechanized process of thinning forest stands, thereby reducing the growth and technical quality of the remaining trees, which would then be exposed on the increased vulnerability to fungal diseases. For these reasons, it is critical to support quality monitoring of harvesting machines. One way to support quality monitoring is through the application of machine vision solutions. In this study, the damaged stems were photographed systematically from a strip road. The success of the stem-damage detection was analyzed to determine the relationships between successful detection, stand condition, and the image-processing technique. Statistically meaningful relationships were identified via logistic regression analysis, which can be used in selection of tailored image processing technique. The study indicated that the quality-monitoring system of mechanized harvesting could be improved by an increased focus on developing the multi-view photogrammetry of stem damages according to different stand conditions. Further, refining the machine learning system would support the need to determine accurate image-processing thresholds of the texture of stem damages. Then, the overall proportion of successful stem-damage detections will be 89%. These improvements of the quality monitoring system will provide the efficient thinning process in the sustainable wood supply from forests to forest industry. The implementation of such a system could be much broader, initially under Nordic conditions and then in other countries as well, given that its development takes into considerations the significant calibration factors of local conditions.
Keywords: forwarder, image processing, quality monitoring, single-grip harvester, tree damage, sustainable wood supply

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Introduction

In Finland, consistent forest growth has yielded abundant wood resources. Annual growth in Finnish forests is higher than the annual harvested volume (23 million m³, solid cubic meter over bark). This situation causes limited care and development of forests by silviculture and logging on some forest areas, which threats viability of carbon sink in the sustainable forestry. Therefore, the sustainability strategy regarding national forestry has included setting a goal to provide the bigger volume of industrial wood harvesting from the current 65 million m³ to 90 million m³ by 2025 (Anonymous 2015, Anonymous 2017a). Actually, new investments of forest industries will increase the demand for pulpwood.

Thinning has vastly increased importance as a potential source of pulpwood. However, the practice of thinning is fraught with environmental challenges concerning the cutting quality of mechanized harvesting (Harstela 1997, Han & Kellogg 2000a). As such, the wood harvesting industry would clearly benefit from a quality monitoring system that takes into account those aspects of sustainable forestry (ecological, economic, environmental, social) that have been recommended for comprehensive timber harvesting management in the Borealis Forest region (Laukkanen et al. 2004). In practice, poor harvesting quality consists largely of stand and soil damage, which bear directly on ecological sustainability. Such poor quality results in growth losses, rot defects, and a decline in the technical quality of residual trees, which in turn lead to economic losses (Vasiliauskas 2001, Mäkinen et al. 2007, Picchio et al. 2011). In forests, it is conventional for harvesting quality systems to be determined manually according to the following criteria: intensity of thinning, selection of trees, damage to residual trees, damage to the root system, damage to terrain, density of strip roads, and width of strip roads (Hassler et al. 1999, Han & Kellogg 2000b).

From an international perspective, the amount of wood-harvesting damage in Finland is low (Waters et al. 2004, Naghdi et al. 2009; Adekunle & Olagoke 2010, Behjou & Mollabashi 2012). There are several reasons for serious wood-harvesting damages abroad, including harvesting method (Eroğlu et al. 2009, Tavankar et al. 2013) and adverse stand conditions for harvesting (Egan 1999, Camp 2002, Košir 2008, Nakou et al. 2016). Actually, the amount of tree damage in Finland has been on the rise and, in recent years, tree damages have been the single most significant factor contributing to the deterioration of harvesting quality (Anonymous 2017b). Damage can be inflicted on various parts of the trees however this study only considers stem damages. According to the Finnish Forestry Centre (Anonymous 2017c), stem damage falls under the more general category of damage to residual trees (after thinning). Such damage is located above the presumed cutting surface of the stem. Further, a designation of stem damage obtains if the bark is damaged and the phloem layer is exposed more than 12 cm² under stem's 1.3 m height or more than 30 cm² on whole stem surface.

The cut-to-length method (CTL) synchronizes timber harvesting operations of the single-grip harvester and forwarder in the mechanized harvesting process (Ovaskainen & Heikkilä 2007). Recent studies concerning harvesting damage have focused on limited efforts to identify damage in so-called uneven-aged stands (Apafaian et al. 2015). There are several studies in Scandinavia for this issue which focus on terrain damage caused by the forwarder (Granhus & Fjeld 2001, Surakka et al. 2011, Modig et al. 2012, Nevalainen et al. 2017). This study considers the single-grip harvester because stem damage usually occurs when the harvester's boom strikes the remaining trees. In addition, the impact of felled trees, along with the size of the tree that strikes the stems, contributes to stem damage sustained by the residual trees (Athanassadis 1997).

In Finland, the responsibility for managing the quality of wood harvesting is assumed by the government authorities and wood procurement organizations (Palander 1999). In practice, the quality of wood harvesting (e.g. stem damages) is mainly a matter of self-monitoring by forest machine operators. The need for such self-monitoring reduces the productive work time of the human-machine system (i.e. forwarder or single-grip harvester). As such, self-monitoring can be regarded as a productivity-decreasing and cost-increasing factor that affects timber harvesting, because human resources are withdrawn from productive work to monitor the quality of harvesting (Ovaskainen & Heikkilä 2007, Pryor et al. 2010, Spinelli et al. 2014). Self-monitoring can also be susceptible to psychological stress because the additional work demand generates a hectic pace and imposes a psychological burden (Ovaskainen & Heikkilä 2007). In addition to the environmental and ecological aspects of sustainability, there is clearly room for improvement related to the economic and social sustainability of timber harvesting; such improvement could be achieved via computerized systems. The practice of manual quality monitoring could be replaced by introducing a digital image processing technique, first proposed in the 1960s, into the system (Rosenfeld 2015). Since the original inception of the digital image processing method, hundreds of similar techniques have been developed for image processing (Sonka 2015). For example, integrated machine learning and classification systems can be used in image processing (Luo et al. 2016). So far, however, a system tests have yielded unsatisfactory cost/benefit ratios that have prevented their implementation in the everyday operation of mechanized harvesting.

In Finland, sophisticated terrestrial laser scanning systems have been tested in relation to wood harvesting. In addition to these systems, forest technology aims to combine multi-view photogrammetry and image processing, both of which have performed successfully in operational tests requiring the automated volumetric measurement of truckloads in timber transportation (Acuna 2017). Recent forestry-related studies indicate that multi-view photogrammetry, an affordable alternative to laser scanning systems (Rose et al. 2015, Rodríguez-García et al. 2014), could be implemented operationally in timber harvesting (Nevalainen et al. 2017, Forsman et al. 2016, Borz et al. 2017, Hyyppä et al. 2018). Future research should compare the efficacy of photogrammetry and laser scanning systems for timber harvesting decision support regarding their accuracy and costs. So far, the quality monitoring systems that collect digital information about the cutting quality are not well known.

This research aimed to determine whether it is possible analyze/process stem damage information via terrestrial camera-based digital photographs. Further, this experimental study carefully analyzed an image processing algorithm to evaluate its viability for improving quality monitoring in forest thinning. It is hypothesized that, with respect to stem damage detection, an automatic monitoring system based on image processing could provide decision support to the stakeholders when they are evaluating the quality of sustainable wood supply during daily timber harvesting operations.

Material and methods

Materials

The research material consisted of 104 digital photographs, featuring various instances and perspectives of stem damage. The photography was carried out in the context of a timber harvesting experiment subsidized by the forest industry company of Stora Enso in June 2016 at a forest of Finnish Park Service (N6882431.114, E401591.172 (ETRS-TM-35FIN)) in southern Finland. The damage simulations were generated manually, by removing a long or square piece of bark from the surface of the stem and the phloem (Figure 1). Alternatively, the bark was removed, exposing the wood material by extending the damage at the xylem. The damages were simulated at roughly a 90º angle in relation to the strip road, in such a way as to make them observable from a harvester's workstation. The workstations were at a distance of ten meters along the strip road. From each workstation, zero to four stems were selected for photographs, depending on the amount of suitable stems and their respective locations. Damaged stems were tagged with labels for identification purposes.

The stem damage was simulated on 23 Scots pines (*Pinus sylvestris* L.) and 31 Norway spruces (*Picea abies* Karst) (Table 1). The mean diameter of the damaged trees was 22.4 cm at a 1.3 m height. The stem damage was photographed on a location 1.5 m above the ground surface, first with number labels and then without. The number of stem damage observations was 248. The average length of the stem damage was 31.8 cm (min 7 cm and max 117 cm) and the average width was 5.7 cm (min 2 cm and max 14 cm).

The damaged stems were photographed from three vantage points at 15 workstations (Figure 2). Due to difficult harvesting conditions, 19 trees were photographed from one vantage point at 11 workstations. If the stem damage was photographed from three vantage points, the camera was shifted 3.5 m forward and backward along the strip road (Figure 2). The average distance from point of photography to the damaged stems was 6.4 m.

The photography was carried out during summer daylight hours in cloudy, partly cloudy, and sunny weather conditions. Seasonal variation in the color values of the stem damage and the forest was avoided by photographing the damage immediately following the damage simulation. The stem damage was photographed with a Canon EOS 60D DSLR digital camera. The focal length of the camera lens was set at 18 mm. The camera was connected to a tripod to maximize stability (Figure 2). Images were recorded and archived in JPEG format. The images were 5,184 pixels in width and 3,456 pixels in height. The color profile of the images was sRGB with a bit depth of 24.

(a) (b)

Figure 1 Features of stem damage: a) phloem is revealed in long stem damage, b) xylem is revealed in square stem damage.

Table 1 Basic information about stem damage in the photographs

Successful stem damage detection	Total sample statistics		Texture		Damage location		Image-filming angle		Sun		Species	
	N	SD	n_1	n_2	n_1	n_2	n_1	n_2	n_1	n_2	n_1	n_2
Yes	126	242	122	4	117	9	73	53	65	61	67	59
No	122	215	54	68	80	42	35	87	47	75	67	55
Summary	248	223	176	72	197	51	108	140	112	136	134	114

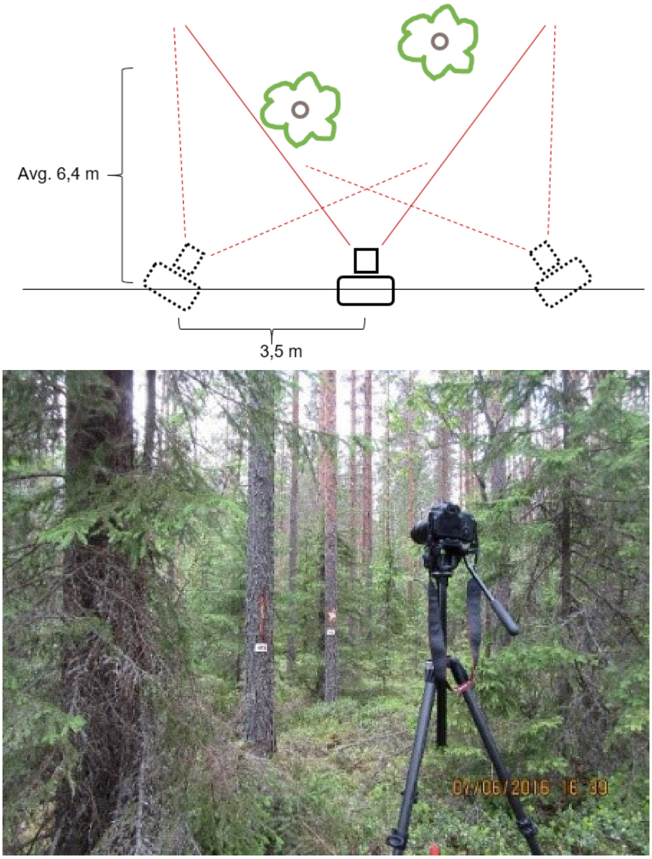

Figure 2 The camera position at the edge of the strip road

The stem damage detection process

Computer detection of the stem damage was achieved by applying the threshold-based linear classification method in the image processing by using MATLAB and ImageJ program. The algorithm was designed to identify pixel clusters characterized by the typical yellowish color of fresh wood, given the exposure of the phloem or xylem of trees caused by damaged stems. Stems are also assumed to be dark or brownish in color on trees such as Scots pine and Norway spruce. The detection process consisted of eleven steps, of which six were aimed at detecting the stem; steps seven through ten were focused on the stem damage detection (Figure 3).

In Step 2, the stems are roughly delineated by removing the background vegetation and the sky from the original RGB image (the creation of which was Step 1). This is achieved by excluding pixels that were too green (the vegetation), and too white or blue (the sky) from the image, by setting the pixel value to 0, if the RGB values of the corresponding colors are above the empirically defined threshold values. In Step 3, a median classifier is applied, which smooths out randomly-distributed pixels and can be used to identify vertical objects like the stems. In Step 4, pixel clusters smaller than the established threshold value are removed from the image, leaving only the stems. In Step 5, the possible holes remaining in the stems are filled. In Step 6, the stem textures are restored. In Step 7, pixels that deviate from the average stem color, including yellowish damaged stem, are highlighted. In Step 8, pixels that are too green, blue or white are removed, using a similar threshold technique to that in Step 2. The purpose of Step 8 is to scrub out any vegetation, lichen or sunlight reflections that might misidentified as the stem damage (false positives). In Step 9, a median classifier is applied again to smooth out randomly-distributed pixels, further reducing the potential number of false positives. In Step 10, any remaining potential false positives are removed from the image, by excluding pixel clusters that are too qualify as actual stem damage. The detection process concludes in Step 11, when the result materializes; this final step produces an image, in which the stem damage is visible.

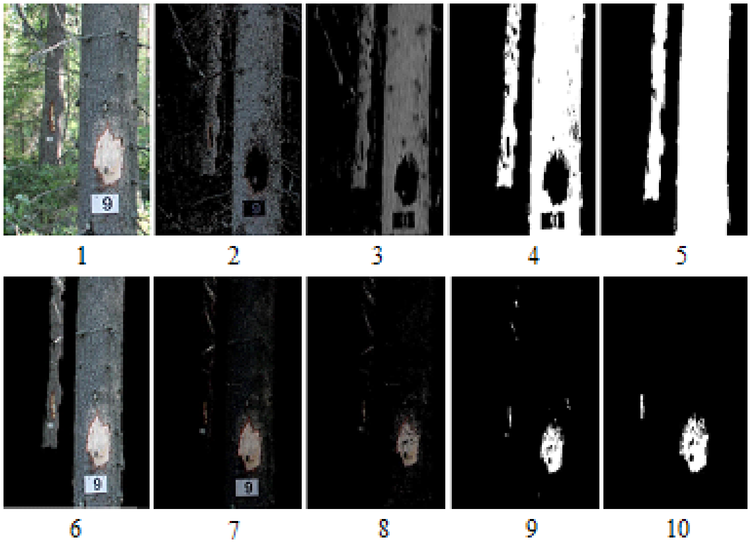

Figure 3 The depiction of the stem damage detection: 1) The original RGB image; 2) the image after removal of the background sky and vegetation; 3) median classifier; 4) removal of small, non-stem objects; 5) hole-filling; 6) texture restoration, 7) the highlighted image after the mean stem color subtraction, 8) removal of too-green, too-blue or too-white pixels, 9) median classifier, 10) removal of too-small pixel clusters (false positives).

The software package ImageJ was used to quantify stem damages. We wrote a macro for ImageJ, which worked on bimodal distributions and presented the image to the user. After that, the values of threshold were used to segment the image, until a satisfactory result was achieved.

Analysis of the stem damage detection process

The success of stem and stem damage detection is an index of information quality; the success was evaluated on the basis of visualized phases of the color processing algorithm (Figure 3). In fact, successful stem detection was determined by the sixth step of the algorithm, which restored the stem texture. The detection was designated successful if the texture and stem feature were successfully recovered, relative to the original image. The size and area of restored texture had to match the stem in terms of feature, shape, and position. A successful detection designation was applied to cases where multiple branches at different heights on stem compromised visibility, but permitted detection of the lower part of the stem to be detected. Further, detection was classified as successful in cases where the small fractions of texture at the stem's edge were missing due to light reflections, for example, but the stem was still clearly recognizable.

The success of the stem damage detection was determined from the step 10 of the algorithm. Correct findings were evaluated and recorded if the stem damage was comparable to that of the original image. For further analysis of the success of the detection process, the detections were divided into two categories by stand condition. Construction of classifying categories was based on the features due to variation in damage, photographing point, sunlight, tree species and in the calculated relations of the distance from the photographing point to the stem damage divided by stem diameter at 1.3 m height, damage length or damage width. On the other hand, the causes of detection failures were analyzed by classifying the steps of detection algorithm into separate groups, which lead to failures in the image processing. The consistency of the algorithm examined from two sets of digital photographs (with labels and without labels) that were filmed from the same photographing point (Figure 4).

In addition to the visual analysis of successful detection of data presented in Table 1, we demonstrated the relationships between the predicted outcome (e.g. successful stem damage detection) and certain characteristics of stand conditions (e.g. photographic distance) and image-processing technique found in ob-

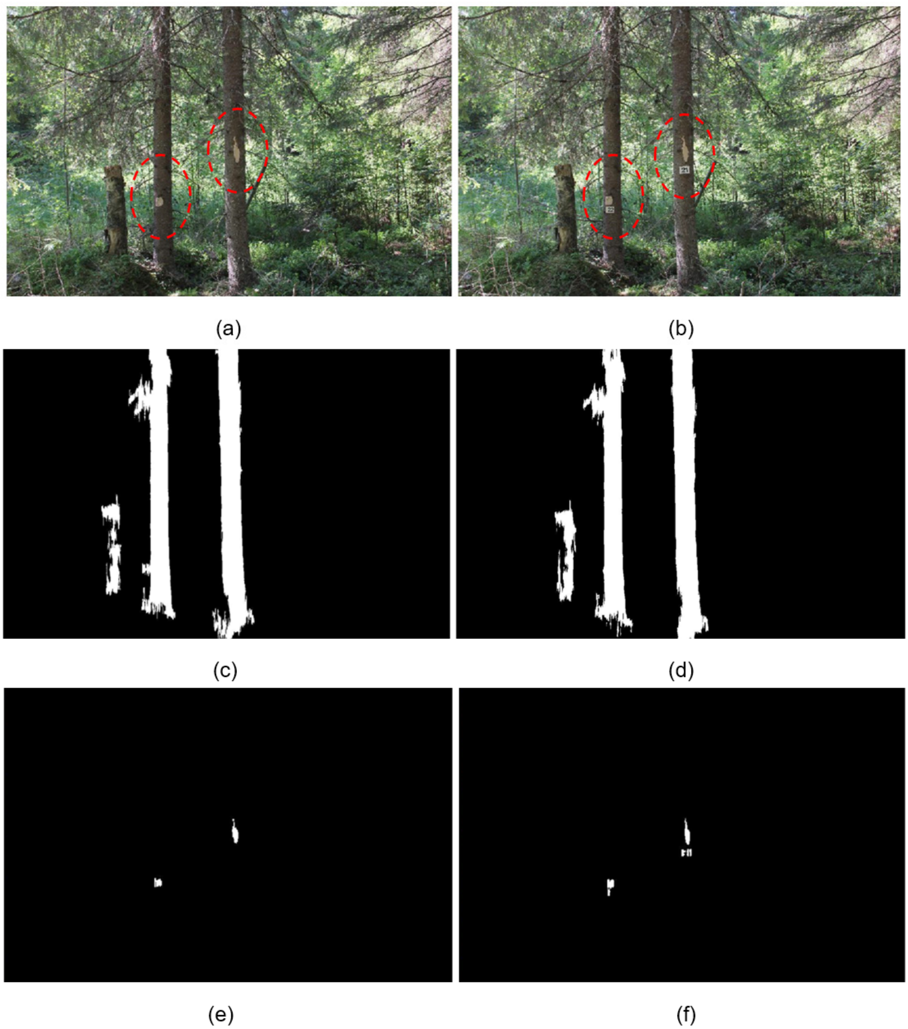

Figure 4 The image pairs of research material (a, c, e) and (b, d, f). There are successful detections of stems (c, d) and stem damages (e, f) in both photography series.

servations by using logistic regression models (Hosmer & Lemeshow 2000, Huang et al. 2017). Logistic regression was developed in 1958 (Cox 1958). Logistic regression is a multivariate analysis method that studies the relationship between independent variables and dependent variables i.e. variable *y* and a series of influencing features *x* (Huang et al. 2017).

A first logistic regression model demonstrated the relationship between the successful stem damage detection (outcome) and all stand conditions (independent variables). Another model demonstrated the significant relationship between the successful stem damage detection and image-processing technique (texture) and selected stand conditions. We made judgments concerning whether any discrepancies observed will likely affect the use of the model for its intended purpose i.e., for improving the stem damage detection system with regard to the association between the independent variable and the outcome. The measures of effect are divided into "total" and "local" measures. For the present data, measures are described in Table 2, which is used in the logistic regression analysis. Data are entered into the analysis as 0 or 1 coding for the dichotomous outcome, continuous values for continuous predictor "distance", and dummy coding (e.g., 0 or 1) for categorical predictors. For example, there are 73 observations of category 1 (image-filming angle = 90°) and 53 observations of category 2 (image-filming angle ≠ 90°) when stem damage detection was successful (Yes) in Table 2. Categories of the stand conditions are described in Table 3. In testing of the logistic regression model, higher sensitivity and specificity of the classification table indicate a better performance of the model (Hosmer & Lemeshow 2000).

Results

The success of detection process in image processing was assessed by grouping the detections according to stand conditions. The stem detection (81%) succeeded better than the stem-damage detection (51%) for all stand-condition groups (Table 3). The stem detection succeeded best when there were no sunlight reflections on the surface of the stems surface (92%) and no visible sunlight (88%). The success rate of stem detection was 59% if stem damages were on the side of the stem or notably low on the stem. The most successful stem-damage detection (68%) was attained when the damage was photographed from the middle of the workstations (90°), and when the sun was not lightening the image (61%). If the stem damage was situated at the side and on the low part of the stem (<50 cm), the success rate was 18%. In the categories of these stand-condition groups, the differences between the successful detections were statistically significant (Table 3).

The number of concurrently successful detections of the stem and stem damage was 121 (49%). In addition to the group analysis of suc-

Table 2 Description of data for logistic regression model consists of total statistics and local measures of stand conditions and image-processing technique (Texture)

Successful stem damage detection	Total sample statistics		Texture		Damage location		Image-filming angle		Sun		Species	
	N	SD	n_1	n_2	n_1	n_2	n_1	n_2	n_1	n_2	n_1	n_2
Yes	126	242	122	4	117	9	73	53	65	61	67	59
No	122	215	54	68	80	42	35	87	47	75	67	55
Summary	248	223	176	72	197	51	108	140	112	136	134	114

Note. Abbreviations: N - number of observations, SD - standard deviation, n_1 - number of observations of category 1, n_2 - number of observations of category 2.

Table 3 The successful stem and stem-damage detections, by the stand conditions

Group	Cat	Observation Stand condition	Stem detection N	n	%	χ^2	Stem damage detection n	%	χ^2
X_1	1	Image-filming angle = 90°	108	92	85	2.5	73	68	21.5
	2	Image-filming angle ≠ 90°	140	108	77		53	38	(***
X_2	1	Sunlight reflection at the stem	80	46	58	40.5	23	29	22.9
	2	No sunlight reflection at the stem	168	154	92	(***	103	61	(***
X_3	1	Sunlight in image	136	102	75	6.1	61	45	4.2
	2	No sunlight in image	112	98	88	(*	65	58	(*
X_4	1	Norway spruce	114	95	83	0.9	59	52	0.1
	2	Scots pine	134	105	78		67	50	
X_5	1	Square stem damage	144	115	80	0.1	75	52	0.2
	2	Long stem damage	104	85	82		51	49	
X_6	1	Damage is located at middle of stem	197	170	86	19.5	117	60	28.2
	2	Damage is not located at middle of stem	51	30	59	(***	9	18	(***
X_7	1	Distance and DBH ratio <28.75	124	106	86	3.7	70	57	3.1
	2	Distance and DBH ratio >28.75	124	94	76	(*	56	45	
X_8	1	Distance and damage height ratio <28.55	124	106	86	3.7	68	55	1.6
	2	Distance and damage height ratio >28.55	124	94	76	(*	58	47	
X_9	1	Distance and damage size ratio <120	124	104	84	1.6	69	56	2.3
	2	Distance and damage size ratio >120	124	96	77		57	46	
Total observations			248	200	81		126	51	
Statistical significance of Chi-square test value, (* - p<0.05, (** - p<0.01, (*** - p<0.001									

Note. Abbreviations: N - total number of observations, n - local number of observations, % - share of successful detections, Cat - category, χ^2 - chi-square test value.

cessful detections by stand conditions, causes of unsuccessful detection were analyzed by examining the operations of the image-processing algorithm. There were several steps combined into one category, which led to detection failure, but it was possible to attribute the failure to one main single step (Table 4). These results were determined visually, using images to evaluate the cause-effect relationship between that step and the detection failure.

Step 4 of the algorithm, in which unreal stem objects were removed, was the most significant contributing factor to detection failure. Step 5, in which the holes inside the stem were filled, was another problematic phase. Finally, Step 10, in which the false stem damages were removed by eliminating small pixel clusters, ultimately removed real stem-damage observations in 12 cases.

The other statistical analysis aimed to investigate the relationships between successful stem-damage detection, stand condition, and image-processing technique. To this end, a logistic regression method was used to develop two prediction models for successful detection (Tables 5 and 6). When all previously presented stand condition variables were included in the model (Table 5), the model indicated that the overall proportion of successful stem-damage detection was 77% (Table 7). When the image's texture and the statistically significant stand conditions were selected for incorporation into the model (Table 6), the overall proportion of successful stem-damage detections was 89% (Table 7). The proposition was 74%, when the statistically significant stand conditions were included in the model.

Table 4 Stem and stem-damage detection failures of the algorithm in the image processing

Category	Step	Definition of image-processing operation	n	%
Original image	1	Reads new image from the database	0	0
Stem detection	2	Removes background sky and vegetation	11	4
	3	Median classifier	14	6
Stem processing	4	Removes small non-stem objects	55	22
	5	Fills holes	22	9
	6	Restores texture	0	0
Stem-damage detection	7	Mean trunk color subtraction	9	4
	8	Removes too-green, too-blue and too-white pixels	3	1
	9	Median classifier	1	1
False stem-damage removal	10	Removes small pixel clusters	12	5
Report	11	Reports successful detections	0	0

Note. Abbreviations: *n* - number of detection failures, % - share of false detections.

Table 5 Relationships between successful stem damage detection and stand conditions in image processing of photograph taken from the strip road in timber harvesting. Statistically meaningful stand conditions are marked with bold font.

Model	$Y = a + b_1X_1 + b_2X_2 + b_3X_3 + b_4X_4 + b_5X_5 + b_6X_6 + b_7X_7 + b_8X_8 + b_9X_9$
The cut value is .500	where Y - successful stem-damage detection (1 - yes, 0 - no) a - constant X_1 - filming angle (1 - 90°, 0 - no 90°) X_2 - sunlight reflection on stem (1 - yes, 0 - no) X_3 - sunlight on image (1 - yes, 0 - no) X_4 - species (1 - spruce, 0 - pine) X_5 - damage feature (1 - square, 0 - long) X_6 - damage location (1 - middle, 0 - side) X_7 - distance/stem damage diameter at 1.3 m >28.75 (1 - yes, 0 - no) X_8 - distance/damage length >28.55 (1 - yes, 0 - no) X_9 - distance/damage width >120 (1 - yes, 0 - no) $b_1, b_2, b_3, b_4, b_3, b_4, b_5, b_6, b_7, b_8, b_9$ - coefficients of the variables

Predictor	Parameter estimate, β	Standard error, β	Wald's χ^2	*df*	*p*-value	Odds ratio $\exp^{\beta}$
a	9.822	1.909	26.465	1	**.000**	18428.281
b_1	-1.087	.348	9.769	1	**.002**	.337
b_2	-1.241	.417	8.858	1	**.003**	.289
b_3	-.324	.419	.597	1	.440	.724
b_4	-.287	.321	.804	1	.370	.750
b_5	-.965	.533	3.275	1	.070	.381
b_6	-1.786	.452	15.642	1	**.000**	.168
b_7	-.226	.326	.482	1	.487	.797
b_8	-.966	.479	4.074	1	**.044**	.381
b_9	-.169	.362	.218	1	.640	.847

Goodness-of-fit test	χ^2	*df*	*p*-value
Hosmer and Lemeshow	6.767	8	.562

Note: Cox and Snell R^2 = .242, Nagelkerke R^2 (Max rescaled R^2) = .322

Table 6 Effects of image-processing technique and stand conditions on the successful detection of stem damage in image processing of photograph taken from strip road in timber harvesting. Statistically meaningful stand conditions and image-processing technique effects are marked with bold font.

Model	$Y = a + b_1X_1 + b_2X_2 + b_3X_3 + b_4X_4 + b_5X_5 + b_6X_6$
The cut value is .500	where: Y - successful stem damage detection (1 - yes, 0 - no) a - constant X_1 - distance from stem to photography point, cm X_2 - image texture (1 - yes, 0 - no) X_3 - damage location (1 - middle, 0 - side) X_4 - filming angle (1 - 90°, 0 - no 90°) X_5 - sunlight on image (1 - yes, 0 - no) X_6 - species (1 - spruce, 0 - pine) $b_1, b_2, b_3, b_4, b_5, b_6$ - coefficients of the variables

Predictor	Parameter estimate, β	Standard error, β	Wald's χ^2	*df*	*p*-value	$\exp^{\beta}$ odds ratio
a	4.007	.863	21.581	1	**.000**	54.999
b_1	-.004	.001	12.968	1	**.000**	.996
b_2	-5.148	.741	48.247	1	**.000**	.006
b_3	-1.242	.517	5.765	1	**.016**	.286
b_4	1.558	.461	11.403	1	**.001**	.475
b_5	-.966	.401	5.791	1	**.016**	.381
b_6	-.901	.426	4.483	1	**.034**	.406
Goodness-of-fit test			χ^2	*df*	*p*-value	
Hosmer and Lemeshow			32.886	8	.000	

Note: Cox and Snell R^2 = .477, Nagelkerke R^2 (Max rescaled R^2) = .636

Discussion

In Finland, managers of wood procurement organizations need decision support for related to quality monitoring of sustainable wood harvesting (Laukkanen et al. 2004, Palander 1999). At the system level, data and information should be collected during the harvesting operations by automatic quality monitoring. So far, this kind of decision support is not available, and the current manual or terrestrial laser scanning-based monitoring methods are resource-intensive (Forsman et al. 2016, Hyyppä et al. 2018). Therefore, the aim of this research was to determine whether it is possible to generate the requisite stem damage information from normal terrestrial camera-based digital photographs. Further, in this experimental study, an image-processing algorithm was analyzed carefully for the development of a quality monitoring system of timber harvesting. The research material was photographed during normal summer weather (Table 1). The study revealed the stem-damage detection success in actual harvesting circumstances, but there are needs for the future tests to show that the system works during winter conditions. The detection algorithm operated very similarly in the image pairs, when the lighting conditions did not change significantly between capturing of images. As expected, abundant sunlight and reflections caused by lighting are significant issues that bear on the performance of image processing and monitoring of stem damages. In the future, the image-processing algorithm can be developed in such a way as to render the system cognizant of varying lighting conditions in timber harvesting.

Table 7 Classification of successful stem-damage detections (No - 0, Yes - 1) from the strip road in thinning, using two prediction models in respect to different predictor variables: A - with stand conditions, B - with stand conditions and image-processing technique. Prediction models are described in Tables 5 and 6.

		Predicted				Correct prediction, %	
		A	B	A	B		
		No		Yes		A	B
Observed	No	85	105	37	17	69.7	86.1
	Yes	21	10	105	116	83.3	92.1
Overall percentage						76.6	89.1

The analysis of the effects of stand conditions succeeded well, identifying most important stand conditions. In addition to the statistically significant stand conditions, tree species (Norway spruce, Scots pine) and stem damage shape (square, long) were selected for the logistic regression analysis as important stand conditions for additional tests. On the other hand, it was clear that the detection algorithm affected the success of stem-damage detection. There was no information about stem features or a suitable image-processing technique in the literature for constructing an efficient algorithm for the stem damage detection (Forsman et al. 2016). To evaluate the performance, the success of stem and stem-damage detections was determined visually from images by assessing the cause-effect relationships between the steps of the algorithm and detection failure. The algorithm yielded detection failures due to thin holes in the recovered matrix of stems, which were caused by the sun's reflections, damage situated at the side of the stem or twigs of the vegetation. The results revealed that determination of thresholds and the size of pixel groups used as criteria for filling holes in image texture were important features of the algorithm. This information can be used to develop a more effective image-processing technique for the future. Consequently, the texture of the image was also selected for another logistic regression analysis, which increased the overall proportion of successful stem-damage detections to 89% (Table 7).

The image processing requires a careful determination of thresholds for image-texture operations, because the algorithm had not been integrated with any advanced mechanism. For example, in Step 4, filling of the holes could malfunction, if there were small open connections between the stem matrix and the background. As a result, the stem texture recovery (Step 5), often missed a part of the texture, and that missing piece may have represented stem damage in the original image. A solution to this problem requires a better threshold-based matrix correction mechanism, which can be developed for the current system by utilizing the logistic regression (Huang et al. 2017).

The importance of the physical dimensions of stem damage emerged when image texture was included in the analysis of the successful stem-damage detection. If the algorithm did not detect the stem damage, its distance to the photographic point was often found to be too far. In this preliminary study, we did not actively try to determine the optimum thresholds for a false damage elimination or a real damage definition. The size of the removed pixel clusters (<1,000 pixels) was defined heuristically (as rule of thumb) for the used image material. It should be noted that the average size of simulated damage was 31.8 cm high and 5.7 cm width in this study. In practical wood harvesting, the damage can be smaller and have different feature, so the detection of distant damages can be a challenging for image processing without the adaptively resizing removed pixel clusters (thresholding) for used image material. This will be implemented with training data, using computer learning theory and methods. In fact, it would be interesting to develop an algorithm that can also estimate the size of the damage in addition to detection of the damage. Then, the size could be used as an additional quality criterion in the quality monitoring system.

As mentioned, the logistic regression analysis determined relationships between the stand conditions and the image-processing technique for prioritization of future studies on adaptive threshold techniques related to the successful stem-damage detections. On the other hand, Tables 5 and 6 show interactions (correlations) between the several independent variables (predictors, features) which affect the successful stem damage detection. For example, tree species became the statistically significant predictor, when image's texture was added to the consideration (Table 6). Besides, filming angle and damage location retained statistically meaningful independent variables in both models, which interact with each other; there were significant detection problems, when the damage was located at the side of the stem from the point of view of photographing position. Damage location itself had a minor effect on the stem detection, but in situations where damage was situated on the side, the distance between the photographic point and stem was also longer, and there were more forest objects near the stem in the image, which reduced stem detection success. For example, branches between the observed stem and the photgraphic point may cause problems within the stem-damage detection processes, especially in Norway-spruce-dominated forests.

The abovementioned problems can be avoided by developing the stem damage detection via multi-view photogrammetry, in which the algorithm estimates and forms one interface as the average of several consecutive detected interfaces from the strip road of thinning, when a harvester is forwarding in a stand (Nevalainen et al. 2017, Rose et al. 2015, Forsman et al. 2016). In this study, we just used direct observation made by the algorithm without that kind of estimation. Recent studies have suggested that multi-view photogrammetry is an affordable alternative for implementation in operational wood procurement (Acuna 2017, Borz 2017). As to future implementation, terrestrial photographing from a moving harvester (or forwarder) and increasing the number of images are recommended steps for image acquisition, to ensure adequate overlap between views.

In this study, the logistic regression model was applied to determine the relationships between certain features and successful stem damage detection. Besides, the logistic regression can also be called as a linear classifier because it provides a decision boundary which is linear in nature. So, the classification of image features made by the logistic regression would be linear classification, which can be utilized in machine learning applications (Luo et al. 2016, Huang et al. 2017). Accordingly, future studies about machine learning will reveal the effectiveness of multi-view UAV photogrammetry for detection of successful outcomes in image processing. Based on the literature and this experimental study, both terrestrial multi-view UAV photogrammetry and machine learning are suggested for use in the construction of an image-processing algorithm for more advanced quality monitoring of timber harvesting. The automatic quality monitoring system described above, in detail, would have several advantages in mechanized wood harvesting relative to current systems. In practice, the forest machine operators' obligation to self-monitor can be avoided with this kind of decision support, which yields more cost-efficient cutting work and the required quality (features) of sustainable wood harvesting to the forest industry and forest owners. Lessons have been learned during this study, and the image-processing system will be developed further.

Conclusions

In Finland, forestry companies that operate in compliance with standards for sustainable forest management are recognized by sustainability certificates awarded by impartial third parties. This study analyzed a quality-monitoring system that will provide a decision support to the stakeholders to account for quality aspects of sustainable forestry in mechanized wood harvesting. The study revealed that it is possible to implement automatic image-based detection of stem damage in normal harvesting conditions. The terrestrial detection system was promising in the context of the current development stage, where the algorithm lacked advanced neural mechanisms and detections were based on direct and separate observations without multi-view UAV photogrammetry. Further, it was possible to explain most of the unsuccessful detections via algorithmic analysis and logistic regression modeling. Therefore, the results obtained from the image-processing analysis indicate that the automatic stem damage detection software can be employed to create a quality-management system applicable to Finnish forestry. Subsequently, a stem damage index-based monitoring system would be able to provide wood harvesting operators and entrepreneurs the requisite information to minimize the damage sustained during daily harvesting operations. Relative to human field measurements, the time spent on monitoring can be significantly reduced, albeit at a cost of some omitted instances of stem damage and a minimally reduction in precision. The implementation of such a system could be much broader, initially under Nordic conditions and then in other countries as well, given that its development takes into considerations the significant calibration factors of local conditions.

References

Acuna M., 2017. Automated volumetric measurement of truckloads through multi-view photogrammetry and 3D image processing software. In: FORMEC 2017: 50th anniversary of the International Symposium on Forestry Mechanization, September 25-29, 2017, Braşov, Romania, pp. 1–4.

Adekunle V.A.J., Olagoke A.O., 2010. The impacts of timber harvesting on residual trees and seedlings in a tropical rainforest ecosystem, south-western Nigeria. International Journal of Biodiversity Science, Ecosystem Services & Management 6(3-4): 131–138.

Anonymous 2015. National Forest Strategy 2025. Publications of the Ministry of Agriculture and Forestry 6b/2015. http://mmm.fi/en/nfs. Accessed 02 January 2018.

Anonymous 2017a. Official Statistics of Finland (OSF): Wood Consumption & Cutting areas [e-publications]. Helsinki: Natural Resources Institute Finland.

Anonymous 2017b. Statistical information about the quality of harvesting for the years 2011–2015. Finnish Forest Centre. http://www.metsakeskus.fi/sites/default/files/. Accessed 02 January 2018

Anonymous 2017c. Finnish Forest Centre. Field audit manual. Web: http://www.metsakeskus.fi/sites/default/files/smk-maastotarkastusohje-2016.pdf. Accessed: 02 January 2018

Apafaian A., Boghian V., Bratu A., 2015. A Literature Review Related to the Modern Harvesting - Forwarding Equipment and the Main Topics Concern of the Research Community. Horticulture and Forestry - Review articles 72(1): 1–16.

Athanassadis D., 1997. Residual stand damage following cut-to-length harvesting operations with a farm tractor in two conifer stands. Silva Fennica 31(4): 461–467. DOI: 10.14214/sf.a8541

Behjou FK., Mollabashi OG., 2012. Selective logging and damage to unharvested trees in a Hyrcanian forest of Iran. BioResources 7(4): 4867–4874. DOI: 10.15376/biores.7.4.4867-4874

Borz SA., Acuna M., Heinimann HR., Palander T., Spinelli R., 2017. Innovating the competitive edge: from research to impact in the forest value chain": the half-century of FORMEC. Annals of Forest Research 60(2): 199–201. DOI: 10.15287/afr.2017.914

Camp A., 2002. Damage to residual trees by four mechanized harvest systems operating in small-diameter, mixed-conifer forests on steep slopes in North-eastern Washington: a case study. Western Journal of Applied Forestry 17(1): 14–22.

Cox DR., 1958. The regression analysis of binary sequences (with discussion). Journal of the Royal Statistical Society 20: 215–242.

Egan AF., 1999. Residual stand damage after shovel logging and conventional ground skidding in an Appalachian hardwood stand. Forest Products Journal 49(6): 88–92.

Eroğlu H., Öztürk UÖ., Sönmez T., Tilki F., Akkuzu E., 2009. The impacts of timber harvesting techniques on residual trees, seedlings, and timber products in natural oriental spruce forests. African Journal of Agricultural

Research 4(3): 220–224.
Forsman M., Börlin N., Holmgren J., 2016. Estimation of tree stem attributes using terrestrial photogrammetry with a camera rig. Forests 7(3): 61. DOI: 10.3390/f7030061
Granhus A., Fjeld D., 2001. Spatial distribution of injuries to Norway spruce advance growth after selection harvesting. Canadian Journal of Forest Research 31(11): 1903–1913. DOI: 10.1139/x01-103
Han H-S., Kellogg LD., 2000a. Damage characteristics in young Douglas-fir stands from commercial thinning with four timber harvesting systems. Western Journal of Applied Forestry 15(1): 27–33.
Han H-S., Kellogg LD., 2000b. A comparison of sampling methods and a proposed quick survey for measuring residual stand damage from commercial thinning. Journal of Forest Engineering 11(1): 63–69.
Harstela P., 1997. Decision support systems in wood procurement. A review. Silva Fennica 31(2): 215–223. DOI: 10.14214/sf.a8520
Hassler CC., Grushecky ST., Fajvan MA., 1999. An assessment of stand damage following timber harvests in West Virginia. Northern Journal of Applied Forestry 16(4): 191–196.
Heitzman E., Grell A.G. 2002. Residual tree damage along forwarder trails from cut-to-length thinning in Maine spruce stands. Northern Journal of Applied Forestry 19(4): 161–167.
Hosmer D.W., Lemeshow S., 2000. Applied logistic regression. John Wiley & Sons, New York. ISBN: 0-471-35632-8. DOI: 10.1002/0471722146
Huang T., Li B., Shen D., Cao J., Mao B., 2017. Analysis of the grain loss in harvest based on logistic regression. Information Technology and Quantitative Management. Procedia Computer Science 122: 698–705. DOI: 10.1016/j.procs.2017.11.426
Hyyppä J., Virtanen J-P., Jaakkola A., Yu X., Hyyppä H., Liang X., 2018. Feasibility of Google Tango and Kinect for crowdsourcing forestry information. Forests 9(6): 6.
Košir B., 2008. Modelling stand damages and comparison of two harvesting methods. Croatian Journal of Forest Engineering 29(1): 5–14.
Laukkanen S., Palander T., Kangas J., 2004. Applying voting theory in participatory decision support for sustainable timber harvesting. Canadian Journal of Forest Research 34(7): 1511–1524. DOI: 10.1139/x04-044
Luo L., Tang Y., Zou X., Wang C., Zhang P., Feng W., 2016. Robust grape cluster detection in a vineyard by combining the AdaBoost framework and multiple color components. Sensors 16(12): 2098. DOI: 10.3390/s16122098
Mäkinen H., Hallaksela A-M., Isomäki A., 2007. Increment and decay in Norway spruce and Scots pine after artificial logging damage. Canadian Journal of Forest Research 37(11): 2130–2141. DOI: 10.1139/X07-087
Modig E., Magnusson B., Valinger E., Cedergren J., Lundqvist L., 2012. Damage to residual stand caused by mechanized selection harvest in uneven-aged *Picea abies* dominated stands. Silva Fennica 46(2): 267–274. DOI: 10.14214/sf.442
Naghdi R., Bagheri I., Taheri K., Akef M., 2009. Residual stand damage during cut-to-length harvesting method in Shafaroud forest of Guilan province. Journal of Environmental Sciences 60: 931–947.
Nakou A., Sauter UH., Kohnle U., 2016. Improved models of harvest-induced bark damage. Annals of Forest Science 73(2): 233–246. DOI: 10.1007/s13595-015-0530-5
Nevalainen P., Salmivaara A., Ala-Ilomäki J., Launiainen S., Hiedanpää J., Finér L., Pahikkala P., Heikkonen J., 2017. Estimating the Rut Depth by UAV Photogrammetry. Remote Sensing 9(12): 1279. DOI: 10.3390/rs9121279
Ovaskainen H., Heikkilä M., 2007. Visuospatial cognitive abilities in cut-to-length single-grip timber harvester work. International Journal of Industrial Ergonomics 37(9–10): 771–780. DOI: 10.1016/j.ergon.2007.06.004
Palander T., 1999. A hierarchical participatory methodology for tactical decision-making based on a decision-analytic model for balancing timber stock. Scandinavian Journal of Forest Research 14(6): 567–580. DOI: 10.1080/02827589908540822
Picchio R., Neri F., Maesano M., Savelli S., Sirna A., Blasi S., Baldini S., Marchi E., 2011. Growth effects of thinning damage in a Corsican pine (*Pinus laricio* Poiret) stand in central Italy. Forest Ecology and Management 262(2): 237–243. DOI: 10.1016/j.foreco.2011.03.028
Pryor MG., Toombs L., Anderson D., White JC., 2010. What management and quality theories are best for small businesses? Journal of Management and Marketing Research 3: 20–32.
Rodríguez-García C., Montes F., Ruiz F., Canellas I., Pita P., 2014. Stem mapping and estimating standing volume from stereoscopic hemispherical images. European Journal of Forest Research 133(5): 895–904. DOI: 10.1007/s10342-014-0806-6
Rose J.C., Paulus S., Kuhlmann H., 2015. Accuracy analysis of a multi-view stereo approach for phenotyping of tomato plants at the organ level. Sensors 15(5): 9651–9665. DOI: 10.3390/s150509651
Rosenfeld A., 2015. Picture processing by computer. Academic Press, New York.
Sonka, M., Hlavac, V., Boyle, R., 2015. Image processing, analysis and machine vision. Fourth edition. ISBN 1-133-59360-7.
Spinelli R., Lombardini C., Magagnotti N., 2014. The effect of mechanization level and harvesting system on the thinning cost of Mediterranean softwood plantations. Silva Fennica 48(1): 1–15. DOI: 10.14214/sf.1003
Surakka H., Sirén M., Heikkinen J., Valkonen S., 2011. Damage to saplings in mechanized selection cutting in uneven-aged Norway spruce stands. Scandinavian Journal of Forest Research 26(3): 232–244. DOI: 10.1080/02827581.2011.552518
Tavankar F., Majnounian B., Bonyad A.E., 2013. Felling

and skidding damage to residual trees following selection cutting in Caspian forests of Iran. Journal of Forestry 59(5): 196–203.
Tsioras, P.A., Liamas, D.K., 2015. Residual tree damage along skidding trails in beech stands in Greece. Journal of Forestry Research 26, 523–531. DOI: 10.1007/s11676-015-0056-6
Vasiliauskas R., 2001. Damage to trees due to forestry operations and its pathological significance in temperate forests: a literature review. Forestry 74(4): 319–336. DOI: 10.1093/forestry/74.4.319
Waters I., Kembel S.W., Gingras J.F., Shay J.M., 2004. Short-term effects of cut-to-length versus full-tree harvesting on conifer regeneration in jack pine, mixed wood, and black spruce forests in Manitoba. Canadian Journal of Forest Research 34(9): 1938–1945. DOI: 10.1139/x04-064