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A personalized automated system designed to assign hazardous noise exposures to tasks among agricultural workers

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ABSTRACT

Farming is a noisy occupation, resulting in a high prevalence of hearing loss among agricultural workers. The aim of this study was to improve the accuracy of an automatic algorithm designed to cluster individual sound events into tasks. This work is part of the HearSafe Study, which aimed to increase agricultural workers' use of hearing protection devices by providing personalized information on hazardous noise to workers. Participants in the study interacted with the HearSafe System: a small sound level meter, a website, and an algorithm to associate noise with tasks. They wore the sound level meter that recorded loud ($\geq$ 80 dBA) sound "events," their location, and audio clips. They interacted with the website to view where and when participants were exposed to hazardous noises during the day. To simplify interpretation, an algorithm clustered individual sound events into tasks based on their proximity in time and location. The system's effectiveness hinges on the accuracy of this clustering algorithm. In Phase I, the accuracy was determined using parameters for time between events (2, 5, and 10 min) and distances between tasks (5, 9, and 18 m). In Phase II, the algorithm was refined to account for pauses in work and riding on equipment. Researchers manually clustered events into tasks by listening to the audio clips. Algorithm accuracy was measured as the percentage of events matching the manual clustering. The automating accuracy was improved from 57% with the base algorithm to 87% with the most accurate algorithm ($p = 0.02$; 10 min between events, 9 m average distance between tasks, and added the condition to combining consecutive tasks that were within 9 m of each other). Increased accuracy in identifying noisy tasks will improve the efficacy of the HearSafe System to communicate when and where use of hearing protection devices are needed among agricultural workers.

KEYWORDS

Agricultural workers; exposure assessment; hearing protection devices; noise exposures

Introduction

Occupational noise induced hearing loss is the most common work-related disease in the United States (Blackwell et al. 2014). Agricultural workers are particularly vulnerable, with the second highest prevalence among all occupations (Tak et al. 2009). The Occupational Safety and Health Administration (OSHA) regulates noise in occupational settings in the U.S., setting an 8-hr time weighted average (TWA) Permissible Exposure Limit (PEL) of 90 dBA (OSHA 2008). Agricultural sources such as grain bins, vacuum pumps, feed unloaders, and tractors often exceed the OSHA PEL (McCullagh 2011; Humann et al. 2012). However, many agricultural workers are self-employed, employ family members, or work at a facility with 10 or fewer employees, making them exempt from OSHA enforcement (Suter 2009; OSHA 2020). While farm operations must still follow regulations, lack of enforcement and awareness often leads to poor adherence.

Although hearing protection devices (HPDs) are effective in preventing occupational noise-induced hearing loss among workers, their use among agricultural workers remains low (McCullagh 2011). Schenker et al. (2002) found that only 23% of agricultural workers wear HPDs at least half of the time when exposed to noise, while 56% reported rarely or never using them. Similarly, McCullagh et al. (2016) reported that only half of farm operators had ever worn HPDs. In a study by Cramer et al. (2017),

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Midwestern farmers reported wearing HPD in noisy environments 54% of the time among younger farmers and 39% among older farmers. Masterson et al. (2013) emphasized that education, training, proper use, and strategic placement of HPDs are critical to increasing their adoption. Limited HPD use is often attributed to a lack of knowledge about personal hazardous noise exposure, the risks of hearing loss, and how to use HPDs effectively (McCullagh 2011). Consequently, experts suggest that providing highly personalized information to workers about their noise exposure may result in heightened awareness of their health risks and increased use of HPDs (Trautner et al. 2023).

Sensors have increasingly been used to alert workers to health hazards, enabling a range of automated interventions. For instance, accelerometers are widely implemented to detect falls, highlighting the potential of wearable technology to monitor occupational health risks (Nooruddin et al. 2022). However, noise sensors for hazard detection are less common. Picaut et al. (2020) describe low-cost sensors design to monitor urban noise in ambient settings. Sigurdsson et al. (2011) developed an automated noise measurement system capable of attributing high noise levels (>55 dB) to workers in an occupational setting. Rudolphi et al. (2022) found that swine workers who engaged with a smartphone-based noise application increased their use of HPDs immediately following the intervention, although this effect did not persist after 3 months. They mentioned the specific information on tasks with hazardous noise exposure, unavailable with the smartphone application, may help the situation. Stroh et al. (2023) introduced a device worn on the upper arm that tracked noise exposure and positional data to indicate when and where a worker should use HPD. They found that the external noise dosimeter measured within ±2 A-weighted decibels of a Class 2 reference dosimeter 59%, and the positioning system had an average error less than 4 m.

The monitor developed by Stroh et al. (2023) was integrated into the HearSafe Study, which aimed to promote the use of HPDs through automated, personalized instruction focused on recognizing hazardous noise and proper HPD placement. The equipment used in the study, the HearSafe System, is illustrated in Figure 1. Participants wore an upper-arm monitor equipped with a sound level meter (SLM) that measured sound pressure levels (SPLs) every second. When the monitor detected an elevated SPL (≥80 dBA), defined as a noise "event", it stored the corresponding time, geographic location, and an audio clip. We selected 80 dBA to be consistent with OSHA regulations. The permissible exposure limit governed by the Occupational Safety and Health Administration is 90 dBA expressed as an 8-hr, time-weighted average, with an exchange rate of 5 dBA (OSHA 2004). In OSHA's 1910.95 (d)(2)(i) "All continuous, intermittent and impulsive sound levels from 80 decibels to 130 decibels shall be integrated into the noise measurements" (OSHA 2008). From their technical manual, they state that noise dosimeters should be setup with a threshold of 80 dBA to determine compliance with Action Level.

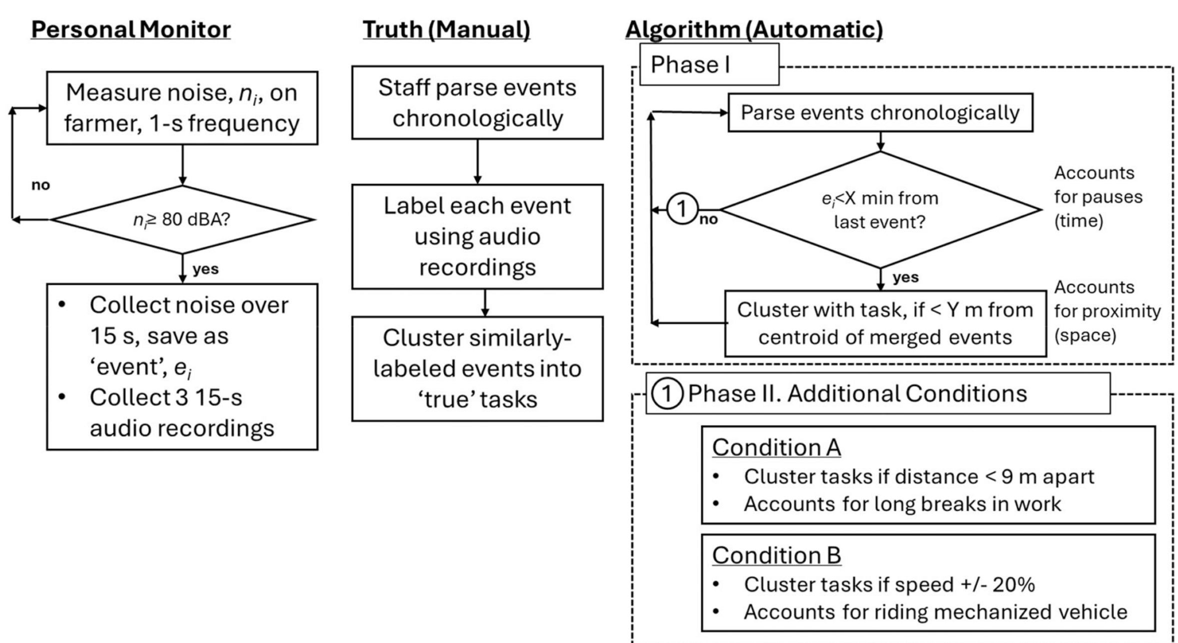

Figure 1. Depiction of how data were collected with the personal monitor, how "true" tasks were determined manually by listening to audio recordings, and how tasks were determined automatically with an algorithm.

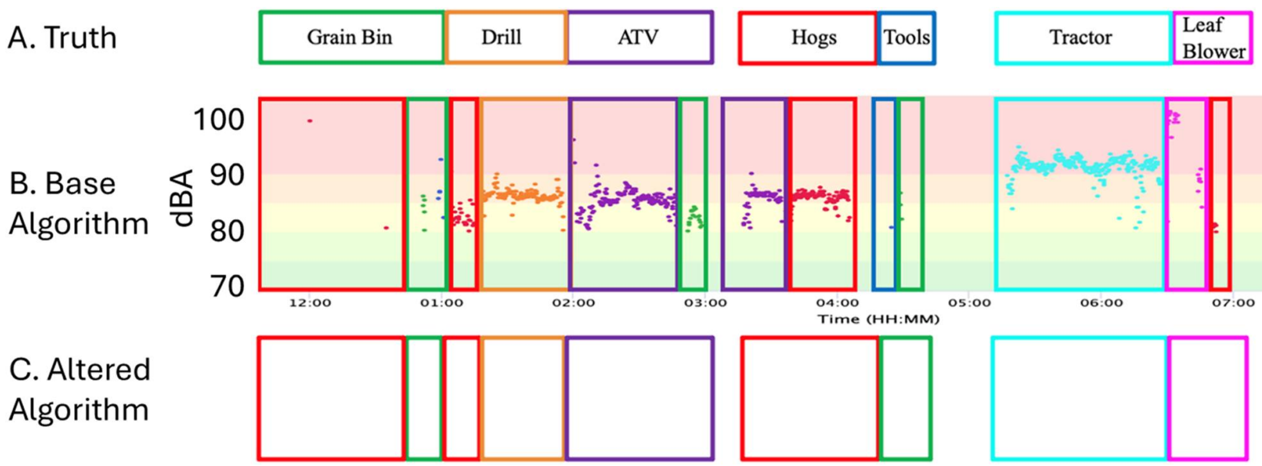

Figure 2. Events and tasks observed for one HearSafe subject over a single workday. Research staff manually identified tasks by listening to audio clips, Panel A "Truth." The output from the HearSafe Base Algorithm is shown in Panel B "Base Algorithm" with colored dots representing each event with noise greater or equal to 80 dBA and colored boxes depicting the automatically clustered tasks. The colored boxes in Panel C depict the automatically clustered tasks with the "Altered Algorithm."

At the end of a workday, data from the monitor was automatically uploaded to a secure website, allowing the participant to explore where and when they encountered hazardous noise during their workday. The website featured an algorithm that clustered events into "tasks" if the events occurred within a certain time and distance from each other (the base algorithm used 2 min and 9 m). Tasks and events were displayed to the worker on a website with a plot of dBA by time with events marked with a dot and clusters of events, tasks, identified as boxes (Figure 2; labeled "Base Algorithm"). Events and tasks were also plotted on a map of the worker's farm. The website also provided audio clips from each task and labeled the task according to their location and activity at the time. This information was intended to help train workers on tasks that exposed them to hazardous noise and where it occurred. A report was provided to the worker suggesting HPD placement, addressing accessibility and proximity barriers. The system's effectiveness hinges on the accuracy of this clustering algorithm.

The intention of the study reported here was to improve the accuracy of HearSafe's automatic task identification component by optimizing parameters and methods used in the clustering algorithm. Accuracy was defined as the number of events automatically clustered into their "true" task divided by the total number of events. True tasks were identified manually by audible review of data collected during the HearSafe Study.

Methods

Data source

The current work uses eight datasets from the HearSafe Study. This study was reviewed and approved by the Institutional Review Board at the University of Iowa. Each dataset contains the time, place, and audio clips when a participant experienced noise ≥80 dBA through a single workday. Participants included a convenience sample of farm owners in the Midwest with fewer than 10 employees. The datasets were manually selected to ensure a wide variation in the total time the worker was exposed to noise ≥80 dBA, the number of events, and the number of tasks. The characteristics of the selected datasets are listed in Table 1. The length of the workday ranged from 280 to 870 min with a mean of 580 min and standard deviation of 190 min. The percent of the day workers were exposed to noise greater or equal to 80 dBA varied widely from 4.0% to 64%. The number of events observed ranged from 55 to 983, and the mean number of tasks performed ranged from 4 to 23.

Figure 1 depicts of how data were collected with the personal monitor, how "true" tasks were attributed, and how events were algorithmically clustered into tasks. Throughout the workday, participants wore a custom, wearable sound level meter (SLM) that measured 1-sec sound pressure levels (SPLs). If SPL was greater than 80 dBA, an event was triggered to record the time, location by Global Positioning System (GPS), a 15-sec sound clip, and the SPL. At

Table 1. Characteristics of datasets selected from the HearSafe project.

Data Set	Workday Length (min)	Percent of workday exposed to noise $\geq$ 80 dBA (%)	Number of events observed	Number of tasks performed
1	280	64	673	8
2	510	50	947	16
3	790	14	496	20
4	870	28	983	23
5	380	4.0	66	11
6	530	42	840	7
7	380	23	338	4
8	580	7.0	234	12
Mean	580	29	570	13
St. Dev.	190	21	340	6.6
Range	280 to 870	4.0 to 64	66 to 983	4 to 23

the end of a work shift, the SLM data were uploaded to the local website via a router. Individual events were clustered automatically into a task if the event occurred within 2 min of the previous event and within 9 m from the centroid of the previously clustered events (the base algorithm).

Manual identification of "true" tasks

A researcher manually analyzed each event in each dataset to cluster them into "true" tasks (Figure 2A). Events were labeled according to the sound heard on the audio recording (e.g., tractor, disking, drilling, sawing, grain bin, loading hogs, etc.). True tasks were identified by clustering consecutive events with identical labels. Task information was recorded in an spreadsheet (Excel, Version 2021, Redmond, WA).

Automated detection of tasks and automating accuracy

The output of the base algorithm as displayed to workers on the website of the HearSafe System is shown in Figure 2B, labeled "Base Algorithm." Each small colored dot represents an event, and dots of the same color were automatically clustered by the base algorithm into tasks, which are represented as colored boxes. The base algorithm clustered events if the event occurred within 2 min of the previous event and merged the event into a task if the event occurred within 9 m of the centroid of previously clustered events in a task.

Automating accuracy was calculated as the number of events automatically clustered into their true task divided by the total number of events in that dataset. If the automating accuracy was 100%, the colored clusters of the Base Algorithm would be identical to those identified as Truth (Figure 2A). This, however, was not the case. For example, the initial cluster of red events produced by the base algorithm (Figure 2B) do not match the green color task identified by researchers as Truth (Figure 2A), indicating incorrect automation. In contrast, the first cluster of purple events were correctly clustered by the base algorithm, corresponding to the purple task identified as Truth.

Optimization

Phase I: Optimizing algorithm parameters used to cluster tasks

Automating accuracy was computed across all datasets with the parameters used in the base algorithm (time interval = 2 min; distance = 9 m) and additional ones. These parameters included all possible combinations of time (2, 5, and 10 min) and distance (5, 9, and 18 m). The task clusters identified for one test subject using new parameters are shown in the lower panel of Figure 2C, labeled "Altered Algorithm."

Time intervals were selected based on preliminary observations that the base algorithm incorrectly clustered many events incorrectly into multiple tasks due to pauses in work longer than 2 min. Workers would often pause a task, such as driving a tractor, to talk with other workers or adjust equipment. If the SPL dropped below 80 dBA for longer than 2 min during the pause, a new task was formed even though the worker was still engaged in the same task. In general, the work pauses ranged from 2 to 12 min. The average distances used in the algorithm were based on preliminary observations that workers perform a single task within the same general area.

Phase II: Refining conditions

During Phase II, two additional conditions were added to the algorithm to improve automating accuracy. Condition A was intended to override the time limit and address the error caused by pausing work for an extended time. When in place, this condition clustered consecutive tasks if the last location of the first task occurred within 9 m of the first location of the second task.

The intent of adding Condition B was to improve task clustering when a worker rides on mobile farm equipment, a common occurrence in modern farming. When in place, this condition clustered tasks when their average speed was within 20% of each other. Average speed was the distance recorded by the GPS divided by the time over which the move occurred.

Mean automating accuracy and percent increase in automating accuracy were calculated for the following conditions:

- Base (2 min) + Condition A
- Phase I Best (10 min) + Condition A
- Base (2 min) + Condition B
- Phase I Best (10 min) + Condition B

Table 2. Automating accuracy for Phase I.

Algorithm parameters (time, distance)[a]	Mean (%)	StDev (%)	95% CI (%, %)	Tukey grouping
2 min, 5 m	57	20	(43, 72)	A
2 min, 9 m (Base)	57	22	(43, 72)	A
2 min, 18 m	58	23	(43, 72)	A
5 min, 5 m	60	22	(45, 74)	A
5 min, 9 m	63	23	(48, 77)	A
5 min, 18 m	66	23	(51, 80)	A
10 min, 5 m	***80***	***16***	***(65, 94)***	***A***
10 min, 9 m	***80***	***16***	***(65, 94)***	***A***
10 min, 18 m	79	16	(65, 94)	A

[a]Events clustered if occurring within the stated time and distance from each other.

Base conditions were a time of 2 min and distance of 9 m. The greatest increase in automatic accuracy is italicized and bolded. Results of the one-way ANOVA results with Tukey groupings are shown. The hypothesis that all means are equal was accepted ($n = 9$; $p = 0.07$). These data are plotted in Figure 3.

The distance parameter used in all tests was 9 m having been found to yield the greatest accuracies in Phase I. Automating accuracy and percent increase were computed in a spreadsheet (Excel, Version 2021, Redmond, WA).

Statistical analyses

A one-way ANOVA with a Tukey pairwise comparison (alpha = 0.05) was conducted to analyze differences between the automating accuracies obtained with different algorithms. Percent increase in automating accuracy from the base algorithm was calculated for all alternative algorithm parameters evaluated. A two-way ANOVA with a Tukey pairwise comparison (alpha = 0.05) was further conducted to examine the effects of time interval and distance on automating accuracy. Results from Phase I were used to determine the algorithm parameters to analyze Condition A and Condition B with during Phase II of this study. For Phase II, a two-way ANOVA with a Tukey pairwise comparison (alpha = 0.05) was conducted to analyze differences between the automating accuracies obtained with different conditions. Results were also graphically depicted by mean automating accuracy and standard deviation. All statistical analyses were conducted using R (Version 4.5.1, R Core Team 2025).

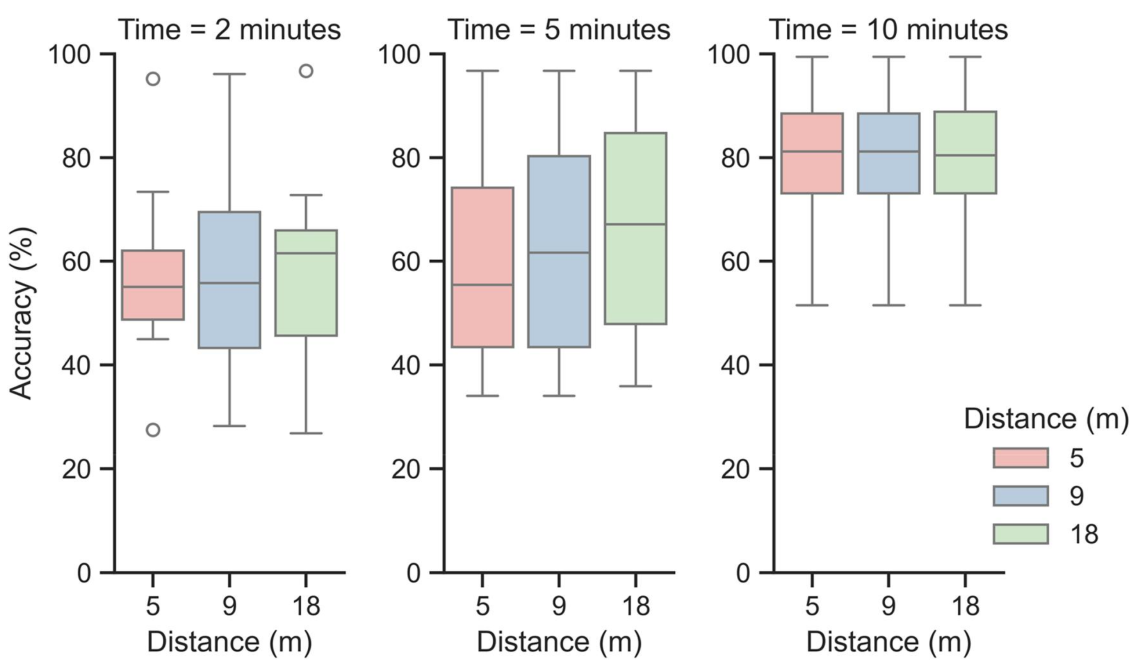

Figure 3. Phase I results. Accuracy of automatically clustering tasks when time and distance parameters were altered in the algorithm. Base conditions were a time of 2 min and distance of 9 m.

Results

The results from Phase I are presented in Table 2 and Figure 3. For a given distance, the accuracy of automatically clustering tasks increased with increasingly long time-averaging intervals. For a time interval of 2 min, accuracy typically ranged from 40% to 70% regardless of distance. There was slight improvement in accuracy when using a time interval of 5 min. The greatest improvement in accuracy was observed when using a time interval of 10 min, regardless of distance although the means of all tests were statistically equal (one-way ANOVA, Table 2, $p = 0.07$). A two-way ANOVA was conducted to examine the effects of time interval and distance on automating accuracy. The analysis revealed a significant main effect of time interval ($p = 0.001$). However, there was no significant main effect of distance on accuracy ($p = 0.94$), and the interaction between time interval and distance was not significant ($p = 0.99$). Post hoc comparisons using Tukey's multiple comparison test indicated that mean accuracy of 10 min was statistically different from 2 or 5 min.

Table 3. Automating accuracy for Phase II.

Algorithm parameters	Mean (%)	StDev (%)	95% CI (%, %)	Tukey grouping
Base (2 min, 9 m)[a]	57	22	(44, 70)	A
Base + Condition A[b]	66	19	(53, 79)	A, B
Phase I Best (10 min, 9 m) + Condition A	***87***	***16***	***(74, 100)***	***B***
Base + Condition B[c]	82	15	(69, 95)	A, B
Phase I Best (10 min, 9 m) + Condition B	83	20	(70, 96)	A, B

[a]For Phase I, the algorithm clustered events if sequential events were within X min of each other and within Y m from the centroid of all previously clustered events. The base was $X = 2$ min and $Y = 9$ m. In Phase I, the best automating accuracy was $X = 10$ min and $Y = 9$ m.

[b]In Condition A, consecutive tasks were clustered if they were 9 m from each other, even if they were separated by longer than X min of each other.

[c]In Condition B, consecutive tasks were clustered if the speed at the end of one task was within 20% the speed at the beginning of the next task.

The greatest increase in accuracy is italicized and bolded. Results of the two-way ANOVA with Tukey groupings are shown. The hypothesis that all means are equal was rejected ($n = 5$; $p = 0.02$). These data are plotted in Figure 4.

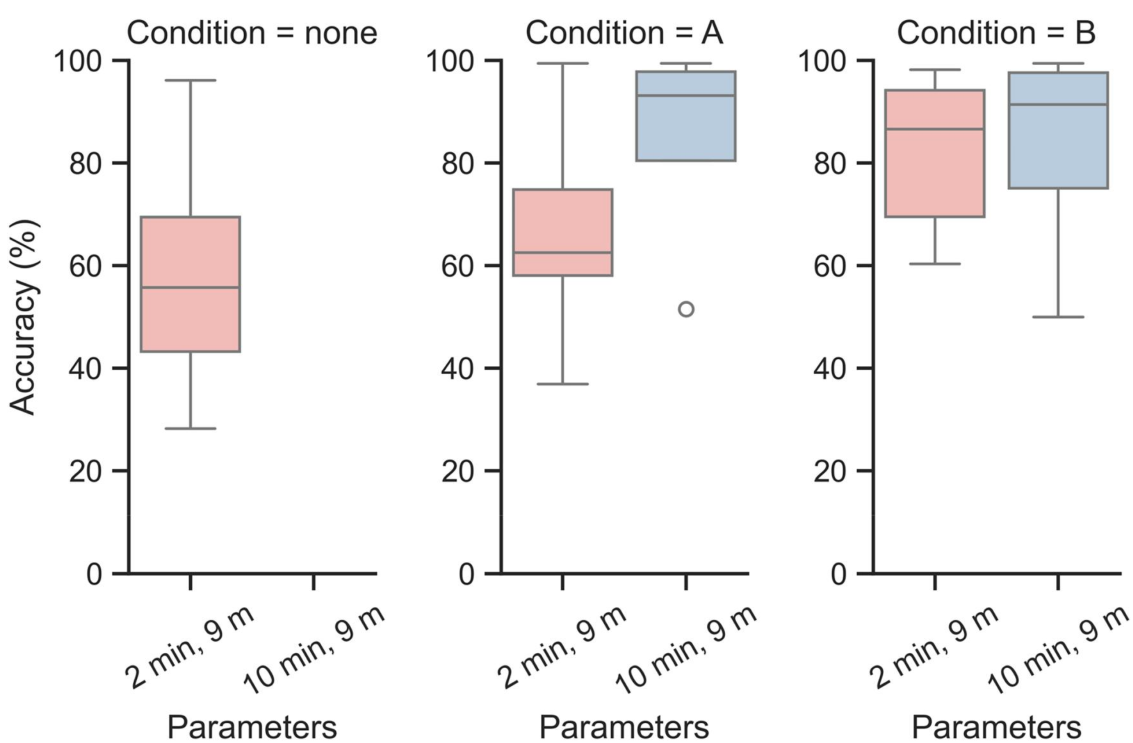

Figure 4. Phase II results. Accuracy of automatically clustering tasks when additional conditions were added to the algorithm. Base parameters were 2 min and 9 m without extra conditions. With Condition A, consecutive tasks were clustered if the last location of the first task occurred within 9 m of the first location of the second task regardless of the time between them. With Condition B, consecutive tasks were clustered if their average speed was within 20% of each other.

In Phase II, the inclusion of additional conditions to the algorithm improved accuracy in all cases tested (Table 3 and Figure 4). The greatest increase in accuracy from the base algorithm (mean = 57%; SD = 22%) was for the algorithm operated with the best results from Phase 1 (10 min, 9 m) and Condition A (mean = 87%; SD = 16%). The results were not as favorable when Condition A was used with the base parameters (2 min, 9 m) alone (mean 66%; SD = 19%), only a 15% increase over the base algorithm. The use of Condition B resulted in a substantial increase in accuracy when combined with the base algorithm (mean = 82%; SD = 15%) and with altered parameters of 9 m and 10 min (mean = 83%; SD = 20%).

A one-way ANOVA revealed that there was a statistically significant difference in automating accuracy between at least two algorithm parameters ($p = 0.02$). Tukey's HSD Test for multiple comparisons found that the mean automating accuracy was significantly different between algorithm parameters of Phase 1 Best + Condition A and all other conditions.

Discussion

This study aims to improve the accuracy of HearSafe's automatic task identification component was achieved. The accuracy of the algorithm to cluster events into tasks improved from 57% with the original base algorithm to 87%. This outcome was achieved primarily by modifying the algorithm parameters of time and distance. Improved accuracy was anticipated because the original base algorithm improperly assigned events to multiple tasks when a worker paused for an extended period in one location.

With Condition A imposed, the tasks were merged if they were 9 m from each other, even if separated by a long pause, resulting in the correct clustering of events into a single task. Nine meters was thought sufficient of a threshold for a farmer to move around a farm vehicle during a pause without incorrectly combining different tasks. This hypothesis is worth further investigation.

The inclusion of a constraint based on the speed of the worker determined by GPS (Condition B) produced interesting results. The mean accuracy was substantially increased from 57% for the base algorithm to more than 82% for Condition B, regardless of underlying time and distance parameters (Table 3). Moreover, the standard deviation in these results was reduced, indicating that Condition B may help explain underlying variability that is unaccounted for in other versions of the model. Further work to identify specifics of how this condition is applied, such as optimizing speed cutoffs, may produce further gains in accuracy.

Automating accuracy depended strongly on the time interval between events used in the clustering algorithm. In Phase I, a time interval of 10 min produced the greatest improvement to automating accuracy, raising the accuracy from 57% for the base algorithm to 79% or greater (Table 2). These results suggest that the time interval was a more important parameter than distance in automatic task detection. These results were expected because analysis of the datasets revealed that the original time interval of 2 min was not sufficient to correctly differentiate common tasks. The observed trend of increasing automating accuracy with increasing time intervals suggests that future work to optimize the time interval would be useful to improve the algorithm.

Minimal literature is available to compare our study design or results to others. No literature was found for automatically detecting the location of hazardous noises, although there is work for other hazards. Liu and Lockhart (2014) conducted a study to evaluate the sensitivity and specificity of an algorithm to detect prior-to-impact falls using an accelerometer. They then attributed falls to activities of daily living, which were automatically detected by accelerometer. They defined a base algorithm and altered the logic of the algorithm to improve activity detection. Similar to the current study, Liu and Lockhart were able to substantially improve the accuracy of the algorithm.

The accuracy of automatically clustering events into tasks is central to the effectiveness of the HearSafe System. The relatively low mean accuracy of task identification (base algorithm, 57%) resulted in suboptimal information provided to the worker with considerable task misclassification. As a result, study participants were required to aid in reassigning tasks by review of audio clips at the end of a workday. Although this effort may have helped a worker understand when, where, and why loud noises occur in their environment, it required substantial effort and was likely unsustainable. The substantial improvements to the task detecting algorithm (best mean accuracy = 87%) will help dramatically improve the overall quality of information provided to the worker. Providing users the most accurate information will improve the speed by which data collected during the workday can be processed and used for the intended purpose of training a person about their environment and ultimately increasing the use of HPD when needed. If this system proves effective as a noise intervention, then workers who use it may benefit from reduced risk of developing occupational hearing loss.

There were limitations of this study. Datasets were not randomly selected due to time constraints in identifying true tasks by listening to audio clips for each event. Instead, they were selected from the broader HearSafe Study population to represent the range of variables important for the generalization of this optimization work. This subjected the sample to selection bias. The sample size of eight was small and quite variable, which reduces generalizability of the results but was necessary due to time constraints. Manual auditory identification of events also posed limitations. Participant identity was protected during the HearSafe Study, therefore confirmation of the true sound from an event was unattainable. Task labels from workers were assigned based on three of the loudest events from each task, which were not always accurate representatives for that cluster of events. Each event was labeled according to the task that best fit the sound. Some events may have had different sources, but sounded similar, which would have caused them to be incorrectly labeled.

Conclusions

The aim of this study was to improve the accuracy of automatic classification of noise into clusters by the algorithm in the HearSafe System. The base algorithm chronologically parsed loud events, clustering them into a task if they occurred within 2 min of each other and within 5 m of the centroid location of all events in a task. The accuracy of this base algorithm (mean = 57%) was statistically and substantially improved by modifying the parameters in the algorithm (time interval = 10 min; distance = 9 m) and adding an additional restraint (Condition A) to account for extended breaks in work (mean accuracy = 87%). Although this study had promising results, further research is needed to evaluate additional algorithm parameters to optimize the accuracy of the task classification algorithm in the HearSafe System. Ultimately, the improved algorithm may prove useful in providing personalized information on hazardous noise exposure to workers, contributing to an increase HPD use and reducing noise-induced hearing loss among this high-risk occupational group. Improved accuracy will improve usability and acceptance of the HearSafe System and ultimately may reduce noise-induced hearing loss among agricultural workers.

Disclosure statement

No potential conflict of interest was reported by the author(s).

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Data availability statement

The data that support the findings of this study are available on request from the corresponding author, TMP. The data are not publicly available due to their containing information that could compromise the privacy of research participants.

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