Warning systems triggered by trains could reduce collisions with wildlife

J.A. Backs a, b,*, J.A. Nychka a, C.C. St. Clair b

a Department of Chemical and Materials Engineering, University of Alberta, Edmonton, Alberta, Canada T6G 1H9
b Department of Biological Sciences, University of Alberta, Edmonton, Alberta, Canada T6G 2E9

A R T I C L E   I N F O

Article history:
Received 16 January 2017
Received in revised form 24 May 2017
Accepted 12 June 2017

Keywords:
Railway
Strikes
Animals
Associative learning
Train detection
Sensors
Vibration
Infrared
Magnetism
Machine learning

A B S T R A C T

Ecosystems are degraded by transportation infrastructure partly because wildlife mortality from collisions with vehicles can threaten the viability of sensitive populations and alter ecosystem dynamics. This problem has attracted extensive study and mitigation on roads, but little similar work has been done for railways despite the occurrence of wildlife–train collisions worldwide. We propose a method for reducing wildlife losses on railways by providing animals with warning signals that are triggered by approaching trains, particularly in areas of high strike risk. Analogous to the warning signals provided for people at road–rail crossings, our system emits flashes of light and bell sounds approximately 20 s before train arrival at the location where the system is deployed. Learning theory predicts that animals will associate these warning signals with train arrival if the warning signal (conditioned stimulus) consistently precedes train arrival (unconditioned stimulus). We tested two designs for a warning system: one that detects passing trains and wirelessly relays this information to warning devices further along the track, and one that integrates detection of trains at a distance with warning signals in a single device. The most reliable design detected passing trains with magnetic or vibration sensors and relayed the information to warning devices. We have developed an affordable and publicly available prototype of this design that can be built for a material cost of US$225. With refinement, this technology could become an inexpensive means of protecting wildlife and people around the world from fatal train strikes wherever strike risk is known or predicted to be unusually high.

© 2017 The Authors. Published by Elsevier B.V. This is an open access article under the CC BY license (http://creativecommons.org/licenses/by/4.0/).

1. Introduction

Wild animals interact with transportation networks in complex ways. Through habitat loss, fragmentation, and degradation as well as direct mortality, the abundance of many species is reduced near roads (reviewed by Fahrig and Rytwinski, 2009; Benítez-López et al., 2010; Rytwinski and Fahrig, 2012) with potential to alter community composition and ecosystem dynamics (van der Ree et al., 2015). Although the effects of roads on wildlife are typically negative, some species have been found to increase in abundance near roads (e.g., Morelli et al., 2014; Fahrig and Rytwinski, 2009) while others are attracted to the vicinity of roads despite high risk of mortality (e.g., Nielsen et al., 2006). Strikes on railways have received less attention, perhaps because they present less risk to people (Langbein, 2011; Morse et al., 2014) or because railways are less prevalent than roads (Dulac, 2013). Nevertheless, train strikes have been associated with population effects (reviewed by van der Griff, 1999; Seiler et al., 2011; Dorsey et al., 2015) and animals are sometimes struck more often on railways than on adjacent roads (Huber et al., 1998; COST 341 Management Committee, 2000; Waller and Servheen, 2005). Additional incentive for strike reduction on railways applies for sensitive or threatened populations and charismatic, keystone, or culturally important species.

The best methods for reducing wildlife–vehicle collisions on roads are often impractical on railways. Collision reduction is increasingly achieved through the installation of wildlife exclusion fencing and crossing structures, which can reduce the frequency of wildlife–vehicle collisions by up to 80% (Clevenger et al., 2001) while maintaining habitat connectivity (reviewed by Glista et al., 2009). These road mitigation measures are costly, however, and despite the consumptive, passive-use, and management values of animals killed by vehicles (Boyle and Bishop, 1987; Conover, 1997; Schwabe and Schuhmann, 2002), mitigations may be less...
The association sensing stimuli associate As approach the cannot safely. Concept become device assets the strikes wildlife railway fencing, detector change to travel lower on (cf. Huijser in-rail; Huijser 1999; Hedeen railways, Huijser 1984, excluding traffic railways, sometimes). As mentioned (2010), “in-train warnings, some new principles govern the logic behind road–railway crossing signals for people and wildlife (Babińska-Werka et al., 2015). Although effective, these systems rely on close integration with railway infrastructure and require expensive proprietary hardware. Lower-cost wildlife warning devices used on roads, such as headlight reflectors and deer whistles, are largely ineffective (D’Angelo et al., 2006; Valitzski et al., 2009). This may be because reflectors and whistles lack the spatial and temporal precision of association between the conditioned warning stimuli and the unconditioned stimulus of close approach by a vehicle.

Here, we describe an electronic system for reducing wildlife–train collisions that combines the precise signalling of active warning systems (e.g., road–railway crossing signals) with the flexibility of installation and affordability of passive warning systems (e.g., headlight reflectors). We tested two designs for such a system (Fig. 1(b) and (c)). One is based on paired but spatially separated devices in which the first device detects a passing train and relays that information to a distant warning device positioned within the strike zone (hereafter, the passing relay). The other is based on a single device positioned within the strike zone that predicts train arrival time from a distance and activates integrated warning stimuli at the desired time (hereafter, the approach detector). Both methods can be implemented with low-cost, off-the-shelf components, assembled with basic electronics tools, and installed without affecting railway infrastructure or operations.

2. Methods

2.1. Study area

The two methods were tested on a freight railway owned and operated by Canadian Pacific within Banff National Park, Alberta, Canada (hereafter, Banff) and Yoho National Park, British Columbia, Canada (hereafter, Yoho). This railway bisects the two parks, runs alongside the four-lane Trans-Canada Highway, and was the largest single source of direct human-caused mortality for grizzly bears (Ursus arctos) within Banff between 1990 and 2008 (Bertch and Gibeau, 2009). Black bears (Ursus americanus), wolves (Canis lupus),

reduction may be ineffective unless it is drastic (Rea et al., 2010), especially where deep snow, steep topography, or adjacent water bodies encourage animals to retreat along the track (e.g., Becker and Grauvogel, 1991).

An alternative approach to reducing wildlife–train collisions is to increase the probability that animals will leave the track after detecting an approaching train. For people and other animals, failure to detect an oncoming train can lead to a collision directly or via a maladaptive escape response (Lima et al., 2015), perhaps induced by panic. Such detection failures are especially likely if the visual or acoustic cues of an approaching train are obscured by vegetation, topography, or deep snow, especially around track curves, or if the cues are masked by competing stimuli from nearby roads and rivers (Fig. 1(a)). When these conditions occur in areas used frequently by animals, heightened collision risk presumably results. The risk of detection failures in these areas (hereafter, strike zones) might be reduced if warning signals were provided in advance of train arrival in a way that could not be obscured or masked. Animals could learn to associate these warning signals with train approach if the signals were provided at a consistent time relative to train arrival and if the signals differed from stimuli that occur in other contexts (Domjan, 2005). The warning signal need not be aversive because the close approach of a vehicle is, itself, an aversive unconditioned stimulus (e.g., Rea et al., 2010). Similar behavioral principles govern the logic behind road–railway crossing signals for people and wildlife (Babińska-Werka et al., 2015). Although effective, these systems rely on close integration with railway infrastructure and require expensive proprietary hardware. Lower-cost wildlife warning devices used on roads, such as headlight reflectors and deer whistles, are largely ineffective (D’Angelo et al., 2006; Valitzski et al., 2009). This may be because reflectors and whistles lack the spatial and temporal precision of association between the conditioned warning stimuli and the unconditioned stimulus of close approach by a vehicle.

Here, we describe an electronic system for reducing wildlife–train collisions that combines the precise signalling of active warning systems (e.g., road–railway crossing signals) with the flexibility of installation and affordability of passive warning systems (e.g., headlight reflectors). We tested two designs for such a system (Fig. 1(b) and (c)). One is based on paired but spatially separated devices in which the first device detects a passing train and relays that information to a distant warning device positioned within the strike zone (hereafter, the passing relay). The other is based on a single device positioned within the strike zone that predicts train arrival time from a distance and activates integrated warning stimuli at the desired time (hereafter, the approach detector). Both methods can be implemented with low-cost, off-the-shelf components, assembled with basic electronics tools, and installed without affecting railway infrastructure or operations.

2. Methods

2.1. Study area

The two methods were tested on a freight railway owned and operated by Canadian Pacific within Banff National Park, Alberta, Canada (hereafter, Banff) and Yoho National Park, British Columbia, Canada (hereafter, Yoho). This railway bisects the two parks, runs alongside the four-lane Trans-Canada Highway, and was the largest single source of direct human-caused mortality for grizzly bears (Ursus arctos) within Banff between 1990 and 2008 (Bertch and Gibeau, 2009). Black bears (Ursus americanus), wolves (Canis lupus),

reduction may be ineffective unless it is drastic (Rea et al., 2010), especially where deep snow, steep topography, or adjacent water bodies encourage animals to retreat along the track (e.g., Becker and Grauvogel, 1991).

An alternative approach to reducing wildlife–train collisions is to increase the probability that animals will leave the track after detecting an approaching train. For people and other animals, failure to detect an oncoming train can lead to a collision directly or via a maladaptive escape response (Lima et al., 2015), perhaps induced by panic. Such detection failures are especially likely if the visual or acoustic cues of an approaching train are obscured by vegetation, topography, or deep snow, especially around track curves, or if the cues are masked by competing stimuli from nearby roads and rivers (Fig. 1(a)). When these conditions occur in areas used frequently by animals, heightened collision risk presumably results. The risk of detection failures in these areas (hereafter, strike zones) might be reduced if warning signals were provided in advance of train arrival in a way that could not be obscured or masked. Animals could learn to associate these warning signals with train approach if the signals were provided at a consistent time relative to train arrival and if the signals differed from stimuli that occur in other contexts (Domjan, 2005). The warning signal need not be aversive because the close approach of a vehicle is, itself, an aversive unconditioned stimulus (e.g., Rea et al., 2010). Similar behavioral principles govern the logic behind road–railway crossing signals for people and wildlife (Babińska-Werka et al., 2015). Although effective, these systems rely on close integration with railway infrastructure and require expensive proprietary hardware. Lower-cost wildlife warning devices used on roads, such as headlight reflectors and deer whistles, are largely ineffective (D’Angelo et al., 2006; Valitzski et al., 2009). This may be because reflectors and whistles lack the spatial and temporal precision of association between the conditioned warning stimuli and the unconditioned stimulus of close approach by a vehicle.

Here, we describe an electronic system for reducing wildlife–train collisions that combines the precise signalling of active warning systems (e.g., road–railway crossing signals) with the flexibility of installation and affordability of passive warning systems (e.g., headlight reflectors). We tested two designs for such a system (Fig. 1(b) and (c)). One is based on paired but spatially separated devices in which the first device detects a passing train and relays that information to a distant warning device positioned within the strike zone (hereafter, the passing relay). The other is based on a single device positioned within the strike zone that predicts train arrival time from a distance and activates integrated warning stimuli at the desired time (hereafter, the approach detector). Both methods can be implemented with low-cost, off-the-shelf components, assembled with basic electronics tools, and installed without affecting railway infrastructure or operations.
Table 1
Sensors tested in this work, including the sensing modality and chosen detection thresholds. Costs may be significantly lower for parts purchased in bulk. (See Appendix S1 for suppliers, manufacturers, and part numbers.)

<table>
<thead>
<tr>
<th>Sensor</th>
<th>Method</th>
<th>Mode of train detection</th>
<th>Threshold chosen</th>
<th>Cost (US$)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Digital compass</td>
<td>Passing relay</td>
<td>Residual magnetization of train steel</td>
<td>Vector magnitude of signal &gt;700 arb. units</td>
<td>10</td>
</tr>
<tr>
<td>Infrared rangefinder</td>
<td>Passing relay</td>
<td>Intensity of infrared light reflected</td>
<td>Rolling mean of 5 readings &gt; 100 arb. units</td>
<td>15</td>
</tr>
<tr>
<td>Infrared motion detector</td>
<td>Passing relay</td>
<td>Motion of heat source</td>
<td>“On” duration &gt; 80 s</td>
<td>10</td>
</tr>
<tr>
<td>Accelerometer</td>
<td>Passing relay</td>
<td>Slow rail vibrations</td>
<td>Vertical signal &lt; 800 arb. units</td>
<td>15</td>
</tr>
<tr>
<td>Vibration switch, weak</td>
<td>Passing relay</td>
<td>Weak rail vibrations</td>
<td>Activation rate &gt; 5 Hz</td>
<td>1</td>
</tr>
<tr>
<td>Vibration switch, medium</td>
<td>Passing relay</td>
<td>Moderate rail vibrations</td>
<td>Activation rate &gt; 2 Hz</td>
<td>1</td>
</tr>
<tr>
<td>Vibration switch, strong</td>
<td>Passing relay</td>
<td>Strong rail vibrations</td>
<td>Activation rate &gt; 1 Hz</td>
<td>1</td>
</tr>
<tr>
<td>Piezoelectric film, shielded</td>
<td>Approach detector</td>
<td>Fast rail vibrations</td>
<td>Random forest model</td>
<td>30</td>
</tr>
</tbody>
</table>

elk (*Cervus canadensis*), and moose (*Alces alces*) are also struck (Parks Canada Agency, unpublished data).

Road–rail crossing signals in our study area generally activate near 20 s before train arrival (cf. Richards and Heathington, 1990). To mimic the effectiveness of these signals, we chose a target warning time for our tests of (20 ± 5) s. Both of the methods we propose can provide longer warning times if desired.

2.2. Passing relay

The passing relay comprises two types of devices placed along a railway track: sensing devices are placed at a distance from either side of a strike zone to detect trains that pass them, and warning devices are placed within the strike zone to provide warning signals along the length of the zone (Fig. 1(b)). When a sensing device detects a train, it transmits a wireless radio signal that activates all warning devices within the strike zone. Sensing devices are placed far enough from the strike zone that a train moving at average speed takes 20 s to reach the centre of the strike zone.

Seven commercially available sensors were used to detect trains at close range (Table 1): a digital compass, an infrared rangefinder, an infrared motion detector, an accelerometer, and three vibration switches designed to trigger on weak, medium, and strong vibrations. Each sensor was placed in a plastic enclosure and attached with a magnet to the outside web of the track rail (vibration sensors) or laid flush with the ballast rock between the track rails (infrared sensors and compass). Data from each sensor were logged continuously (Arduino Uno and Data Logging Shield, Adafruit Industries, USA) for a minimum of ten train passages over one or more recording sessions. An adjacent stereo audio recorder (SM2+GPS, Wildlife Acoustics, USA) measured the time of each train arrival according to its internal clock, which was synchronized with the Global Positioning System (GPS). All recordings were made at a single site within Banff.

Train arrival times were estimated from spectrograms of the audio recordings to within ±0.2 s. Sensor data were then examined for changes coinciding with train arrival. Thresholds could be set part-way between the noise floor and the train signal, yielding no false positives or negatives for most sensors (Table 1). Each sensor’s data were then searched by computer for signals exceeding the corresponding threshold (hereafter, a detection), skipping 6 min of data after each detection to allow trains to pass. Detections were matched to train arrivals from the audio recordings if their times coincided within 60 s. Detections with no matching arrival were recorded as false positives; arrivals with no matching detection were recorded as false negatives. Other track vehicles (e.g., maintenance trucks) were treated identically because most sensors had no trouble detecting them.

We were unable to closely synchronize the internal clock of the data logger with that of the audio recorder, and this limited our ability to compare detection accuracy among the sensors. While the clocks were within 10 s of each other at the beginning of every recording session, the actual value changed each time the data logger was reprogrammed. Further, the compass and rangefinder recordings used a different internal clock that drifted by 10 s per day. We assumed a model for these effects where the detection times from each recording session were given an unknown offset and an offset that changed with time. To recover detection precision, we linearly regressed the difference of detection and arrival times against the recording time for each recording session. For recording sessions whose models had a significant slope (*p* < 0.05), we report the regression residuals rather than the raw differences of detection and arrival times; for recording sessions with non-significant models, we report the differences of detection and arrival times with the mean value subtracted. Recording sessions comprising less than three detections were excluded. This transformation of the data reflects the loss of information about sensor accuracy (systematically early or late detection) caused by the clock synchronization problem (but see Section 4).

Hypothetical warning times were estimated from this measure of detection precision. Since train detections can be relayed from the sensing device to the warning device in a negligibly short time, a highly precise sensor would provide an equally precise warning time only at the centre of the strike zone and only if train speeds in the area were always the same. If a particular train had a higher speed than average, the passing relay would provide a warning time shorter than the target time. Moreover, an animal nearer to the train than the strike zone centre would perceive a warning time shorter than the target time. To simulate these effects, speed was measured for each train detected by the accelerometer using a pair of GPS-synchronized audio recorders (SM2+GPS, Wildlife Acoustics, USA) placed 200 m apart along the track. A hypothetical strike zone of 200 m length (12 s at 60 km h⁻¹) was then centred 20 s away from the sensor at the average speed of this sample of trains. For each train, a hypothetical animal was placed randomly within the strike zone. Assuming each train maintained its speed, the warning time provided to the animal was the time elapsed between train detection by the accelerometer and train arrival at the animal.

2.3. Approach detector

The approach detector is a standalone device placed within the strike zone that detects trains at a distance (Fig. 1(c)). When a detected train is determined to be 20 s from the device, integrated warning signals are activated. Each approach detector detects trains and activates independently.

To detect trains at long range, we chose to use the train-generated vibrations that travel long distances in track rails. Rail vibrations cannot be obscured by vegetation or topography because they are confined to and guided by the track rails. Moreover, noise from rivers or roads near the track (Fig. 1(a)) cannot vibrate the rails, allowing rail-attached vibration sensors to achieve a higher signal-to-noise ratio than in-air microphones. Similar vibrations are commonly used to detect defects in track rails (Loveday, 2012), and train-generated vibrations have been observed over 2 km
ahead of train arrival (Rose et al., 2004), but to our knowledge they have never been used to predict train arrival time.

Piezoelectric film sensors (Table 1) were used as contact microphones to transduce rail vibrations into electrical signals. The sensors were adhered with epoxy to rare earth magnets, which enabled secure attachment to the outer web of track rails. Signals from these sensors were received by a custom preamplifier (Appendix S2) and recorded (SM2BAT and SM2BAT+; Wildlife Acoustics, USA) at sample rates of 192 kHz or 384 kHz, allowing us to measure acoustic signals from 10 Hz to 48 kHz for all recordings (Mandal and Asif, 2007).

To sample a range of conditions that could affect the generation and transmission of rail vibrations, trains were recorded with the piezoelectric sensors at six sites along the railway within Banff and Yoho and as well as one site along the Canadian Pacific railway south of Edmonton, Alberta, Canada. Sites and recording times were selected to sample many possible track conditions, including curved and straight track, the inside and outside rails on curves, and locations near to and far from track joints and rail lubrication equipment. For Banff and Yoho sites, recordings were collected at winter and summer temperatures.

Because we could not discern any clear threshold from vibration spectrograms to indicate when trains were 20 s away, we chose to automate the classification of patterns with machine learning. We first split recordings for each train approach into smaller intervals (Appendix S3). Each interval was then assigned a class of “true” or “false” to indicate whether the interval fell within 20 s of train arrival. Classification models were trained with 10-fold 10-repeat cross-validation (using Kuhn et al., 2015; R Core Team, 2015) on a data set containing all intervals from a site-stratified random sample of 80% of approach recordings (the training set). One model was trained for all sites together and another model for each site alone. The random forest classifier (using Liaw and Wiener, 2002; R Core Team, 2015) was chosen for its robustness to overfitting (Breiman, 2001). Approaches of non-train track vehicles were excluded from this analysis to optimize the models for train detection.

Warning times provided by this method were estimated from the predictions of the trained models on the remaining 20% of approach recordings (the test set). The first interval a model classified as “true” gave the time at which an approach detector would have activated its warning signal. Activation times more than 60 s before train arrival were recorded as false positives; approaches for which the model did not predict a trigger were recorded as false negatives.

3. Results

For the passing relay, we compared 183 combinations of seven sensor types and 105 unique vehicle passages (103 trains and 2 other track vehicles) to arrival times from the audio recordings. As expected, the slopes in the linear models to remove clock drift were statistically significant (at \( p < 0.001 \)) only for the compass and infrared rangefinder; means were subtracted for the other sensors (with two extreme outliers excluded from the mean for the infrared motion detector). Five of the seven sensors detected every passage and did so with high precision (85–100% within 2 s of the mean; Fig. 2). Of these, only the compass and accelerometer achieved no false detections and precision within ±2 s for all detections, but the compass achieved this result with triple the sample size. The single false positive reported for the infrared rangefinder (Fig. 2) may have been caused by the passage of an animal. The other two sensors were so imprecise (less than 50% within ±2 s for the medium switch) or missed so many passages (82% missed by the strong switch) that we did not consider them further and their results are not shown.

Warning times provided by the passing relay were simulated using the speeds of the 13 trains detected by the accelerometer (mean and standard deviation: (61.7 ± 2.4) km h\(^{-1}\)) and 13 random animal locations within a hypothetical 200 m strike zone (range: −99 m to +95 m). This simulation yielded a range of values largely within or very near to the target interval ((20 ± 5) s; Fig. 3, left).

For the approach detector, we assessed 430 combinations of up to four simultaneous recording locations and 116 unique train passages. On average, site-specific classification models detected 80% of train approaches in its test set. These models provided a median warning time 1.8 s earlier than the 20 s target and an interquartile range (i.e., the middle 50% of values) of 15.9 s (Fig. 3, centre). The model incorporating all sites detected more approaches from the same test set (88%) but with reduced accuracy and precision: The median warning time was 4.7 s earlier than the target with an interquartile range of 18.5 s (Fig. 3, right). In spectrograms of the approach recordings, we could see vibration signals from approaching trains at least 20 s and sometimes as much as 210 s before arrival. However, background noise from other frequency bands was often strong enough that these signals did not affect the time-average signal level until 5 s to 10 s later.

Comparisons of the accuracy, precision, and false detection rates of the two wildlife warning methods (Fig. 3) clearly favour the passing relay.

4. Discussion

Our results show that a highly precise train detector can be built with simple, off-the-shelf components. The passing relay missed no trains and triggered only when trains passed, and the timing of triggers was highly precise for both the compass and accelerometer
sensors. The model of the approach detector built with data from all sites achieved fewer false detections than models built with data from each site alone, but with less accuracy and precision. Even with variations in train speed and animal location, the passing relay provided warning times largely within the target interval and did so far more consistently than the approach detector.

Three of the remaining passing relay sensors performed nearly as well as the compass and accelerometer. For instance, the infrared rangefinder yielded similar precision—apart from the single false positive—and was tested far longer than the accelerometer. However, the mechanisms of detection for the infrared sensors are inherently different: the passage of animals could easily trigger false positives in both infrared sensors but not in the compass or accelerometer. Furthermore, the infrared motion detector has an activation time threshold of 80 s (Table 1). The extra distance the train would travel during this time means that communication between the sensing and warning devices would require signal repeaters that would increase the cost and complexity of the system.

For all five sensors presented, our use of linear regression or mean subtraction to transform the data could have removed real differences in the median detection times among the sensors. However, one could easily compensate for any such differences by changing the spacing between the sensor and the strike zone. Train speed and animal location will more strongly affect the warning times.

Because true positive and true negative signals are so similar in train approach recordings, approach detection is much harder than passage detection. This similarity in signals is likely driven by variation in train speed; differences in how well rail sections transmit vibration; and the complex interactions of train wheels, rail surface, car mass, train speed, and track curvature that produce the vibrations (Rudd, 1976; Remington, 1976). Our visual comparison of spectrograms derived from the train recordings suggested that the time before train arrival of each first observable signal was related to the train speed as well as the proximity of track lubrication equipment. Moreover, the in-rail acoustic train signals detectable at the greatest distances were exclusively ultrasonic (typically 20–40 kHz), but lower in frequency than the 40–80 kHz range expected from other work (Rose et al., 2004) (Appendix S4).

Our >80% detection rates are nonetheless promising for a first use of in-rail acoustic signals to detect trains, and the approach detector could be improved with further effort. Alternative data processing strategies could separate the approach signal into frequency bands before computing mean signal levels. Such strategies might be identified automatically using unsupervised feature learning algorithms on large datasets (Coates et al., 2011). At the cost of including a more sophisticated computer in each device, approach detectors could iteratively improve their accuracy and precision with each train passage via online machine learning techniques (Shalev-Shwartz, 2011). The cost of such technology continues to decline.

If the approach detector could be improved, it would have four advantages over the passing relay. First, the classification model may (with sufficient training sample size) learn to account for variations in train speed. Second, independent triggering of each warning system within the strike zone would increase the warning time consistency experienced by nearby animals, as long as the warning stimuli of nearby devices are more salient than those of distant devices. Third, the approach detector does not require separate sensing devices, allowing the system to accommodate small strike zones at the same cost per metre as large zones. Fourth, the approach detector should be more reliable because all devices in the zone would be fully redundant and would not depend on wireless communication.

Meanwhile, the passing relay results are strong enough to warrant implementation and further testing for the purpose of wildlife warning. The choice of sensor among compass, accelerometer, and weak vibration switch will depend on factors other than precision of detection, including not only cost (Table 1) but also power requirements and durability (Table S2, Appendix S5). Similar multidimensional comparisons must be made to select a controller; a wireless communication system; a warning signal; a power source; and a means of protecting the components from water, dust, ultraviolet degradation, and mild impact (e.g., shifting ballast rock). The parts for our prototype cost US$100 for the sensing device and US$125 for the warning device (Appendix S5). These costs could be reduced with design refinement and mass production.

The passing relay design is ideal for protecting short sections of track (e.g., 200 m or less for train speeds near 60 km h⁻¹) with a history or predicted risk of high strike rates. Ideally, multiple warning devices should be placed on the track within a strike zone (one every 50 m) with a sensing device placed 20 s (at average train speed) from the strike zone centre to detect trains approaching from either direction. Greater lengths of track could be protected by repeating this pattern on adjacent track sections, as long as care were taken to limit warning times to the same (20 ± 5) s within each consecutive protected zone. An ideal approach may be to combine these warning systems with short sections of fencing, excluding wildlife from the most dangerous areas while also mitigating strike risk at the fence ends (cf. Lehnerd and Bissonnette, 1997; M. Olsson, pers. comm.). Strike risk could be further reduced if these measures were combined with reductions in train speed (Rea et al., 2010), especially in areas of high strike risk.

<table>
<thead>
<tr>
<th></th>
<th>82</th>
<th>14</th>
<th>0</th>
</tr>
</thead>
<tbody>
<tr>
<td>FP</td>
<td>13</td>
<td>82</td>
<td>0</td>
</tr>
<tr>
<td>FN</td>
<td>0</td>
<td>14</td>
<td>10</td>
</tr>
</tbody>
</table>

Table 1. Confusion matrix for simulated data for the approach detector models.
The use of train-triggered warnings for the reduction of wildlife–train strikes makes two assumptions that require further study. First, it assumes that the inconsistent availability of train approach signals increases the risk of animals being struck. Second, it assumes that a warning signal will change animal behaviour so as to reduce their risk of being struck. In a recent test of another train-triggered wildlife warning system, animals reacted to trains earlier and were more likely to leave the track when a precisely timed acoustic warning was provided (Babiﬁska-Werka et al., 2015). This study did not determine whether the success of the system was driven by the temporal consistency of the warning signal, the choice of animal distress calls as warning sounds, or both. However, wildlife are prone to habituate to warning signals that are not followed by reinforcement or punishment (Ujvari et al., 1998; Gilsdorf et al., 2002), suggesting that learning plays a role in the success of this train-triggered warning system (Babiﬁska-Werka et al., 2015). Associative learning in this context requires that the warning stimuli are salient, uniquely associated with trains, and consistently timed relative to train arrival (Domjan, 2005). Learning of this type, especially as part of an avoidance learning process, has been demonstrated in wild animals using auditory and visual cues (Vollrath and Douglas-Hamilton, 2002; Kloppers et al., 2005) as well as olfactory stimuli (Baker et al., 2007). Seemingly similar wildlife warning technologies, such as wildlife warning reflectors (D’Angelo et al., 2006) and deer whistles (Valitzski et al., 2009), have had a limited effect on collision rates, potentially because the warning stimuli could not be associated specifically enough with the unconditioned aversive stimulus of close approach by a vehicle. Although aversiveness of conditioned stimuli is not a requirement for associative learning (Domjan, 2005), the literature offers incomplete guidance on the design of non-aversive warning stimuli for animals (Appendix S5). Optical and acoustic signals are natural choices because they can be turned on and off quickly and are easily produced with low-cost, low-power technologies such as light-emitting diodes and piezoelectric speakers. Visual and auditory perceptual ranges have been measured for some wild mammals (e.g., white-tailed deer, Cohen et al., 2014; Heffner and Heffner, 2010; D’Angelo et al., 2008), but data are incomplete or unavailable for many other species (for reviews see Jacobs, 2010; Ahnelt and Kolb, 2000; Fay, 1988). Additional work is needed to explore the effects of flashing versus steady light (but see Blackwell and Seamans, 2009), the effects of light colour on night vision (in humans, Mertens, 1955), and the interaction of light colour with a possible magnetoreceptive sense (cf. Poot et al., 2008; Niessner et al., 2016).

Ultimately, this work allows conﬁdent selection of a train detection method for train-triggered wildlife warning systems. Our system potentially achieves the temporal and spatial speciﬁcity required for associative learning while limiting the ﬁnancial, logistical, and technical barriers that might apply to similar technology. Warning systems based on our train detection methods may have further application outside of the wildlife protection and train contexts. For instance, pedestrians on railway tracks are sometimes struck while distracted by headphones (Lichenstein et al., 2012), and a visual warning may reduce the frequency of these events. For this application, we recommend the approach detector over the passing relay, because the self-contained approach detector can be deployed at lower densities over larger areas. We expect the inconsistency of warning time of the approach detector to be less of a problem for humans than for wildlife. However, the passing relay could be used by railway workers in countries around the world as a portable, precise, and inexpensive train warning system. The passing relay may also be useful for providing warnings to wildlife and pedestrians on roads, as road vehicles would be detectable with infrared and magnetic sensors: non-train track vehicles were detected flawlessly by these sensors. Vibrations in the road created by vehicles may also be detectable with the accelerometer and piezoelectric sensors, potentially enabling an approach detector. Importantly, vibration-based and magnetic sensing remain reliable under diverse weather and lighting conditions—a distinct advantage over optical headlight detection that has been used previously (Mulka, 2009). This work offers a new way to help wildlife and people coexist with transportation networks worldwide.

Acknowledgements

We are grateful for funding and extensive logistical support from the Joint Initiative for Grizzly Bear Conservation of Parks Canada and Canadian Pacific with matching funds from a Collaborative Research and Development Grant provided by the Natural Sciences and Engineering Research Council of Canada (NSERC; CRDPJ/441928-2012). Additional support was provided by NSERC (Discovery Grants program and CGSD2-475709-2015), Alberta Innovates – Technology Futures, and the University of Alberta. We appreciated assistance from individuals at Parks Canada (Brianna Burley, Anne Forschner, Blair Pyten, Dave Garrow, Don Corrie, Simon Ham, Bill Hunt, Tom Hurd, Rick Kubian, Kris McCleary, Steve Michel, Saundi Norris, Dan Rafia, Jesse Whittingson), Canadian Pacific (Chris Bunce, Perry Busse, Ken Roberge, Lorrie Hoffman, Joe Van Humbeck, Roy McIlveen, Joshua Pemberton, Tim Stroh, Dave Waldhauser, Doug Younger, and NSERC (Theresa Anderson). For assistance with ﬁeld work, data analysis, equipment design, valuable discussions, and manuscript preparation we thank Stan Backs, Sarah Fassina, Alyssa Friesen, Aditya Gangadharan, Patrick Gilhooly, Liam Harrap, Richard Hull, Brittany Jackson, Julia Jackson, Kathy Janzen, Megan Kinley, Isabella Lin, Cole Lord-May, Breda Moriarty, Sonya Pollock, Laurens Put, and Hong Zhang. We also thank three anonymous reviewers for suggestions that improved this manuscript.

Supplementary data

Supplementary data and appendices associated with this article can be found in the online version at http://dx.doi.org/10.1016/j.ecoleng.2017.06.024.

References


