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Digital Image Enhancement and Classification of Thermal Infrared Imagery for Monitoring White-tailed Deer in Missouri Wildlife Game Habitat

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Abstract

Remote sensing is the most suitable method for surveying different wildlife species, particularly big game. It is faster, cheaper, and more accurate than the conventional ground surveys. Among the various remote sensing systems, thermal infrared imagery (TIR) was found to be the most suitable for depicting wildlife animals in their natural habitat. The objective of this study is to find the best method for thermal infrared imagery enhancement and classification for the census taking of big game, and specifically, the white-tailed deer (Odocoileus virginianus).

The process consists of two stages: first, to isolate the emittance signature of an animal. Increasing the contrast between the animal signature and its background using various image enhancement methods can do this. The second stage is to sample the isolated animal signature for signature training, using various image classification methods for making animal censuses.

The results of this study indicated a significant reduction of the emittance signature in the big game census in the TIR. This is a result of canopy interference and the lack of contrast between the emittance animal signature and its background. This problem does not exist under the ideal conditions of no canopy interference and non-vegetated land, such as pare-rock. In this case, the TIR imagery produces clearly identifiable shaped targets, which appear as irregular white or near white colour tone images. The image enhancement and the classified thermal imagery found in this study provided an accurate identification, and a fast method of surveying the white-tailed deer population.

Introduction

Traditional methods of surveying big game species range from line transect counts, spotlight counts, drive counts, mark-recapture methods to helicopter or fixed-wing aircraft counts (Wiggers & Beckerman, 1993). The early use of TIR for big game surveying was restricted due to the limitations of the TIR system operation and the tools for digital image processing of the data (Coon et al., 1968). Early trials involving TIR met with limited success, which precipitated a discontinuous and fragmented history of research in this field.

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In use since the mid-1930s, the traditional methods of surveying suffered from several critical shortfalls. In tests where the numbers of animals present were known, the method failed to detect 12 to 71% of the animals (Otten et al., 1993). Furthermore, the aerial surveying was limited to low altitude helicopter or fixed winged aircraft flights over the desired study areas. This created low area coverage results per flight line (transect widths average of 200-300 meters) (DeYoung, 1985), with a quite large number of flight lines being required to cover an area.

Peterson and Page (1993) note that the grid patterns from flying are too small to eliminate or significantly reduce surveying errors (targets). This, combined with the high cost, has led researchers to gradually move away from attempts at total area surveying in favour of a sampling approach. Most sampling approaches are based on surveying small quadrangles within a study area, with results producing population estimates based on sight ability models and extrapolation graphs.

Certain limitations encountered in early trials involving TIR were attributed to equipment sensitivity (Wyatt et al., 1980). Parker (1972) has found a mean difference of 7.7°C between the deer and snow background. He recommended that a sensor must distinguish a temperature difference of 0.5°C for the technique to be successful, whereas previous studies did not take into consideration the impact of temporal factors on recording the TIR imagery. Specifically, most trials were during daylight hours, increasing the influence and potential for false targets to occur. Solar heating of background objects can cause these 'non-target' objects to radiate long-wave heat energy at or near the same level of emissivity as the desired targets. Testing of TIR by Croon et al. (1968) was at midday (1225 hours) in January, at an air temperature of 25°F. Graves et al. (1972) conducted testing during early morning in November, also at an air temperature of 25°F. Richard and Driscoll (1972) also tested in the early morning, but conducted the test in August at an air temperature of 56°F.

In contrast to the daylight time surveying by various authors, Wiggers and Beckerman (1993) tested in the early evening (2000-2400 hours) in August at an air temperature ranging between 21.1 and 23.8°C, obtaining better results than previous findings. Using Driscoll's data and the application of statistical theory, Wyatt et al. (1980) indicated that the use of TIR is an effective tool in surveying big game populations, with errors in target identification increasing significantly in the absence of snow.

The use of the TIR system of surveying wildlife species has yet to be used to its full potential. Many of the areas the TIR was tested are located in northern areas, where contrasting temperatures between the target and its background are expected. The predominant conifers coverage obscures the target, as well as reducing the signature significantly. To overcome this problem, the TIR system should be more sensitive to temperature variations. In addition, using the advanced techniques of digital image analysis should enhance the present signature.

Big game surveys, using digital and analogue image enhancements of TIR, were carried out by various authors without success (Isakson, 1975; Wride, 1977; and Garner, 1995). The image-slicing techniques used by Wride included false targets, and was not as effective as a visual interpretation of the data. Garner used one known target as a training sample for classifying the total area coverage. This did not include any calibration factors of the variations between the target and the various backgrounds that exist between and within the imagery. Their results showed visual interpretations to be favourable over digital analysis, yet the visual interpretation results may not be inclusive since significant variations in target digital number (Dn) ranges can occur. Factors that can create the significant (Dn) ranges are: variations in altitude, angle of incidence, variations in cloud cover, decreases in ambient air temperature, and variations in wind velocity. These factors can occur with images that are captured only a few seconds apart. Standardization between images must be ensured in order that variations are mitigated before implementing the classification techniques.

All other studies have relied on direct elements of recognition. Targets have been identified solely on their relative size, shape, and colour (intensity of emission – white = hot, dark = cold, etc.). In fact, Parker and Driscoll (1972) employed the use of "three interpreters unfamiliar with the TIR imagery" to identify deer on the imagery. In Wiggers and Beckerman (1993), five biologists viewed fifteen minutes of a TIR tape, which showed identifying features of the white-tailed deer. They were asked to study the TIR tape and identify any deer. In attempting to eliminate bias from their research findings, these researchers eliminated a large advantage offered by TIR imagery, namely, its suitability for digital image enhancement.

One of the key assets of TIR data is the use of digital enhancement techniques to identify visually hidden targets, including the use of digital classification. This represents a significant shortfall in the research done to date on TIR systems. The recorded limitations of TIR imagery were due to lack of system sensitivity, inclusion of false targets, high cost of equipment, and difficulty in penetrating dense canopies. Wyatt (1980) stated, "... Thermal contrast, by itself, is not of value in surveying deer populations." Currently, as part of a comprehensive digital image analysis protocol, there is a significant reduction of the occurrence of false targets by improving target to background contrast. This is a result of the advancements in digital image analysis since Isakson's (1975) and Wride's (1977) research; and with the inclusion of such techniques as filtering and signature training.

Methods

Successful target identification is associated with target visibility. In the case of TIR sensors, target visibility relies on the presence of a significant contrast between target and background temperature. This, in turn, depends on temporal recording conditions of the target, and on the depth of digital image analysis.

Thermal video imagery was recorded by Wiggers and Beckerman (1993) over White Shell Provincial Park, Manitoba, Canada, in mid-winter. The recording occurred at night during the pre-dawn hours, with calm winds prevailing (wind disrupts received heat emissions). Long-wave emissions from trees, rock outcrops and dark surfaces diminish during the night to a relatively constant background noise level, approximating that of the ambient air temperature. The recording in the pre-dawn hours captured most deer, moose, and elk while active; and brought the contrast between the targets to background to its maximum. The TIR database, stored in tape format, displayed captured images (size 640 × 480) at a rate of 15 frames per second using Video-it software package (ITI Technologies Inc.).

Twenty images selected from the TIR tape identified at least two clearly visible deer, using standard direct elements of image recognition such as size, shape, and location. This method was chosen to ensure the signature-training results for any one image were used to analyse remaining images. This meant that each image would have at least two known control points, providing a backdrop against which the effect of the digital image analysis could be evaluated.

Each of the twenty images was saved as 24 bits per pixel Band Interleaved by Pixel (BIP) and Tagged Image File Format (TIFF) files. This data was then transferred to the GIS software package IDRISI (Clark University) for further analysis. Transfer of the data required that the images be converted to eight bits per pixel BIP and IMAGE (IMG) file formats using a subroutine operation within the IDRISI software system.

One image from the set of twenty images was chosen randomly for signature training. Upon examination, six known targets (deer) of the chosen signature-training image were identified. At this point, two forms of supervised classification were implemented. The first was a 'typical' digitization of the known target pixel values, with the application of these values in maximum likelihood and minimum distance supervised classification algorithms. The second classification was modified to a more flexible application of the signature-training value, using the Re-class operating function in IDRISI. It was anticipated that the more flexible modified supervised classification would provide the best results. Five methods of analysis were used to enhance and classify the target Dn value as follows:

1. Signature-training and Maxlike supervised classification
2. Signature-training and minimum distance supervised classification
3. Group target and supervised classification
4. Formula to calculate a simple means of normalization of 95-percentile value as the minimum target Dn.
5. Linear regression to calibrate the time of TIR imagery recording

Results and Analysis

1. Using signature-training and Maxlike supervised classification

Signature training was created through digitizing the pixels, which formed the known targets for the maximum likelihood and minimum distance supervised classification algorithms. The Maxlike subroutine within the IDRISI environment was used to create classified imagery from the signature-training file based on the likelihood of being a target. Despite judicious care in digitizing the known targets, running the Maxlike subroutine resulted in the over-inclusion of non-target pixels being classified as target pixels. Though maximum likelihood classification generally produces the best results, it was expected for certain data to find that minimum distance classification can provide better results.

2. Using signature-training and minimum distance supervised classification

The same signature-training file values were applied to the Mindist subroutine with some improvement of results; but the Mindist subroutine also included several clusters of non-target pixels that were erroneously classed as targets. To ensure that the signature-training values were representative of the target Dn values, a second digitization of the signature-training image was applied and a new signature-training file produced. The above classification procedures were repeated using the second signature-training file, and the results were compared to those obtained from the first signature-training file. However, re-running both the Maxlike and Mindist subroutines using the second signature-training file did not significantly alter the results.

3. Using Group Target and Supervised Classification

The third approach of investigation was based on a coarse inquiry mode, by manually recording the brightness value of each of the pixels within each target (approximately thirty pixels per target). The minimum, average, and maximum brightness value for all six targets was combined and computed. In conjunction with the re-class function within IDRISI, these values were used to perform supervised classification where all pixel values within the image were grouped into five brightness value (Dn) classes. The five Dn classes were chosen to provide reference for background objects, thus aiding in the identification of false targets should they arise. The five classes were as follows:

Class 1: Dn of 40 to Dn values ranging from 0–39.
Class 2: Dn of 60 to Dn values ranging from 40–79.
Class 3: Dn of 80 to Dn values ranging from 80–119.
Class 4: Dn of 160 to Dn values ranging from 120–153.
Class 5: Dn of 255 to Dn values ranging from 154–257.

The first three classes roughly correspond to grasses, shrubs, and trees (respectively), while Class 4 represents weak to medium deer signatures, and Class 5 represents medium to strong deer signatures. Note that for Class 5, the upper limit was set at 257(not the 184 maximum determined through signature-training). The expectation with the high upper limit is the particular data for the existence of other fauna radiating a thermal signature above 184 was remote. Furthermore, any other materials radiating a thermal signature above 184 (such as houses, cars or large rock out-cropping) were screened out using the Group and Area operations functions within IDRISI.

As expected, supervised classification improved target to background contrast resulting in the clear identification of all six targets (Figures 1 and 2).

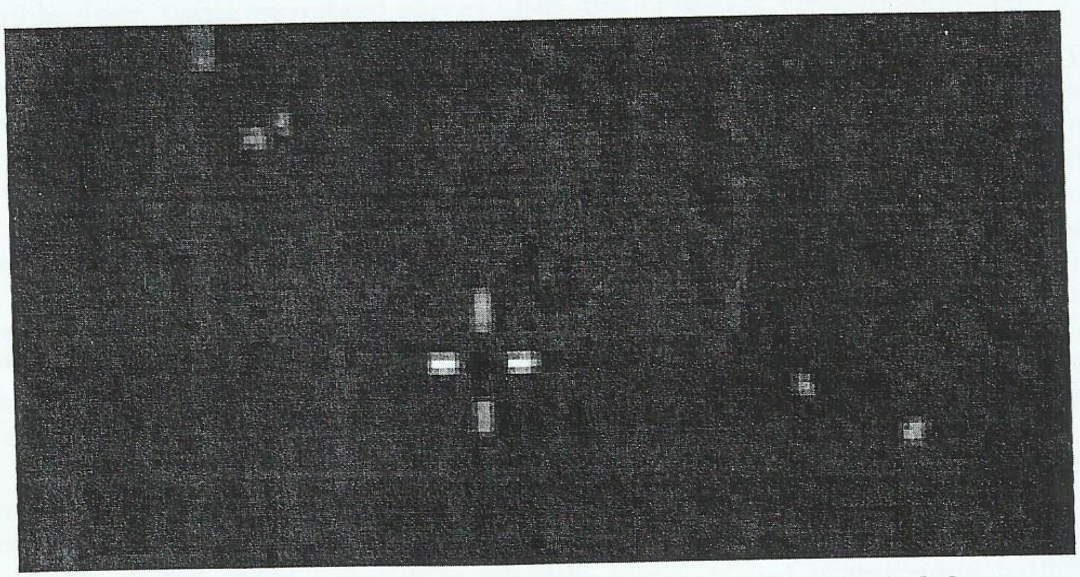

Figure 1: ***The original TIR Imagery of the white-tailed deer.***

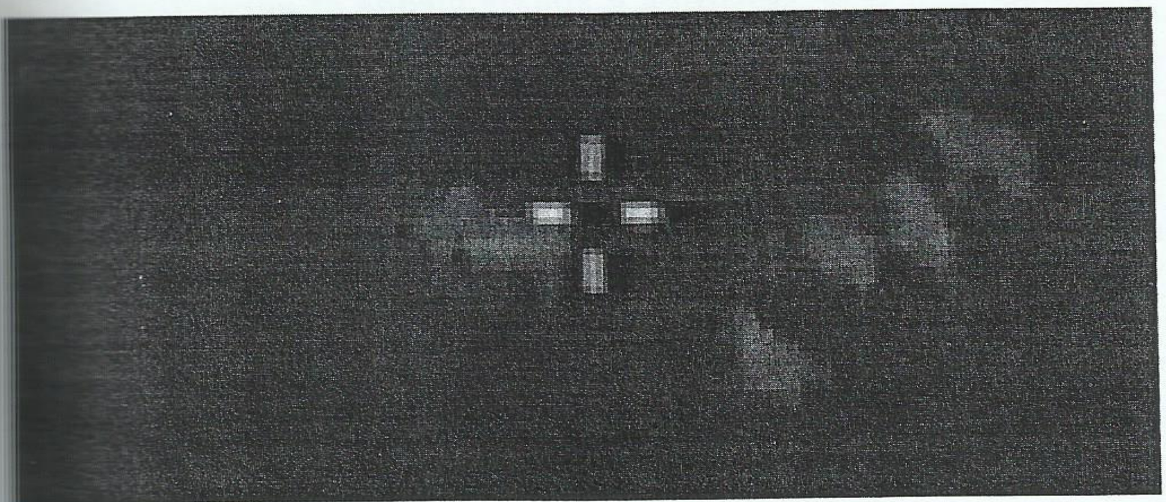

Figure 2: ***The enhanced TIR Imagery of the white-tailed deer***

The group and area functions were applied to the classified image to determine the lower and upper area (size) range of the targets. The target area range, in conjunction with the target brightness values, formed the selection criteria for the modified unsupervised classification of the remaining nineteen images. Specifically, the pixel brightness values and associated classes noted above, form the primary criteria by which any unknown image within the data set is to be reclassified. The area and range of the desired targets forms a filtering function by eliminating false targets that fall within Class 4 or 5 Dn values, but that are larger or smaller in an area than the desired targets.

The next step of the analysis was based on the calculation of the means of the remaining nineteen images. The standardizing of the images and/or the Class ranges was to reflect distribution variations within each image. A cursory review of the nineteen images showed variation of the Mean from one image to the next. Based on this variation, the Class ranges were adjusted to reflect the percentile difference between the signature-training image and any unknown background image. This method proved very effective in enhancing the remaining nineteen images, but the results were unsatisfactory when different images were used as the signature-training image. This prompted a more detailed examination of the Dn distributions for all twenty images. It was found that all images within the data set had non-normal distributions that were strongly bi-model and skewed to the left.

4. *Using formula to calculate a simple means of normalization of 95-percentile value as the minimum target Dn*

Based on the above findings, two formulas were applied on all twenty images based on the median, quartile, and inter-quartile range values. The first formula was used to calculate the minimum Dn, and the second formula to calculate the maximum Dn values. The results of these calculations were used for the standardization of the Dn values in the twenty images. For any image in the data set, the following two formulas were applied:

Formula 1: $I,T,Dn_{min}=(X_1/X_{st}) \times STTDn_{min}$

Where,

I,T,Dn_{min}: image I target Dn minimum
X_1: image I medium value
X_{st}: signature-training image medium value
$STTDn_{min}$: signature-training target Dn minimum

Formula 2: $I,T,Dn_{max}=(X_1/X_{st}) \times STTDn_{max}$

Where,

I,T,Dn_{max}: image I target Dn maximum
X_1: image I medium value
X_{st}: signature-training image medium value
$STTDn_{min}$: signature-training target Dn maximum
(I=1-20)

The minimum and maximum Dn values of target for all twenty images were calculated using the above two formulas. All images within the data set had target Dn values consistently occurring above the ninety-five percentile. Based on the latter finding, target Dn values represented virtual outliers within their own image distribution. This can explain the difficulty in identifying a reasonable response to target Dns using non-normal distribution indicators. Based on this information, a simple means of normalization was calculated with the 95-percentile value as the minimum target Dn, and reclassification was performed in conjunction with the group and area functions. This method of the 95-percentile value had added to the over-inclusion of fragmented areas into the desired target Dn class range. This was especially true for areas exhibiting urban or urban-related structures. Variations in the angle of incidence between images and the use of a zoom feature on the TIR recorder at the time of data capture precluded the effective use of the group and area functions in forming a secondary filter to eliminate false targets based on their size.

For any image in the data set, the expectation was that if an 'unknown' image's 95 percentile value was higher than that of the signature-training image, the target responses for that image would also be higher, and vice versa. Unfortunately, the 95-percentile value failed to provide any significant correlation to variations in target Dn values.

5. *Using linear regression to calibrate the time of TIR imagery recording*

The results were based on incorporating the time of recording. It was immediately evident that target Dn values were increasing with time, particularly the data capture well after sunset. As the sun's angle of incidence and ambient air temperatures decreased, the target to background contrast should, and did, increase. Further, had the sunset and background objects been allowed to cool for several hours, maximum 'non-enhanced' target to background contrast would have resulted. This problem can be calibrated using the linear regression model for the data to aid in the adjustment of target Dn values from one image to the next. As target Dn values represented outliers within their own data sets, the first attempt was to use the 97-percentile value against time. This resulted in an r^2 value of .34. In an attempt to increase the amount of variance explained, we attempted multiple linear regressions using the inter-quartile range and the 97-percentile value against time. The resulting r^2 of .67 was an improvement, but less than satisfactory (as four untrained interpreters, viewing the raw TIR footage, were capable of correctly identifying species 91.5% of the time (aggregate average)).

Conclusion

As with any 'new' technology, hardware and software costs decrease as demand and accessibility increase. Though demand for TIR equipment by wildlife managers has been sporadic at best, there has been a steady increase in the number of companies operating TIR sensor systems for various industrial uses. This has in turn provided accessibility to rentable equipment, and significantly reduced the cost factor.

Penetration of dense canopies remains a limitation of the system. However, the level at which target identification ceases is arguably more consistent for a TIR system than a human observer. Thus, the results from a TIR system may prove more reliable. Though Wride (1977:1095) stated, "Any census method is suspect in such conditions....", further research is needed due to the technical improvements in TIR systems and analysis packages currently available. Lastly, Wyatt's (1980) contention that thermal contrast by itself is not of value is, in our view, misleading as, at the time of Wyatt's comments, system sensitivity may have necessitated additional techniques for image interpretation and target identification. Using signature-training and Maxlike supervised classification, as well as signature-training and minimum distance supervised classification, did not improve target enhancement significantly. Using group target and supervised classification has shown better results, but only on the images where signatures were selected. Both methods used formula to calculate a simple means of normalization of 95-percentile value as the minimum target Dn. In addition, using linear regression to calibrate the time of TIR recording provided good results for the twenty images. The latter two methods were able to overcome external factors hindering the proper image enhancement.

Arguably, such additional analytic techniques are still desirable. However, current system sensitivity often does not require any alteration of recorded data to produce significant target identification. We found that thermal contrast to background will likely continue to be of key importance to the success of any application involving TIR. As the fundamental building block of any data capture run, the thermal contrast will directly influence the results of data capture, and the data's suitability for digital analysis.

It is important to recognize that despite the data having been recorded under less than optimal conditions, digital image analysis was very effective in enhancing target to background contrast on an image-by-image basis. However, due to the temporal conditions, uncontrolled angle of incidence, and use of a zoom feature during data recording, the data was not suitable for total coverage analysis.

The unsuitability of the TIR data for standardization and application of modified unsupervised classification was due to the inappropriate temporal conditions at the time of data capture. Notwithstanding, we were successful in enhancing target to background contrast on an individual image-by-image basis using standard digital image analysis techniques.

Provided the data is recorded with the temporal requirements of a TIR system, there is reason for optimism that digital image analysis has the potential to improve the interpretation of TIR data.

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