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Modified Wavelet Methods for Identifying Transitions in Bean Beetle Maturation

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Modified Wavelet Methods for Identifying Transitions in Bean Beetle Maturation

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Abstract

As bean beetle embryos develop, time lapse photographs of their eggs exhibit varying levels of brightness that correspond to different stages of maturation. This signal can be analyzed to pinpoint the timing of these various stages. We have developed an averaging method based on a modified Haar wavelet technique to identify these changes visually. This method has been studied for both accuracy and precision through a process of randomized simulations at different levels of signal noise. The results of this study have supported the efficacy of this method, demonstrating its usefulness in analyzing a wide variety of signals.

Introduction

Bean beetles (*Callosobruchus maculatus*) are agricultural pests native to Africa/Asia. These insects are poikilothermic, and lay their eggs on bean surfaces. Following embryonic development, they burrow into the bean and consume the inside before emerging as adults. Digital time-lapse microscopy is used to track changes in the eggs, providing a signal of average RGB values to analyze the brightness of each egg corresponding to certain stages of development, concluding with head capsule darkening. Our method facilitates accurate identification of the beginning of head capsule darkening.

Figure 1 (Right): Bean beetles. Female on left, male on right.

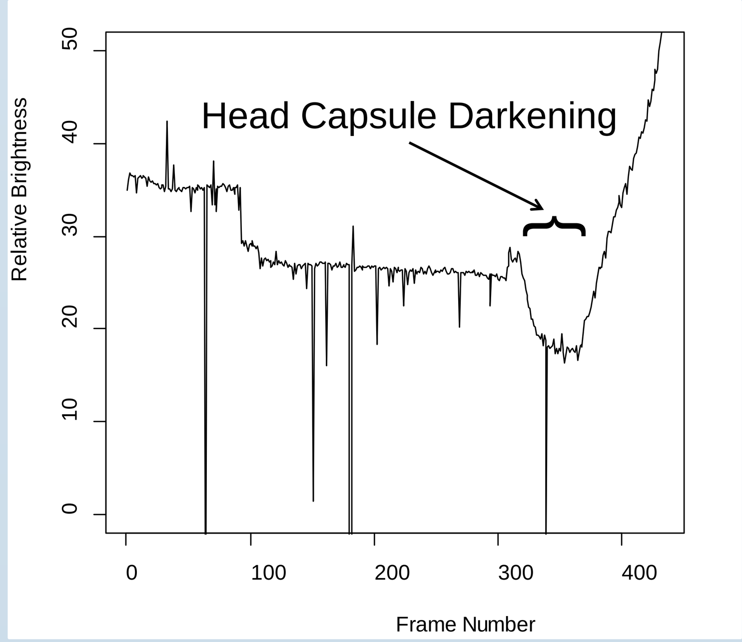


Figure 2 (Above): Time-lapse image showing four bean halves with eggs.
Figure 3 (Right): Brightness curve extracted from image sequence around egg indicated in Figure 2.

The Seaweed Method

We modified the standard Haar wavelet algorithm to increase the resolution in identifying the beginnings of important changes in the signals, such as the darkening of the bean beetle head capsule.

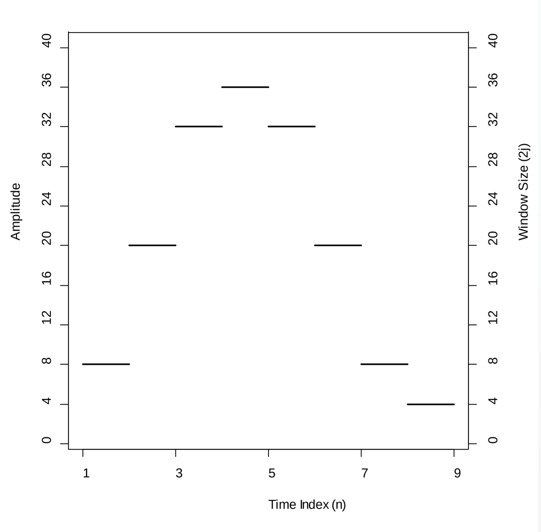
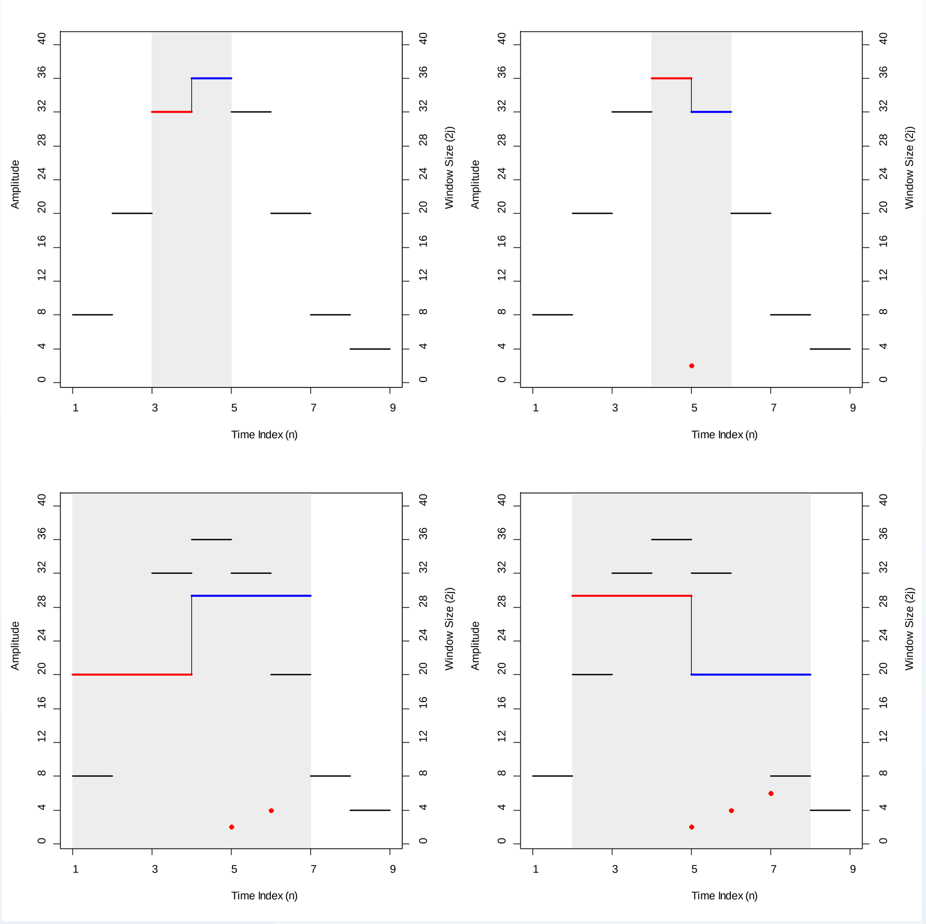


Figure 4 (Left): Example of a discrete signal.
Figure 5 (Right): Identification and marking of points which cause the differences of averages to change sign at window levels 2 and 6.



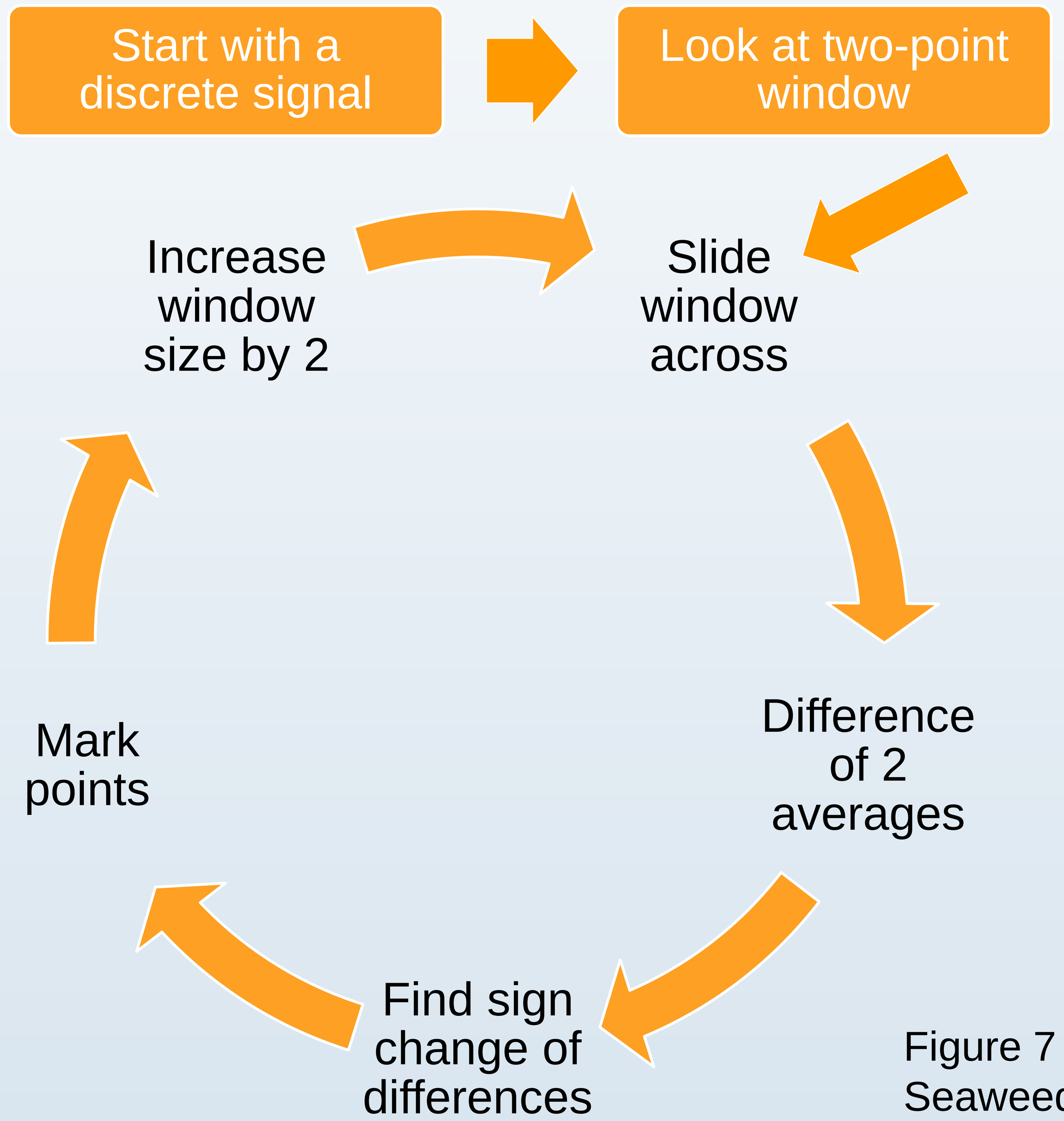
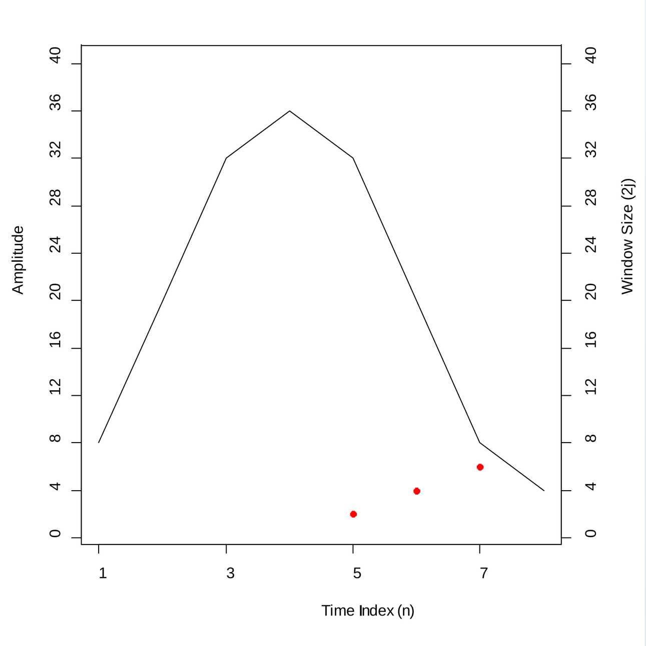
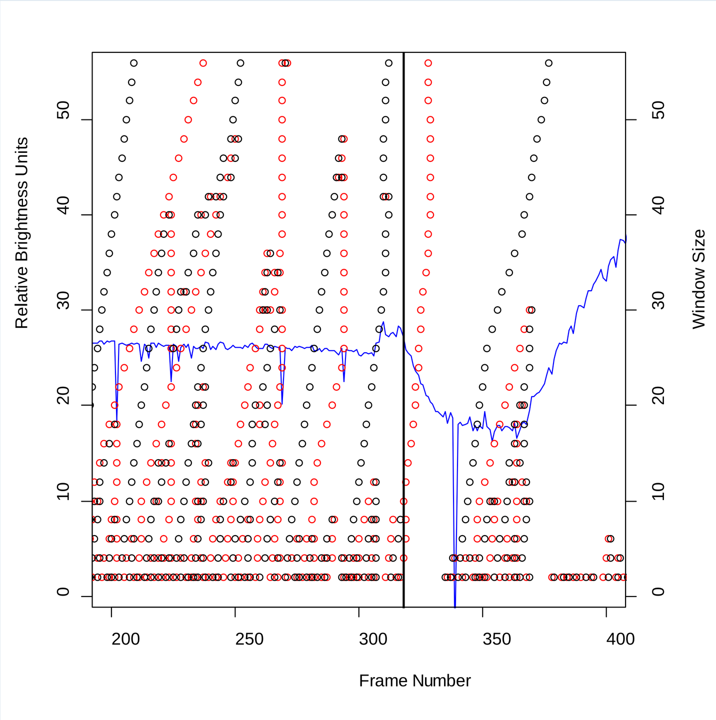


Figure 6 (Right): Final result of seaweed algorithm.



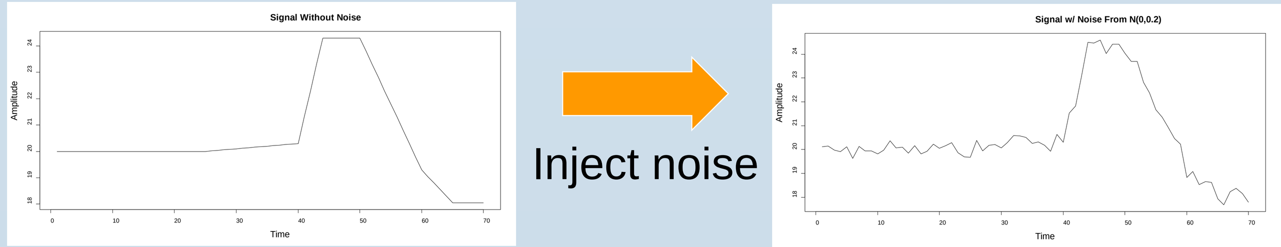
This creates a strand of points (called seaweed) around areas of the signal which represent important changes in the signal. By identifying these strands and tracing them down, we can identify "transition points" accurately. Note that transitions from a negative difference to a positive difference may be present as well.

Figure 7 (Right): Seaweed output for example bean beetle brightness curve. The black line indicates the transition point, (318,4). Red points indicate decreases, black points indicate increases.



Testing The Seaweed Method

We tested the seaweed method at various noise levels by injecting noise into a base signal, and using seaweed to pick randomly positioned transition points. The noise came from normal distributions with mean zero and varying standard deviations.



The signals appeared in random order, and in each case we were kept blind to the true transition point as well as the level of noise. In this regard we were able to minimize any sort of learning in the analyst which may skew the results.

Results

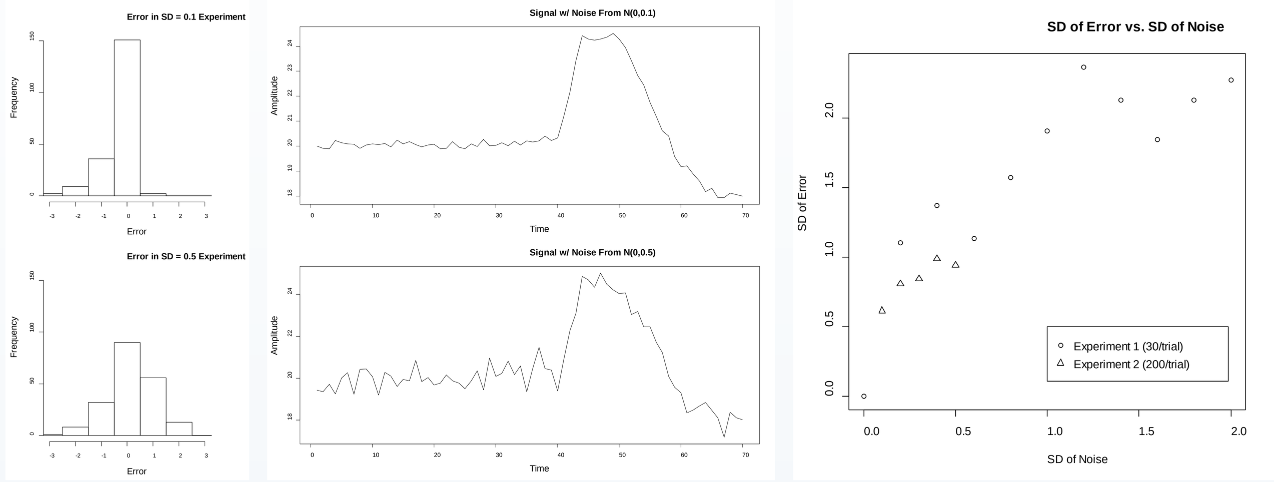


Figure 8 (Above Left): Histograms of transition point identification error from two experiments, sd = 0.1, 0.5.
Figure 9 (Above center): Example signals depicting experimental noise levels.
Figure 10 (Above Right): Scatterplot showing transition point identification error from all experiments.

Conclusions

Based on these results we can conclude that this method is both precise and accurate. This is supported by the low standard deviations of the error distributions, and the centering of each distribution at zero. Furthermore, there is a low standard deviation of error for noise levels of our bean beetle experimental data (sd = [0.0.5]), and even at high levels of noise our method is still accurate. Finally, this suggests that our method is indeed capable of analyzing a much wider range of signals.

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