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# Detecting Insect Flight Sounds in the Field: Implications for Acoustical Counting of Mosquitoes

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**Abstract**

A prototype field-deployable acoustic insect flight detector was constructed from a noise-canceling microphone coupled to an off-the-shelf digital sound recorder capable of 10 h recordings. The system was placed in an urban forest setting 25 times over the course of the summer of 2004, collecting 250 h of ambient sound recordings that were downloaded to a personal computer and used to develop detection routines. These detection routines operated on short segments of sound (0.093 s, corresponding to 4096 samples at 44100 Hz). A variety of approaches were implemented to detect insect flight tones. Simple approaches, involving sensing the fundamental frequency (1st harmonic) and 2nd harmonic, were capable of detecting insects, but generated large numbers of false positives because of other ambient sounds including human voices, birds, frogs, automobiles, aircraft, sirens, and trains. In contrast, combining information from the first four harmonics, from the interharmonic regions, and from the sound envelope, reduced false positives greatly. Specifically, in the 250 h of recordings, 726 clear insect buzzes were detected by the final algorithm, with only 52 false positives (6.5%). Running the final algorithm with all criteria liberalized by 20% increased the number of clear insect buzzes by 8%, to 784, but increased false positives to 471 (28% of total detections). The potential of using this approach for detecting mosquito activity using low-cost sensors is discussed.

**Keywords**

Enumeration, Harmonic, Remote sensing, Wingbeat frequency

**Disciplines**

Agriculture | Bioresource and Agricultural Engineering | Entomology

**Comments**

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**Abstract.** *A prototype field-deployable acoustic insect flight detector was constructed from a noise-canceling microphone coupled to an off-the-shelf digital sound recorder capable of 10 h recordings. The system was placed in an urban forest setting 25 times over the course of the summer of 2004, collecting 250 h of ambient sound recordings that were downloaded to a personal computer and used to develop detection routines. These detection routines operated on short segments of sound (0.093 s, corresponding to 4096 samples at 44100 Hz). A variety of approaches were implemented to detect insect flight tones. Simple approaches, involving sensing the fundamental frequency (1st harmonic) and 2nd harmonic, were capable of detecting insects, but generated large numbers of false positives because of other ambient sounds including human voices, birds, frogs, automobiles, aircraft, sirens, and trains. In contrast, combining information from the first four harmonics, from the interharmonic regions, and from the sound envelope, reduced false positives greatly. Specifically, in the 250 h of recordings, 726 clear insect buzzes were detected by the final algorithm, with only 52 false positives (6.5%). Running the final algorithm with all criteria liberalized by 20% increased the number of clear insect buzzes by 8%, to 784, but increased false positives to 471 (28% of total detections). The potential of using this approach for detecting mosquito activity using low-cost sensors is discussed.*

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Because of their tremendous ecological and economic impact, the automated counting of flying insects is of interest to a variety of scientists, engineers, public health officials, and regulators. Counting has historically been done manually, which is time consuming. An electronic system for detecting and logging moth captures in sex pheromone traps was developed and justified by reason of cost and improved temporal resolution of the resulting data (Hendricks, 1985). It was estimated that scouting costs might be reduced by up to 80% via remote insect detection systems and that such systems would enable the collection of census information previously unavailable to the research community (Hendricks, 1989).

The focus of this work was on mosquito detection, although we are interested in the general problem of flying insect detection, identification, and enumeration. Mosquitoes are the most common blood-sucking insects encountered in residential areas in the U.S., where they annoy people, pets, and livestock, driving people indoors and increasingly transmitting disease organisms to people. For example, over 9000 cases and 264 human fatalities of the mosquito-borne West Nile virus were reported in the U.S. in 2003 (Hayes and Gubler, 2006), and over 100 cases of La Crosse encephalitis were reported among children in the U.S. in 2004 (CDC, 2005). The primary vectors of West Nile virus (*Culex pipiens* complex) are sampled by Centers for Disease Control and Prevention (CDC) light traps that must be deployed on one day and retrieved the next. The vectors of La Crosse virus (*Aedes albopictus* and *Ochlerotatus triseriatus*) are monitored by $CO_2$ baited traps, and by oviposition traps where females come to lay their eggs (Erwin et al., 2002). Sampling and enumeration of mosquitoes collected by all these traps is labor intensive.

In developing countries, combating the resurgence of malaria requires a multifaceted approach, one part of which is the reduction of mosquito vector populations, especially near at-risk human population centers. Integrated vector management (IVM) approaches use surveillance to guide the deployment of vector control measures, and IVM is effective at slowing resistance development in targeted pest populations. Knowledge of mosquito infestations is a critical component of the WHO Expert Committee on Malaria vector control strategy (WHO, 2000, Section 8.11).

The identification of mosquitoes by their flight sounds has a history that began over half a century ago (Offenhauser and Kahn, 1949) and has continued steadily with work by a number of other investigators (e.g., Jones, 1964; Belton and Costello, 1979; Mankin, 1994). Optical determination of mosquito wingbeat frequencies can be used in a similar manner (Moore et al., 1986; Moore, 1991; Caprio et al., 2001). However, no reports exist of field-deployable mosquito enumeration systems that use near-field sound measurements to determine mosquito population densities. Such a device, if made simple, robust, and accurate enough, might decrease

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the costs of scouting, enhance scouting densities, and enhance scouting temporal resolution. Reductions in the cost and power requirements of digital signal processing devices make such approaches increasingly realistic.

Technologically, it has long been possible to detect mosquitoes and other insects acoustically (e.g., Offenhauser and Kahn, 1949; Jones, 1964; Belton and Costello, 1979; Mankin, 1994; Caprio et al., 2001). However, to date, acoustic mosquito detection has either been confined to laboratory experiments or has involved the collection of acoustic energy from swarms of mosquitoes. In contrast, the focus of the work reported here was the development of a mosquito activity monitoring system using relatively inexpensive hardware, coupled with software that could realistically be expected to run on a small signal processing chip, capable of accurate performance in noisy real-world environments.

## Materials and Methods

Detecting the spectra of sounds arising from mosquito flights in a closed chamber is relatively straightforward, and we made such recordings and analyzed them in preliminary stages of this work (unpublished). We also showed that the number of buzzes recorded was approximately proportional to the number of mosquitoes in the flight chamber. Because we could not predict, a priori, the nature of the natural and anthropogenic sounds that would challenge our system, we employed a field test unit (FTU) capable of high-fidelity digital recordings of ambient sounds near a light attractant. The FTU was deployed from May through August of 2004, for 250 h over the course of 30 sampling days in a high-noise urban environment (80% of recordings) and a suburban forest (20% of recordings), and the sounds were stored on a personal computer (PC). The high-noise urban environment was on the campus of the University of Tennessee (35.94679° latitude, –83.93816° longitude). This location was in a woods on a small urban creek, approximately 100 m from a large rail yard, 50 m from a four-lane bridge, less than 1 km from a helipad at a regional hospital, and 20 km from a large regional airport. It was typical to hear jet airplanes, helicopters, screeching trains, and emergency vehicle sirens in the recordings made at this site. The suburban forest was in the Maryville College Woods (35.74586° latitude, –83.95764° longitude). In the high-noise urban environment, the FTU was hung approximately 3 m off the ground, from the eaves of an old shed, while it was hung at a similar height from the limb of a tree in the suburban forest. During this time, the predominant mosquito species in these areas were *Aedes albopictus* (Skuse), comprising about 50% of the total, and *Ochlerotatus triseriatus* (Say), comprising about 25% of the total, with the remainder being six other species. This repository of recordings was used to challenge and refine a variety of detection algorithms. Although we had hundreds of hours of sound files, we never employed detection algorithms requiring more than a few hundred milliseconds of data. This constraint was applied so that any algorithms developed could eventually be transferred to a portable digital signal processing system with relatively limited memory and processing capabilities.

### Instrumentation

The FTU consisted of a noise-canceling electret condenser microphone cartridge (Panasonic WM-55D103, www.panasonic.com) connected to a two-chip preamplifier and high-pass filter that we designed and constructed, the output of which fed into a digital sound player/recorder (Nomad Jukebox 3, Creative Technology, Ltd., www.nomadworld.com) that recorded the microphone signal for up to 10 h at a time. Although the MP3 player/recorder had sufficient disk space to record over 300 h of uncompressed WAV format sound, device firmware limited recording length to 3 h in WAV format and to 10 h in the compressed MP3 format. The compressed format was selected (data rate of 64 kb/s) to enable data collection for 10 h. During sampling in the urban environment, a white LED (CMD333UWC, Chicago Miniature Lamp, Inc.) was used as an attractant, and protruded from the base of the system (fig. 1). A cylindrical foam baffle affixed around the lower part of the FTU, and extending 25 cm below the base of the FTU, was used to enhance the sensitivity of the system to near-field sounds. Power for the system came from two 6 V, 4 Ah rechargeable batteries: one for the LED, microphone, filter, and amplifier stage, and the other for the digital recorder. During the suburban forest sampling, the white LED was replaced by a 12 V, 1 W incandescent lamp powered by a separate battery, and was hung 15 cm below the microphone to serve as an attractant.

### Data Processing

At the end of a 10 h experiment, the MP3 sound file (ca. 280 MB) was downloaded to a PC. To avoid producing excessively large decompressed files, the 10 h long MP3 sound files were split into 2.5 h long (ca. 70 MB) segments using commercially available software (MP3 Splitter & Joiner 2.60, www.ezsoftmagic.com). The smaller MP3 files were decompressed into raw WAV format files (ca. 760 MB each) using freely available software. The resulting WAV files were subsequently processed via computer programs written in the C++ programming language (GCC compiler, Free Software Foundation, Inc., Boston, Mass.). The program went through several iterations in an effort to produce software that would detect insect flight sounds while rejecting the non-insect flight noises recorded in the test environment, including a variety of song birds, peepers, crickets, sirens, trains, aircraft, and human voices.

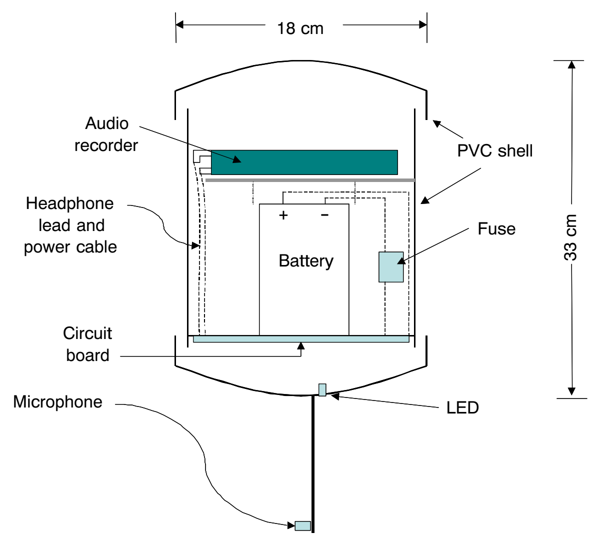


**Figure 1. Schematic of the field test unit (FTU) showing location of major components (not to scale, and cylindrical foam overhang not shown).**

Raw recordings were auditioned to find recordings with multiple insect flight sounds. One of these 2.5 h long files containing over 50 easily identified mosquito buzzes was then used as a test file to do the initial program refinement. The program went through over 25 iterations over the course of the project, including a series of iterations using fuzzy membership functions to detect the buzzes. The final version of the program did not use fuzzy logic, but maintained much of the signal processing structure developed in earlier renditions of the program. We tested revisions to the detection algorithms using a bank of six to ten 2.5 h recordings with a total length of 15 to 25 h and containing over 100 buzzes along with high levels of ambient noise. Such tests could be conducted in well under an hour. Once a revision was complete, we ran the new revision on the entire 250 h bank of recordings. The selectivity of any particular version of the program could be checked by observing the impact of varying detection thresholds on the program output. For example, if lowering detection thresholds resulted in more false positives, but little change in the total number of detections, then the thresholds would be raised back to the previous value. The results of the finalized program were compared with the results from a human listener. Human listeners rated the suspect buzzes as zeros (clearly not any type of insect buzz, or clearly a non-mosquito insect with low wingbeat frequency), threes (sounds like a mosquito, but faint), or fives (clearly sounds like a mosquito).

To allow rapid checking of the program performance, all iterations of the program generated an "excerpt" sound file consisting of a compilation of 1 s long recordings of the suspected flight sounds. This excerpt file was typically two to three orders of magnitude shorter than the original total sound files (a few minutes long vs. 250 h long), and audio editing and recording software (Audacity, Free Software Foundation, Inc., Boston, Mass.) was used to listen to, analyze the spectrum of, and filter the sound segments that had been identified by the detection program.

## Final Detection Program Details

The detection program processed the sound file in segments of 4096 samples (corresponding to 93 ms), centered on a local peak in sound energy (±4 ms). The program analyzed each 4096-sample segment and determined whether a mosquito flight sound was present in the following manner:

**Step 1.** The sound segment was filtered through a Hanning window (e.g., see Stremler, 1982, Chapter 3) to reduce noise associated with the sudden changes at the beginning and end of the segment.

**Step 2.** The power spectrum of the filtered segment was computed using the fast Fourier transform (Flannery et al., 1992) and expressed as decibels (fig. 2). The resulting spectra had a resolution of 10.77 Hz, also known as the frequency bin width. Although sufficient data were present to obtain spectral information to above 20 kHz, the analyses was limited to 8 kHz, corresponding to the first 743 values of the power spectrum. Limiting the analyses to 8 kHz reflected experience early in the project suggesting there was limited information above 6 kHz, and reflected a desire to develop a system that could potentially function with lower sampling rates.

**Step 3.** For each of the first 148 bins (representing frequencies from DC to 1600 Hz), the energy in the bin was summed with the energy at the 2nd, 3rd, and 4th harmonics associated with that bin. The bin with the greatest energy in this sum was identified as the fundamental frequency of the segment.

**Step 4.** Once the fundamental frequency had been determined, the "shape" of the spectra was quantified by computing a series of nine values, corresponding to four average energies around each harmonic (peaks) and five average energies exactly between the harmonics (inter-peaks, fig. 3). The number of bins used to compute these average values increased as the frequency went up, to reflect the possible smearing of the spectrum that occurs. Nine values were needed to cover the fundamental through 4th harmonic, plus the five associated inter-peaks. Based on observation of hundreds of spectra, we determined that there would be limited value in going beyond the 4th harmonic.

**Step 5.** To be identified as a mosquito, these nine values needed to meet the threshold requirements listed in table 1. These thresholds were determined empirically, through a trial an error process using the entire 250 h of sound data to evaluate the system's performance. If a segment failed to meet the threshold requirements, it was discarded and the next segment was read. If the segment fell within the thresh–

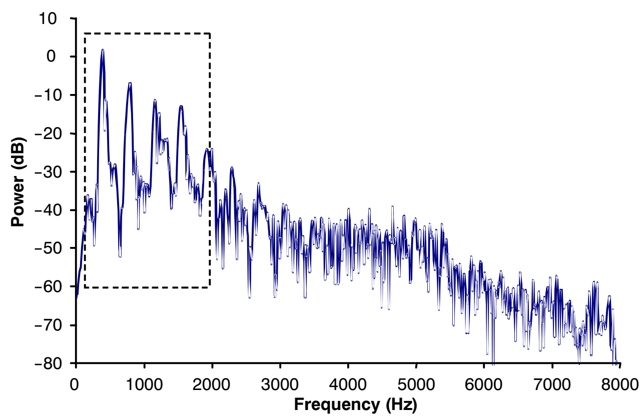


**Figure 2. Mosquito buzz spectra in 0 to 8 kHz range, based on 93 ms window and 4096 samples. The harmonic structure is easily seen. The boxed region is of particular interest, and is magnified in figure 3.**

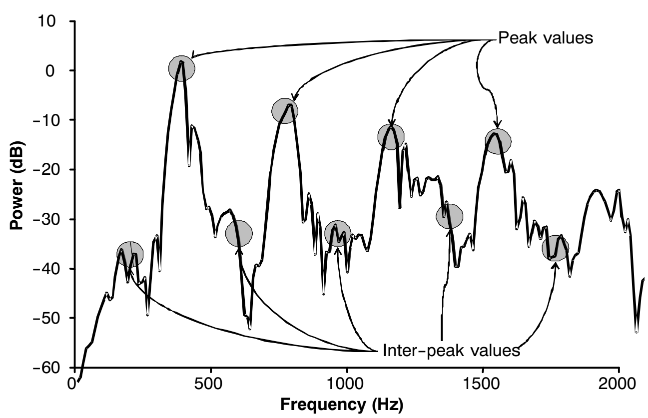


**Figure 3. Same buzz spectra in 0 to 2 kHz range, showing peak values at 1st through 4th harmonics and inter-peak values between harmonics. The relative values of these peaks and inter-peak values were the core of the detection algorithm.**

**Table 1. Summary of threshold values used in final version of detection program.**

| Parameter | Lower Threshold | Upper Threshold |
|---|---|---|
| Difference between 1st harmonic and adjacent inter-peaks | 26 dB | -- |
| Difference between 2nd harmonic and adjacent inter-peaks | 8 dB | -- |
| Difference between 3rd harmonic and adjacent inter-peaks | 4 dB | -- |
| Difference between 4th harmonic and adjacent inter-peaks | 2 dB | -- |
| Difference between 1st and 2nd harmonics | –6 dB | 16 dB |
| Difference between 2nd and 3rd harmonics | 4 dB | 26 dB |
| Difference between 3rd and 4th harmonics | 8 dB | 34 dB |

old scores, then the program generated output to a text file describing the time at which the buzz occurred, as well as the values of the parameters associated with that buzz. In addition, the program copied 1.0 s of sound, centered on the suspected buzz, into an excerpt WAV format audio file. As previously explained, this excerpt file enabled rapid screening of suspected buzzes to evaluate the detector performance.

## Results and Discussion

When the program described above was used on the entire 250 h collection of recordings and the 801 hits were auditioned by a human listener, 90.6% (726) of the hits were rated as fives, that is, being clearly mosquito buzzes. An additional 2.9% (23) were threes, that is, faint buzzes or those that were perhaps not mosquitoes. Only 6.5% (52) of the hits were zeroes, or clearly not mosquitoes, and this was the false positive rate. Although this appeared to be excellent performance from the standpoint of a low false positive rate, we were concerned that perhaps large numbers of mosquito buzzes were being missed by this approach. To see if this were true, each of the thresholds listed in table 1 was relaxed by 20% (i.e., lower thresholds decreased by 20%, upper thresholds increased by 20%). When this was done, the total number of hits increased to 1682. However, the total number of hits rated as being clearly mosquito buzzes only increased by 8%, from 726 to 784. This modest increase in sensitivity was accompanied by a false positive rate of 28%, or over four times worse than previous. The greatest increase was in the middle “maybe” category, which went from 23 (2.9%) to 427 (25%). Increases in this category were not thought to signify a true improvement in performance because of the ambiguity associated with this middle score. The slight increase in sensitivity arising from the more liberal settings comes at too high a price in false positives, and thus finalized the parameters published here. These parameters reflect our bias toward avoiding false positives, and could readily be restructured for different environments.

As noted earlier, the algorithms developed here can essentially be done “on the fly.” The processing time using a 1.7 GHz AMD Athlon XP based PC was 50 to 80 s for each 2.5 h sound file, with approximately half this time devoted to data access. This suggests that real-time implementation of this code could occur on a device with less than 1% of the computing power of the processor used here. In comparison, Hendricks’s first approach was to use an optical sensor linked to an ink and paper event recorder to detect and log the passage of moths into a container; any decision algorithms were strictly limited to those of the experimenter reading the paper event recording disks (Hendricks, 1985). Not surprisingly, Hendricks reported high correlations between electronic and manual counts. In later work, Hendricks (1989) used RF transmission to enable traps to communicate with a base-station computer, much as we envision could be done with a group of acoustic detectors. Because the beam-breaking optical detection system employed by Hendricks produced an output of insect counts, and because highly specific baits were employed, the data-processing needs of his system were relatively low and were met by a timing circuit consisting of five integrated circuit chips supported by a few dozen discrete components. In contrast, the system we have developed requires significant onboard signal processing, which is much more realistic today than it was nearly 20 years ago when Hendricks developed his systems. We have constructed a field-deployable prototype device implementing the detection algorithms described herein on a single digital signal processing chip, and will begin testing it shortly.

Temporal data, such as provided in Table II of Offenhauser and Kahn’s (1949) seminal work, can easily be generated by our system (fig. 4). For example, rather than simply reporting a total number of events per night, the system could be programmed to record the number of events per 10 min interval through the preceding 24 h, and the patterns of activity might be used to determine species. Alternatively, the bait lamp could be cycled (e.g., on a 5 min on/off program), and the resulting temporal pattern of counts used to estimate insect densities. Perhaps more intriguing is the possibility of using multiple bait types sequentially. For example, small methanol fuel cells produce $CO_2$, and could be used to produce $CO_2$ on demand. By using a switched $CO_2$ bait in tandem with an intermittent light and/or acoustic baits, information in the time sequence of insect arrivals could be more valuable than simple counts from a bait that was on continuously.

Since this is a non-destructive method, we do not expect a 1:1 correspondence between the acoustic detection system and conventional CDC light traps. This is not a large weakness, however, because any census method only gives a proxy of the true population; what is critical is that any new method be reasonably well correlated with existing methods. Further experiments are needed to determine whether or not this is the case.

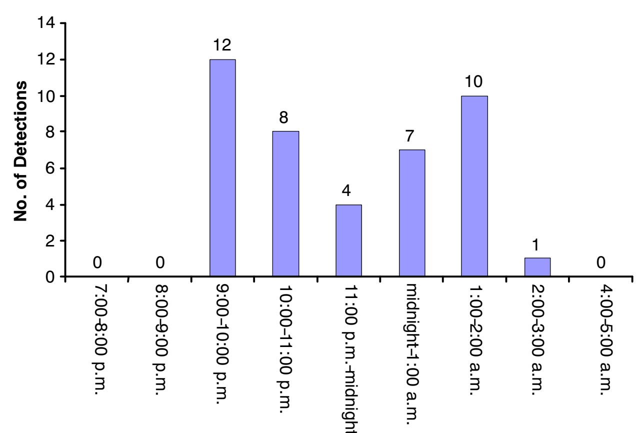


**Figure 4. Number of buzz detections per hour of observation, with the FTU placed in a suburban forest in late August 2004 using an incandescent bulb as an attractant and processing the data with the final detection algorithm. Note the peak in activity that coincided with nightfall (sunset at 7:12 p.m., astronomical twilight at 8:42 p.m.).**

Compared to devices that optically determine fundamental wingbeat frequency of flying insects, the acoustic approach we have taken has advantages and disadvantages. For example, an acoustic approach permits sound pressure level to be used as a detection criterion, thus using the loud, high-powered flight typical of mosquitoes to detect them. In contrast, it is not clear that flight power output is detected optically. We suspect that the magnitude of the optical signal is instead more dependent on the geometry of the light source, receiver, and insect, along with the insect wing size. Several small insects (likely midges) could be heard in the recordings, but at sound pressure levels far below that of the mosquitoes; these insects were not flagged as mosquitoes by the final detection routine. Despite these advantages, there are several disadvantages of an acoustical approach compared to the optical approach. Foremost is the need to reject ambient noise while maintaining sensitivity. The optical approach is only sensitive to high-frequency fluctuations in light intensity, which are unlikely in natural settings, and which can probably be easily limited through good design of the receiver-detector pair. In the acoustical system, we have demonstrated the ability to effectively reject ambient noise, but this rejection comes at a cost of computation. Only further development work with our approach will tell whether we can affordably transfer this technique to a low-power stand-alone system. Although we focused here on a single-sensor device, combining sensing technologies might ultimately yield a more cost-efficient and reliable detection system.

## Conclusions

A field-deployable acoustic insect flight detector was constructed with low-cost electronic components and used to collect 250 h of ambient sound recordings. These recordings were the basis of a programming effort to develop detection routines for mosquito flight sounds. After methodically testing a variety of approaches, an approach involving information from the first four harmonics, from the interharmonic regions, and from the sound envelope was decided upon. This approach yielded 726 clear mosquito buzzes from the 250 h of recordings, with only 52 false positives (6.5% false positive rate). This algorithm should be capable of implementation on low-cost digital signal processing systems and could enable the deployment of a new generation of low-cost insect scouting devices.

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