# Genetic algorithms: Are they the future of hearing aid fittings?

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The "one size fits all" approach has not yet successfully been applied to programming hearing aids. Despite our attempts to start with the best hearing aid settings for each patient, two patients who walk in our door with the same audiometric characteristics may prefer different settings from the initial default settings or different settings from each other. Possible reasons for such differences include the following:

(1) Standard audiometric tests may fail to reflect the particular auditory pathology of a given patient. It's likely that varying pathological conditions produce similar symptoms, collectively labeled as sensorineural hearing loss, yet these pathologies may require different treatment approaches.

(2) Patients have diverse lifestyles, personalities, and cognitive skills that affect their daily listening needs and may require different hearing aid settings. Individuals' preferences may even vary across listening environments.

Added to this challenge is the rapid development of complex new hearing aid technology. Advanced algorithms such as noise reduction, speech enhancement, expansion, occlusion management, frequency transposition, directionality, etc., provide great flexibility. However, they also require that a large number of possible settings be reduced to a manageable set of solutions that will work well for most hearing aid wearers. Manufacturers often offer clinicians alternative settings, but few tools are available to guide clinicians in optimizing these settings to the individual patient. Moreover, the current method of trial and error may be unacceptable to consumers who have a greater sense of entitlement and expect immediate delivery of the latest technological advances.[1]

The aim of this article is two-fold: (1) to introduce a tool—the genetic algorithm (GA)—that may have the potential to efficiently find the best hearing aid settings in the future, and (2) to give an overview of preliminary research that investigated the application of a GA in finding the best settings for a new noise-reduction algorithm.

The results presented here came from young, normal-hearing listeners, as this was one of the first studies that explored the feasibility of the GA for fitting hearing aids systematically. With such a controlled subject group, we expected the variability in data to be minimal, which would enable us to validate with greater confidence the feasibility of using the GA for hearing aid fitting.

## WHAT IS A GENETIC ALGORITHM?

Simply stated, a genetic algorithm is an optimization tool that can quickly and efficiently examine a vast number of parameter combinations and fine-tune them to a desirable solution. Imagine that a new hearing aid algorithm has 10,000 possible parameter settings. To determine the best setting, one could listen to all 10,000 settings and select the one that sounds best. This would be a long and taxing process for the listener. A GA reduces this burden by having the listener compare a subset of all possible settings.

A GA uses a mathematical search routine that borrows ideas from biological concepts such as natural selection, mutation, and crossover. Using the concept of survival of the fittest, the best solutions to a problem evolve while poorer solutions die off. While GAs have been around since the 1960s,[2] the idea of applying them to hearing aid fitting is relatively recent.[3-5]

In a biological model, genes are made up of DNA. Two parents combine their genes through the mating process to create a child with unique DNA. Over time, those in the population who are best suited for survival in a particular environment thrive and pass their genes on to future generations.

In a GA used for fitting a hearing aid, a "gene" is made up of hearing aid parameter settings. A hearing aid wearer listens to several different parameter settings (or genes) and rates their sound quality or speech intelligibility. The top-rated hearing aid settings pass to the next generation, or in other words the next population of genes, to evaluate.

To establish the next generation, two "parent" genes combine their parameter settings to form a "child" gene with unique settings. This is called crossover. Genes may also be mutated, meaning that some parameter settings are changed randomly. Similar to the biological model, the parameter settings best suited for that particular environment eventually survive and the optimal, or near-optimal, settings for a given listener in that situation are provided. For a more detailed description of a GA implementation similar to the present study, see Başkent et al.[6]

The application of the GA to hearing aids can occur in a number of ways: (1) used in R&D to optimize new signal processing algorithms for hearing aids; (2) used by audiologists in the clinic to fit new hearing aid algorithms for which there is no first best fit; (3) used by audiologists to fine-tune algorithms in the field with the additional use of a remote programming device.

All such applications would benefit the wearer by optimizing the hearing aid settings. However, the GA would be required to provide this improvement using listener assessment of different parameter settings in a quick and simple way. The study described here was designed to determine if the GA has this capability.

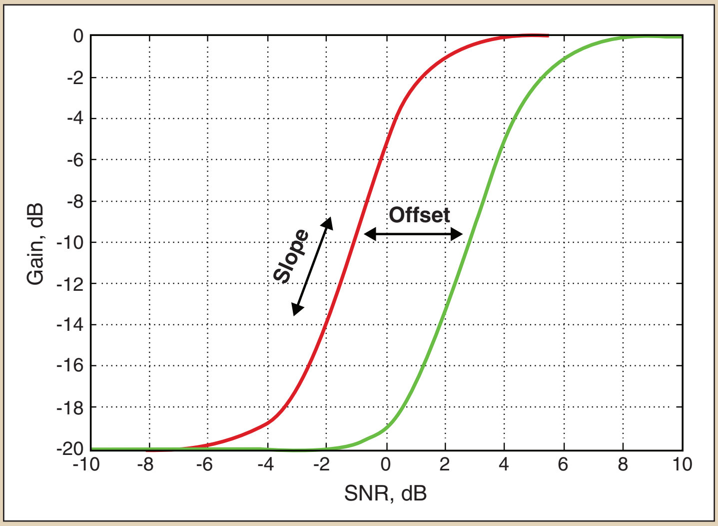


**Figure 1.** *An example of the gain curves of Woods's single-microphone noise-reduction algorithm. The SMNR parameters represented by the green line have the same slope value as those shown by the red line, but a higher offset value.*

## PURPOSE OF INVESTIGATION

Our study used a GA to find the best setting for a new single-microphone, noise-reduction (SMNR) algorithm. The major challenge in using a GA for this type of work is that the outcome is based on human perception, which means the correct solution may differ among patients and may even vary for the same person across tests if he or she changes preference. Therefore, GA solutions for hearing aid algorithms are tricky to validate, as the optimal solutions are usually unknown.

However, previous work with the GA indicates that the GA is a feasible tool for optimizing complex listening problems using subjective input from listeners.[6] In addition, for this study, the best settings were known, as Woods et al. had established them in a previous, traditional experiment that included hundreds of hours of participant listening in various simulated listening conditions and signal-to-noise ratios (SNRs).[7]

In the current study, we first used the GA to select the best settings for each subject, and later validated these settings by having subjects compare them with the Woods-selected settings for sound quality. If subjects judged that the GA-selected settings sounded as good as or better than the Woods-selected settings, then the GA was considered to be validated as an effective tool for finding the best settings for a new hearing aid algorithm. This validation was based on the assumption that the best or near-best settings had already been identified in the empirical investigation by Woods et al.

## METHODS

Thirteen normal-hearing listeners between the ages of 18 and 36 years (mean 25) participated in the study. Normal hearing was defined as having pure-tone thresholds of 20 dB HL or better at 250 to 6000 Hz bilaterally, and tympanometric and acoustic reflex threshold measures consistent with normal middle-ear function in both ears. All subjects were native speakers of American English. Four of them had also participated in the study by Woods et al. [7]

The stimulus was a single sentence taken from the Hearing in Noise Test,[8] presented with speech babble noise.[9] Woods et al. had used only one sentence in order to reduce variability and to encourage identification of subtle differences between various parameter settings. For consistency, we used the same sentence in the GA study. The stimulus was presented over headphones at an equivalent sound field level of 75 dB SPL and an SNR of 5 dB, both selected to replicate one condition of Woods's study. It should be noted that the headphones provided greater bandwidth than would be expected with actual hearing aids.

SMNR signal processing was applied to the speech-plus-noise stimulus by varying three parameters: slope, offset, and time constant. The slope was the degree of change in gain divided by the degree of change in SNR. The value of the slope was calculated at the midpoint of the gain curve. The offset was the halfway point between the top and bottom of each gain curve, and further defined the range of SNRs where gain reduction occurred.

Figure 1 shows two different gain curves with the same slope but different offset values. The time constant was the speed at which gain reduction was implemented (not shown in Figure 1). Each of these settings affected the sound quality in varying ways. For example, if the slope and time constant parameters were not ideal, fluctuating distortions and artifacts could be heard in the processed speech. If the wrong offset parameter was used, there could either be too little gain in the hearing aid, making the speech sound muffled, or there could be no discernible noise reduction.

As in the companion study, the SMNR parameters of slope, offset, and time constant were optimized by the GA. However, listeners in the GA study were given a broader range of SMNR parameter settings than were available to the listeners in Woods's empirical investigation. The total number of possible parameter settings in the GA study was 6600, while in Woods et al. it was only 216. To reduce the required listening time for subjects, Woods et al. excluded parameter settings that were obviously poor through extensive listening assessments made prior to their investigation. This was not done in the GA study, so a much larger range of parameters was available. If successful, this would imply that a GA could significantly reduce an experimenter's efforts by eliminating the need to perform a preliminary evaluation of the test conditions.

After comparing two settings (A and B), listeners marked their preference on a computer using a 7-point scale rating (e.g., "A strongly better," "B fairly better," "A slightly better," "Same," "B slightly better," etc.). Repeated listening to the stimulus was allowed. Subjects were instructed to provide a rating based on the setting they would prefer if they had to listen to it for an extended time. After they provided a rating, they were asked to compare the next pair of settings, and so on.

The GA program automatically stopped after listeners had ranked 10 populations of parameter settings. The highest-ranked settings in the final population were accepted as the best settings for that listener.

After completing the GA listening task, listeners completed a final evaluation comparing the sound quality with the GA settings and Woods's top-ranked settings, and the unprocessed signal without noise reduction. The same 7-point scale was used in the final evaluation.

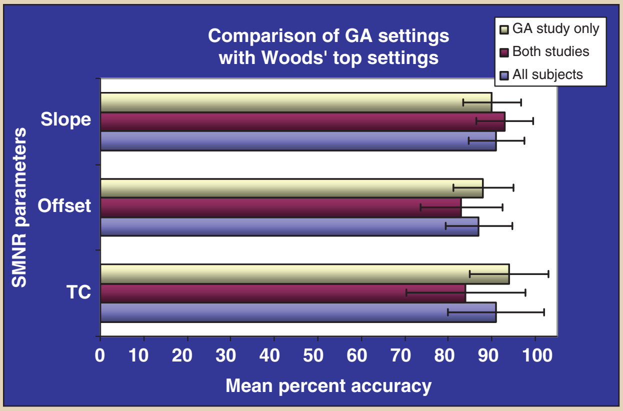


**Figure 2.** *Accuracy with which the settings obtained with the GA matched the best settings from Woods's companion study. The yellow bars show mean results for subjects who participated only in the GA study (n=9). The red bars show mean results for subjects who participated in both studies (n=4). The blue bars show mean results for all subjects (n=13).*

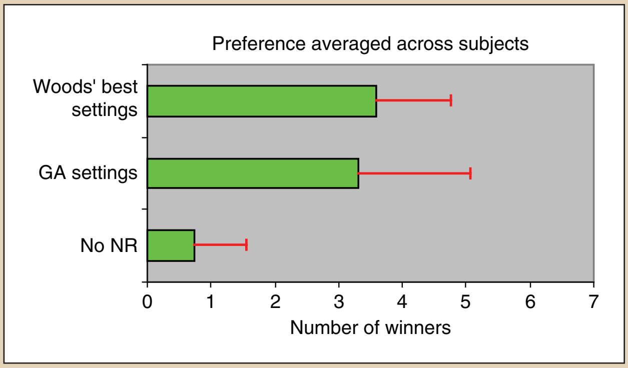


**Figure 3.** *Average preference scores based on the number of times each setting "won" in paired comparisons for: (1) Woods's top-ranked settings, (2) GA settings, and (3) the unprocessed signal without noise reduction.*

## RESULTS

Figure 2 shows the degree of accuracy with which the mean best settings obtained from the GA matched the top-ranked settings that Woods et al. obtained from the corresponding condition in their study. We analyzed the results for three different groupings of subjects including: (1) all subjects, (2) subjects who participated in the GA study only, and (3) subjects who participated in both the GA and Woods study.

The mean percent accuracy with which the GA results matched Woods's results was 83% or greater for all parameters and every subject grouping. When analyzed for all subjects, the mean percent accuracy for individual parameters was 91% for slope, 87% for offset, and 91% for time constant (blue bars in Figure 2). Results were similar for all subject groupings, suggesting little to no influence of previous exposure to the stimulus from the Woods study.

The results of the final evaluation, where subjects compared (1) their best settings from the GA, (2) the top settings from Woods et al., and (3) the unprocessed signal without noise reduction are shown in Figure 3. In each pair comparison, the winner and the loser were assigned 1 or 0 points, respectively. The points were then tallied for each setting to provide an overall score reflecting the number of times that each setting "won." Statistical analysis (one-way Friedman RM ANOVA followed by a post-hoc Tukey test) revealed that Woods's best settings and the GA settings were both significantly better than the setting with no noise reduction. There was no significant difference between Woods's best settings and the GA settings.

Significant individual differences were found in the settings obtained with the GA. For instance, one subject's time constant settings obtained with the GA were vastly different from other subjects' and from those preferred in Woods et al. This subject preferred the time constant obtained by the GA over Woods's settings in the final evaluation as well.

This highlights that the best settings of a multi-parameter algorithm can be difficult to find for a subject even with extensive listening trials—one reason that the GA approach to fitting algorithms to individuals can be valuable.

Subjects also varied in their ranking of the Woods settings, their GA settings, and the no-noise- reduction settings. For example, one subject preferred no noise reduction to the solution obtained with the GA. It could be that this person preferred to hear high levels of noise to reduced noise with some distortion that may have been present with the noise-reduction parameters available in the GA.

One reported advantage of using a GA is greater efficiency over traditional methods of trial and error for finding the best settings for individual listeners. To evaluate this aspect of the GA we recorded the GA run time for each subject. The average time to run a GA was 18 minutes, and ranged from 10 to 34 minutes. The actual listening time in the Woods study was not recorded. However, the time to complete full paired comparisons of 216 parameter settings was estimated at 81 hours per subject, ranging from 65 to 97 hours. Keep in mind that the GA included a much larger number (6600) of possible parameter settings. The GA provided a result similar to that of the Woods study in an average of only 18 minutes despite the considerably broader range of parameter settings.

## CONCLUSIONS

The results of this study support the conclusion from previous research that GAs can successfully optimize hearing aid algorithm parameters based on human listeners' A-B comparison input.[6] The best settings for a new noise-reduction algorithm obtained using a GA were similar to those obtained using empirical research alone. In fact, the accuracy with which the mean GA settings matched those obtained from an empirical study was 83% or better. Moreover, the GA was a much more efficient method than empirical research to find the best settings. In other words, the GA has proven to provide validity and speed in the process of optimization.

One must keep in mind that this research was conducted with young, normal-hearing listeners. It is unknown if the same results would be found with listeners who have hearing loss or are older.

The GA is capable of capturing individual preferences. The results of this investigation suggest that listening preferences for SMNR may differ across individuals, even if they have normal audiometric thresholds. These distinctive preferences were reflected in some listeners' GA results.

The GA has proven useful in the development of new technology. It offers manufacturers a more efficient way than an empirical research method to find the best settings for new algorithms, more global settings for algorithms working simultaneously, and customized settings for specific listening environments. Using the GA in R&D may provide a more effective way to get new technological advances in hearing health care to clinicians and patients.

## POTENTIAL CLINICAL APPLICATIONS OF GA

The feasibility of the GA as a clinical application is still unclear, as GA hearing aid research is in its infancy. Many questions and challenges must be addressed before the GA becomes a viable option to assist with hearing aid fittings in clinics. For example, the current GA implementation required an average of 18 minutes to complete. This average run time needs to be reduced before it can be considered an efficient tool to use in a busy clinical setting or real-world environments. Research is required to investigate how much time and effort patients would be willing to provide to run a GA.

Also, the ergonomics and ease of using the GA interface needs improvement prior to its use by typical hearing aid patients. Validation of successful use of the GA with hearing-impaired listeners and for more complex hearing aid problems, such as those involving multiple hearing aid features and parameters, are needed as well.

Nonetheless, there is an emerging need for such tools. If GAs someday become a reality, they could assist clinicians in finding the best settings for patients who are difficult to fit or face challenging listening situations that would otherwise require multiple appointments in a trial-and-error approach. Outside the office, one could imagine hearing aids communicating wirelessly with a GA on a handheld device, such as a cell phone or PDA, that would enable consumers to fine-tune their hearing aid settings in the situations that are the most important and/or difficult for them. This would allow more time to run the GA than is available during a typical office visit. Such a field-usable version of the GA could be a valuable tool for audiologists as an alternative to troubleshooting in the clinic problems experienced by the patient in specific situations.

It is important to note that a GA is not intended to replace professional clinical expertise, but rather to assist the clinician and patient in achieving optimal hearing aid performance. If GAs prove to be an efficient method of optimizing hearing aid settings in the future, patients will become more involved in the fitting process. Allowing patients to contribute to their own hearing aid settings may give them a more vested interest in their success with amplification.

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