Extraction of the properties of nucleon resonances by means of a Genetic Algorithm

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Our pion photoproduction model



- Nucleons, pions, photons [Born terms]
- Vector mesons (ρ and ω)
- Nucleon resonances
 - Up to 1.8 GeV
 - Up to spin-3/2
 - $^{\circ}$ Δ (1232), Δ (1620), and Δ (1700)
 - N(1440), N(1520), N(1535), N(1650), and N(1720)

Fernández-Ramírez, Moya de Guerra, Udías, AP(NY) 321 (2006) 1408

The underlying physics is embedded in the constants of the model \rightarrow obtained fitting the data

Optimization

 Gradient-based routines are the usual optimization tools (MINUIT, NAG)

> CERN, MINUIT 95.03, CERN Library D506 Edition, 1995 Numerical Algorithms Group Ltd., http://www.nag.co.uk

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- Alternative: Stochastic optimization → Genetic algorithms
- Example: E04FCF from NAG by itself is useless for our problem: gradient based methods alone fail

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- Alternative: Stochastic optimization → Genetic algorithms
- Example: E04FCF from NAG by itself is useless for our problem: gradient based methods alone fail
- Hybrid optimization: combine GA with gradient based routine E04FCF from NAG libraries

E04FCF -

 \rightarrow Parameters

• GA provides E04FCF the initial value

Evolution (optimization)

- Evolution as an optimization scheme
- The different kinds of species evolve to the optimal adaptation to the surrounding environment. Thus, evolution is an 'algorithm' that searchs for the best solution creating a set of individuals (a generation), it decides which individuals are the best ones, and, by means of crossover, keeps the good genetic characteristics for the next generation – that will be closer to the optimal solution – and removes the individuals with worst genetic content

Environment

Individual

Generation (set of individuals) \leftrightarrow

- \leftrightarrow Objective function (v.g. χ^2)
- $\leftrightarrow \quad \text{Set of parameters}$
 - → Set of possible solutions

How a GA works

- We start with a first generation randomly generated (N individuals)
- Each individual encodes a complete set of parameters

 $G_E | G_M | M_\Delta | \cdots$ each parameter is a "gene"

- Scale population, v.g. using the χ^2 , to assign a survival and mating probability to each individual
- Generate the offspring (fight, crossover, and mutation of individuals)
- Repeat process until a given number of generations is reached

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Simulate evolution in a computer!

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We perform several optimizations to obtain a set of minima

Particularities of GAs

- Whereas most methods employ a single solution which evolves to reach the local optimum, GAs work on a population of many possible solutions simultaneously
- GAs only need the objective function to determine how fit an individual is. Neither derivatives nor other auxiliary knowledge are required
- GAs use probabilistic rules to evolve (randomness does not mean directionless!)

Evolution of the optimization





Effect of the gradient-based routine





We have performed several optimizations (20), for each run (x-axis) we get a different minimum (y-axis). We normalize all of the minima to the best one and we plot the minima given by the GA alone and the improvement achieve by the NAG routine for each run

Δ (1232) parameters and E2/M1 ratio





Δ (1232) parameters and E2/M1 ratio





Δ (1700) parameters and model and database effects



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Δ (1700) parameters and model and database effects



2005 SAID database Model up to 1 GeV 2006 SAID database Model up to 1.2 GeV Δ (1700) tail fully covered

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Fits to electromagnetics multipoles





GAs in experimental nuclear physics at JLab



- Hall A experiment E06-007: "Impulse approximation limitations to the (e, e'p) on 208 Pb, identifying correlations and relativistic effects in the nuclear medium"
- Optics calibration using GAs
- Allows to get all the parameters of the optics database at the same time
- More efficient procedure (unattended optimization)
- J.L. Herraiz, PhD Thesis (UCM, expected in 2009)

Conclusions (I)

- Optimization is not a trivial problem
- Traditional optimization tools are often useless for this kind of multi-parameter optimizations when the parameter space is large and the function to fit presents many local minima
- If the parameters of a resonance want to be assessed its energy range has to be fully covered, tail included. If not, misleading results may be obtained

Conclusions (II)

- The hybrid optimization procedure presented in this talk is a powerful and versatile optimization tool that can be applied to many problems in physics that involve the determination of a set of parameters from data
- It is a promising method for extracting both reliable physical parameters as well as their confidence intervals, probably more meaningful than the simple covariance matrices returned by gradient based optimization routines
- Not only the error bars have to be considered when quoting the uncertainty in the determination of a parameter, but also whether the minima are concentrated into one single region or split into several ones, and the possible physical implications of such situation

References

• GAs:

Fernández-Ramírez, Moya de Guerra, Udías, Udías, PRC 77 (2008) 065212

• Pion photoproduction model:

Fernández-Ramírez, Moya de Guerra, Udías, AP(NY) 321 (2006) 1408; PRC 73 (2006) 042201(R); EPJA 31 (2007) 572; PLB 660 (2008) 188

• Extension to nuclei:

Fernández-Ramírez, Martínez, Vignote, Udías, PLB 664 (2008) 57

RPWIA asymmetry prediction for ${}^{16}O(\vec{\gamma},\pi^-p)$ compares well to data from Hicks *et al.* PRC 61 (2000) 054609