# Taking a *NEAT* drive!

Aplicação do Algoritmo NEAT para a Evolução de Redes Neurais em Simulação de Direção Autônoma 2D


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2. FUNDAMENTAÇÃO TEÓRICA
3. MODELAGEM
4. EXPERIMENTOS E RESULTADOS
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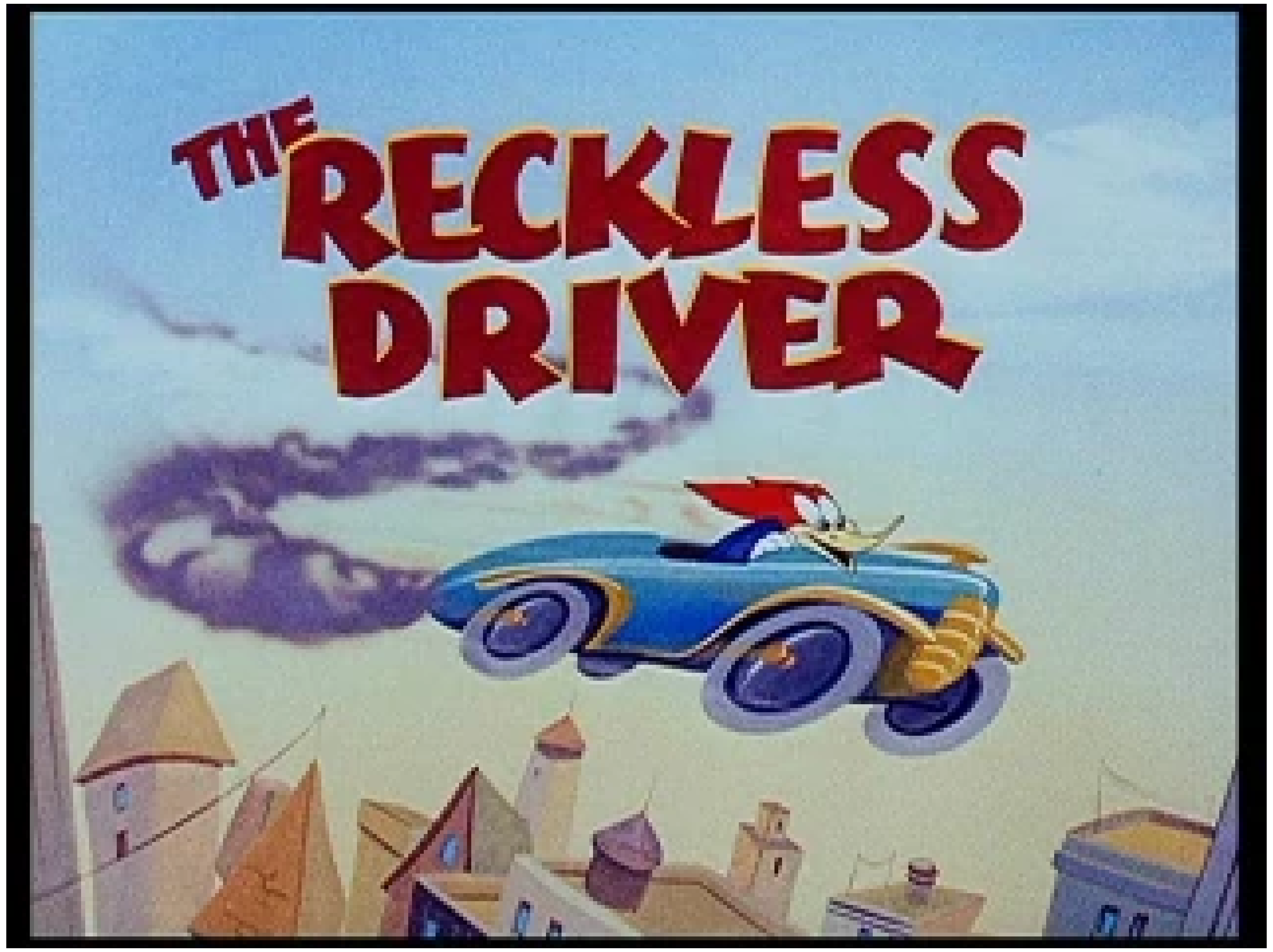
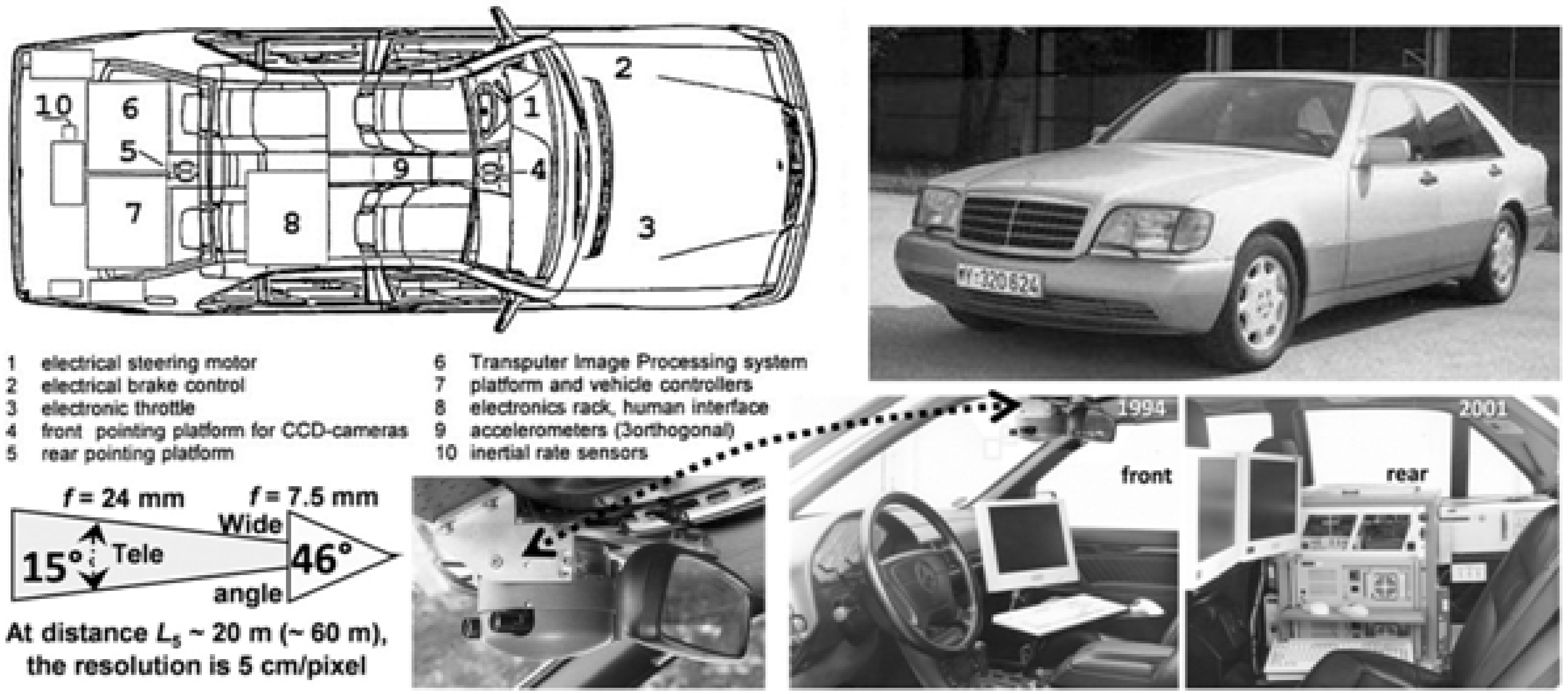
# INTRODUÇÃO

# CONTEXTO




Segundo o UNDRR e o ICS (2025), o erro humano está entre as principais causas de acidentes de trânsito.

# VEÍCULOS AUTÔNOMOS




*Versuchsfahrzeug für autonome Mobilität und Rechnersehen*

Projeto Eureka PROMETHEUS *(1987-1995).*

# PROPOSTA

Aplicar o algoritmo NeuroEvolution of Augmenting Topologies (NEAT) para evoluir redes neurais voltadas ao controle de veículos autônomos.

Objetivos:

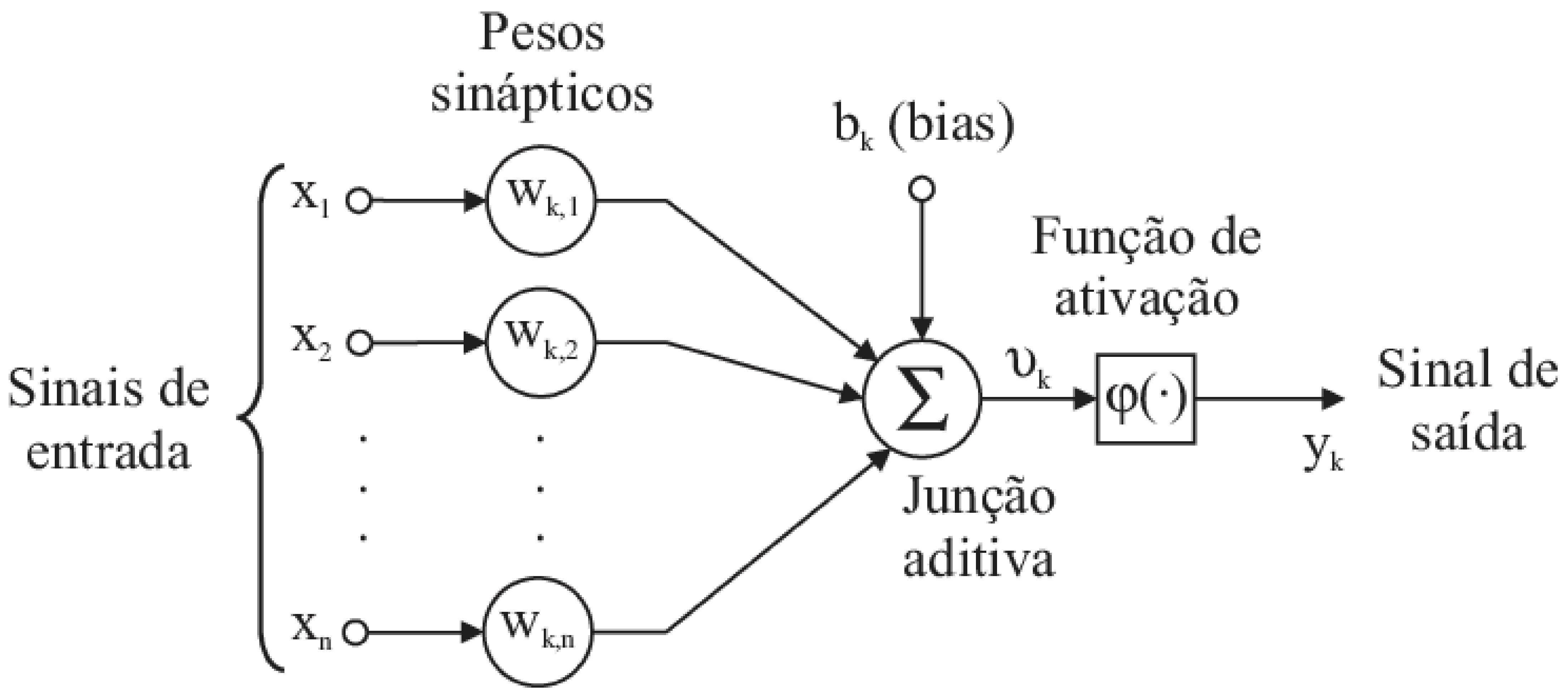
- Validar a capacidade de navegação do agente.
- Investigar os padrões comportamentais emergentes.
- Analisar a evolução topológica das redes neurais.

Dada a complexidade do problema, o ambiente foi simplificado para uma simulação 2D.

O estudo analisa dois cenários: velocidade informada versus sem velocidade informada.

# FUNDAMENTAÇÃO TEÓRICA

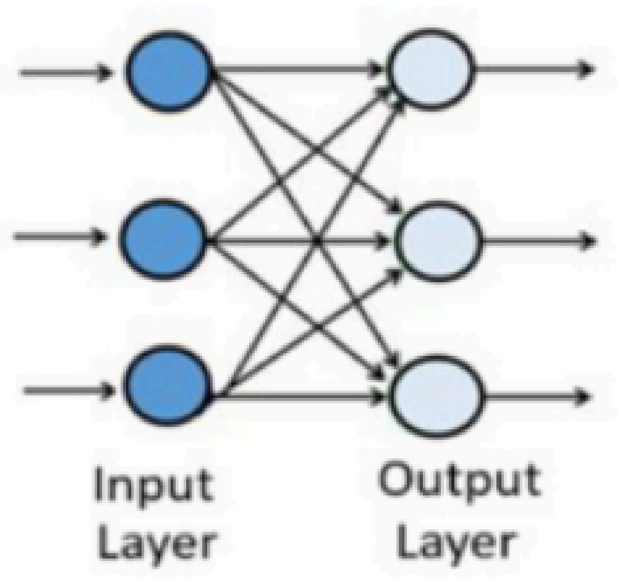
# REDES NEURAIS ARTIFICIAIS



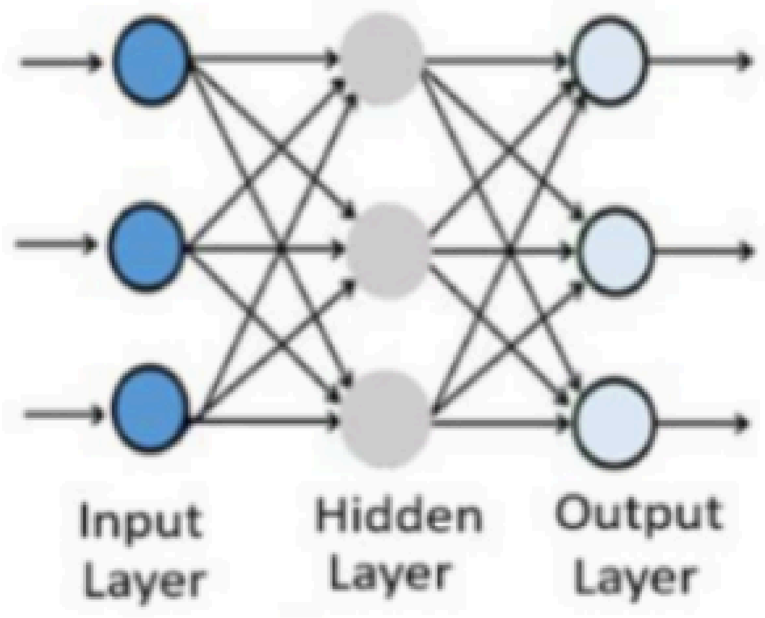

$$y_k = \phi(v_k) = \phi\left(\sum_{i=1}^{m} w_{ki} \cdot x_i + b_k\right)$$

Modelo de neurônio artificial. Adaptado de Haykin (2008).

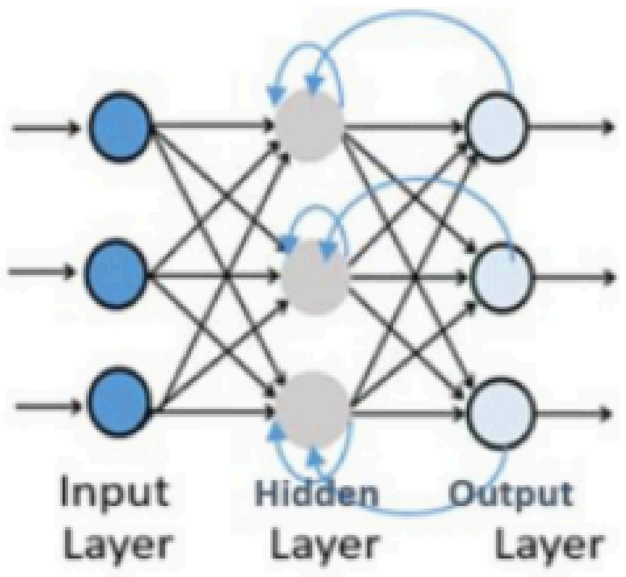
# *REDES NEURAIS ARTIFICIAIS*




(a) Rede *Feedforward* de Camada Única




(b) Rede *Feedforward* Multicamadas

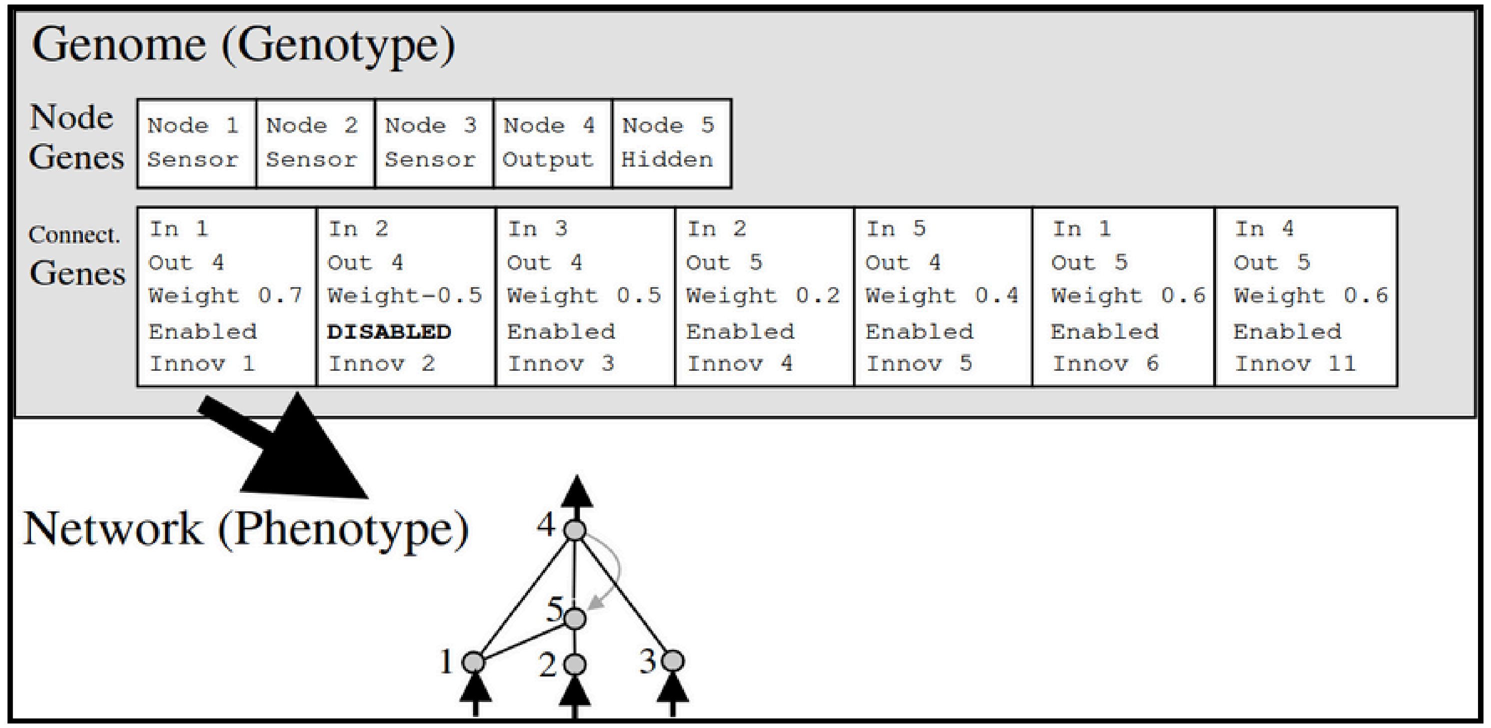



(c) Rede Recorrente

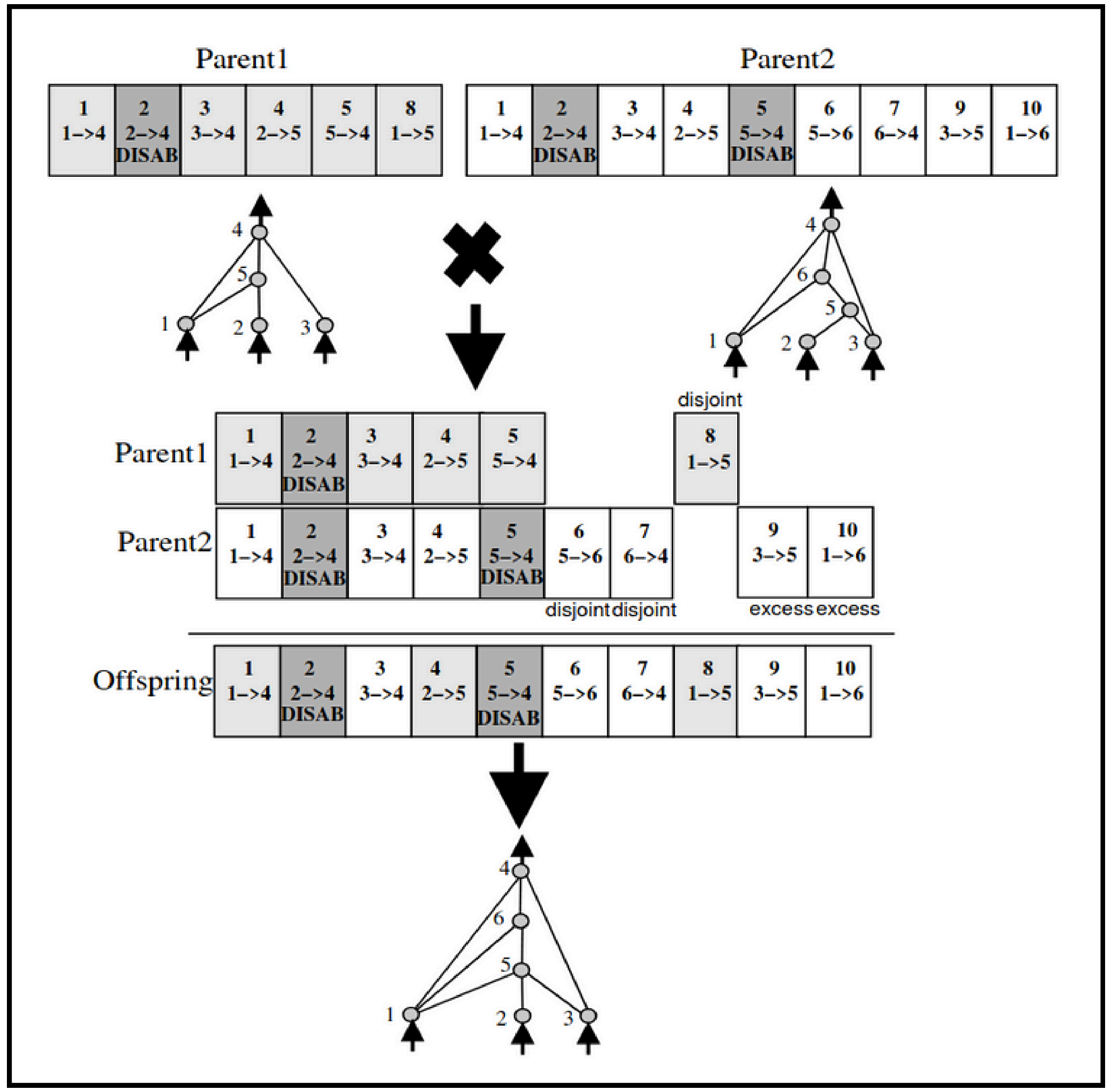
**Representação das principais arquiteturas de redes neurais artificiais (Haykin, 2008; Hagan *et al.*, 2014).**

# NEUROEVOLUTION OF AUGMENTING TOPOLOGIES (NEAT)

*Stanley, K. O., & Miikkulainen, R. (2002). Evolving neural networks through augmenting topologies. Evolutionary Computation.*




Codificação genética de uma rede neural.




Cruzamento genético.

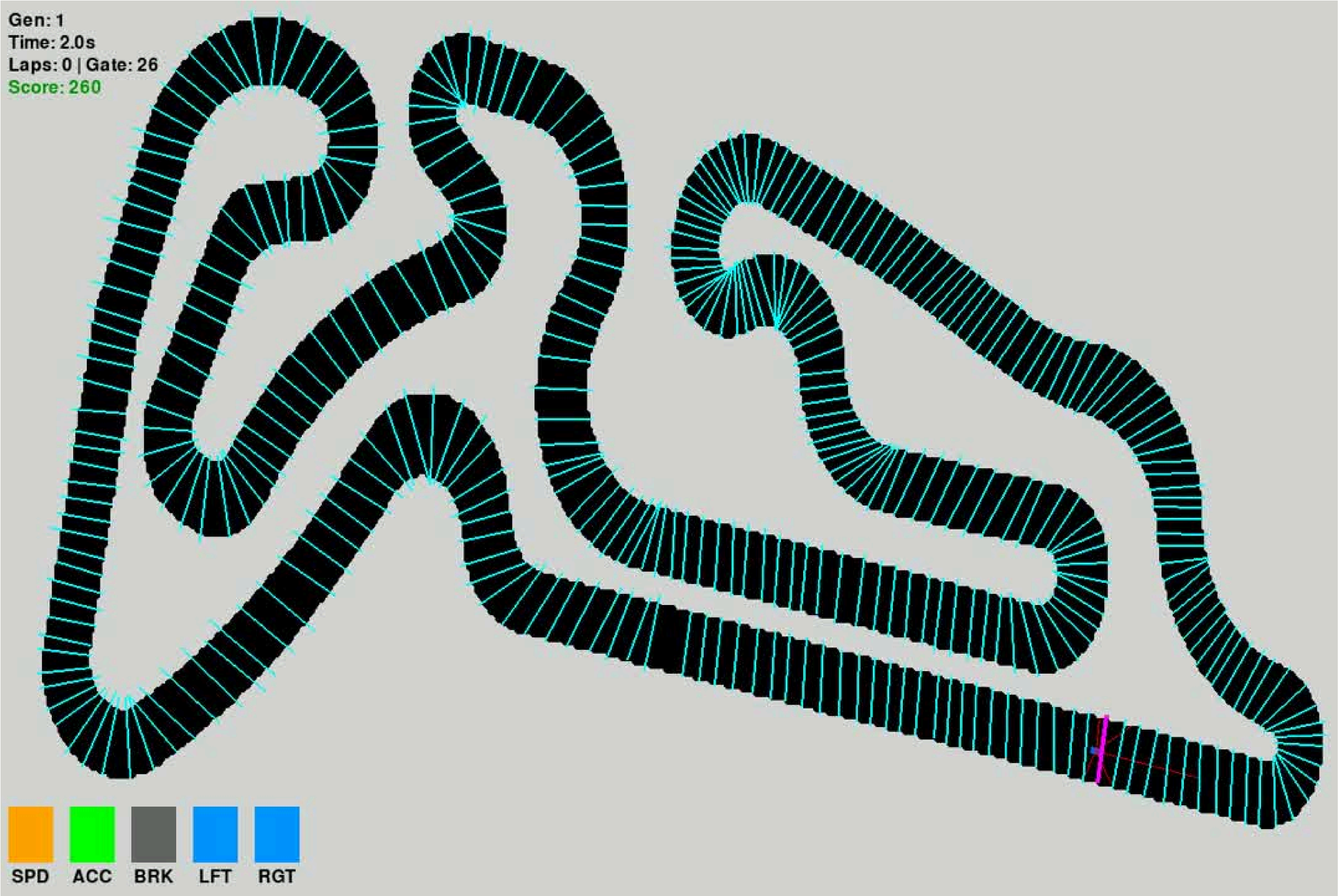
# MODELAGEM

# REPOSITÓRIO DO PROJETO

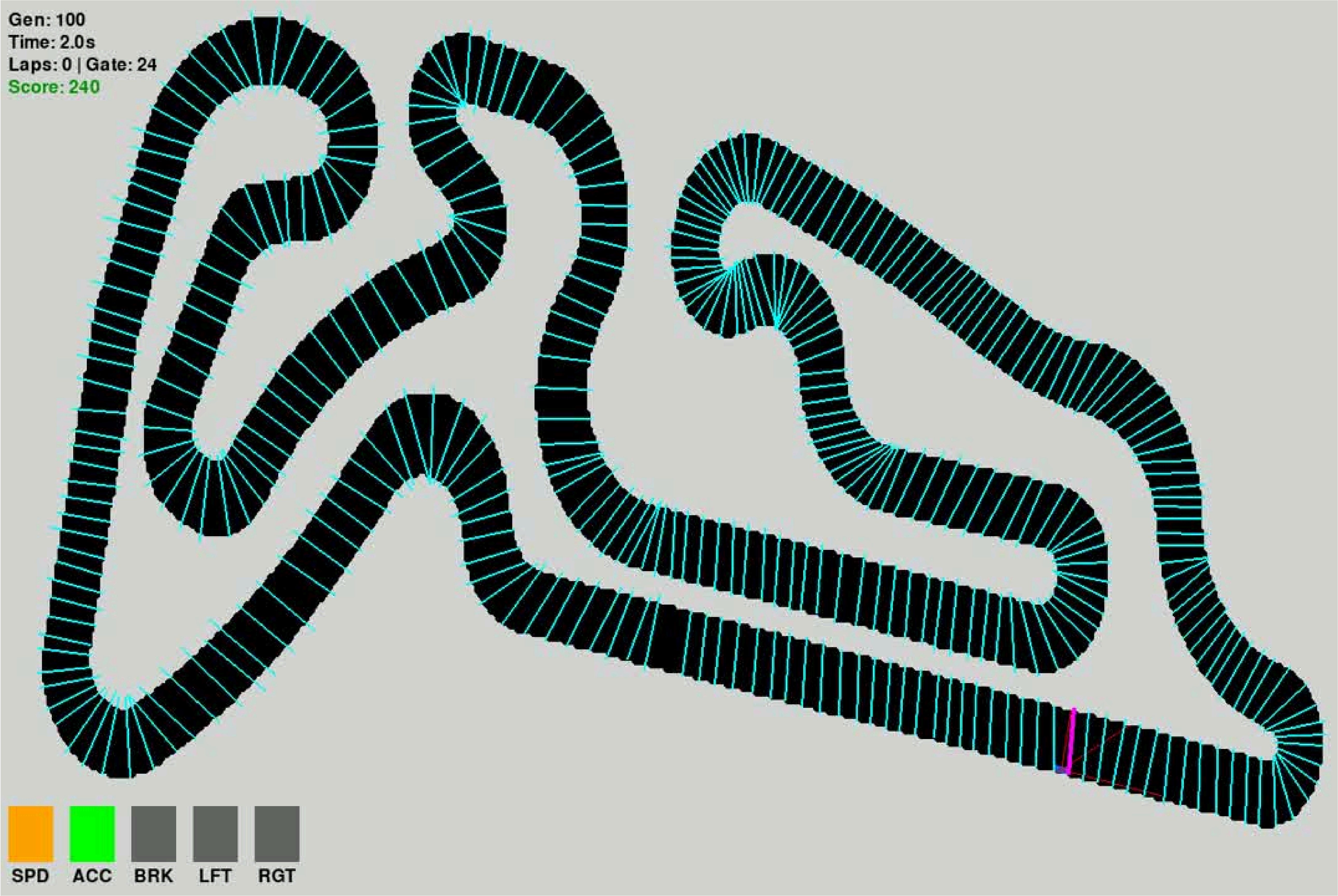
***HTTPS://BIT.LY/BIO-INSPIRED-T3***

# EXPERIMENTOS E RESULTADOS

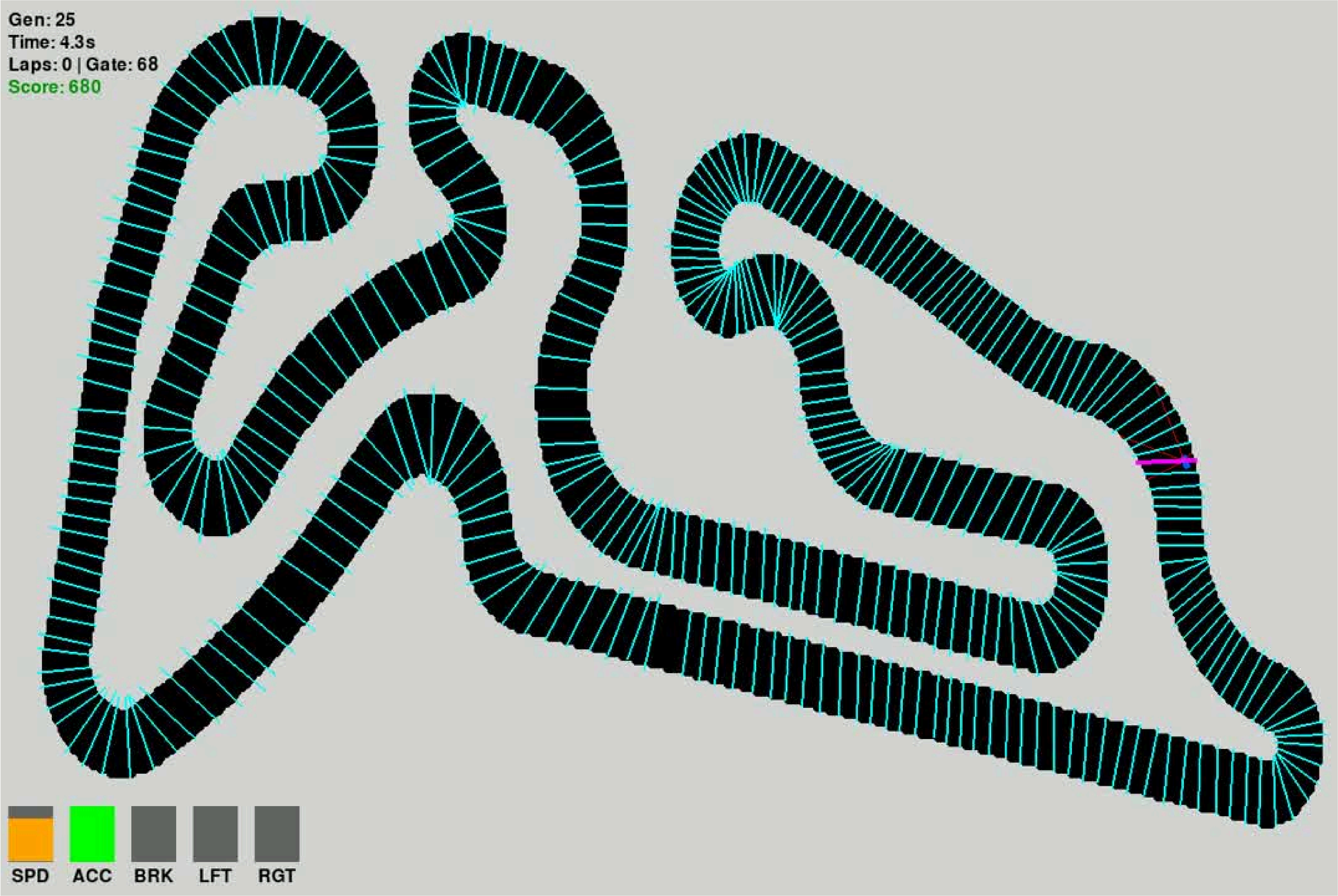
# GEN 1 SEM VELOCIDADE/COM VELOCIDADE



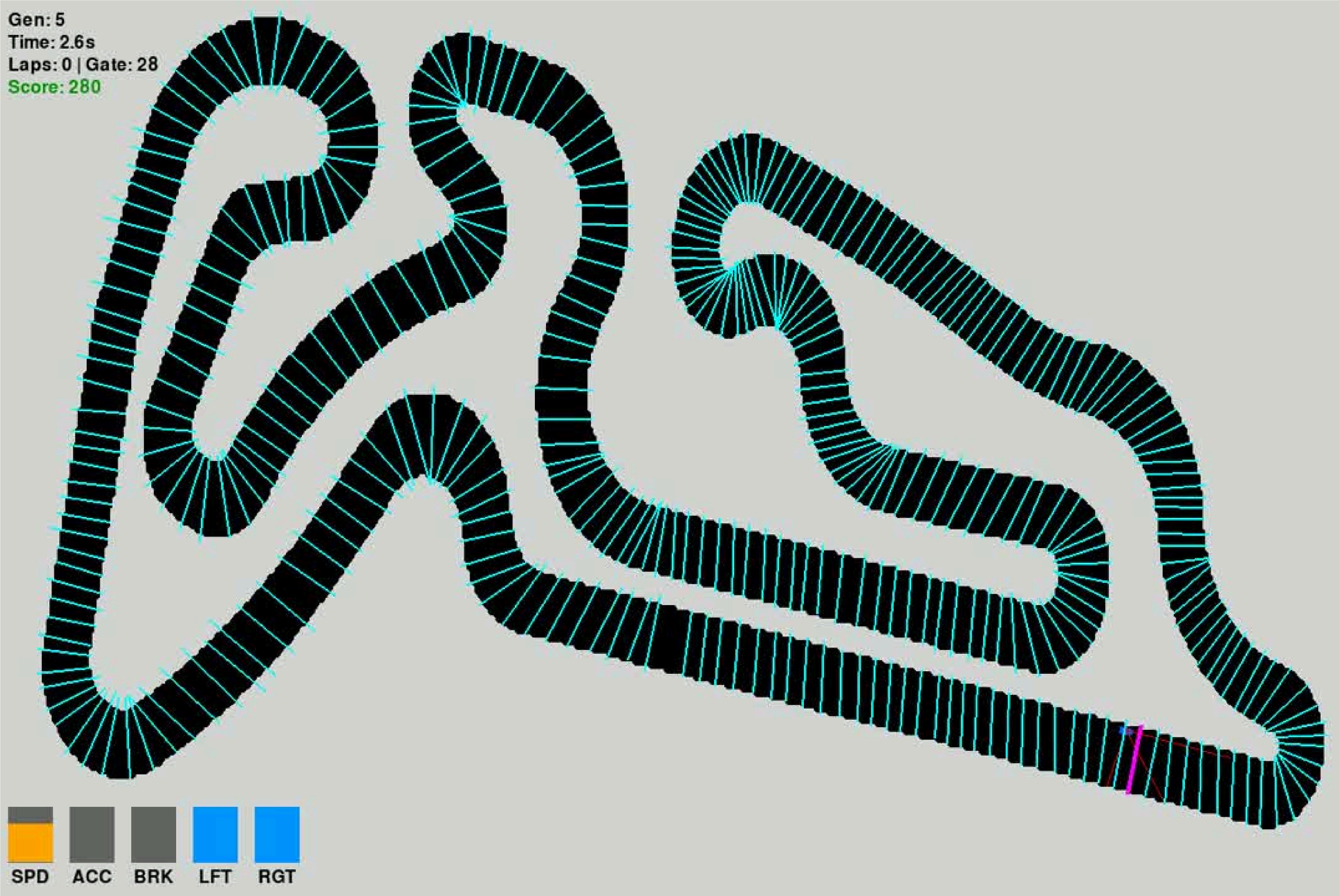
# EXEC 1,2,4,6,9 GEN 100 SEM VELOCIDADE (450 FITNESS)



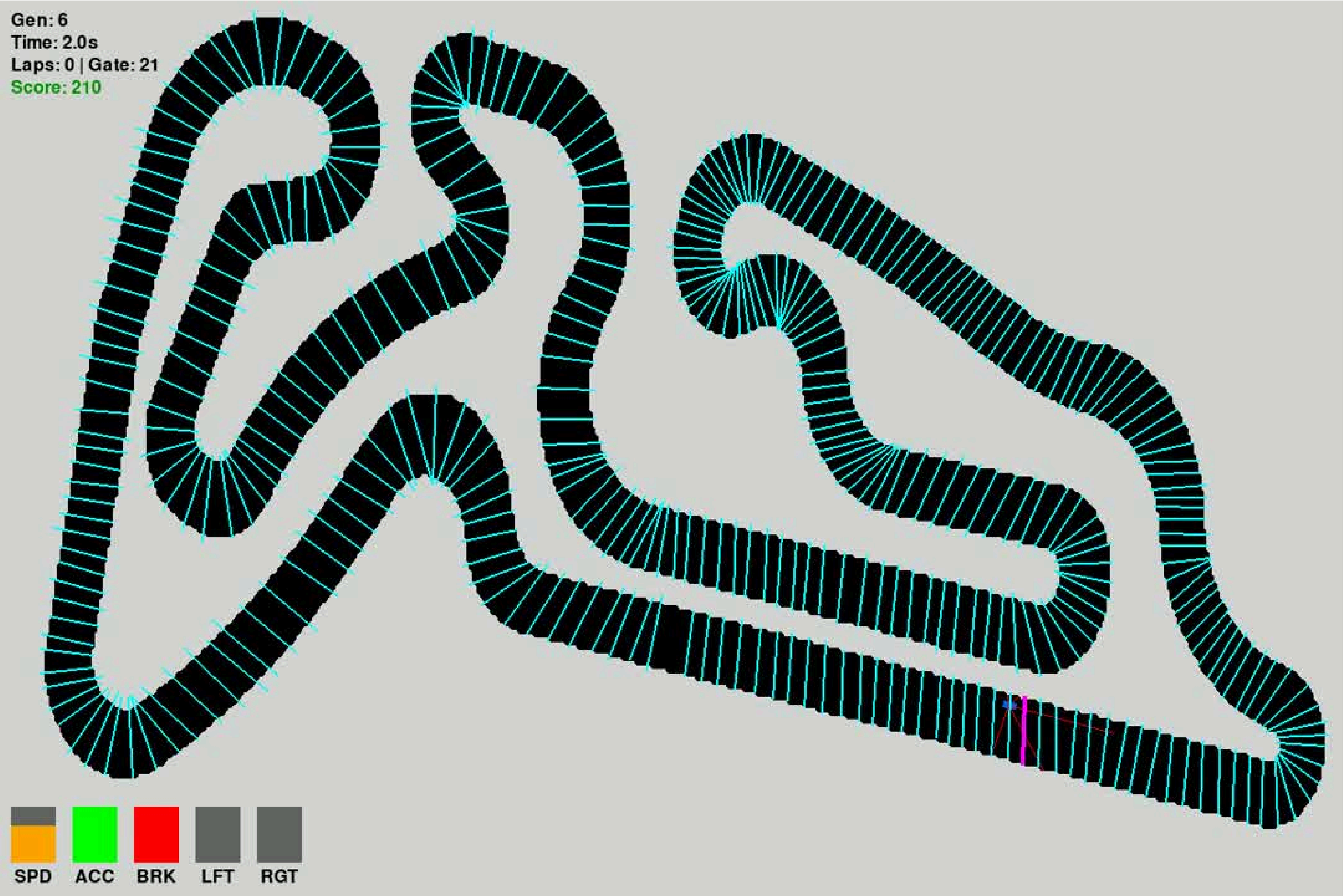
# EXEC 5 GEN 25/100 SEM VELOCIDADE (1730 FITNESS)



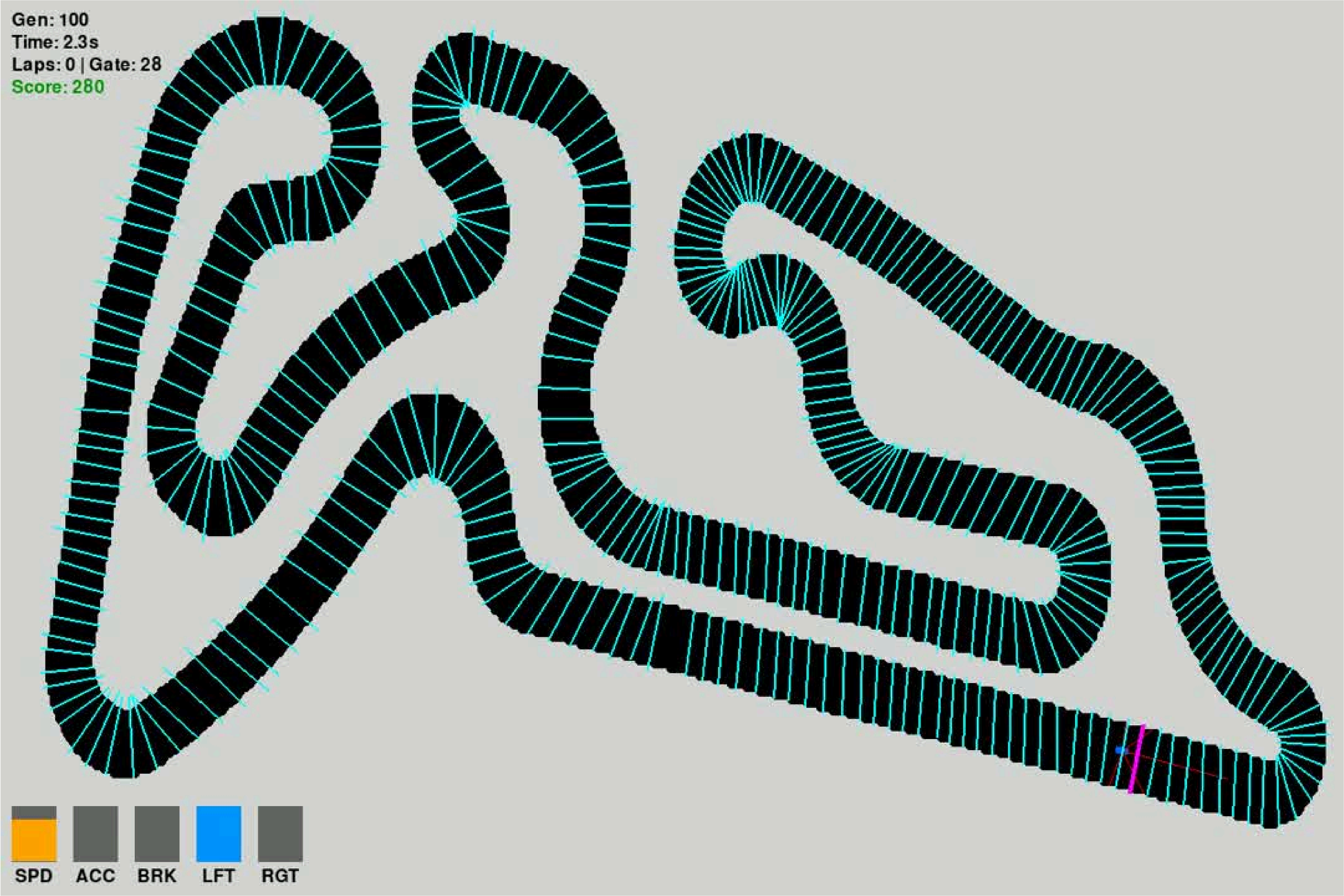
# EXEC 6 GEN 5 COM VELOCIDADE (2680 FITNESS)



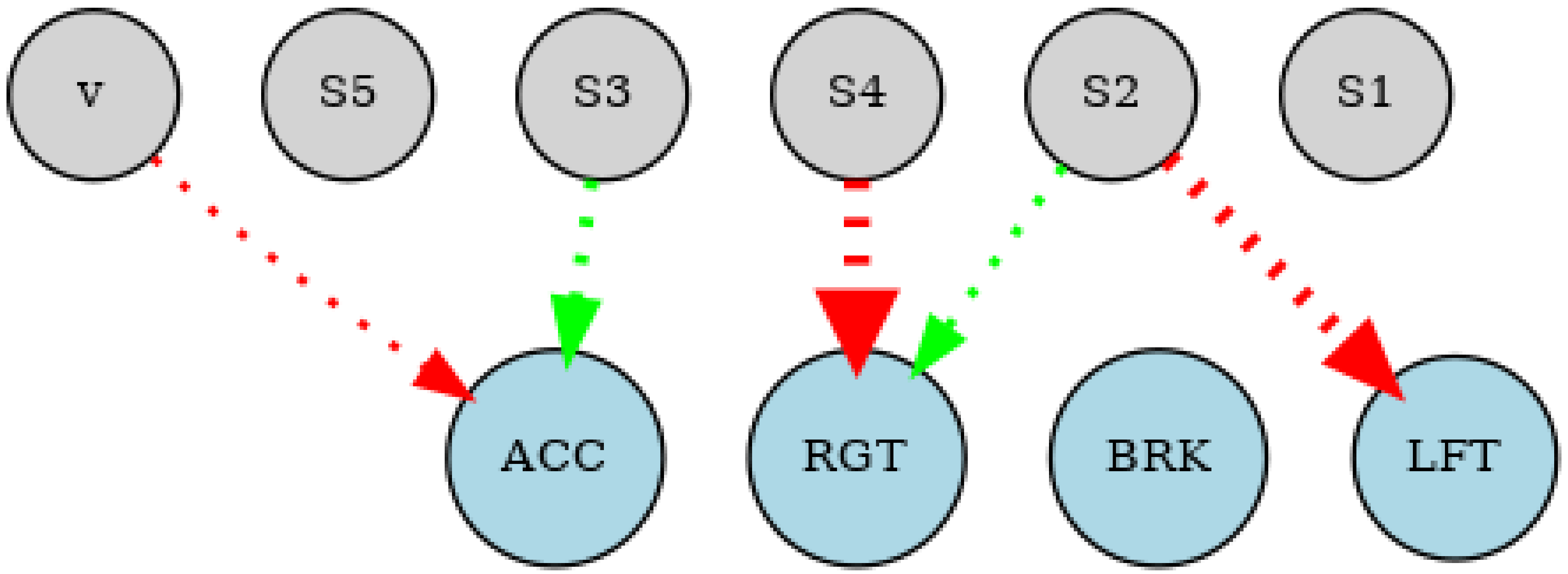
# EXEC 6 GEN 6 COM VELOCIDADE (8790 FITNESS)

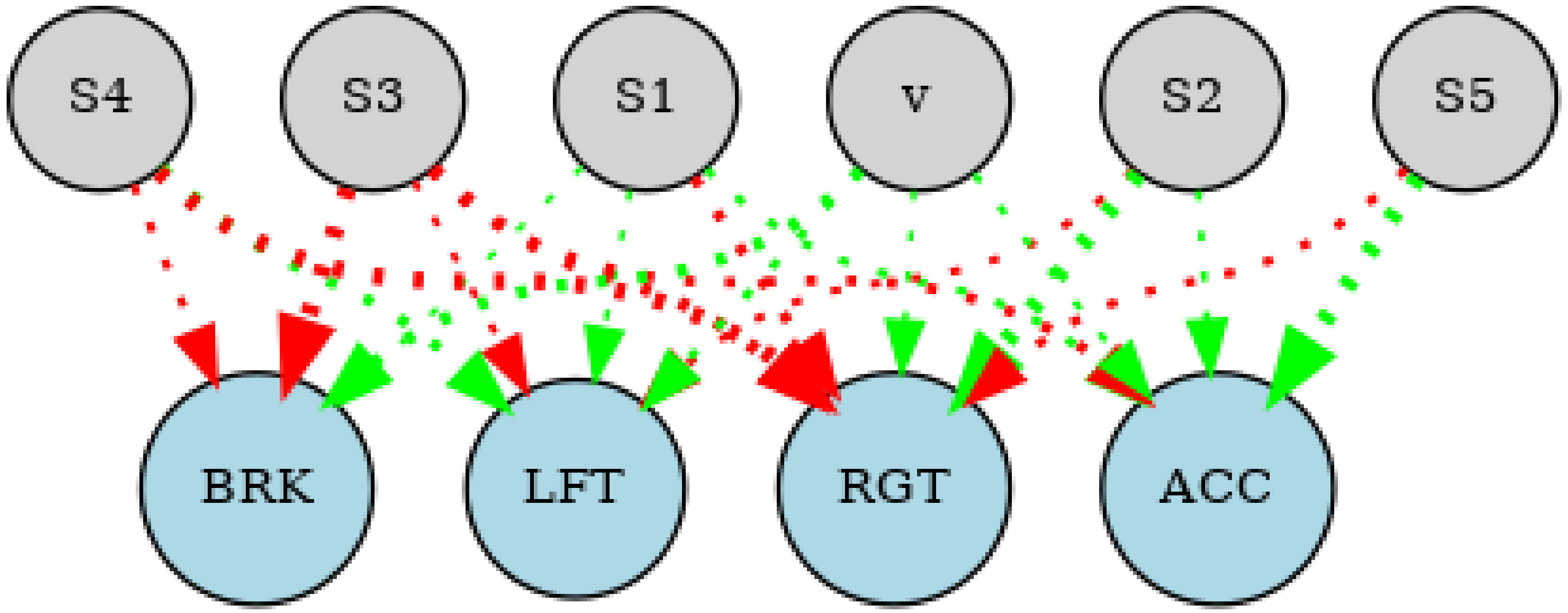


# EXEC 5 GEN 100 COM VELOCIDADE (9320 FITNESS)

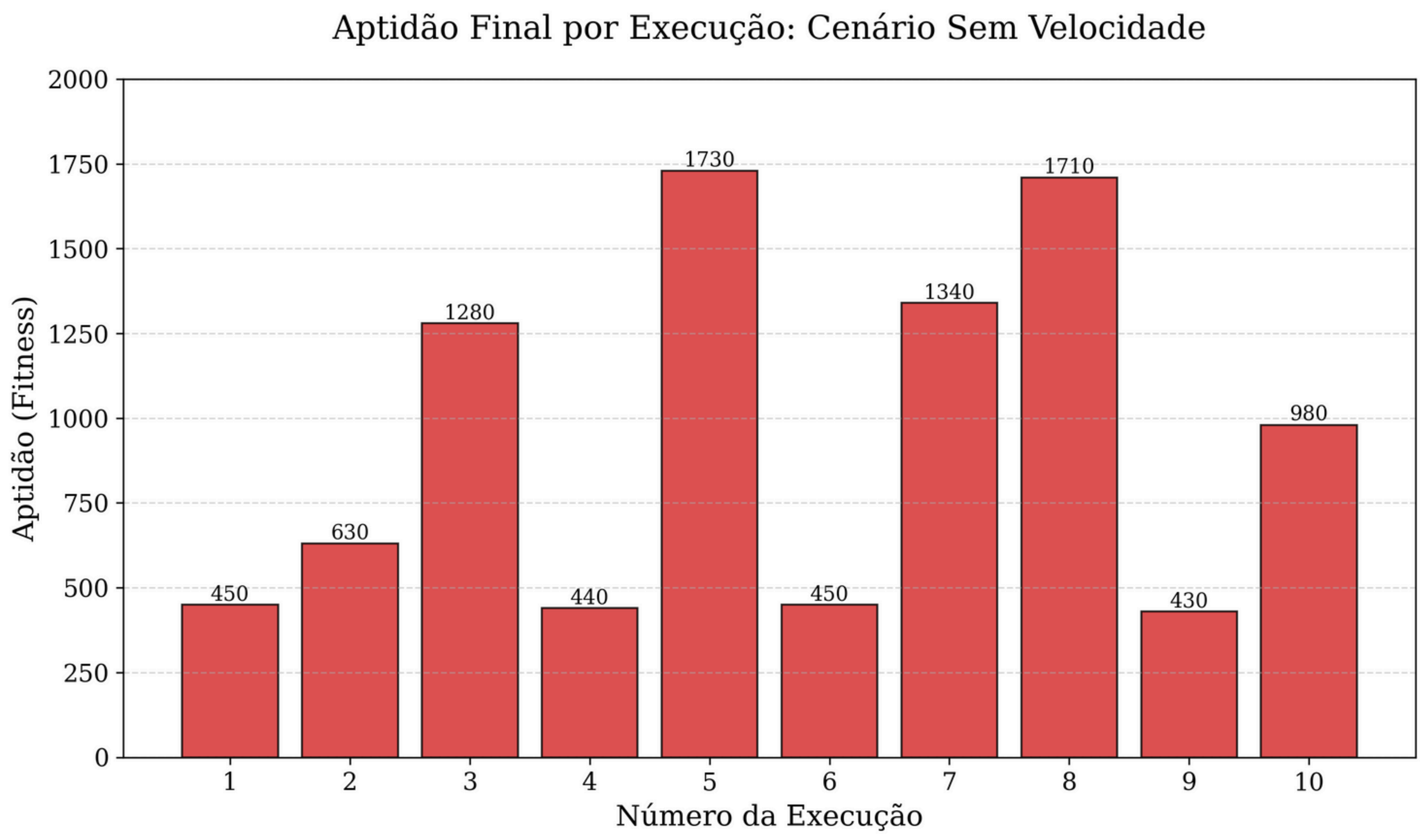


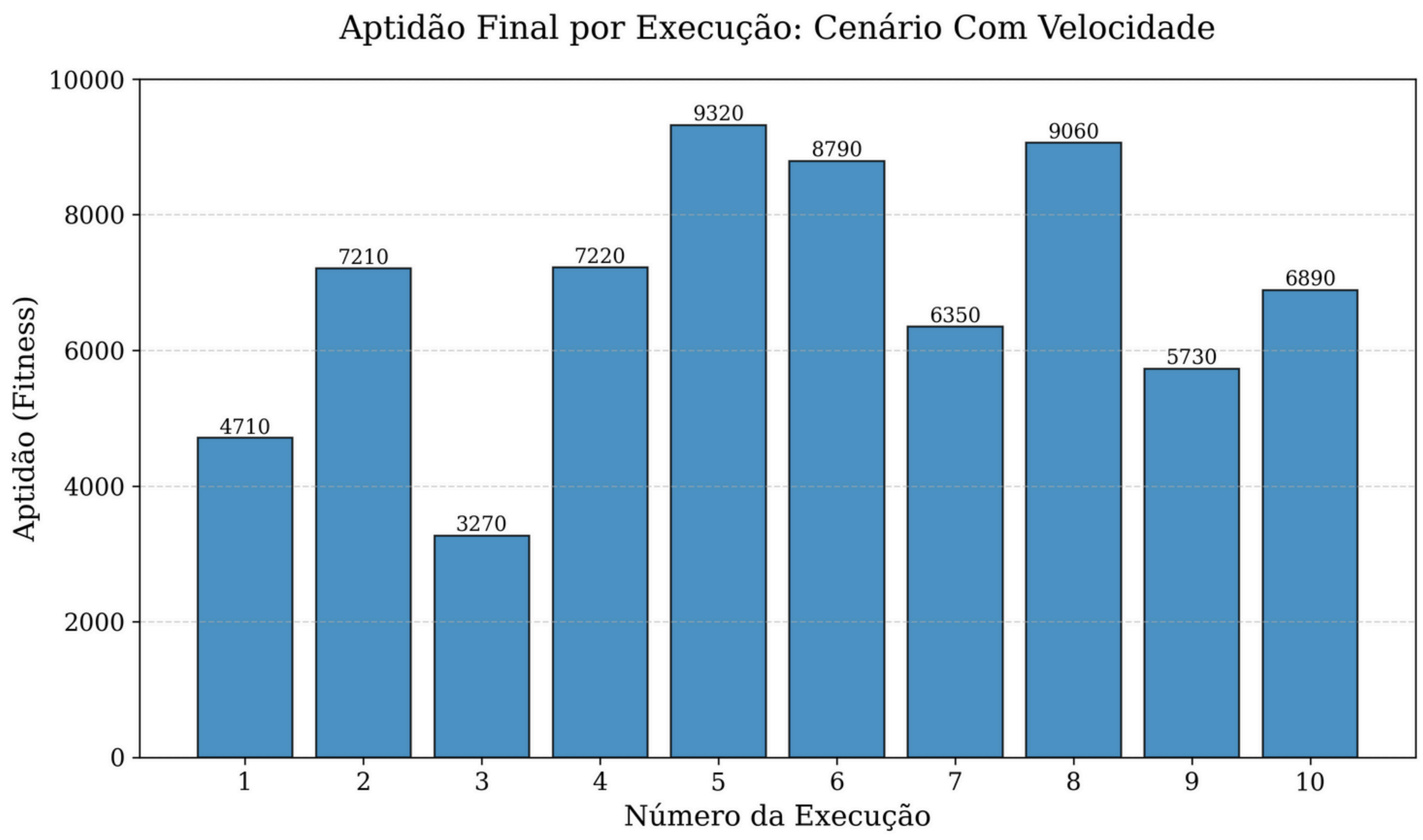
# TOPOLOGIA EXEC 5 E 6 COM VELOCIDADE



# GRÁFICO FITNESS FINAL



# CONCLUSÃO

# CONCLUSÃO

**Principais observações:**

- A eficácia da navegação depende da modelagem.
- Cenário com velocidade informada induziu topologias minimalistas e controle via modulação dos atuadores.

**Limitações:**

- Simulação restritiva.
- Evolução limitada a 100 gerações.
- Hiperparâmetros fixos.

**Trabalhos futuros:**

- Diversificar a modelagem e as configurações experimentais.
- Validar generalização em pistas inéditas.
- Explorar *novelty* e *surprise search*.

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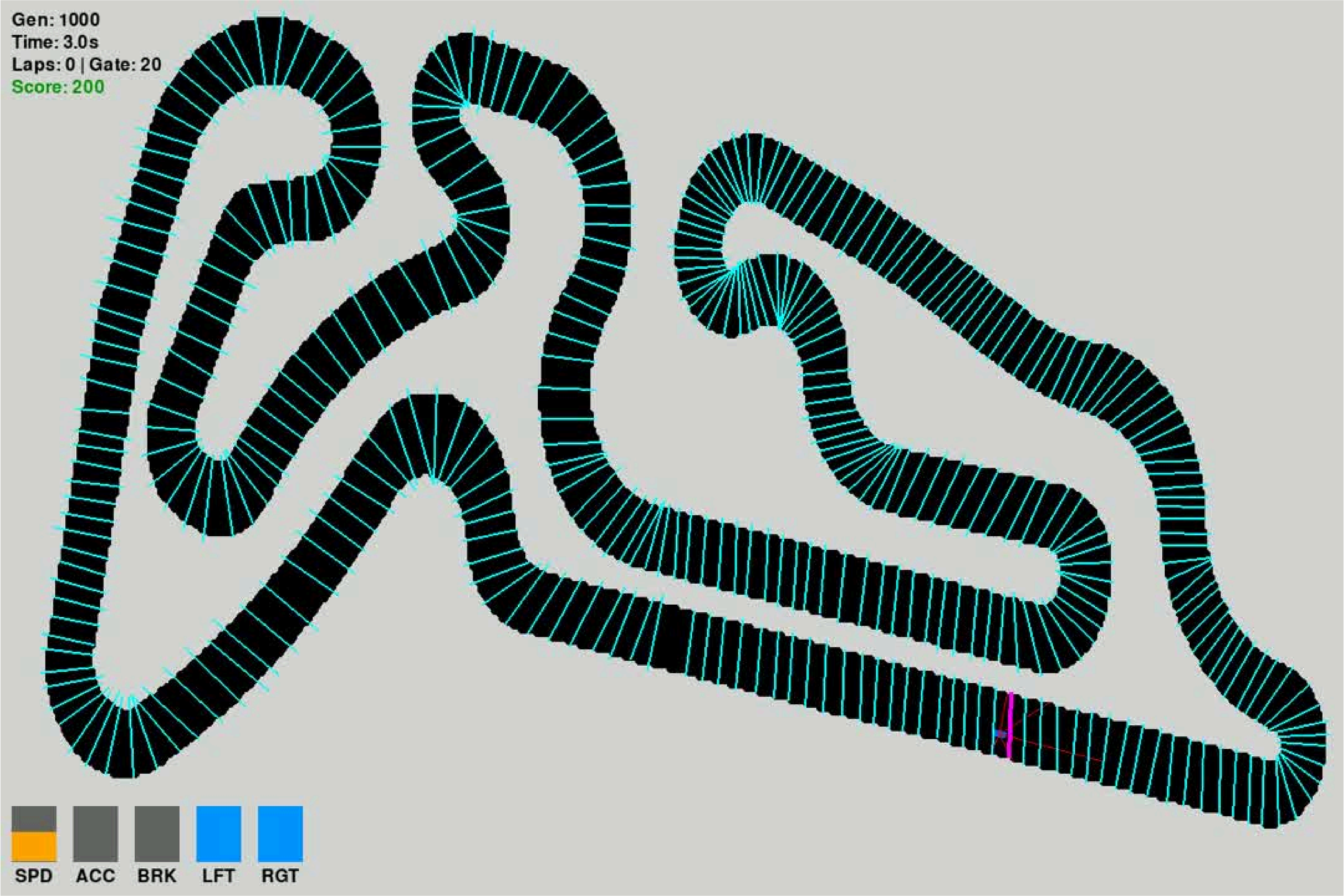
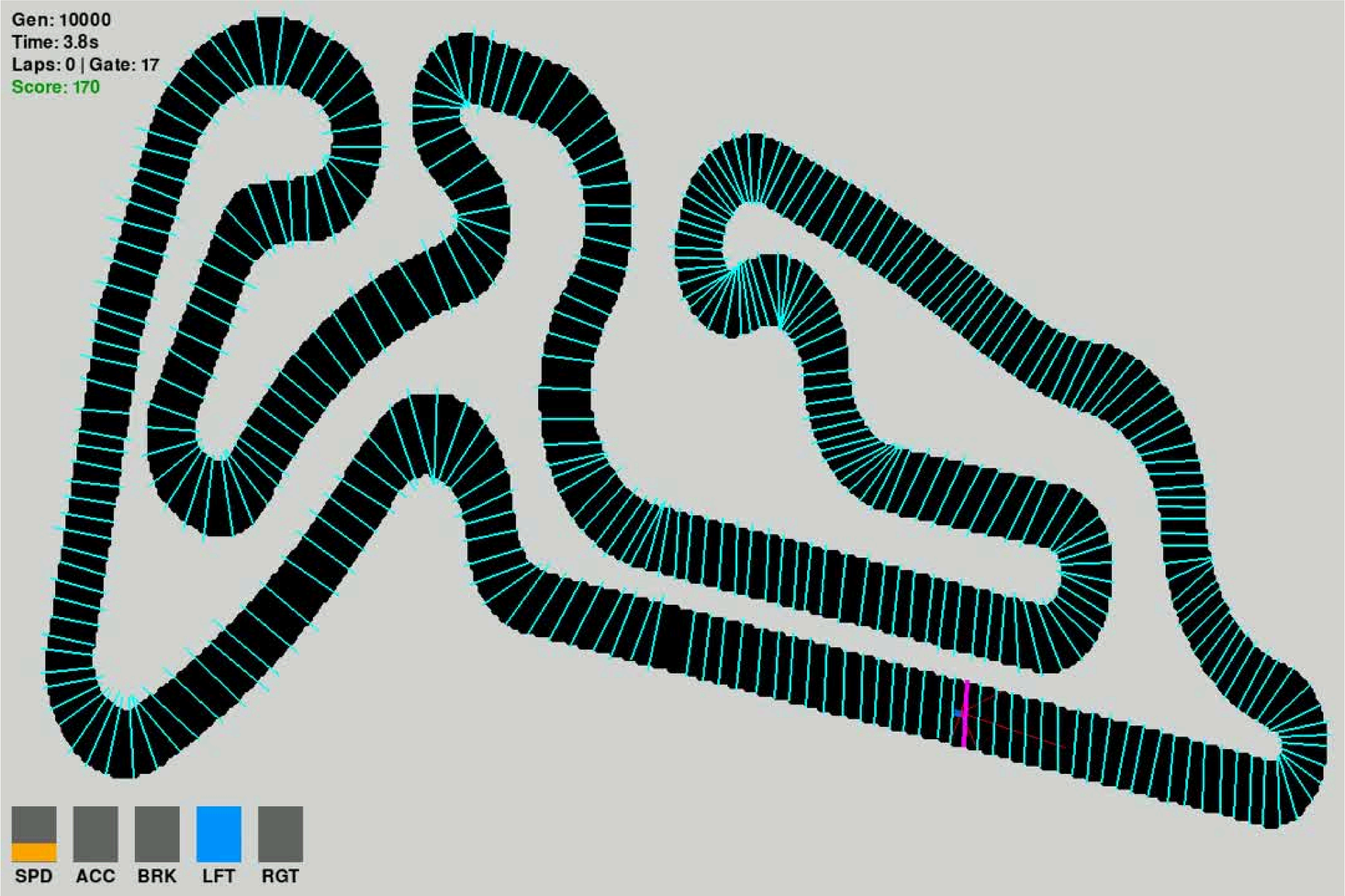
Thank You!

# APÊNDICES

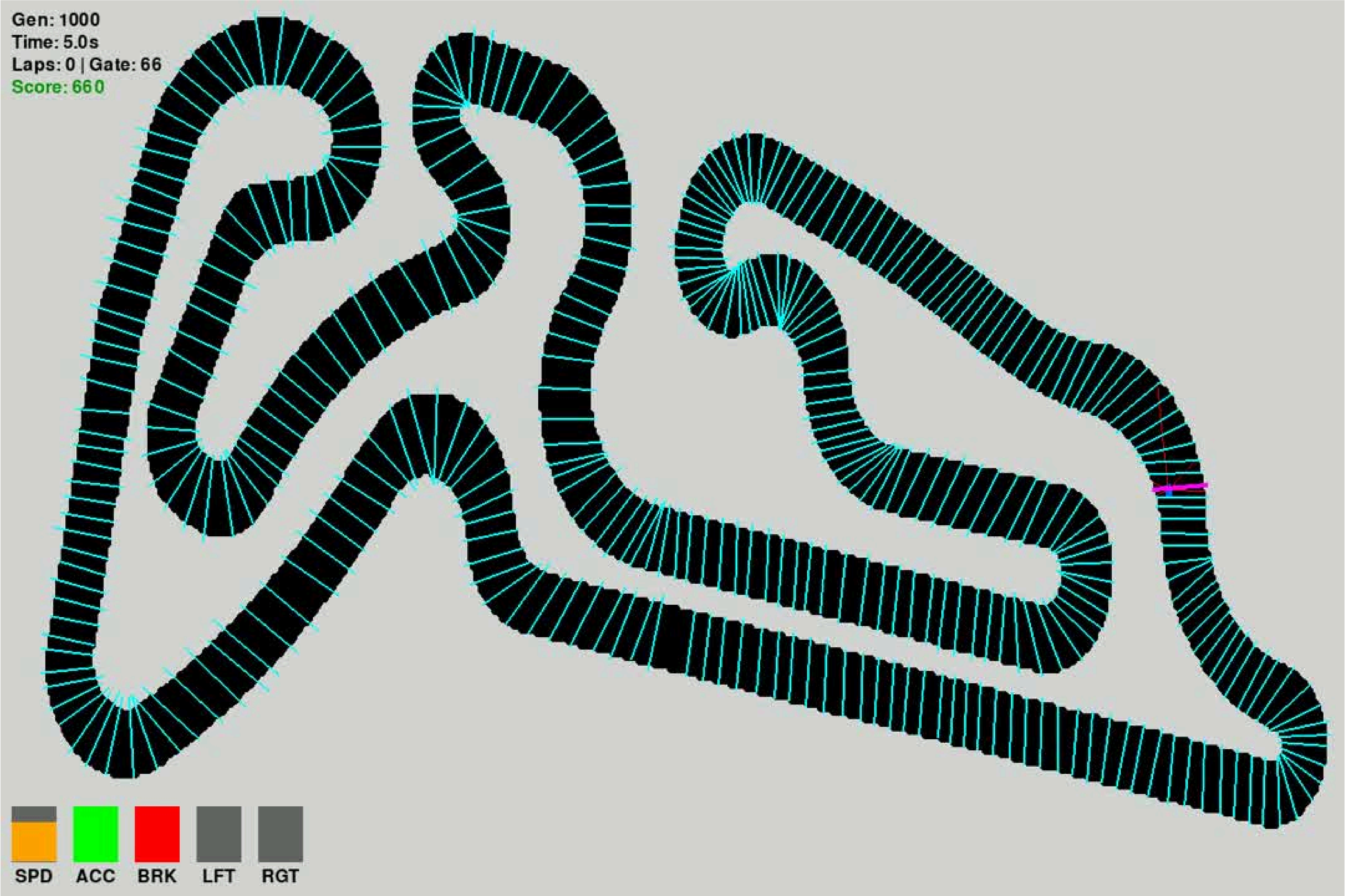
# GEN 1000 SEM VELOCIDADE (1770 FITNESS)



# GEN 10000 SEM VELOCIDADE (2910 FITNESS)



# GEN 1000 COM VELOCIDADE (9030 FITNESS)



# GEN 10000 COM VELOCIDADE (10170 FITNESS)