

Director-Inspired Creative Optimization Algorithm

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Abstract. Directors undertake multiple decision-making tasks in film and television production, including macro-level control of plot pacing, micro-level adjustments to shots and actor performances, and creative experimentation. This paper proposes an optimization algorithm inspired by directors' decision-making behaviors — the Director-Inspired Creative Optimization (DICO) algorithm. This algorithm simulates the decision-making characteristics of directors during the creative process through three mechanisms: macro-weight guidance, local fine-tuning, and emotion-driven creative feedback. This paper details the algorithm's modeling approach, mathematical formulas, and iterative optimization strategies, providing a comprehensive theoretical framework and offering new perspectives for optimization algorithm research and creative decision-making modeling.

Keywords: Director inspiration, creative optimization, mathematical modeling, emotional drive, decision-making simulation.

1 Introduction

In filmmaking, the director is not only a storyteller but also the soul guide of the film or television work. The director's decision-making covers the entire production process, from script conception, shot design, actor performance scheduling to resource allocation. Traditional optimization algorithms such as genetic algorithms, particle swarm optimization, and simulated annealing algorithms have certain advantages in multi-objective optimization, but lack the ability to simulate the characteristics of creative and artistic decision-making [1-41]. The director's decision-making behavior has three core characteristics:

Macro-control: The director controls the overall story rhythm, theme, and visual style.

Local fine-tuning: The director repeatedly adjusts individual scenes, shots, and actor performances.

Creative experimentation: The director attempts to innovate and deviate from the norm under limited risk.

The DICO algorithm proposed in this paper is based on the above-mentioned director's decision-making characteristics and is abstracted into mathematical modeling and optimization algorithms. The algorithm design takes into account global macro-control, local fine-tuning, and creative exploration capabilities. It simulates the director's creative risk-taking behavior through an emotion-driven feedback mechanism, thereby forming a unique optimization strategy.

2 Director-Decision-Inspired Optimization Modeling

2.1 Decision Variables and Objective Function

Let the set of decision variables for the optimization problem be $X = \{x_1, x_2, \dots, x_n\}$. Each variable x_i corresponds to an element that the director can control during creation, such as the intensity of plot points, shot parameters, actor performance intensity, or resource allocation ratio.

Define the optimization objective function as $F_{\text{total}}(X, t)$:

$$F_{\text{total}}(X, t) = \sum_i w_i(t) * V_i(x_i) + \text{EFM}(X, t)$$

Where:

$V_i(x_i)$ represents the contribution function of variable x_i to the overall objective;

$w_i(t)$ is a macro-weight, reflecting the director's focus on different factors and dynamically adjusted with iteration t ;

$\text{EFM}(X, t)$ is an emotion-driven creative feedback mechanism used to guide exploration of the unknown solution space.

This formula reflects the dynamic influence of variables in a director's creative decision-making, combining macro-weights with creative exploration to form an optimizable objective function.

2.2 Macro-Weight Guidance Mechanism

During the creative process, directors assign varying degrees of attention to different factors and dynamically adjust weights w_i . The Global Guidance (GG) mechanism can be formally expressed as:

$$w_i(t+1) = w_i(t) + \alpha * (F_{\text{total_best}} - F_{\text{total}}(t)) / F_{\text{total_best}} + \delta * \Delta_{\text{intuition}_i}$$

Where:

α is the global learning rate, controlling the magnitude of weight adjustments;

F_total_best is the optimal objective function value to date;

δ is the director's intuitive guidance coefficient, which simulates the director's experiential preferences;

$\Delta_intuition_i$ represents the director's shifting intuitive preferences for variable x_i , which can be based on historical experience or artistic judgment.

This mechanism demonstrates the director's ability to dynamically adjust variable weights in global decision-making, while also incorporating "experiential preferences" that distinguish it from purely numerical optimization methods.

2.3 Local Fine-Tuning Mechanism

The director performs fine-tuning within a single scene or shot to achieve the desired artistic effect. The local fine-tuning mechanism (LFT) simulates the director's fine-tuning behavior through iterative variable updates:

$$x_i(t+1) = x_i(t) + \beta * w_i(t) * r * (x_i_best - x_i(t)) + \gamma * N(0, \sigma_i^2)$$

Where:

β is the local learning rate, controlling the fine-tuning amplitude;

r is the random perturbation factor, $0 \leq r \leq 1$;

x_i_best is the optimal decision variable for the current scene or shot;

$\gamma * N(0, \sigma_i^2)$ is Gaussian noise, used for local exploration;

$\sigma_i^2 = f(E_i(t))$ represents the influence of the director's emotional evaluation of the scene/shot on the fine-tuning amplitude.

The local fine-tuning mechanism not only considers the optimal local solution but is also influenced by the director's emotional evaluation, reflecting the director's artistic intuition in micro-adjustments.

2.4 Emotion-Driven Creative Feedback Mechanism

The core innovation of the DICO algorithm lies in the Emotion Feedback Mechanism (EFM), which simulates a director's creative experimentation during creation. The EFM formula is:

$$EFM(X, t) = \lambda * \tanh(E_total(t)) * (X_rand - X) * S(t)$$

Where:

λ is the creative intensity coefficient, controlling the extent of creative exploration;

$E_total(t) = \sum_i e_i(t)$, where $e_i(t)$ is the director's emotional score for variable x_i . Positive values encourage exploration, while negative values inhibit deviation;

X_rand is a randomly generated new variable combination representing potential creative solutions;

$S(t) = \sin(\pi * t / T)$ controls the fluctuation of creative exploration over the iteration cycle, simulating the director's inspiration cycle;

T is the maximum number of iterations.

The EFM mechanism enables the algorithm to conduct bold exploration in the early stages of an iteration and gradually converge in the later stages, reflecting the dynamic nature of a director's inspiration.

2.5 Algorithm Iteration Formula

Combining macro-weight guidance, local fine-tuning, and emotional creativity feedback, the DICO algorithm iteration formula is as follows:

Macro-weight update:

$$w_i(t+1) = w_i(t) + \alpha * (F_total_best - F_total(t)) / F_total_best + \delta * \Delta_intuition_i$$

Local variable update:

$$x_i(t+1) = x_i(t) + \beta * w_i(t) * r * (x_i_best - x_i(t)) + \gamma * N(0, \sigma_i^2) + EFM(X, t)$$

Objective function update:

$$F_total(X, t+1) = \sum_i w_i(t+1) * V_i(x_i(t+1)) + EFM(X, t+1)$$

The above iterative formula achieves optimization through the triple effects of global macro guidance, local fine-tuning, and creative exploration.

3 Algorithm Pseudocode

Initialize variables $X = \{x_1, x_2, \dots, x_n\}$

Initialize weights $w = \{w_1, w_2, \dots, w_n\}$

Compute $F_total(X, 0)$

$F_total_best = F_total(X, 0)$

$t = 0$

Loop until $t \geq T$ or F_total converges:

For each variable x_i :

Update macro weights $w_i(t+1) = w_i(t) + \alpha * (F_{total_best} - F_{total}(t)) / F_{total_best} + \delta * \Delta_{intuition_i}$

Compute emotion feedback $EFM(X, t) = \lambda * \tanh(E_{total}(t)) * (X_{rand} - X) * \sin(\pi * t / T)$

Update local variables $x_i(t+1) = x_i(t) + \beta * w_i(t) * r * (x_{i_best} - x_i(t)) + \gamma * N(0, \sigma_i^2) + EFM(X, t)$

Calculate $F_{total}(X, t+1)$

Update F_{total_best}

$t = t + 1$

Output the optimal solution X_{best}

4 Algorithm Innovations

Triple Decision Structure: Global macro-weighting, local fine-tuning, and emotional creative feedback fully simulate the director's thought process.

Emotion-driven Creative Feedback (EFM): A unique nonlinear mechanism that enables the algorithm to explore creative ideas dynamically.

Intuitive Preference-Guided Weight Adjustment: Integrates the director's experience and artistic judgment to achieve a differentiated optimization strategy.

Inspiration Cycle Control Mechanism ($S(t)$): Simulates the temporal fluctuations of a director's creative inspiration.

Global and Local Fusion: Combines macro-optimization and micro-adjustment to improve the algorithm's applicability to complex multivariable problems.

5 Algorithm Theoretical Analysis

5.1 Convergence Discussion

The convergence of the DICO algorithm depends primarily on the following conditions:

The weight $w_i(t)$ maintains a finite increment during the iteration process:

$$|w_i(t+1) - w_i(t)| \leq \varepsilon_w$$

The local fine-tuning step size is controlled by Gaussian noise and sentiment evaluation:

$\sigma_i^2 = f(E_i(t)) \rightarrow$ gradually decreases in the later iterations, stabilizing local exploration.

The creative feedback factor $EFM(X, t)$ decays with iteration t :

$$\lim_{t \rightarrow T} S(t) \rightarrow 0$$

Based on the above conditions, the DICO algorithm tends to stabilize the solution X_{best} at the end of the iteration, ensuring convergence while maintaining early exploration capabilities.

5.2 Multi-Objective Optimization Extension

If the optimization problem involves multiple objectives F_1, F_2, \dots, F_m , the objective function can be extended using a weighted sum form:

$$F_{\text{total}}(X, t) = \sum_{k=1}^m \theta_k * F_k(X, t) + EFM(X, t)$$

where θ_k represents the weight of each objective and can be dynamically adjusted based on the director's experience or creative preferences, enabling multi-objective optimization and style control.

6 Conclusion

This paper proposes the Director-Inspired Creative Optimization (DICO) algorithm. Based on the three major decision-making characteristics of directors' creative work: macro-control, local fine-tuning, and creative experimentation, a novel emotion-driven creative feedback mechanism (EFM) is designed. The algorithm modeling, weight updating, local optimization, and creative exploration mechanisms are described in detail using mathematical formulas and iterative strategies. The DICO algorithm not only simulates the director's creative behavior but also exhibits theoretical analyzability, providing a new modeling approach for multivariable optimization problems. Future applications of this algorithm include creative design optimization, parameter tuning, and complex system planning, providing a quantitative approach for creative decision-making.

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