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Dipl.-Ing. Nikola Aulig,
Darmstadt

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Generic Topology Optimization Based on Local State Features

Berichte aus dem

Institut für
Automatisierungstechnik
und Mechatronik
der TU Darmstadt

Generic Topology Optimization Based on Local State Features

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Elektrotechnik und Informationstechnik
der Technischen Universität Darmstadt
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eines Doktor-Ingenieurs (Dr.-Ing.)
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The work at hand addresses engineers, designers and scientists who face the challenging task of devising concept structures in a virtual product design process that involves more and more sophisticated physical simulations. Using methods of evolutionary optimization and machine learning, this dissertation explores a novel generic topology optimization algorithm, which is able to provide concept designs even for problems involving complex, black-box simulations. A self-contained learning component utilizes physical simulation data to generate a search direction. The generic topology optimization is studied in conjunction with statistical models such as neural networks or support vector regression. In empirical experiments, the novel method reproduces reference structures with minimum compliance and provides innovative solutions in the domain of vehicle crashworthiness optimization.

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Symbols and Abbreviations

Symbols

ρ	Density, topology optimization design variable
F	Objective function
$\mathbf{u}$	State vector
G	Constraint
Ω	Design domain
$\mathbf{x}$	Point in design domain
V	Volume of structure
L	Number of extra constraints
ρ	Vector of densities, topology optimization design variables
N	Number of finite elements in design space mesh
E	Material Young's modulus
p	Penalization coefficient
c	Compliance
$\mathbf{l}$	Load vector
$\mathbf{K}$	Stiffness matrix
f	Volume fraction
v	Finite element volume
μ	Number of parent individuals
ϱ	Number of parent individuals used for creating new offspring individuals
κ	Individual lifetime
λ	Number of offspring individuals
$\boldsymbol{\theta}$	Vector of ES design variables, update-signal model parameters
k	Iteration number
Θ	Number of search dimensions in ES
$\mathbf{z}$	Random mutation vector
$\mathbf{C}$	Covariance matrix of ES mutation operator
$\mathcal{N}$	Normal distribution
σ	Standard deviation of normal distribution, global step size
$\boldsymbol{\sigma}$	Vector of strategy parameters
z	Random mutation number

τ	Learning parameter
$\mathbf{m}$	Distribution mean
$\mathbf{v}$	Adjoint state vector
S	Update-signal model
J	Number of LSFs
$\mathbf{s}_i$	LSF Vector
u	Nodal displacement
B	OC-input
m	Move limit
η	OC damping parameter
$\widehat{S}$	Filtered update-signal model
Λ	Lagrange multiplier for volume constraint
$\widehat{H}$	Sensitivity filter weights
$r_{\min}$	Sensitivity filter radius
ΔF	Design improvement
M	Number of evluations
g	MLP activation function
H	Number of hidden neurons
$\mathcal{V}$	Data set of LSF samples
$\mathbf{c}$	LSF prototype
P	Number of LSF prototypes
Ψ	Mapping from LSF space to finite set of indices
ζ	Cluster index
ϵ	Finite difference step length
T	Number of training samples
y	Prediction target
$\mathcal{G}$	Set of element or node ids
$\hat{k}$	SVR kernel function
$\hat{L}$	Number of support vectors
ν	Poisson's ratio
SED	Strain energy density
ϱ'	Volumetric mass density
σ_{Y}	Yield stress
E_{h}	Elasticity hardening modulus
q	Penalization coefficient for plasticity
$\mathrm{E}_{\mathrm{abs}}$	Energy absorption
IED	Internal energy density
$\mathbf{r}$	Simulation residual
t	Time

I	Intrusion

Abbreviations

BESO	Bi-directional Evolutionary Structural Optimization
CMA	Covariance Matrix Adaptation
CPPN	Compositional Pattern Producing Network
EA	Evolutionary Algorithm
EC	Evolutionary Computation
ES	Evolution Strategy
ESL	Equivalent Static Load
FD	Finite Difference
FEA	Finite Element Analysis
HCA	Hybrid Cellular Automata
LIN	Linear Regression
LSF	Local State Feature
LSM	Level Set Method
MLP	Multi-Layer Perceptron
NE	Neuro-Evolution
NEAT	Neuro Evolution for Augmenting Topologies
OC	Optimality Criteria
PCM	Piecewise-Constant Model
RBF	Radial Basis Function
SERA	Sequential Element Rejections and Admissions
SVR	Support Vector Regression
SIMP	Solid Isotropic Material with Penalization
TOPAS	Topology Optimization by Predicting Aggregated Sensitivities
TOPS	Topology Optimization by Predicting Sensitivities

Abstract

The automatic creation of optimal concepts for mechanical structures in the computer-aided design process has become an important area of research. Continuum topology optimization methods determine the distribution of material within a pre-defined design space and, thus, not only the shape, but also the fundamental geometric layout of a structure. For this task, the majority of the existing, numerical optimization methods requires mathematical gradient information. However, when addressing optimization problems that involve highly non-linear or black-box simulations, it can be difficult to obtain satisfactory results or gradient information at all. In order to provide design concepts also for these types of problems, this thesis presents a generic topology optimization approach. The novel method realizes a self-contained learning component that utilizes physical simulation data to generate a search direction. Based on a continuous problem formulation, every design variable is improved iteratively by a learned update-signal. The individual update-signals are computed from local state features and substitute sensitivities of the design variables. Evolutionary optimization or supervised learning adapt the model parameters for determination of the update-signals to the chosen optimization goal. In empirical studies, the novel method reproduces reference structures with minimum compliance. When applied to a practical problem from the challenging domain of vehicle crashworthiness optimization, specifically the minimization of intrusion, it provides superior design concepts when compared to a frequently applied heuristic method. The results confirm that the proposed method is capable to yield innovative solutions to so far unsolved topology optimization problems.

Zusammenfassung

Die automatische Erstellung von optimalen Entwurfskonzepten für mechanische Strukturen im rechnergestützten Entwicklungsprozess ist ein wichtiger Forschungszweig. Methoden der Topologieoptimierung bestimmen die Materialverteilung in einem vordefinierten Entwurfsraum und daher nicht nur die Form, sondern auch die grundsätzliche geometrische Ausgestaltung einer Struktur. Die Mehrheit der verfügbaren numerischen Optimierungsmethoden benötigen hierfür mathematische Gradienteninformation. Betrachtet man jedoch Optimierungsprobleme, die stark nichtlineare oder Blackbox-Simulationen beinhalten, kann es schwierig sein, zufriedenstellende Ergebnisse oder überhaupt Gradienteninformation zu erhalten. Um auch für solche Probleme Entwurfskonzepte zu finden, wird in dieser Dissertation ein generischer Topologieoptimierungsansatz präsentiert. Die neue Methode realisiert eine eigenständige Lernkomponente, welche in der Lage ist, aus physikalischen Simulationsdaten eine Suchrichtung zu erstellen. Basierend auf einer kontinuierlichen Formulierung des Problems wird jede Entwurfsvariable durch ein gelerntes Updatesignal iterativ verbessert. Die individuellen Updatesignale berechnen sich aus lokalen Zustandsmerkmalen und ersetzen die Sensitivitäten der Entwurfsvariablen. Evolutionäre Optimierung oder überwachte Lernverfahren passen die Modellparameter zur Bestimmung der Updatesignale an das gewählte Optimierungsziel an. In empirischen Studien reproduziert die neue Methode Referenzstrukturen mit minimaler Nachgiebigkeit. Bei der Anwendung auf ein Problem aus dem anspruchsvollen Gebiet der Optimierung des Fahrzeug-Unfallverhaltens, speziell der Minimierung der Eindringtiefe, liefert sie überlegene Entwurfsvorschläge im Vergleich mit einer häufig verwendeten heuristischen Methode. Die Ergebnisse bestätigen, dass die vorgeschlagene Methode in der Lage ist, innovative Loṡungen für bisher ungelöste Topologieoptimierungsprobleme zu erzeugen.