AUTOMATED RULE GENERATION FOR COMPLEX EVENT PROCESSING

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Degree of Master of Science

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DECLARATION

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Signature of the supervisor: Name: Dr. Surangika Ranathunga	Date:

Abstract

The key concept of Complex Event Processing (CEP) is setting up accurate queries to pick up the important events. Since all CEP engines support SQL like queries, this rule setup requires some technical skills plus domain knowledge. The best solution to address this issue is to automate the query generation of CEP. Existing automated query generation methodologies are computationally expensive and are not fully automated processes. This study addresses the above two issues by proposing a shapelet based approach. This new approach is not computationally expensive, and it is a fully automated process with zero manual user intervention required. The proposed method uses the computationally efficient algorithm called Fast Shapelet Selection (FSS) algorithm. This FSS algorithm is used to extract the shapelets from data set. Then extracted shaplets are used to generate CEP queries. This proposed method can be used analyze to multivariant time series and this is more efficient than previously proposed shapelet based approaches.

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LIST OF ABBREVIATIONS

AEP Admissible Entropy Pruning

BF Brute Force Algorithm

CEP Complex Event Processing

DBMS Database Management Systems

EDL Event Description Language

FS Fast Shapelet Discovery

FSS Fast Shapelet Selection Algorithm

GRSF Generalized Random Shapelet Forest

HMM Hidden Markov Model (HMM)

IDP Important Data Point

LS Learning Shapelet Algorithm

nHMM noise Hidden Markov Model

PLR Piecewise Linear Representation (PLR)

PLR_IDP Piecewise Linear Representation based on Important Data Points

RS Random Shapelet (RS)

ST Shapelet Transformation Algorithm (ST)

SDEA Subsequence Distance Early Abandon (SDEA)

LFDP Local Farthest Deviation Points (LFDP)