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APPENDICES

APPENDIX A

DATASETS

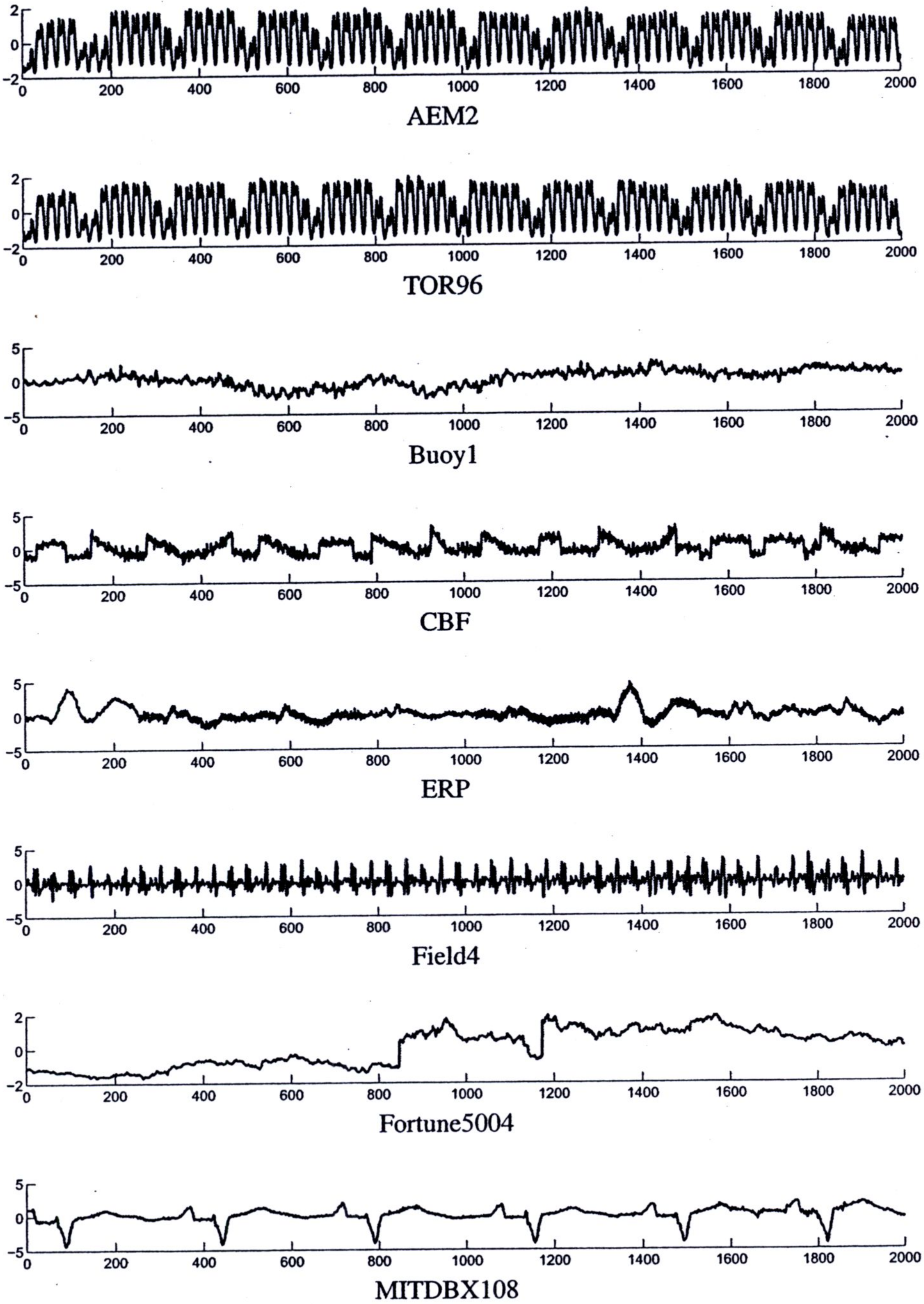


Figure A.1: Datasets from TSDMA used in the experiments of Chapters II, IV, and VI.

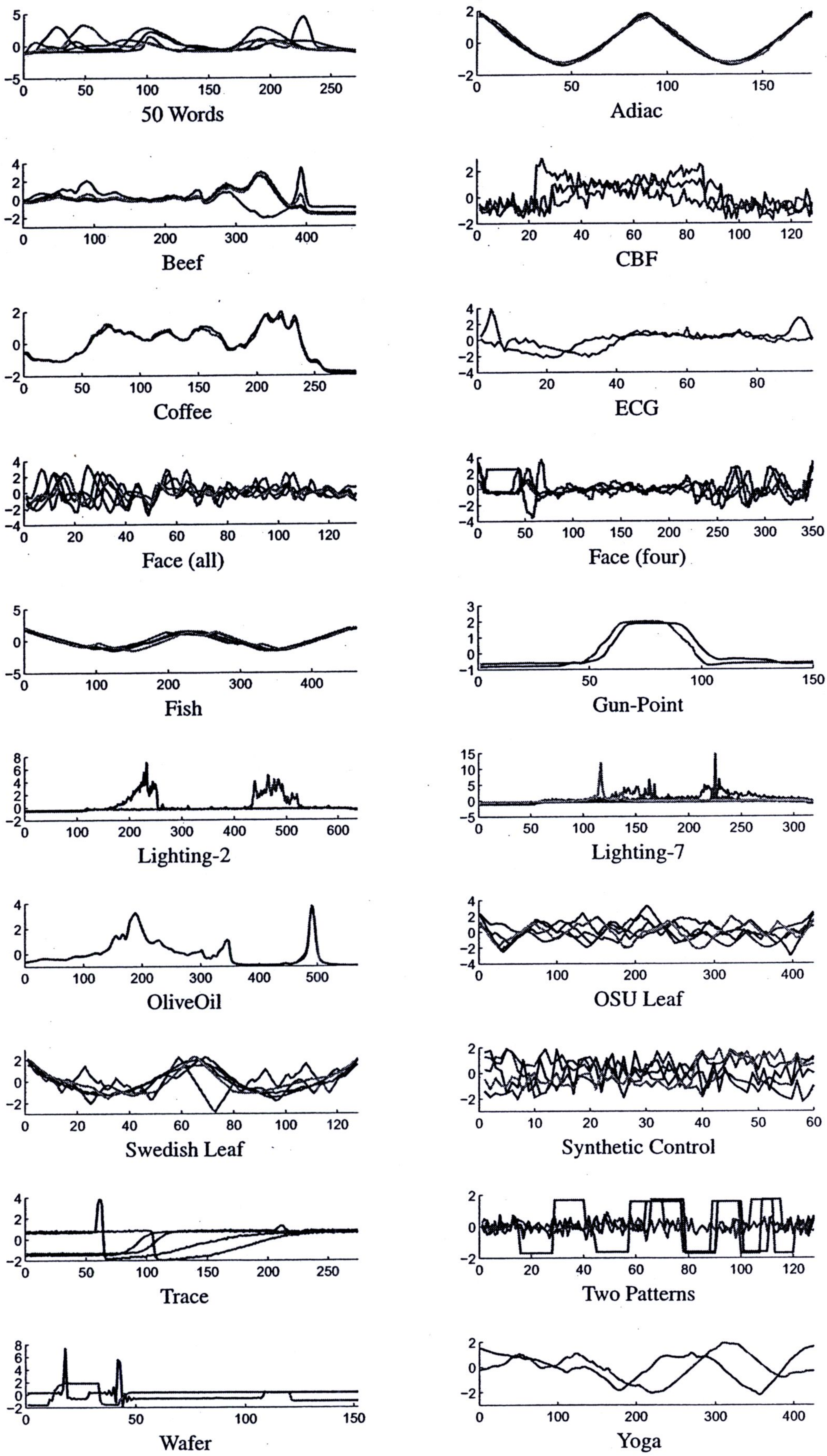


Figure A.2: Examples of some classes of the UCR classification/clustering datasets used in Chapters III and V.

Table A.1: Details of the UCR classification/clustering datasets used in Chapters III and V

Dataset	Number of classes	Length	Size of datasets
50words	50	270	905
Adiac	37	176	781
Beef	5	470	60
CBF	3	128	930
Coffee	2	286	56
ECG	2	96	200
Face (all)	14	131	2250
Face (four)	4	350	112
Fish	7	463	350
Gun-Point	2	150	200
Lighting-2	2	637	121
Lighting-7	7	319	143
Oliveoil	4	570	60
OSULeaf	6	427	442
SwedishLeaf	15	128	1125
Synthetic	6	60	600
Trace	4	275	200
TwoPatterns	4	128	5000
Wafer	2	152	7174
Yoga	2	426	3300

APPENDIX B

COMPLETE EXPERIMENTAL RESULTS OF THE FIRST EXPERIMENT IN CHAPTER II

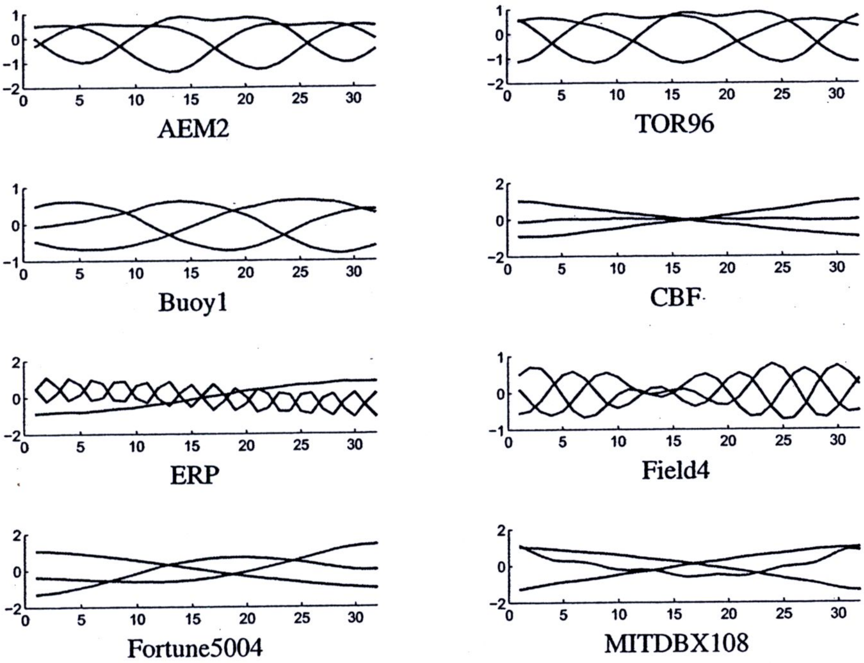


Figure B.1: Cluster representatives generated from STSC using k-means clustering when $k = 3$ and $w = 32$.

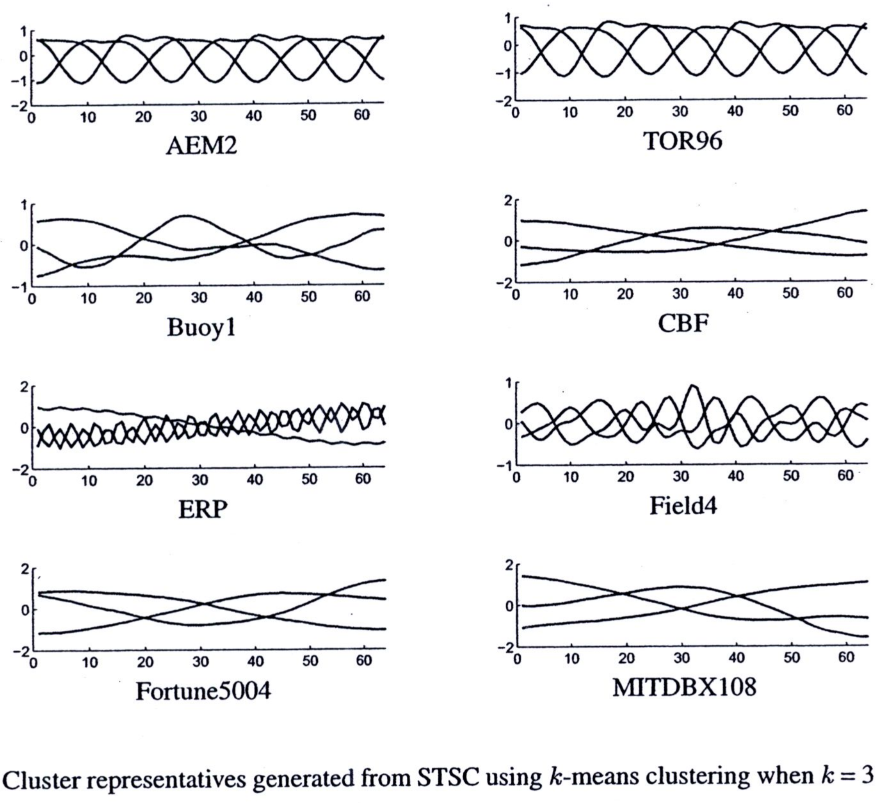


Figure B.2: Cluster representatives generated from STSC using k-means clustering when $k = 3$ and $w = 64$.

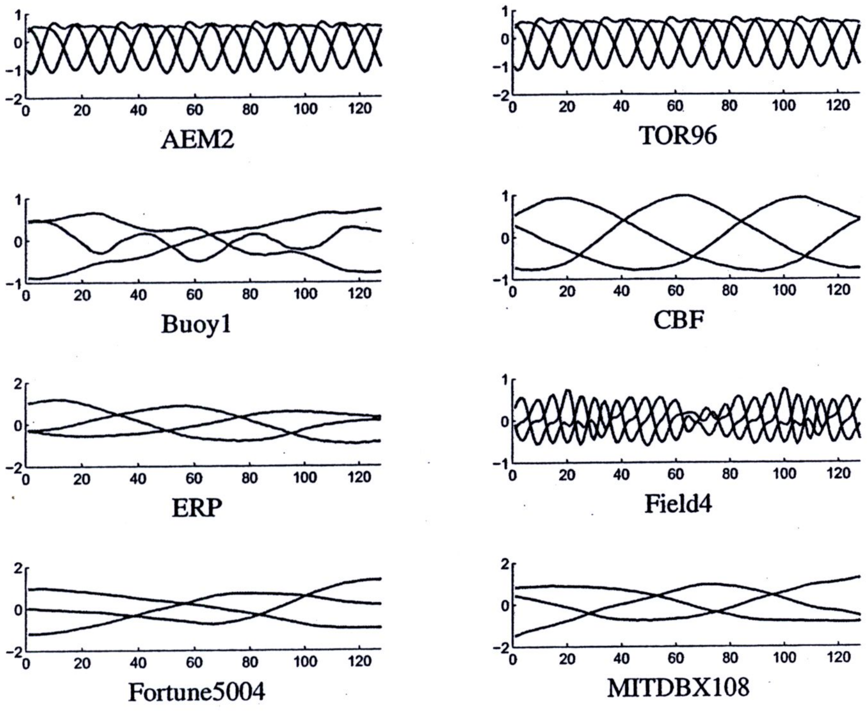


Figure B.3: Cluster representatives generated from STSC using k-means clustering when $k = 3$ and $w = 128$.

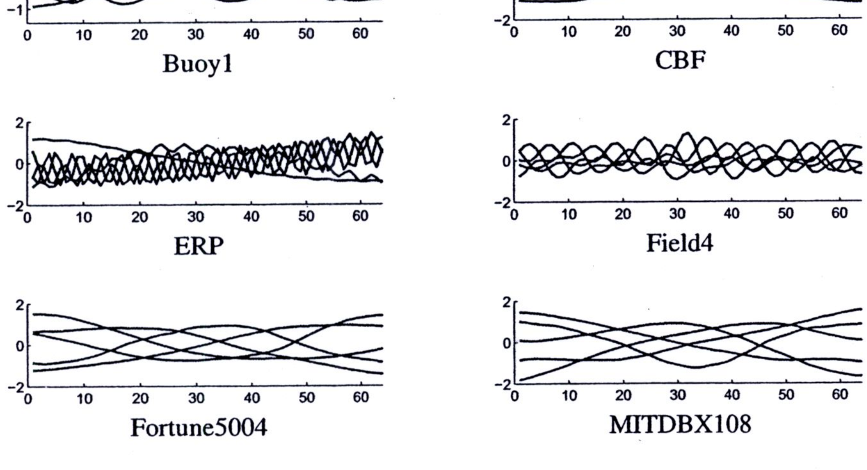


Figure B.4: Cluster representatives generated from STSC using k-means clustering when $k = 5$ and $w = 64$.

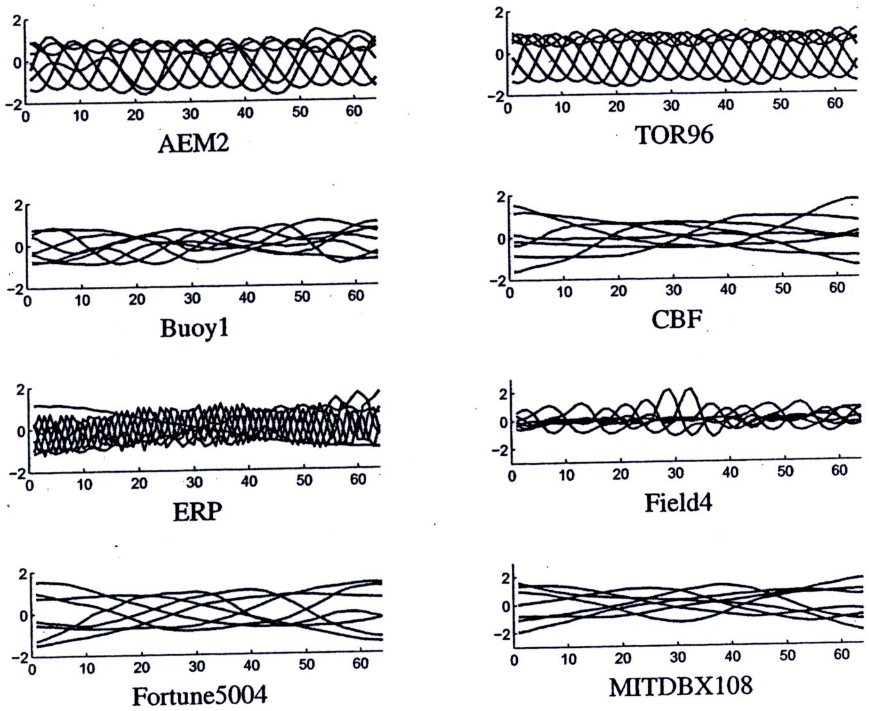


Figure B.5: Cluster representatives generated from STSC using k-means clustering when $k = 7$ and $w = 64$.

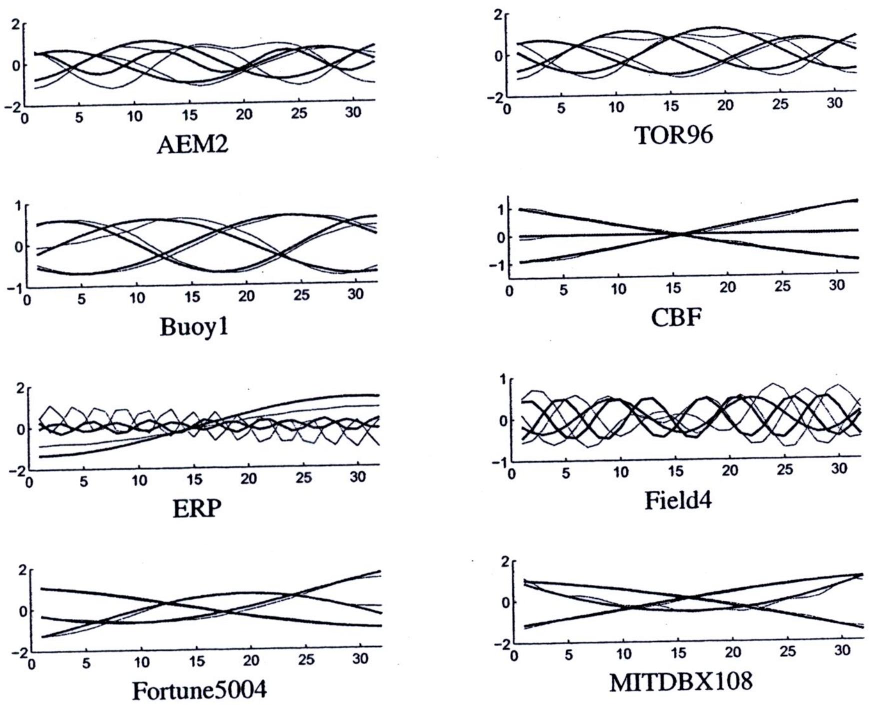


Figure B.6: Constructed sine waves generated from STSC using k-means clustering when $k = 3$ and $w = 32$.

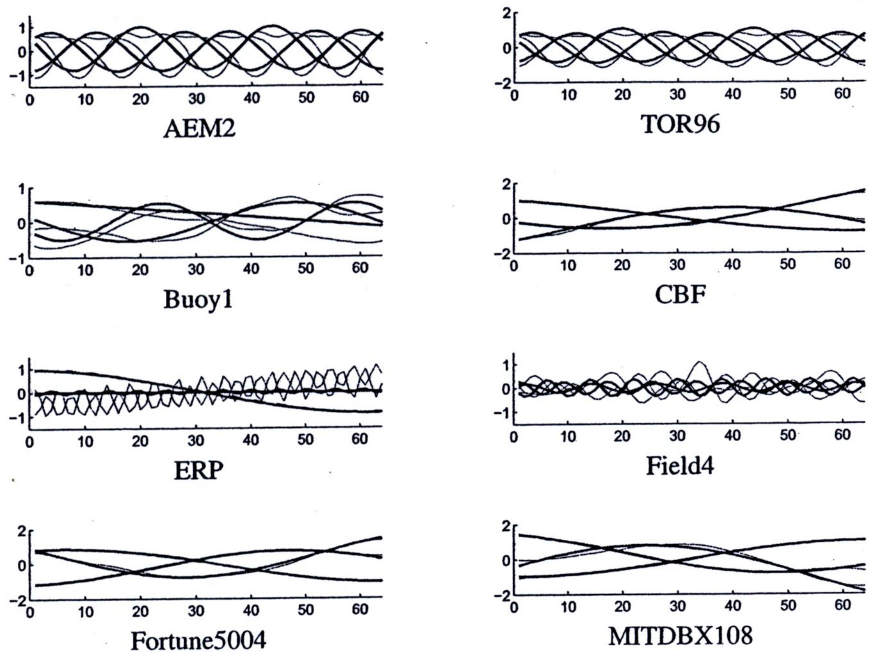


Figure B.7: Constructed sine waves generated from STSC using k-means clustering when k = 3 and w = 64.

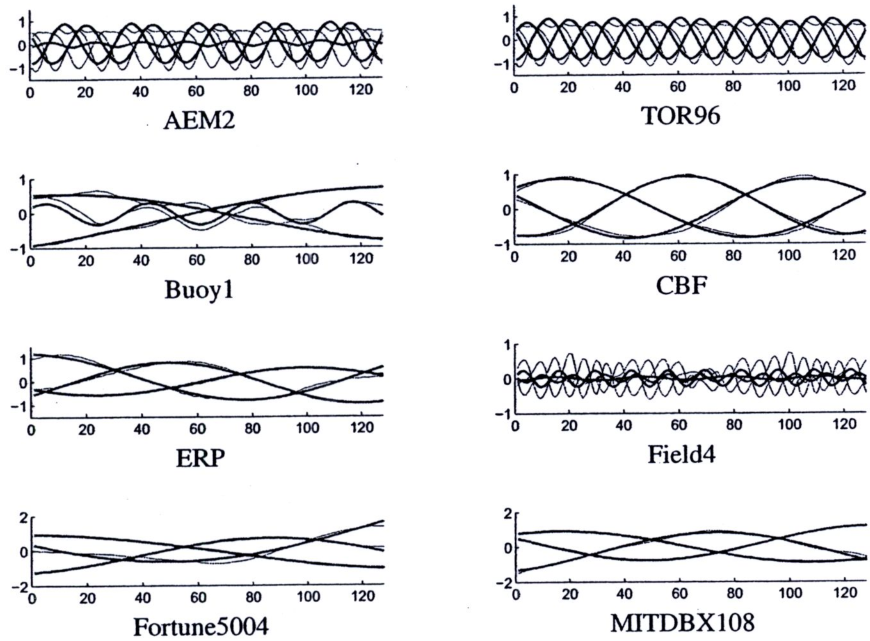


Figure B.8: Constructed sine waves generated from STSC using k-means clustering when k = 3 and w = 128.

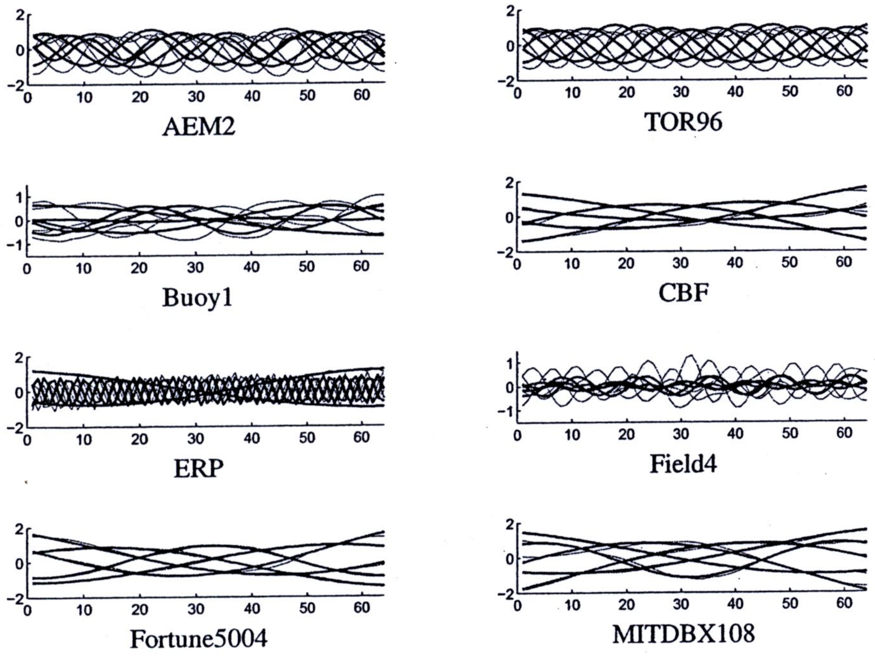


Figure B.9: Constructed sine waves generated from STSC using k-means clustering when k = 5 and w = 64.

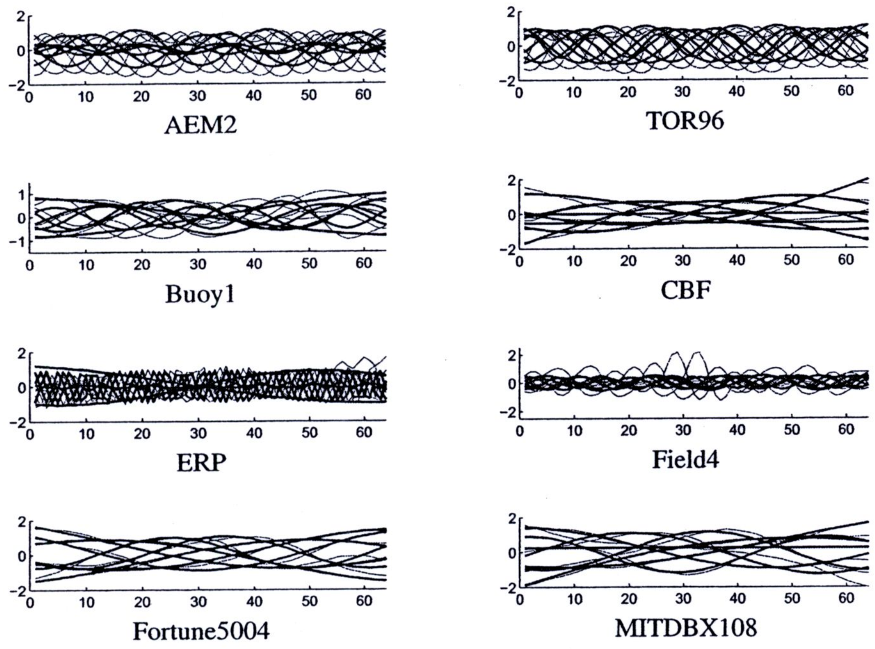


Figure B.10: Constructed sine waves generated from STSC using k-means clustering when k = 7 and w = 64.

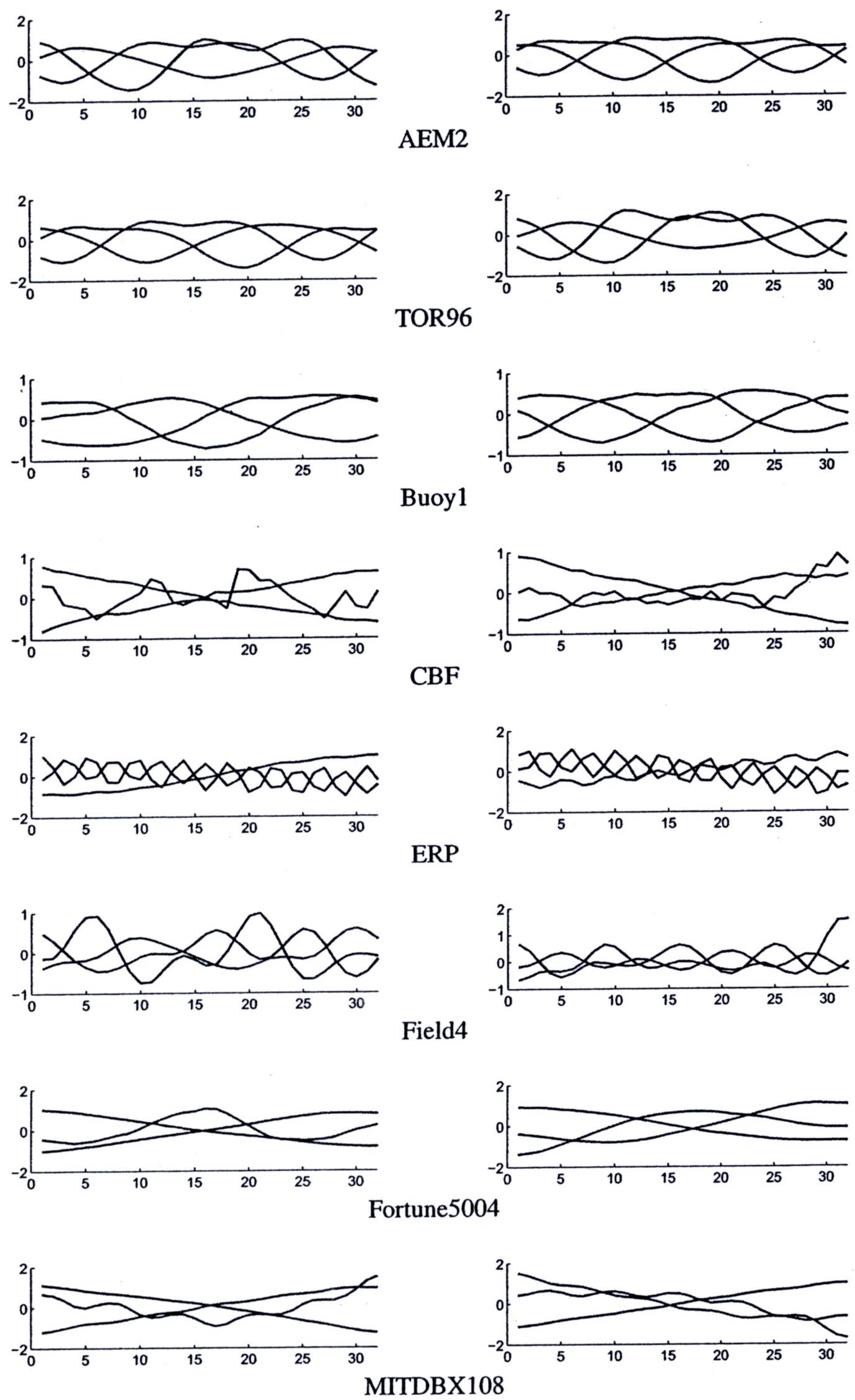


Figure B.11: Cluster representatives generated from STSC using k-hierarchical clustering with complete linkage (left) and average linkage (right) inter-distance functions when $k = 3$ and $w = 32$.

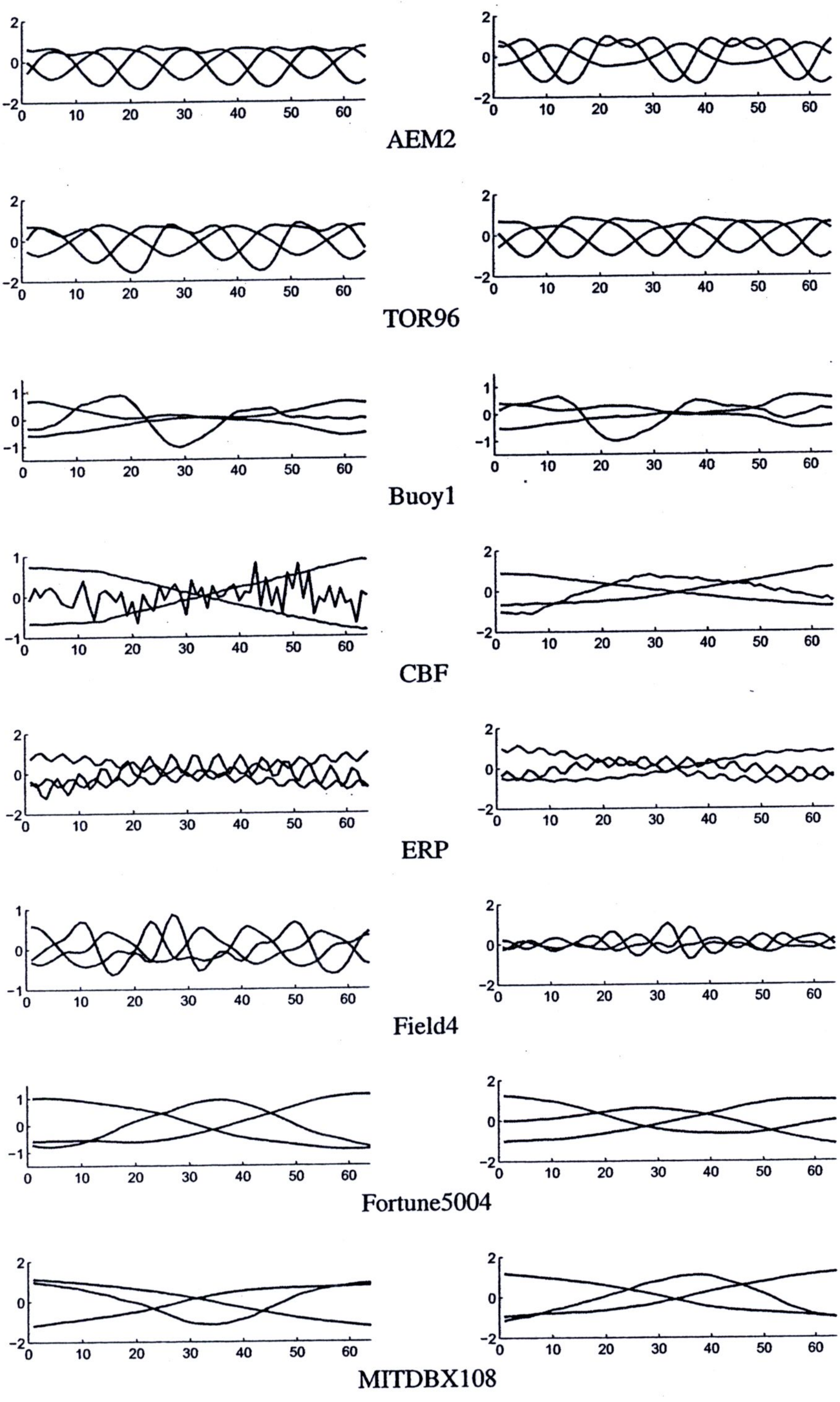


Figure B.12: Cluster representatives generated from STSC using k-hierarchical clustering with complete linkage (left) and average linkage (right) inter-distance functions when $k = 3$ and $w = 64$.

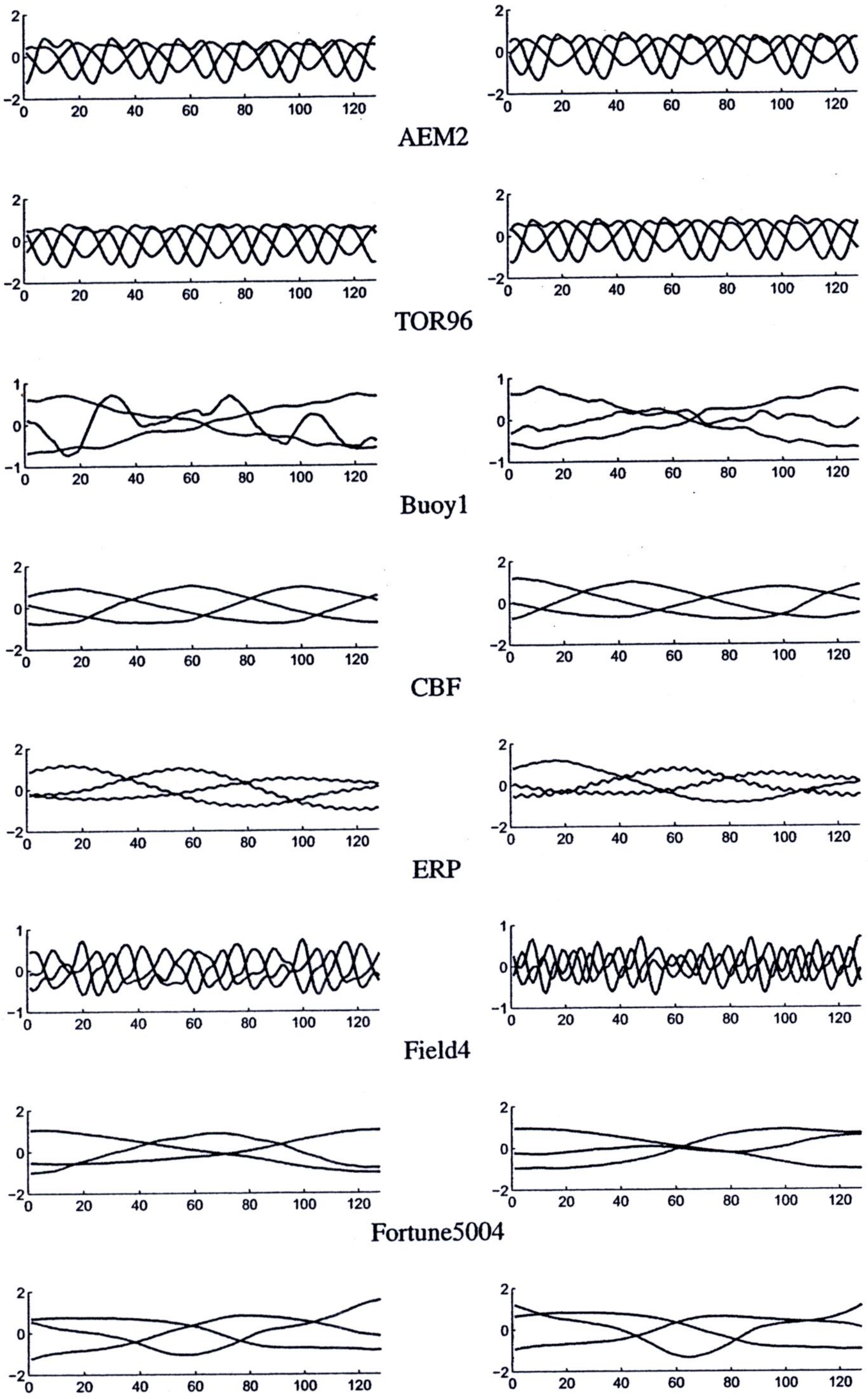


Figure B.13: Cluster representatives generated from STSC using k-hierarchical clustering with complete linkage (left) and average linkage (right) inter-distance functions when $k = 3$ and $w = 128$.

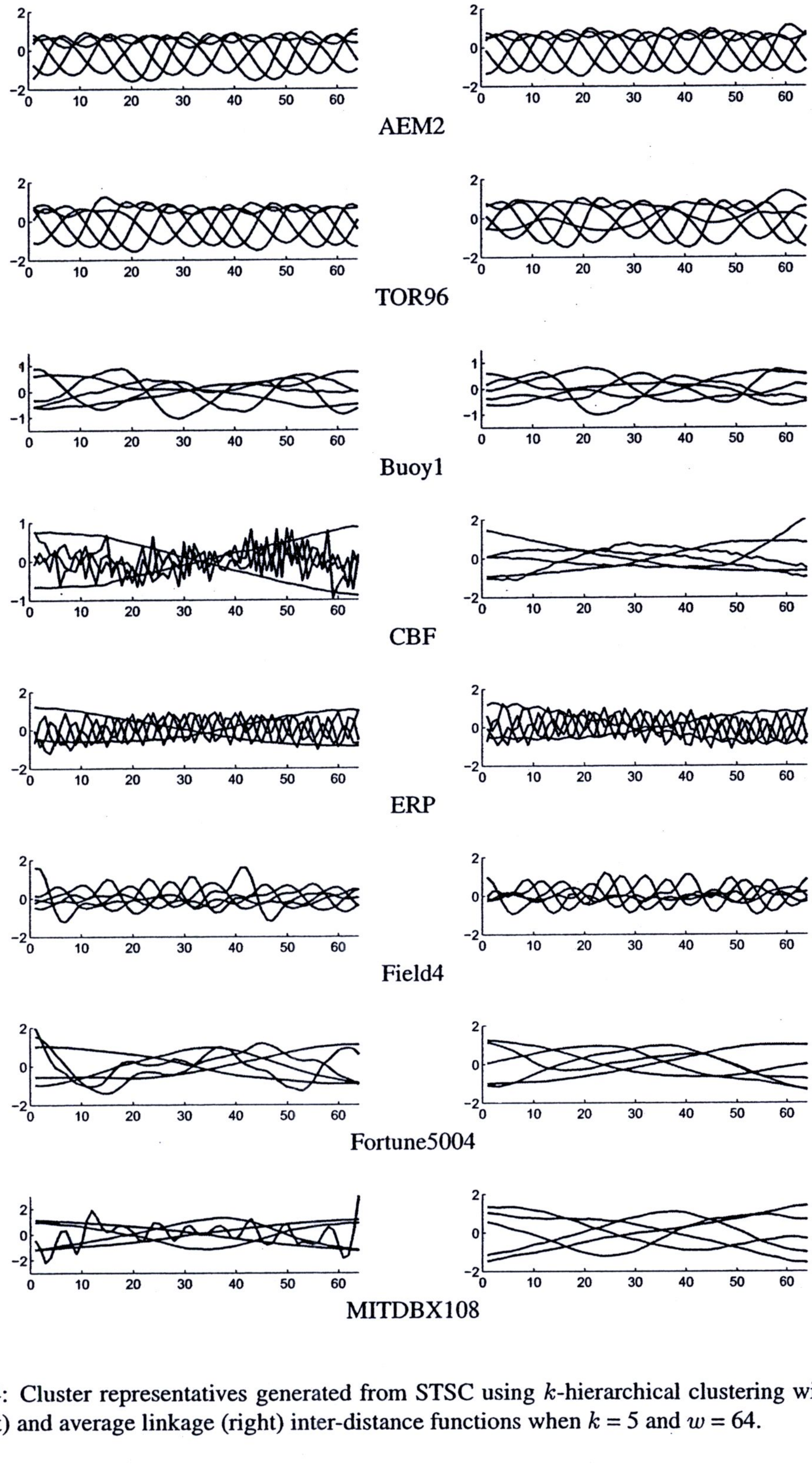


Figure B.14: Cluster representatives generated from STSC using k-hierarchical clustering with complete linkage (left) and average linkage (right) inter-distance functions when $k = 5$ and $w = 64$.

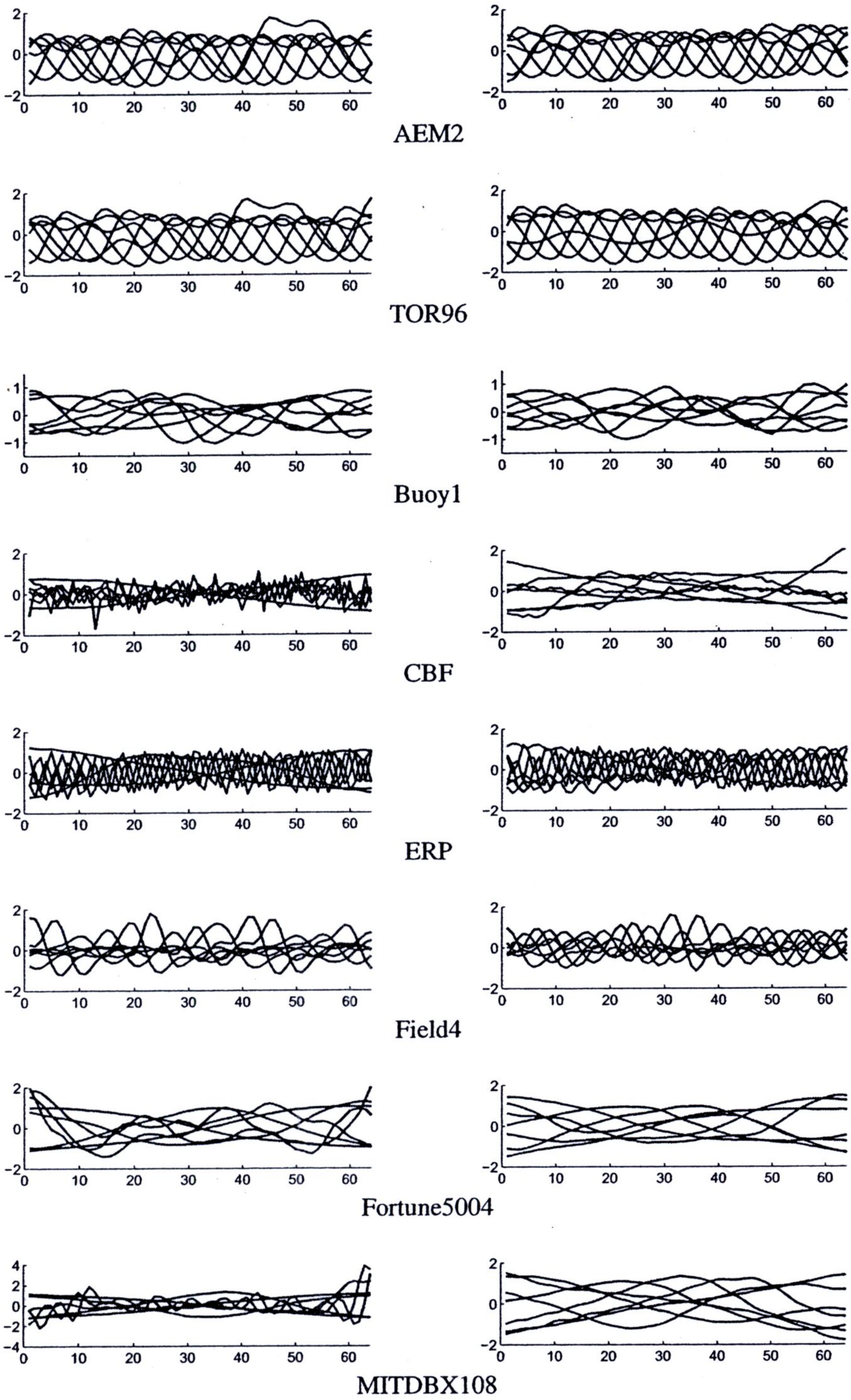


Figure B.15: Cluster representatives generated from STSC using k-hierarchical clustering with complete linkage (left) and average linkage (right) inter-distance functions when $k = 7$ and $w = 64$.

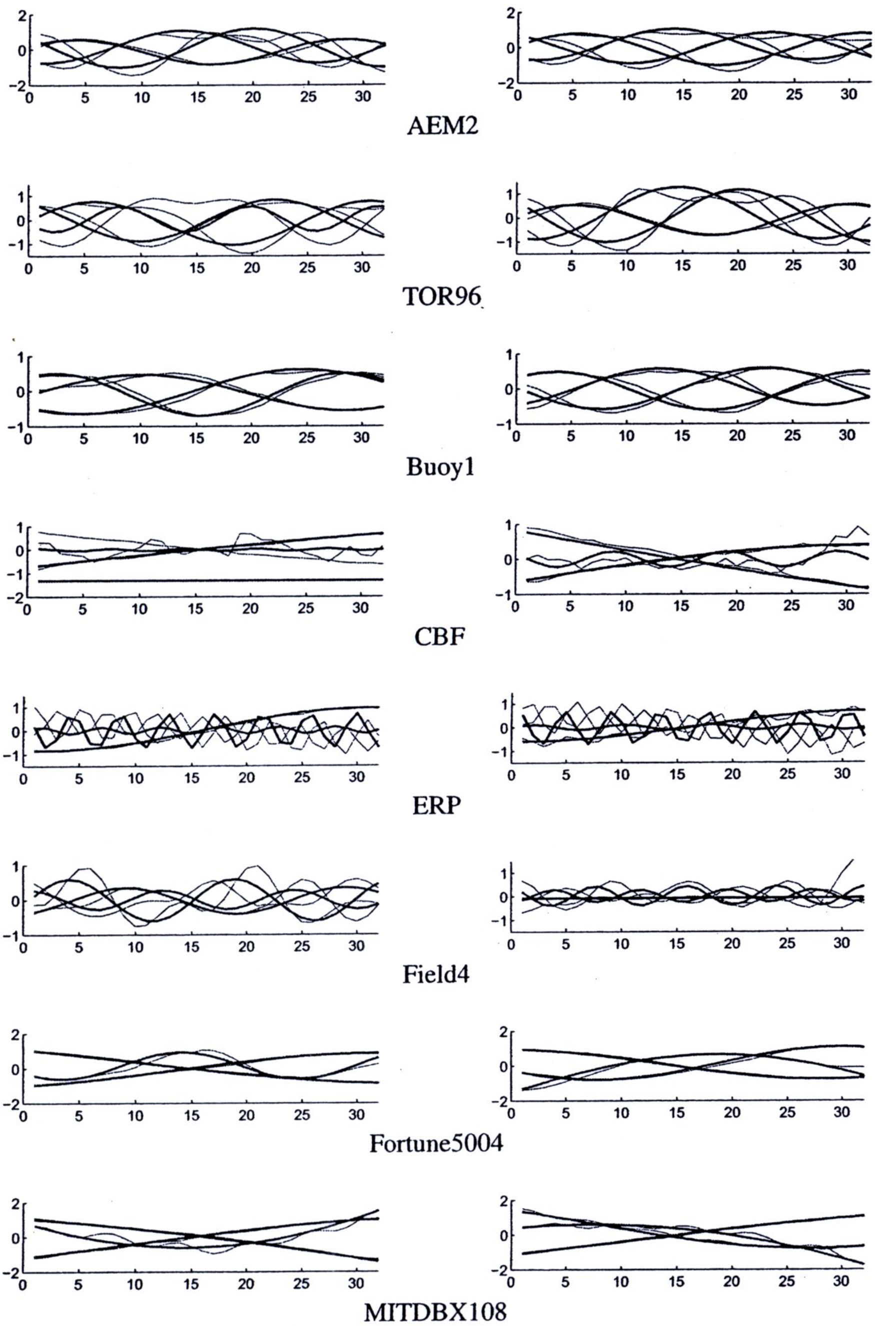


Figure B.16: Constructed sine waves generated from STSC using k-hierarchical clustering with complete linkage (left) and average linkage (right) inter-distance functions when $k = 3$ and $w = 32$.

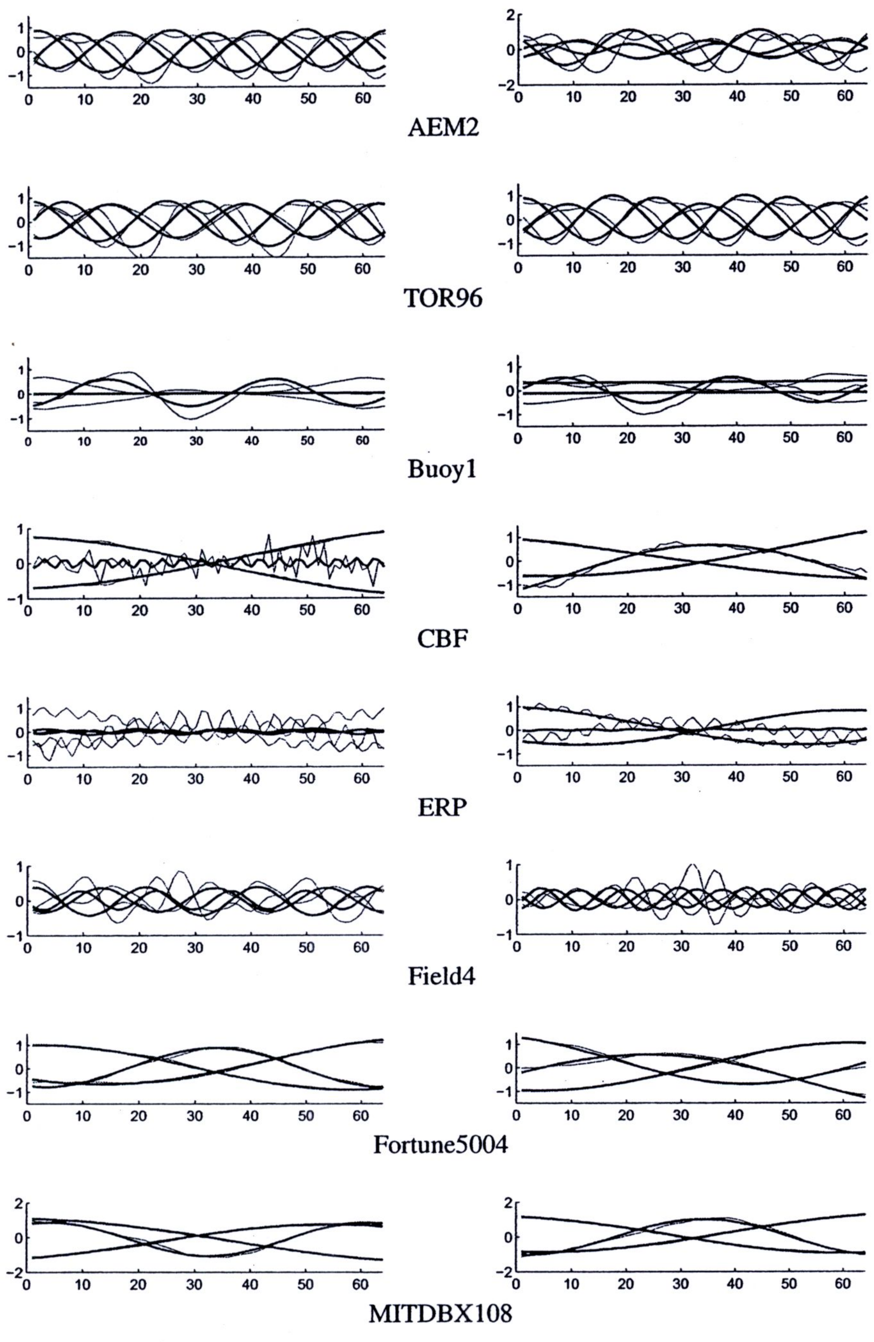


Figure B.17: Constructed sine waves generated from STSC using k-hierarchical clustering with complete linkage (left) and average linkage (right) inter-distance functions when $k = 3$ and $w = 64$.

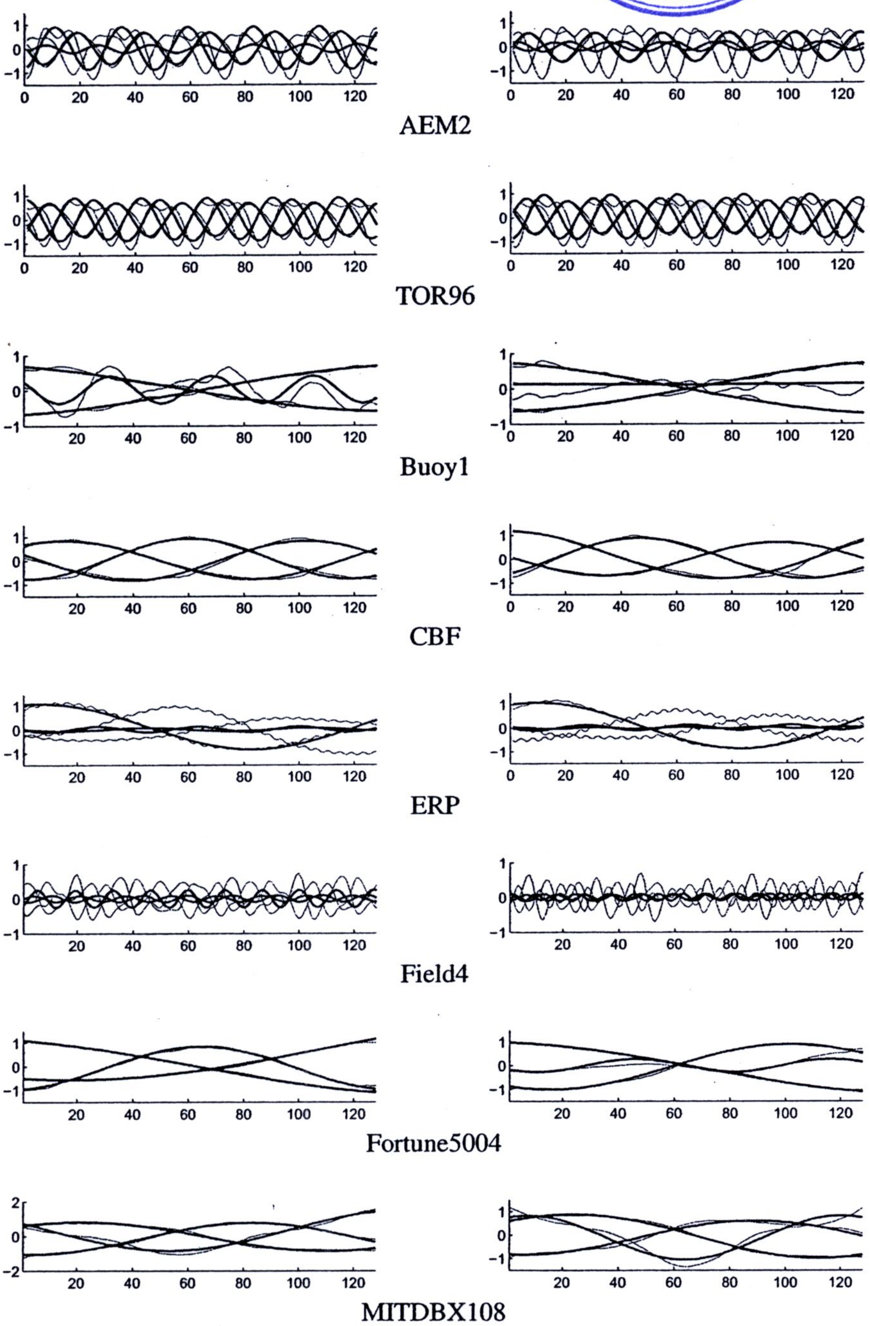


Figure B.18: Constructed sine waves generated from STSC using k-hierarchical clustering with complete linkage (left) and average linkage (right) inter-distance functions when $k = 3$ and $w = 128$.

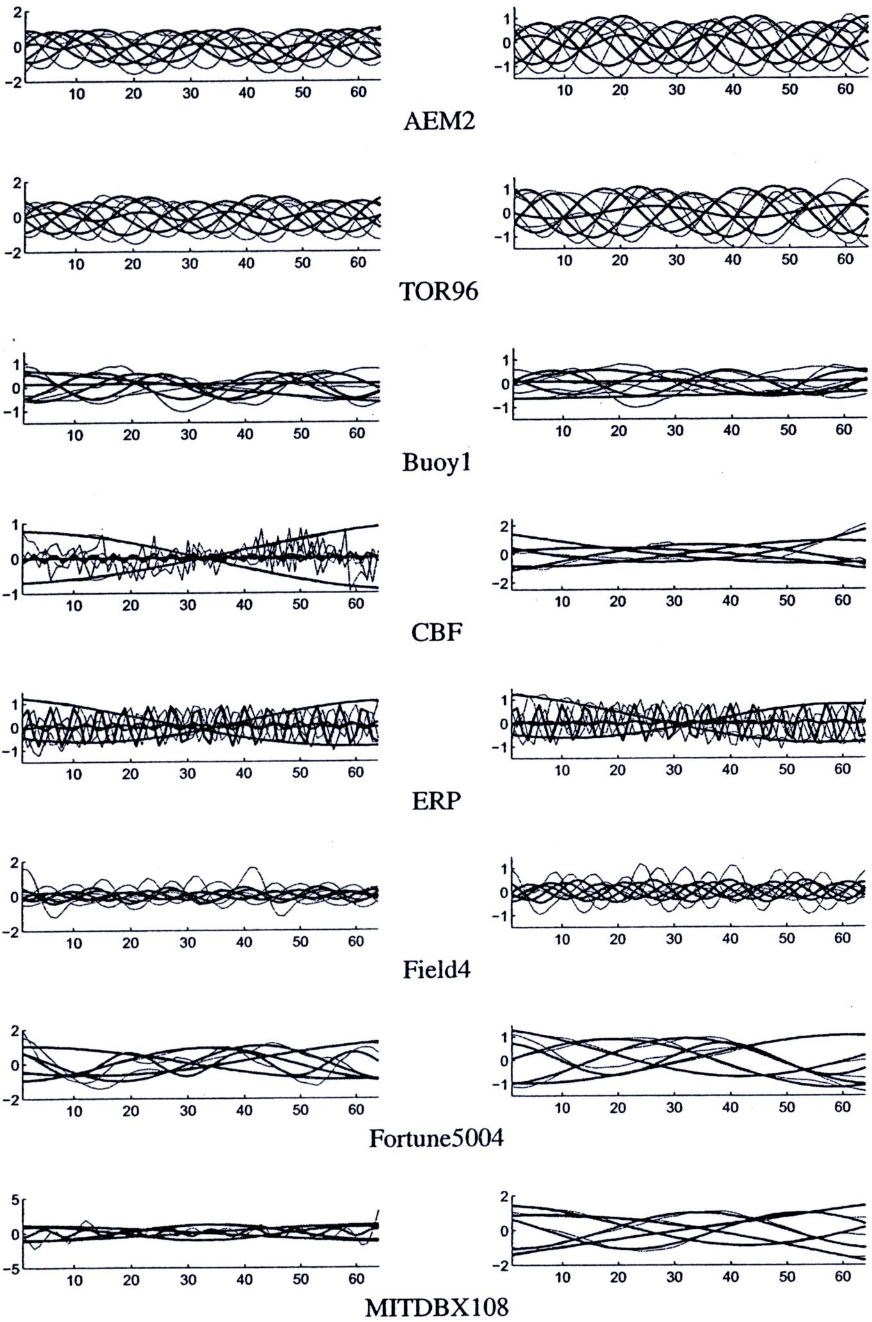


Figure B.19: Constructed sine waves generated from STSC using k-hierarchical clustering with complete linkage (left) and average linkage (right) inter-distance functions when $k = 5$ and $w = 64$.

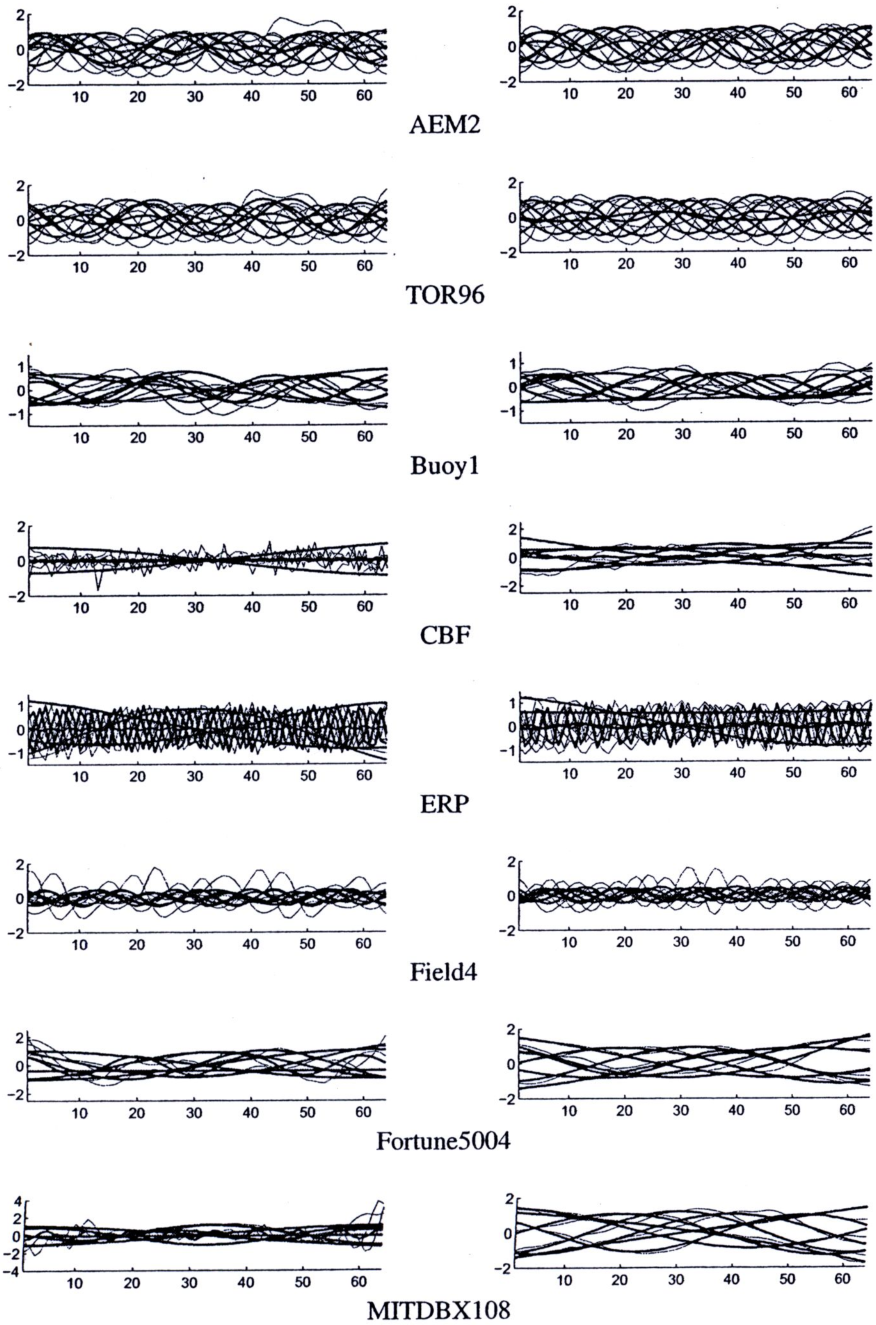


Figure B.20: Constructed sine waves generated from STSC using k-hierarchical clustering with complete linkage (left) and average linkage (right) inter-distance functions when $k = 7$ and $w = 64$.

APPENDIX C

COMPLETE EXPERIMENTAL RESULTS OF THE EXPERIMENT IN CHAPTER III

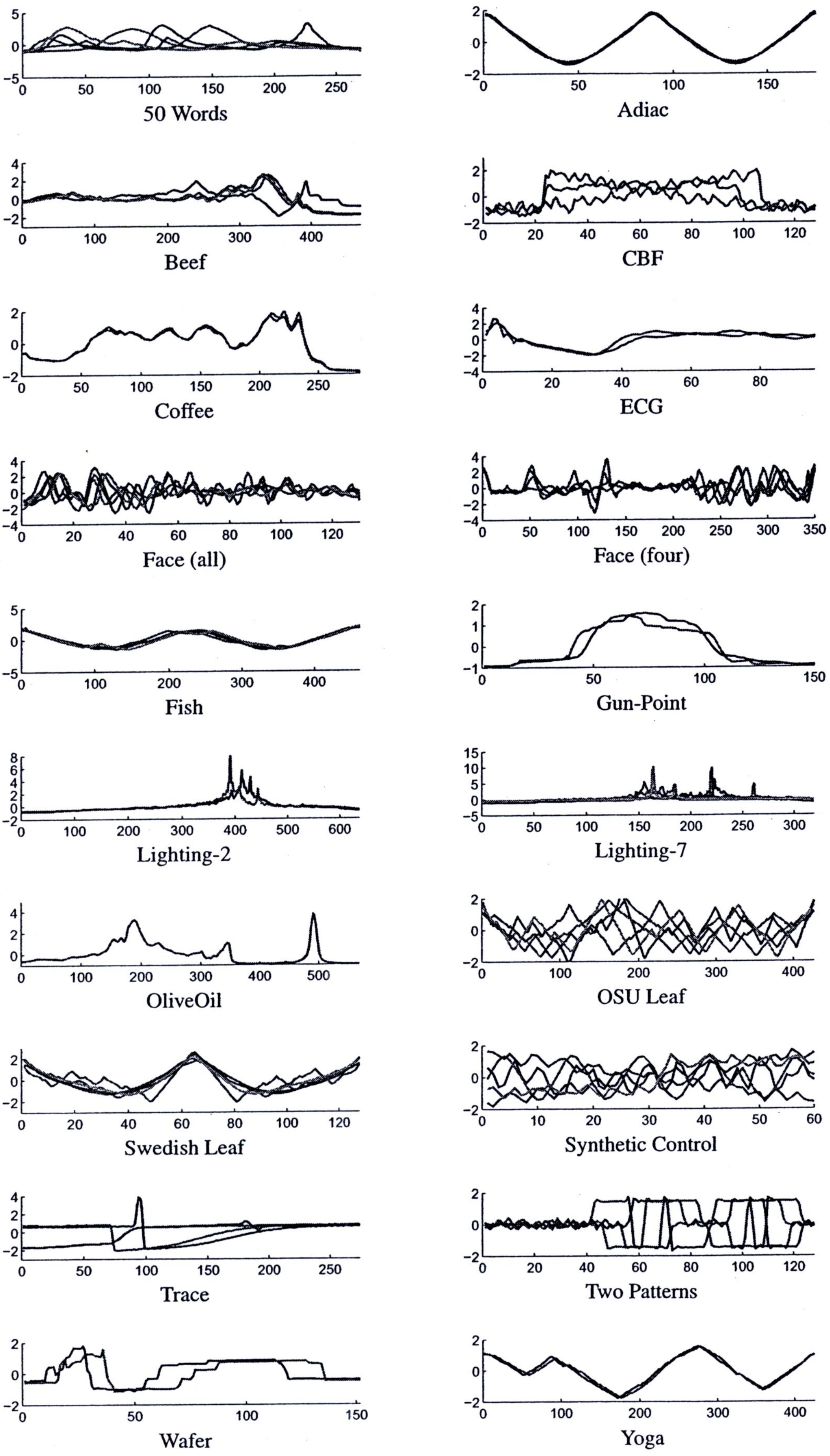


Figure C.1: Averaged results generated from CDTW function of each dataset

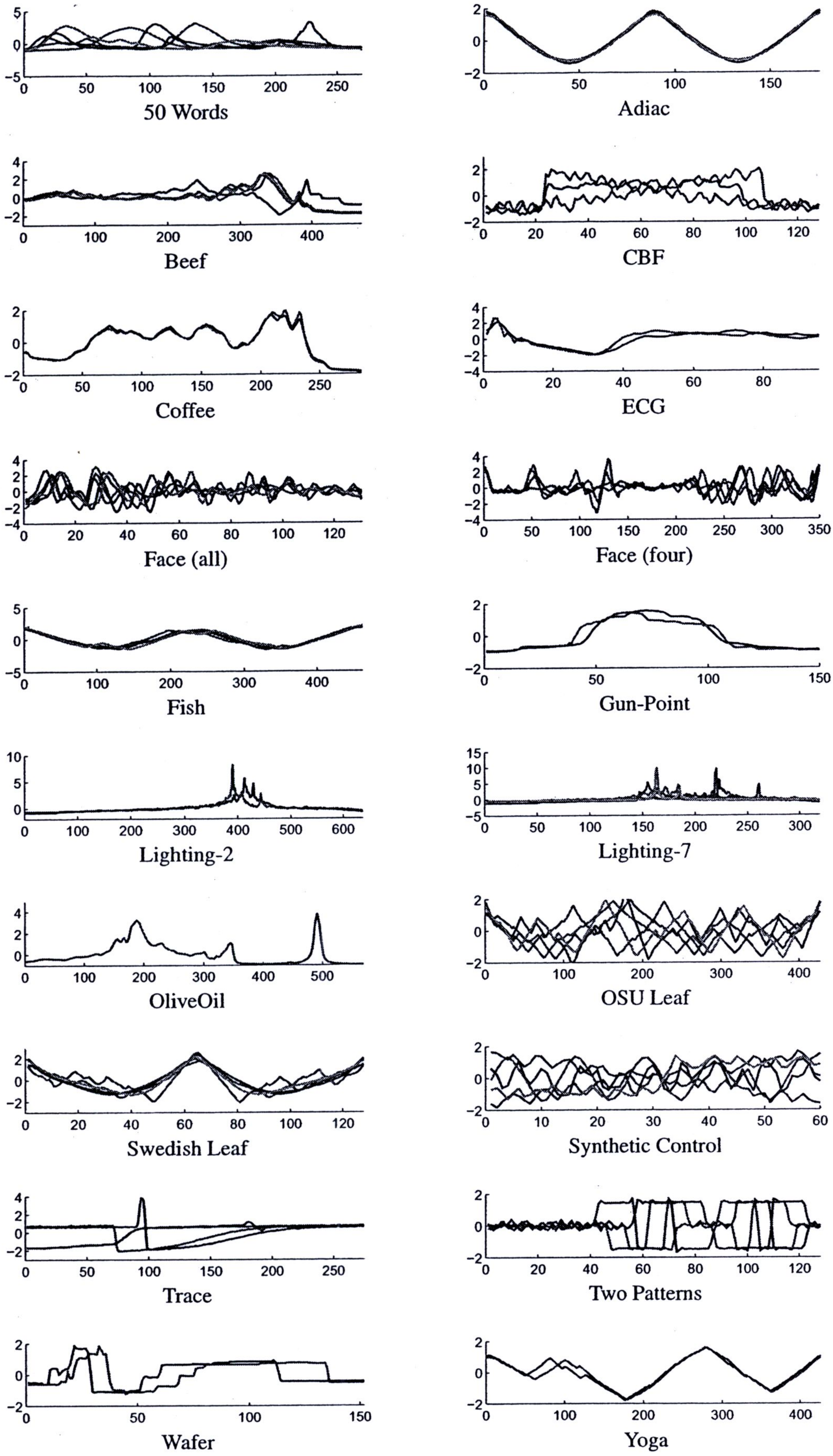


Figure C.2: Averaged results generated from ICDTW function of each dataset

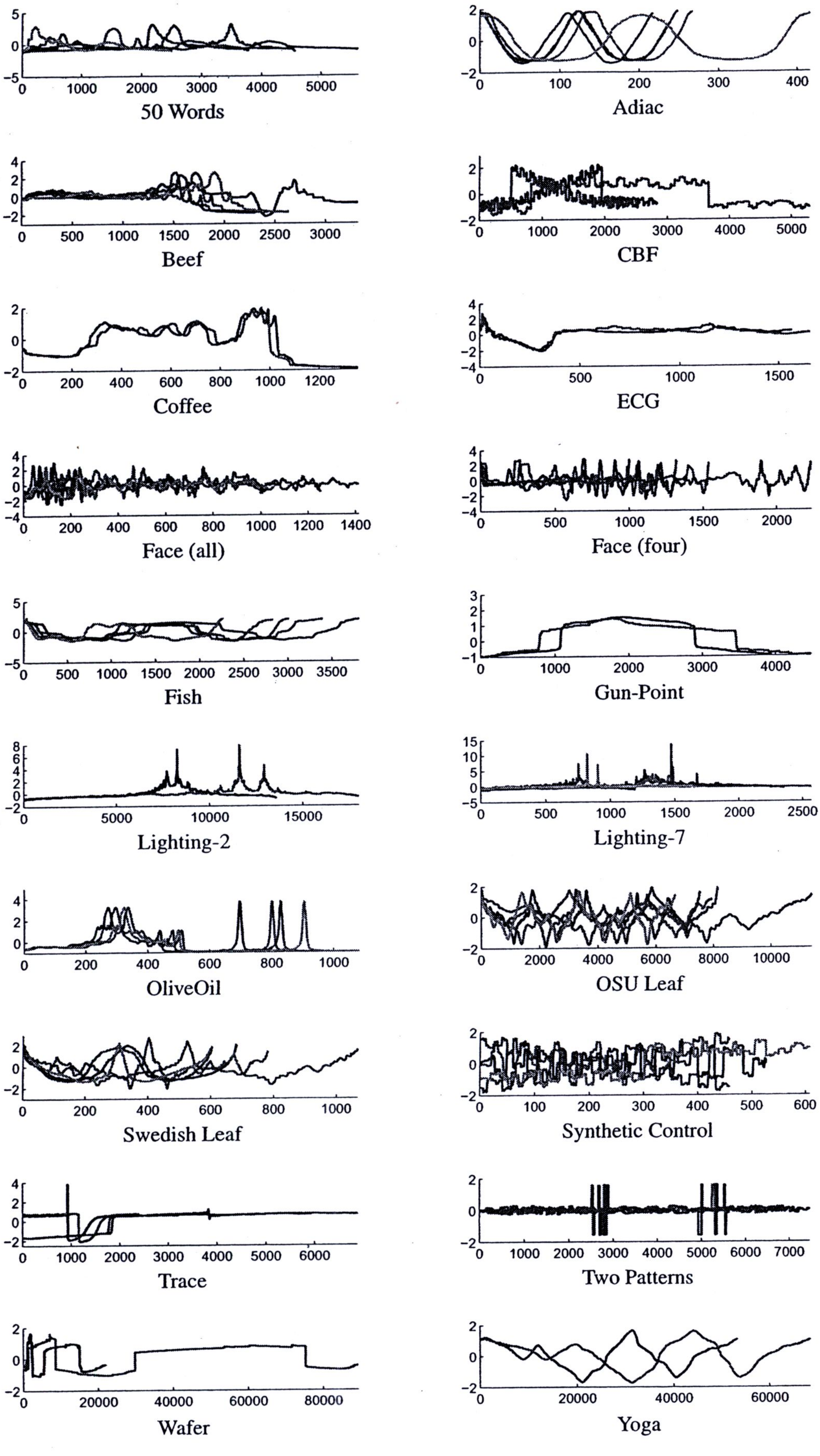


Figure C.3: Averaged results generated from NLAAF of each dataset.

APPENDIX D

COMPLETE EXPERIMENTAL RESULTS OF THE EXPERIMENT IN CHAPTER IV

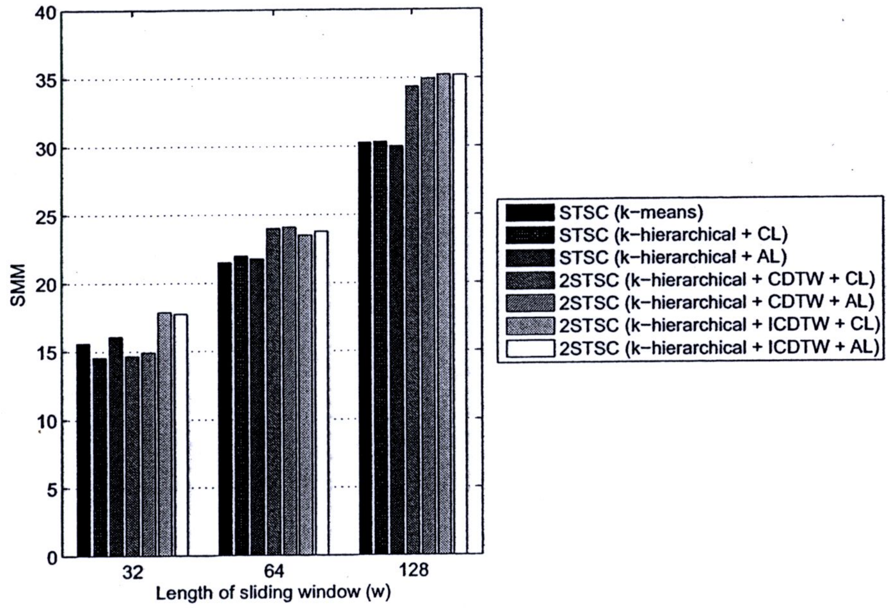


Figure D.1: SMMs of AEM2 when the number of clusters (k) is 3 and the length of sliding window (w) is varied.

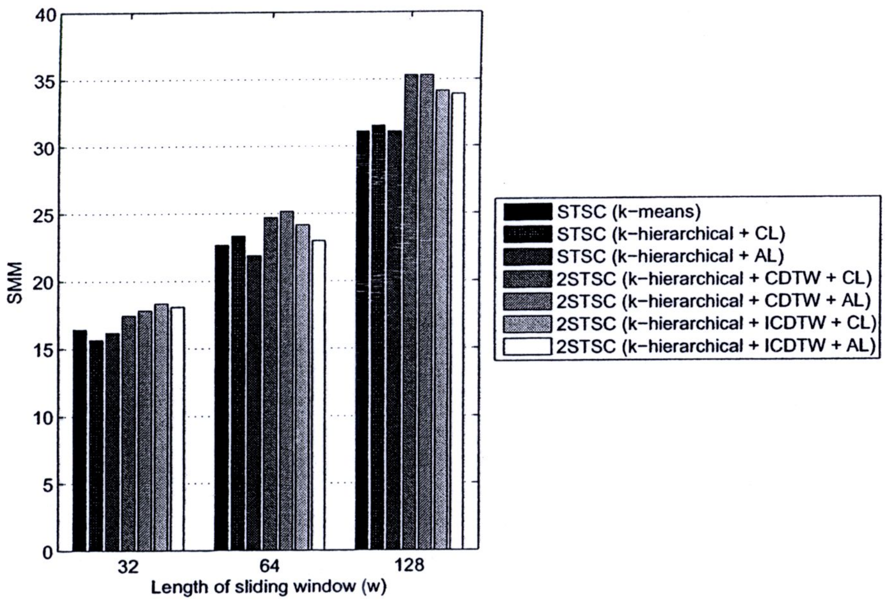


Figure D.2: SMMs of TOR96 when the number of clusters (k) is 3 and the length of sliding window (w) is varied.

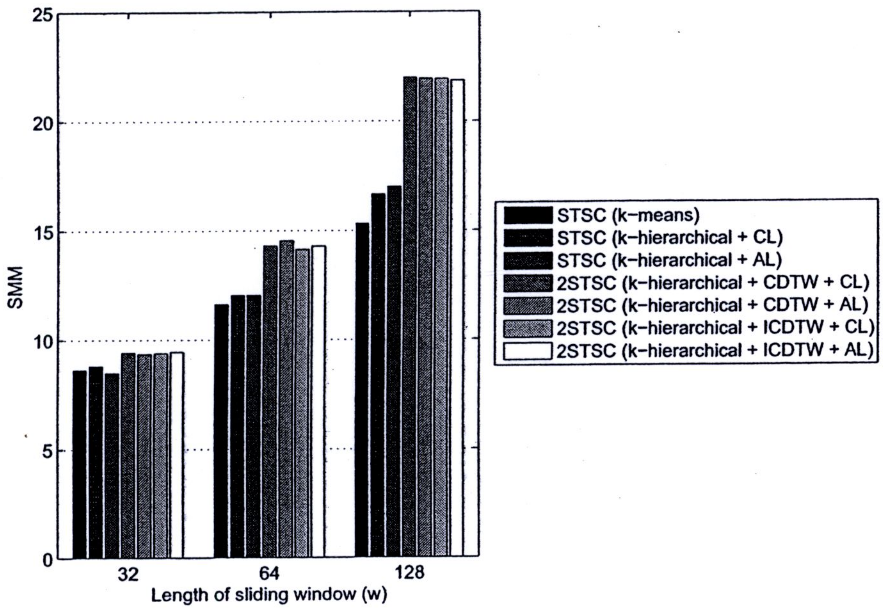


Figure D.3: SMMs of Buoy1 when the number of clusters (k) is 3 and the length of sliding window (w) is varied.

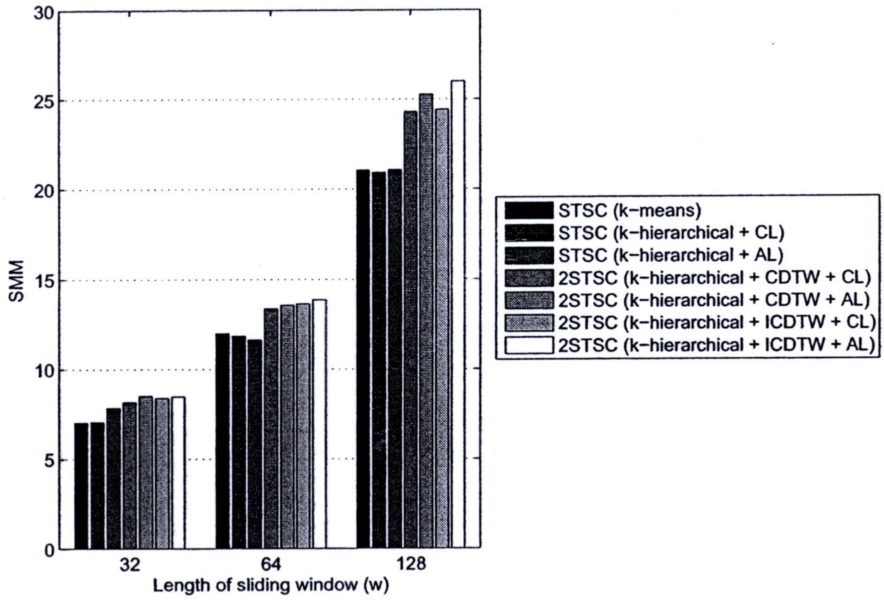


Figure D.4: SMMs of CBF when the number of clusters (k) is 3 and the length of sliding window (w) is varied.

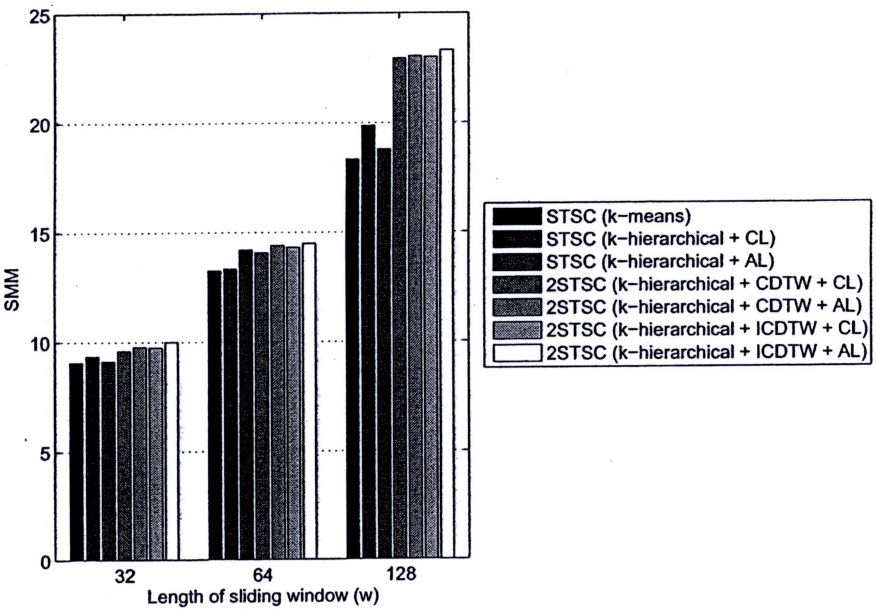


Figure D.5: SMMs of ERP when the number of clusters (k) is 3 and the length of sliding window (w) is varied.

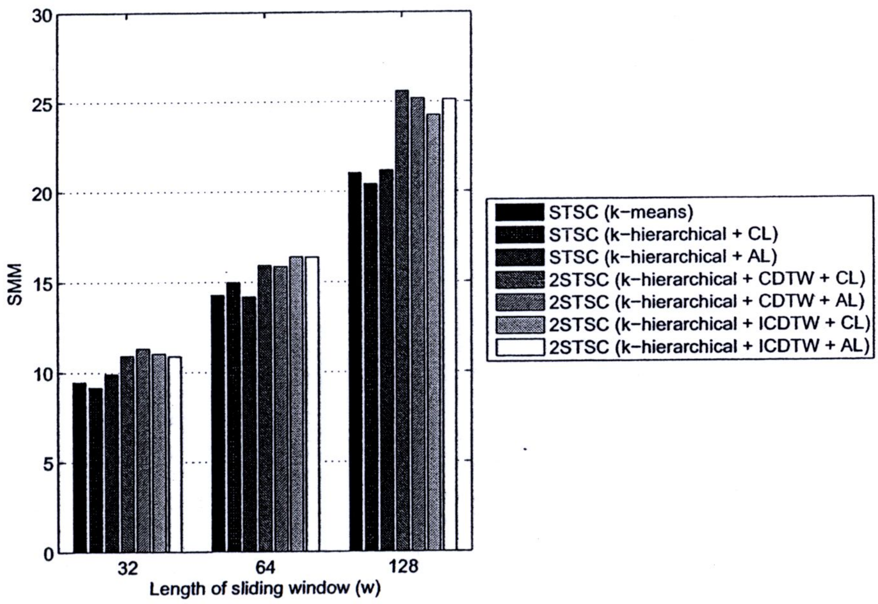


Figure D.6: SMMs of Field4 when the number of clusters (k) is 3 and the length of sliding window (w) is varied.

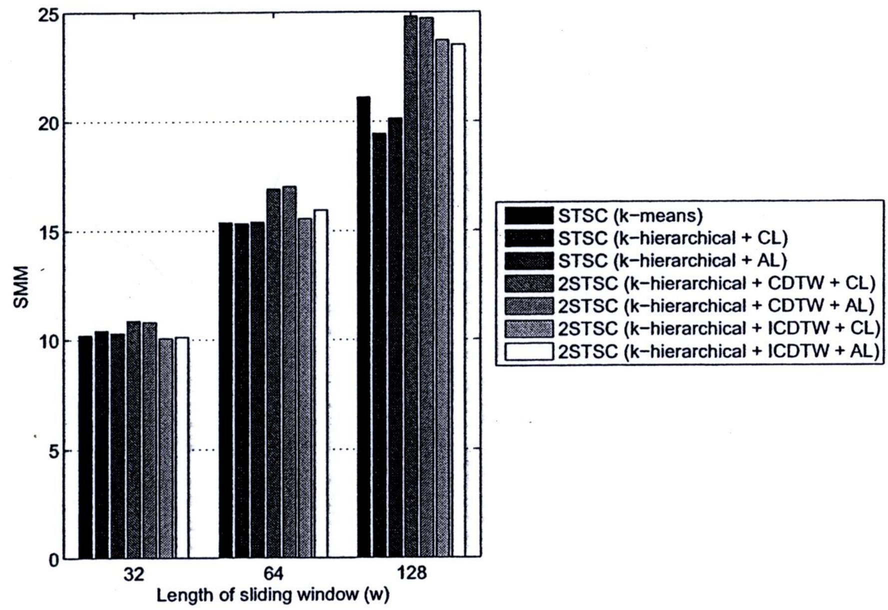


Figure D.7: SMMs of Fortune5004 when the number of clusters (k) is 3 and the length of sliding window (w) is varied.

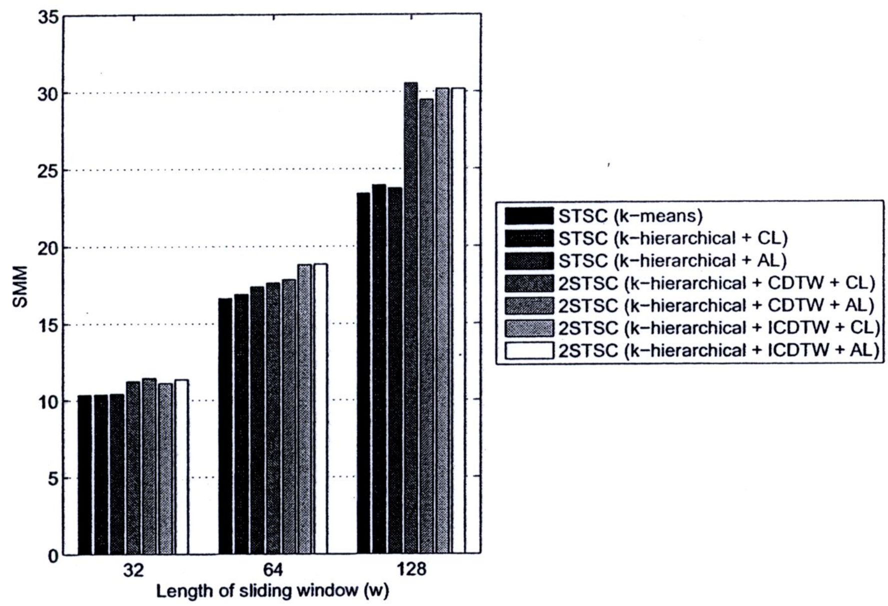


Figure D.8: SMMs of MITDBX108 when the number of clusters (k) is 3 and the length of sliding window (w) is varied.

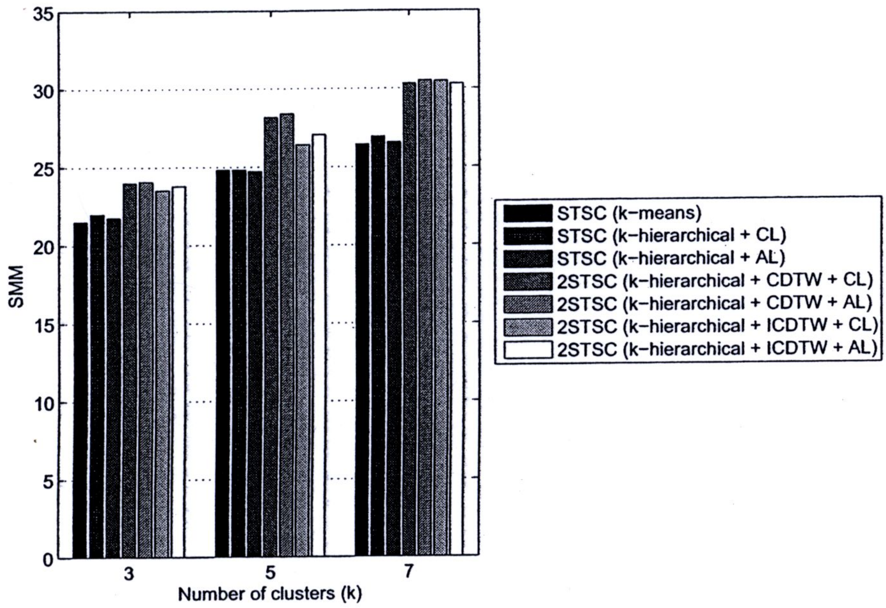


Figure D.9: SMMs of AEM2 when the length of sliding window (w) is 64 and the number of clusters (k) is varied.

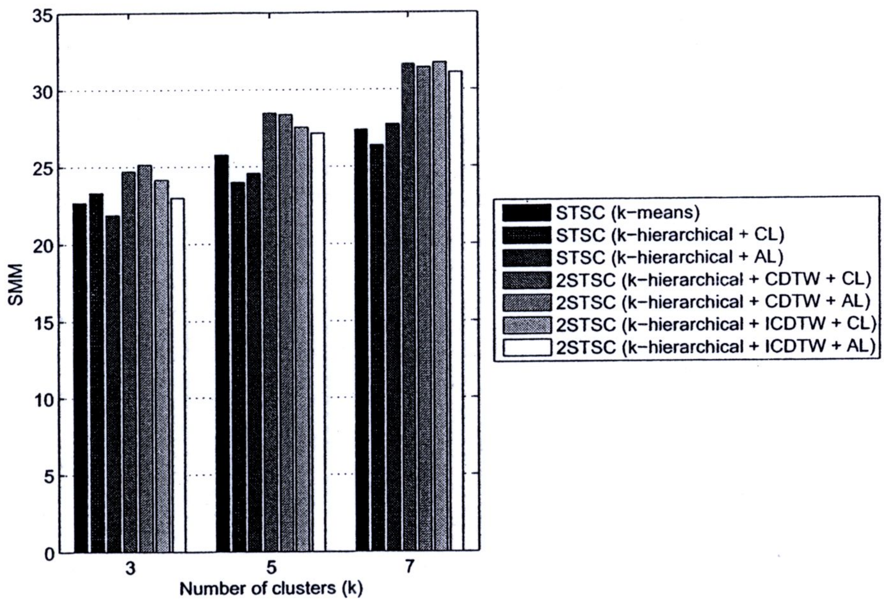


Figure D.10: SMMs of TOR96 when the length of sliding window (w) is 64 and the number of clusters (k) is varied.

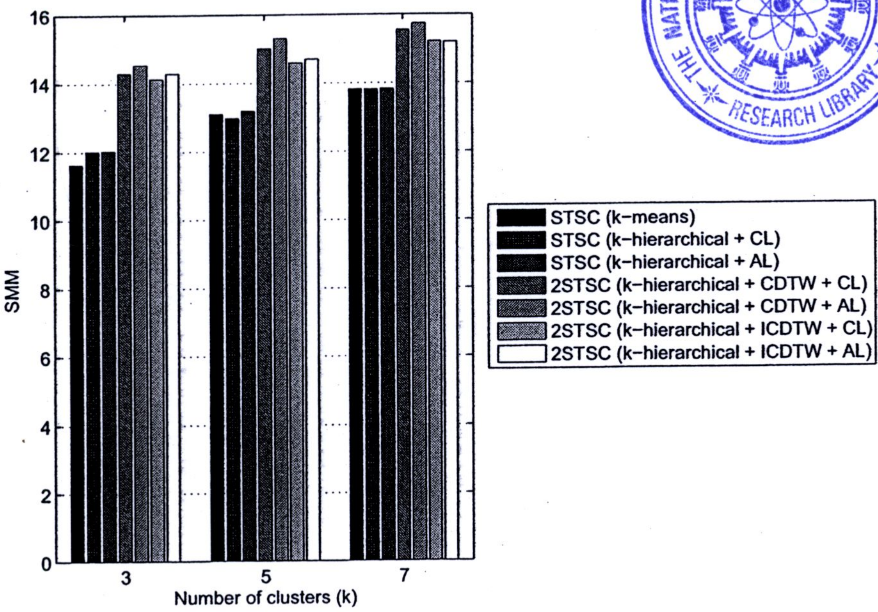


Figure D.11: SMMs of Buoy1 when the length of sliding window (w) is 64 and the number of clusters (k) is varied.

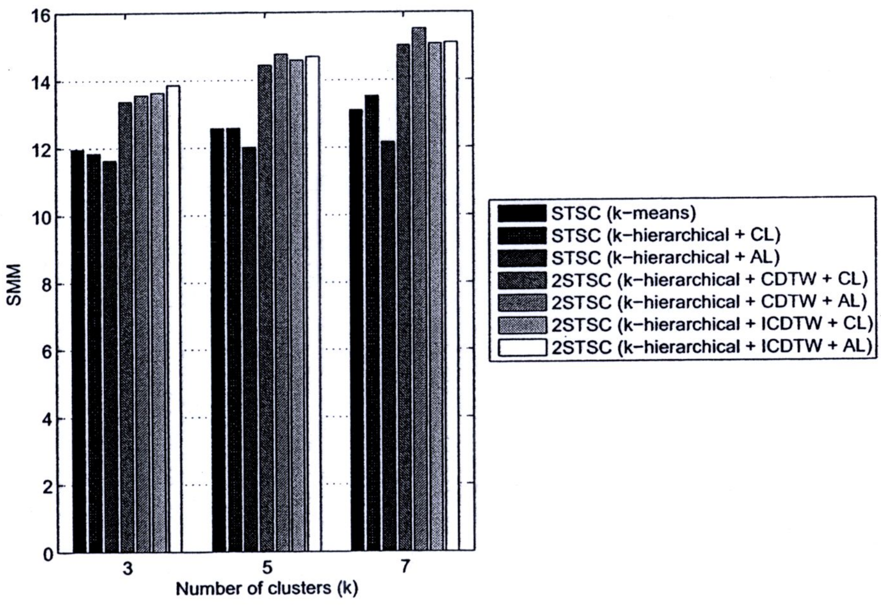


Figure D.12: SMMs of CBF when the length of sliding window (w) is 64 and the number of clusters (k) is varied.

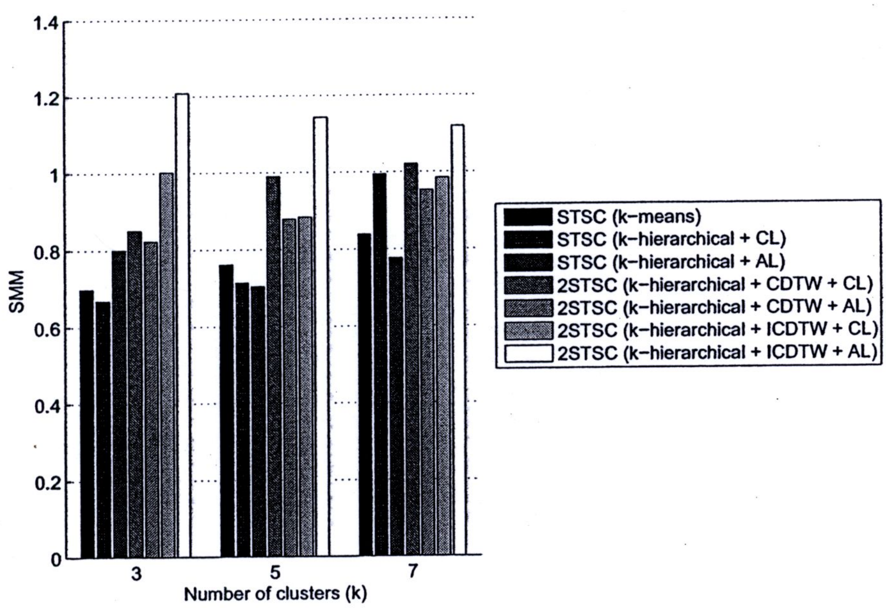


Figure D.13: SMMs of ERP when the length of sliding window (w) is 64 and the number of clusters (k) is varied.

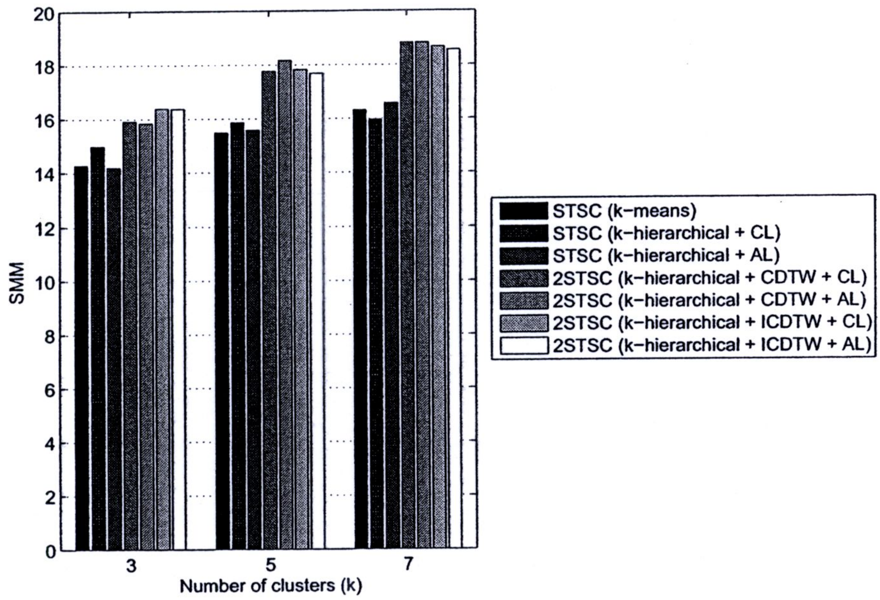


Figure D.14: SMMs of Field4 when the length of sliding window (w) is 64 and the number of clusters (k) is varied.

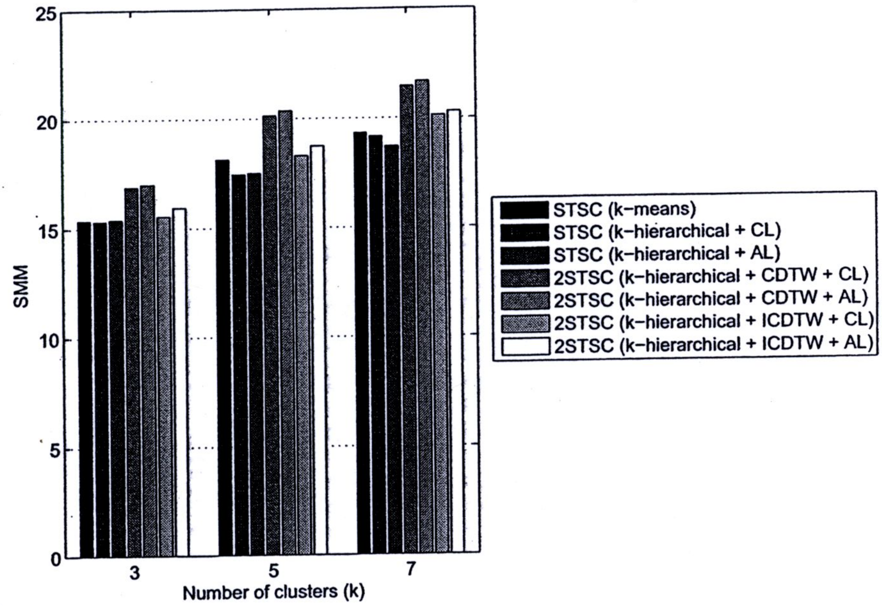


Figure D.15: SMMs of Fortune5004 when the length of sliding window (w) is 64 and the number of clusters (k) is varied.

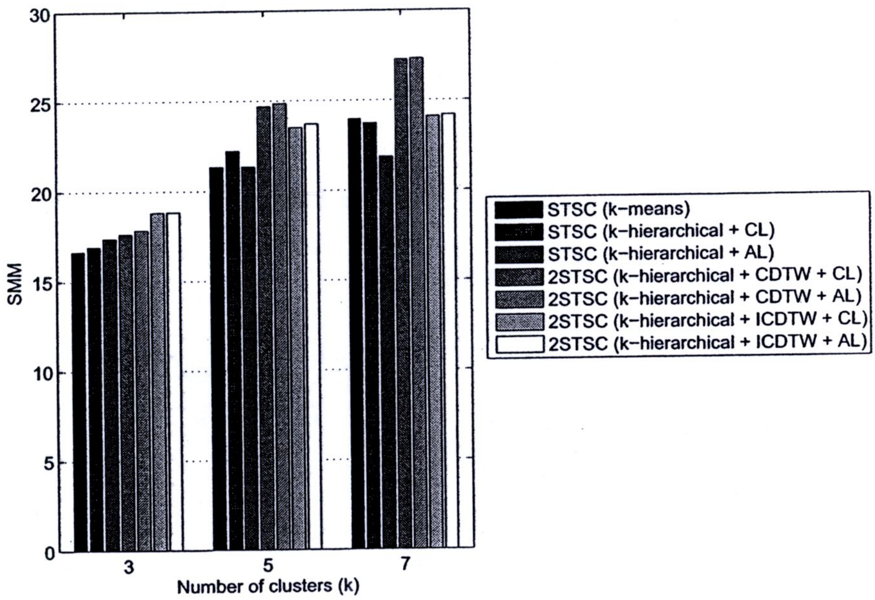


Figure D.16: SMMs of MITDBX108 when the length of sliding window (w) is 64 and the number of clusters (k) is varied.

AEM2

TOR96

Buoy1

CBF

ERP

Field4

Fortune5004

MITDBX108

Figure D.17: Cluster representatives generated from 2STSC with complete linkage (left) and average linkage (right) using CDTW function when $k = 3$ and $w = 32$.

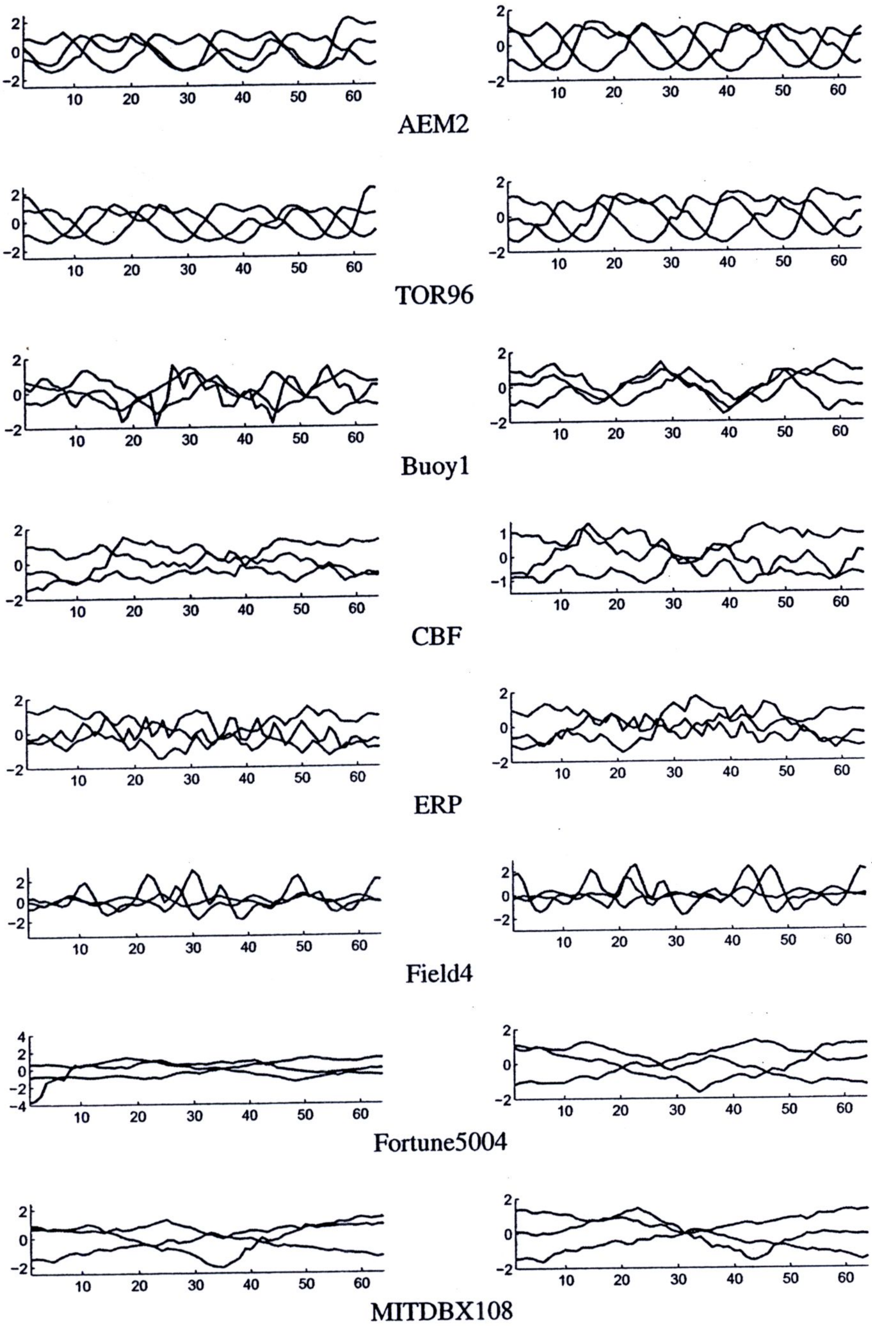


Figure D.18: Cluster representatives generated from 2STSC with complete linkage (left) and average linkage (right) using CDTW function when $k = 3$ and $w = 64$.

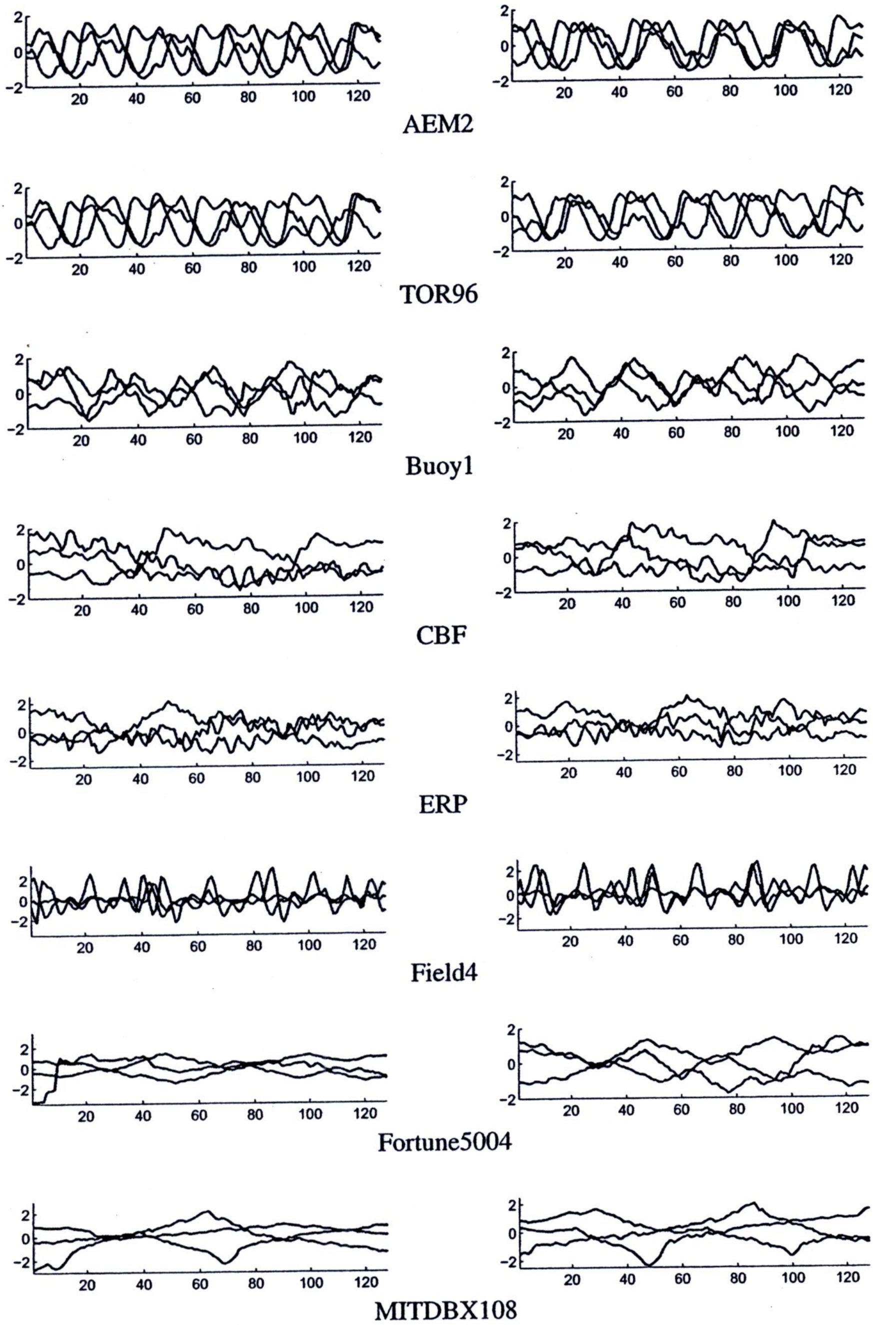


Figure D.19: Cluster representatives generated from 2STSC with complete linkage (left) and average linkage (right) using CDTW function when $k = 3$ and $w = 128$.

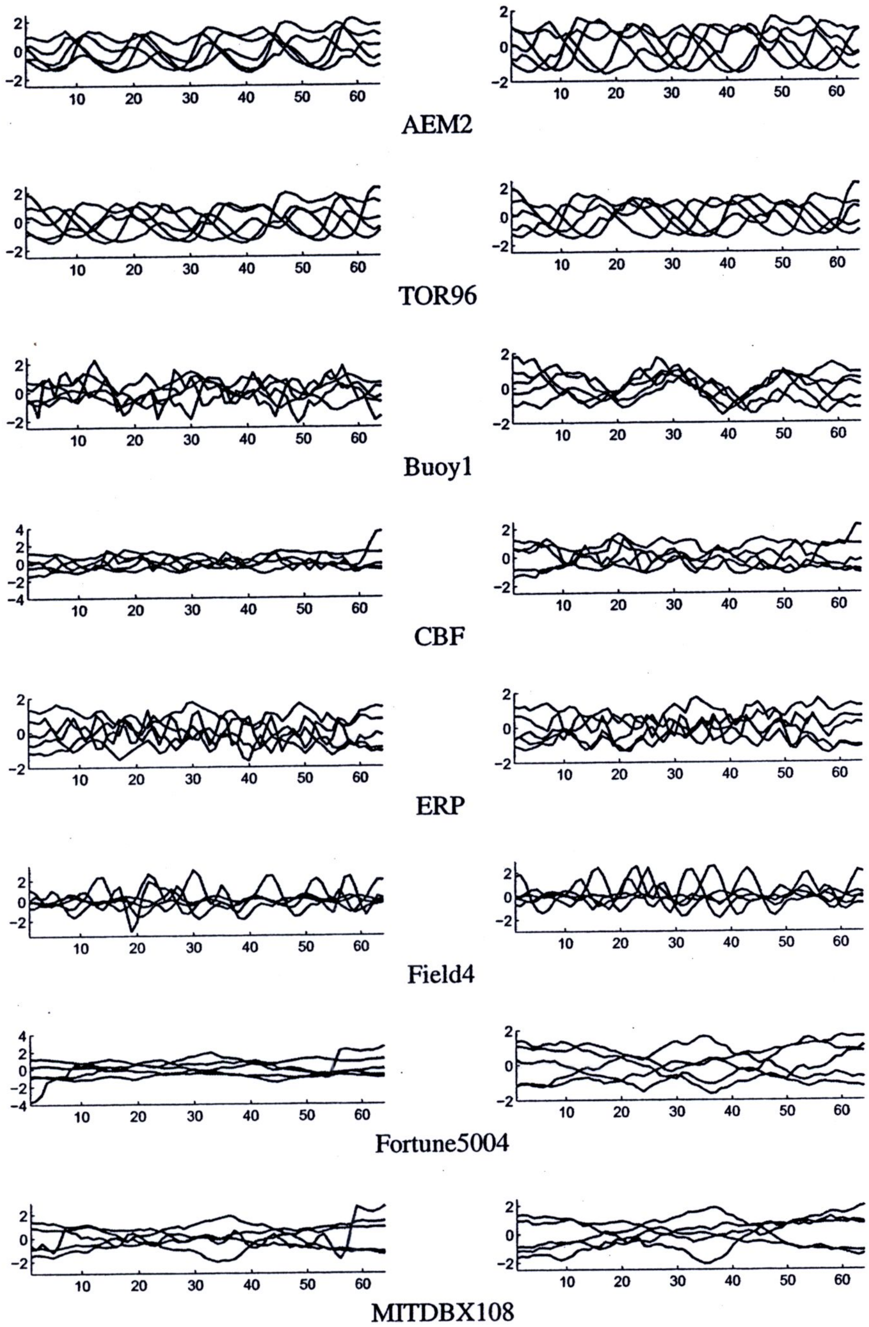


Figure D.20: Cluster representatives generated from 2STSC with complete linkage (left) and average linkage (right) using ICDTW function when $k = 5$ and $w = 64$.

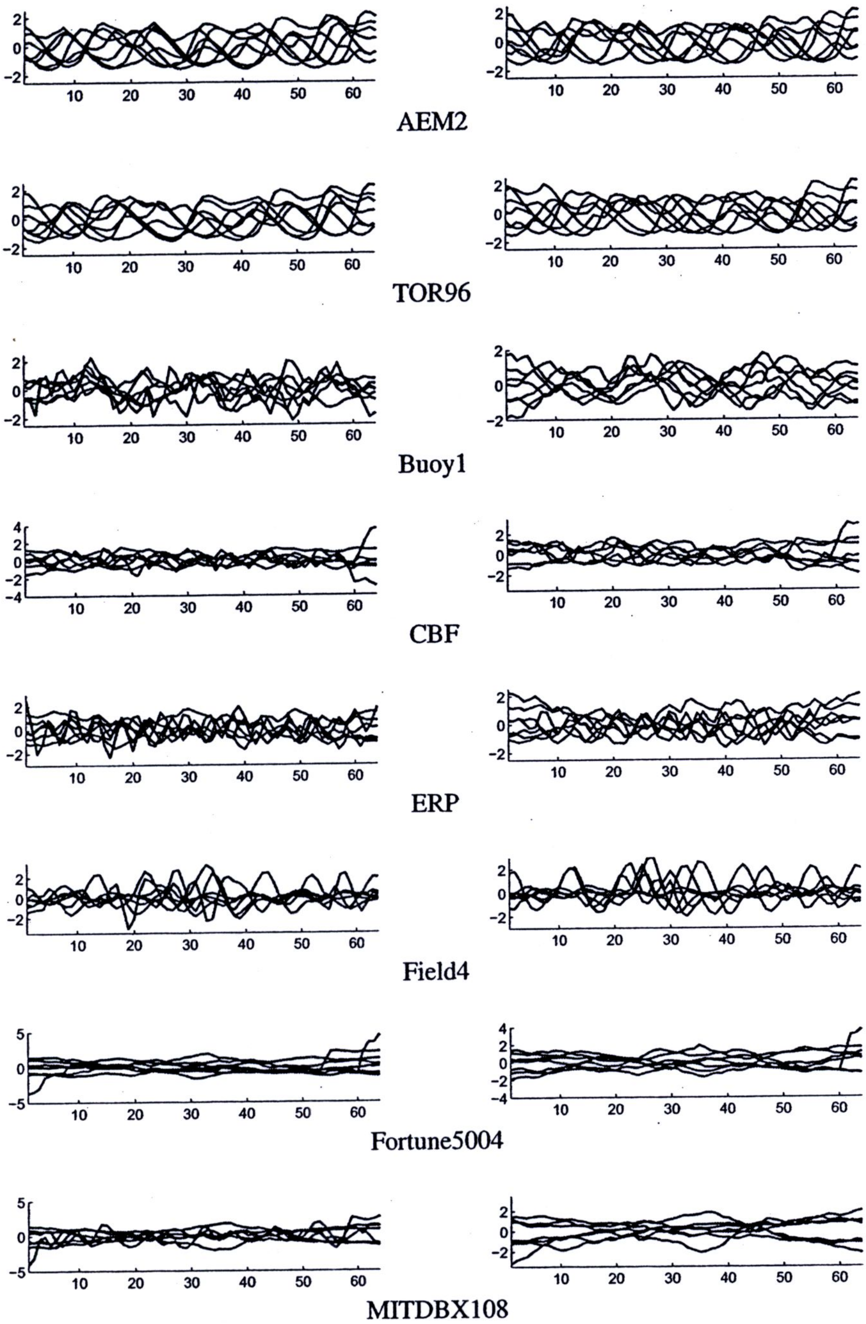


Figure D.21: Cluster representatives generated from 2STSC with complete linkage (left) and average linkage (right) using ICDTW function when $k = 7$ and $w = 64$.

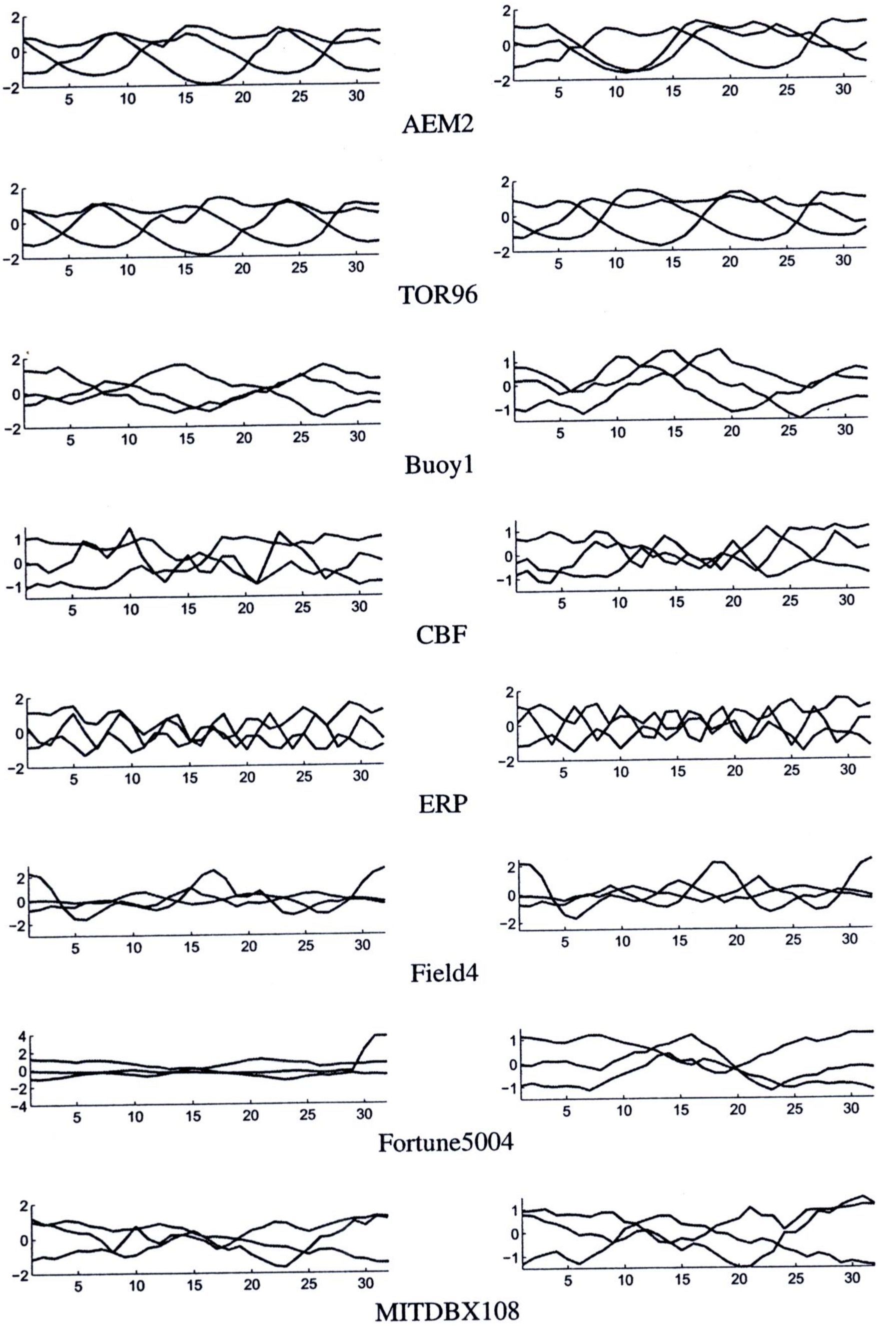


Figure D.22: Cluster representatives generated from 2STSC with complete linkage (left) and average linkage (right) using ICDTW function when $k = 3$ and $w = 32$.

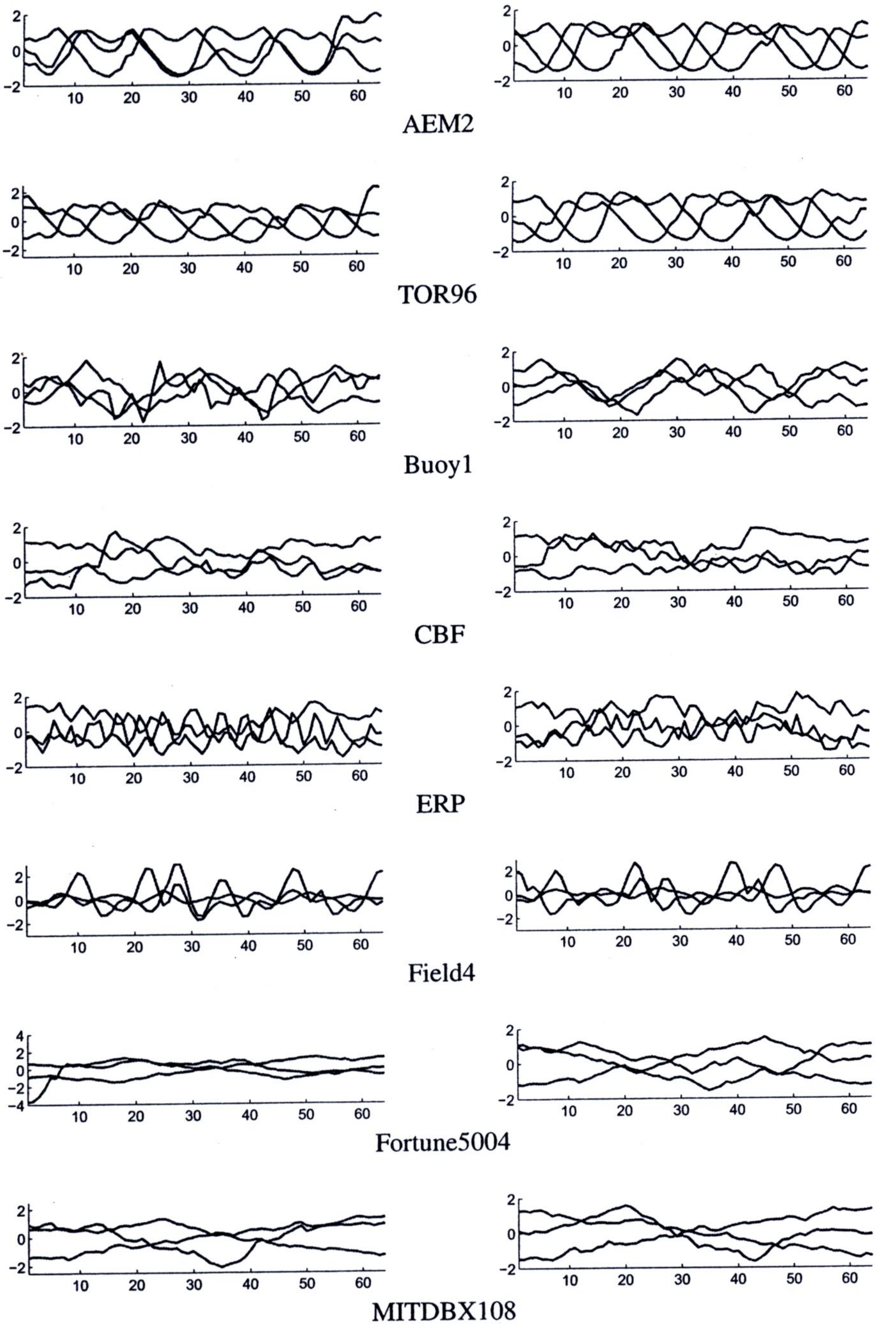


Figure D.23: Cluster representatives generated from 2STSC with complete linkage (left) and average linkage (right) using ICDTW function when $k = 3$ and $w = 64$.

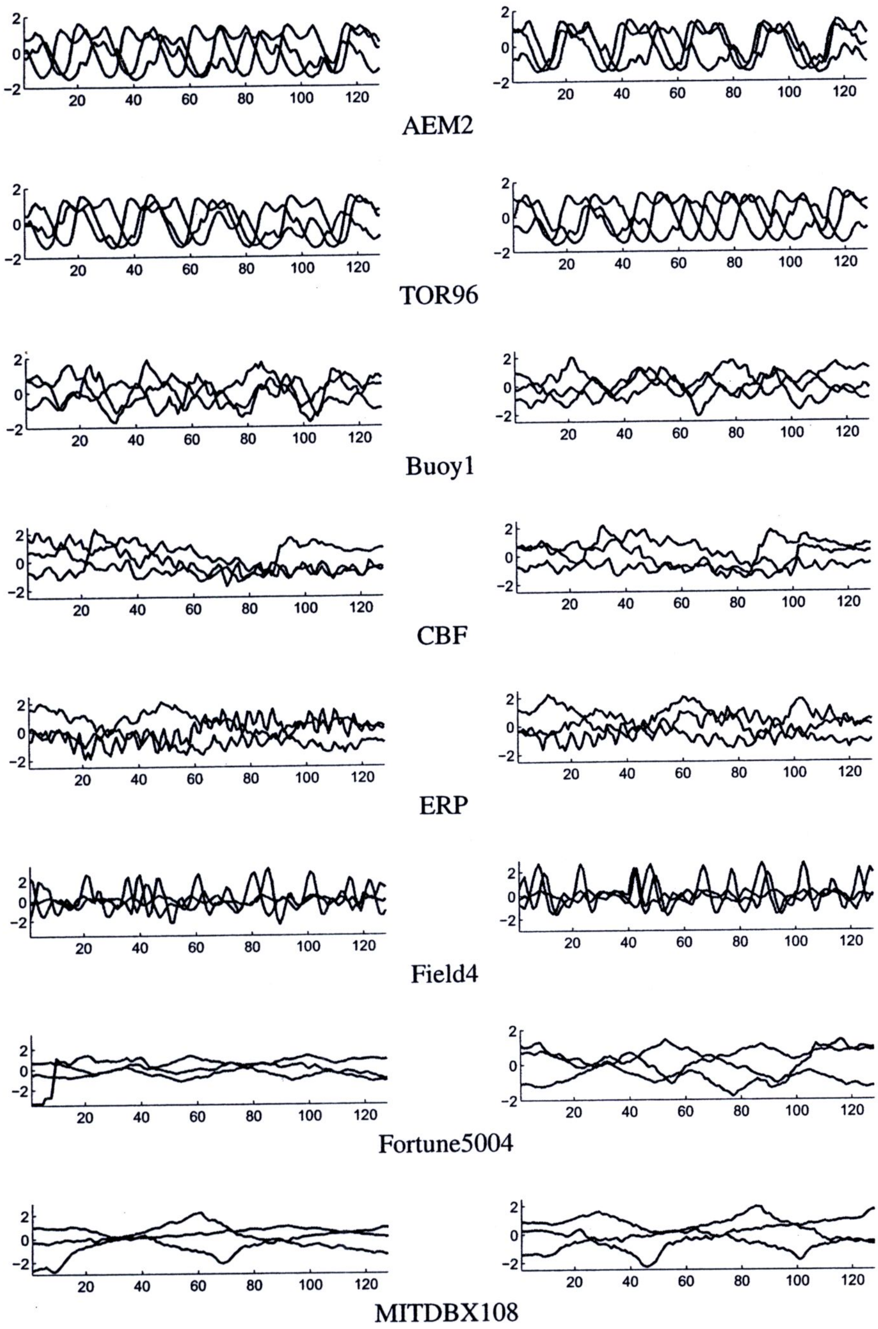


Figure D.24: Cluster representatives generated from 2STSC with complete linkage (left) and average linkage (right) using ICDTW function when $k = 3$ and $w = 128$.

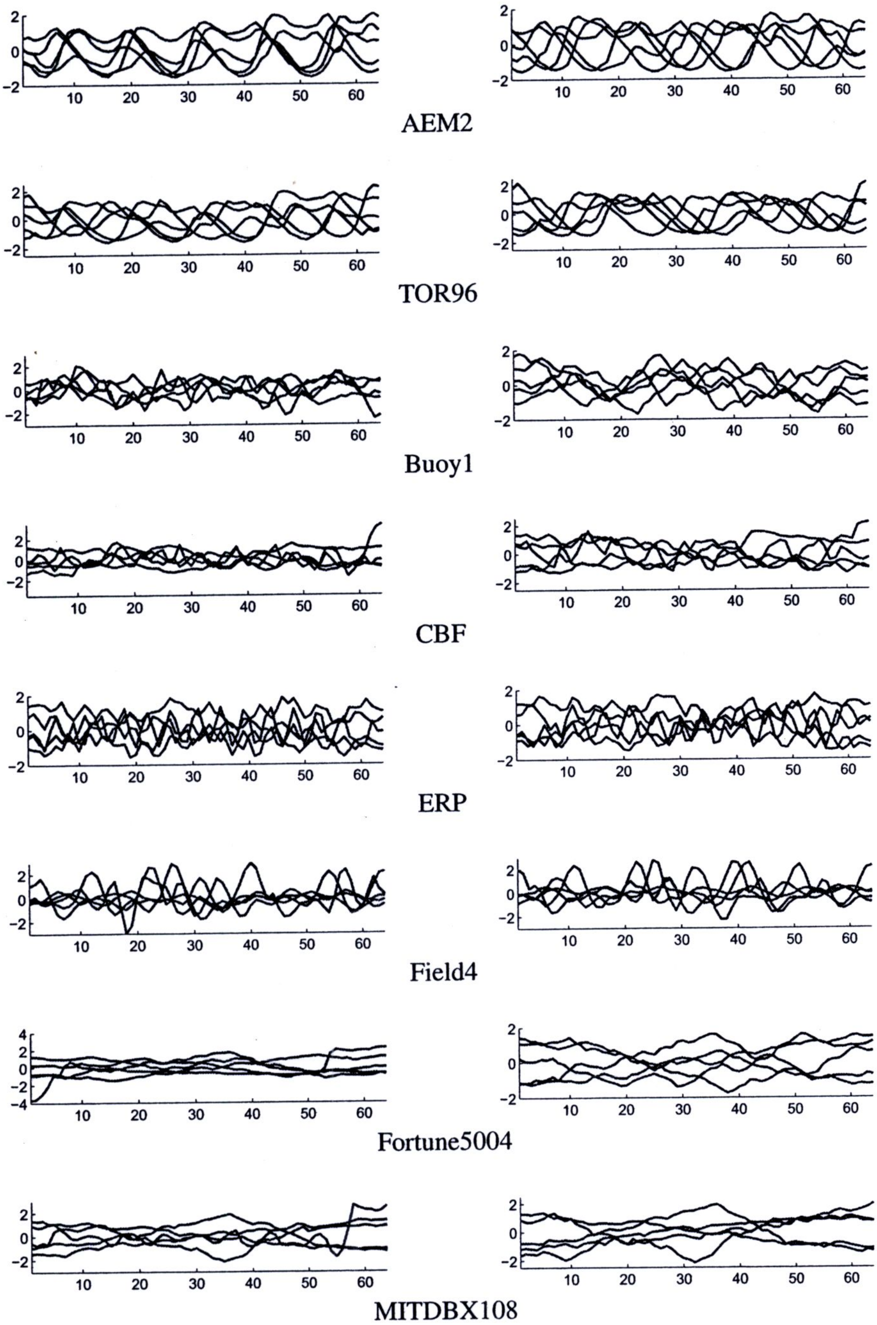


Figure D.25: Cluster representatives generated from 2STSC with complete linkage (left) and average linkage (right) using ICDTW function when $k = 5$ and $w = 64$.

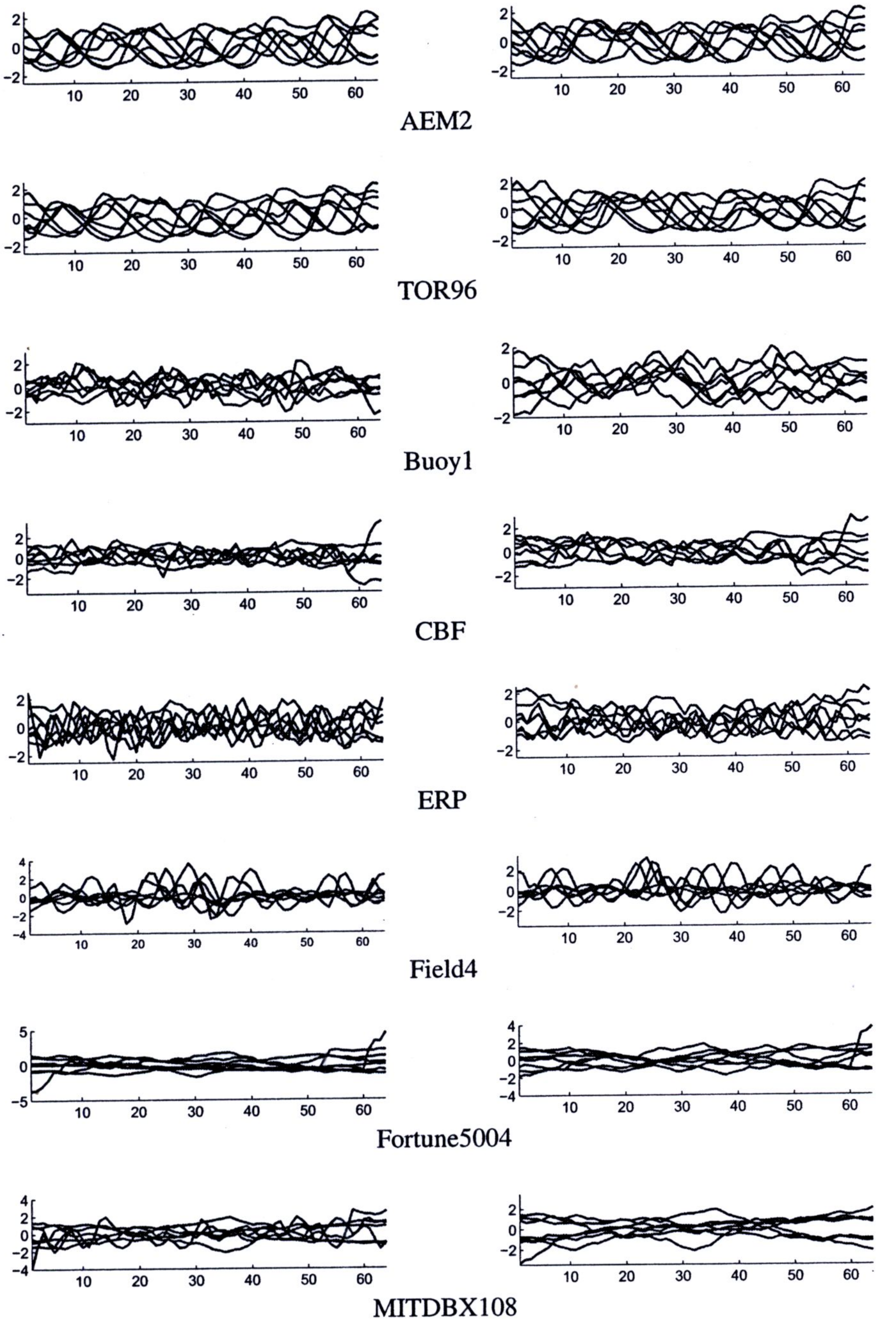


Figure D.26: Cluster representatives generated from 2STSC with complete linkage (left) and average linkage (right) using ICDTW function when $k = 7$ and $w = 64$.

APPENDIX E

COMPLETE EXPERIMENTAL RESULTS OF THE FIRST EXPERIMENT IN CHAPTER V

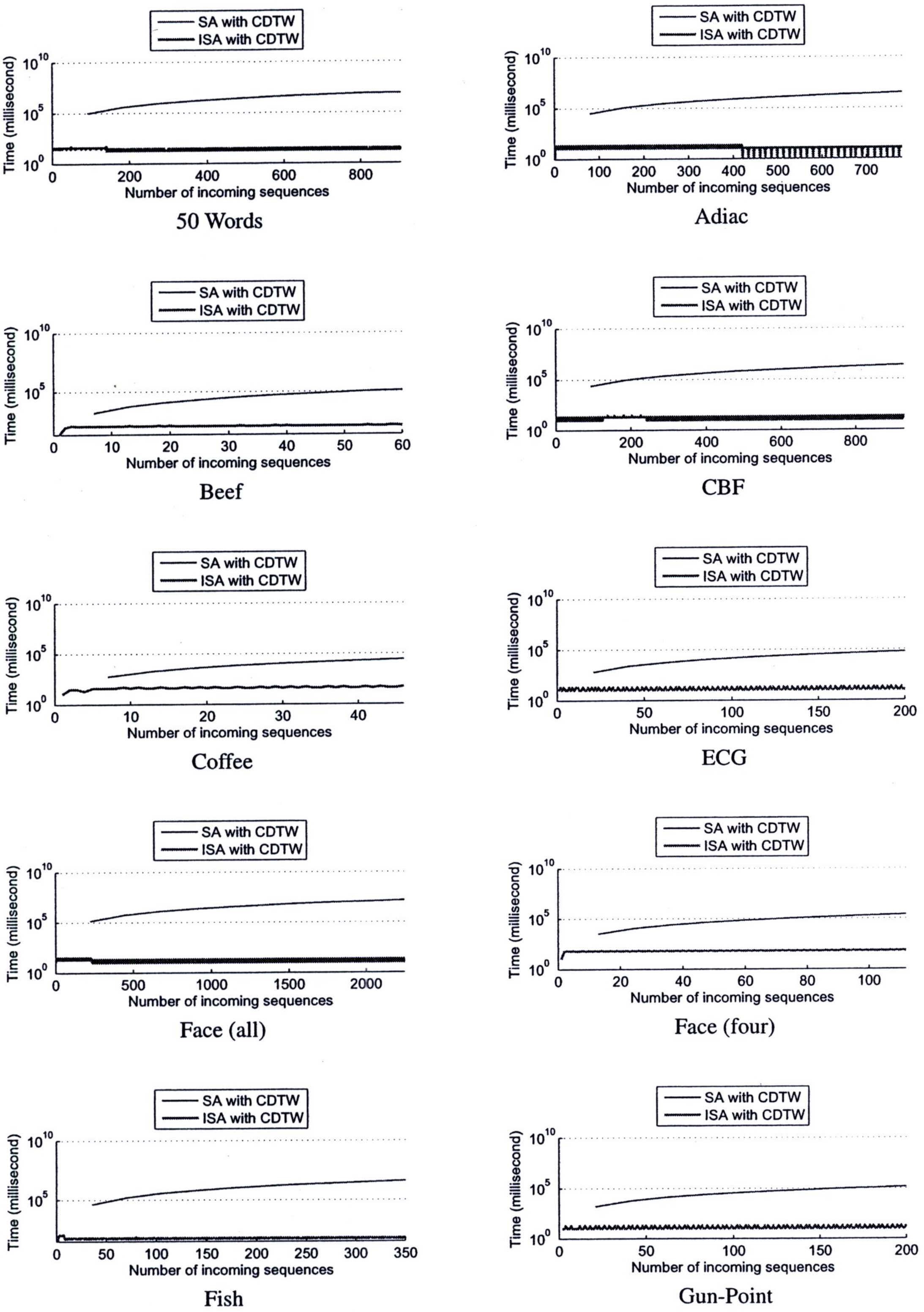


Figure E.1: Computational time of Incremental Shape-based Averaging and Shape-based Averaging with CDTW function when a new incoming sequence arrives.

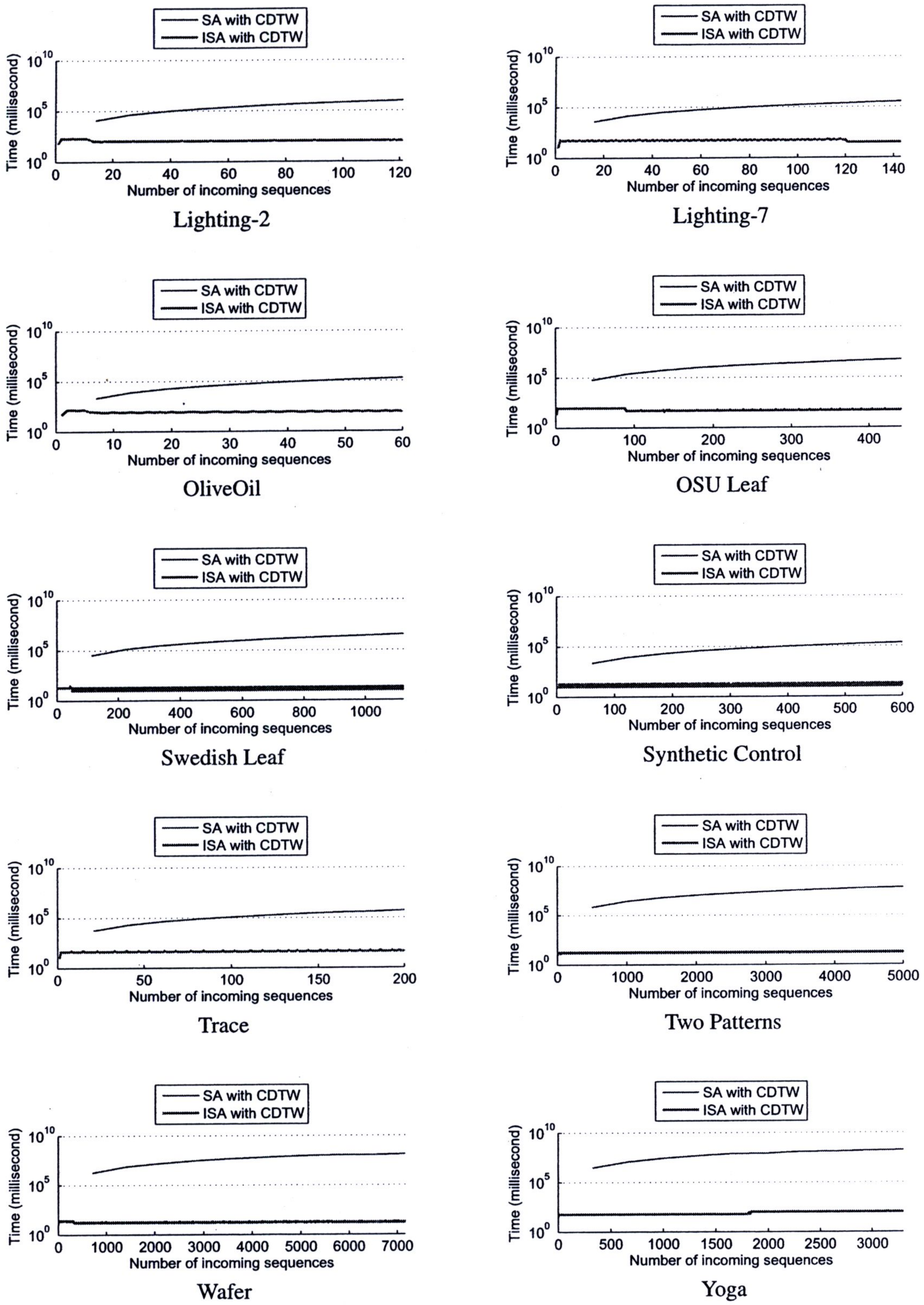


Figure E.2: Computational time of Incremental Shape-based Averaging and Shape-based Averaging with CDTW function when a new incoming sequence arrives. (cont.)

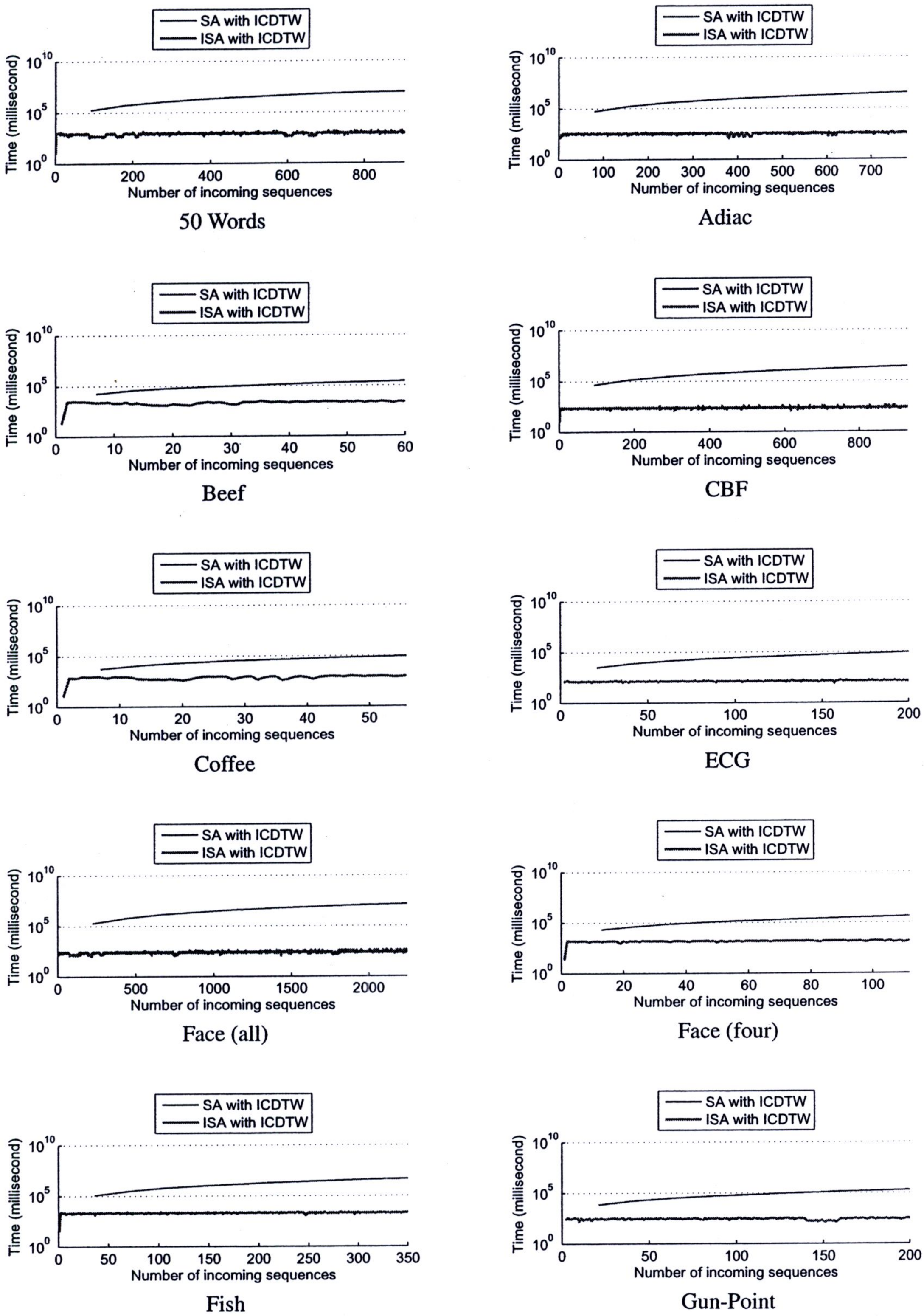
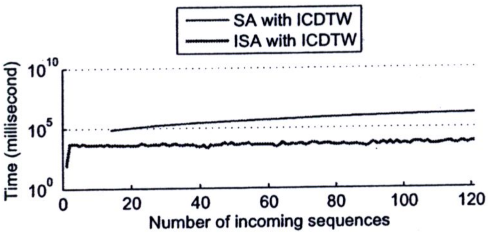
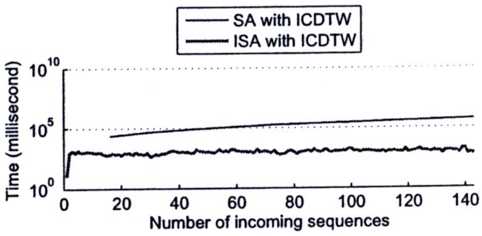


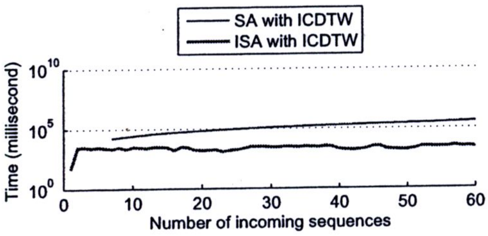
Figure E.3: Computational time of Incremental Shape-based Averaging and Shape-based Averaging with ICDTW function when a new incoming sequence arrives.



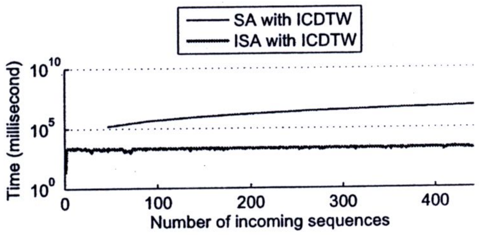
Lighting-2



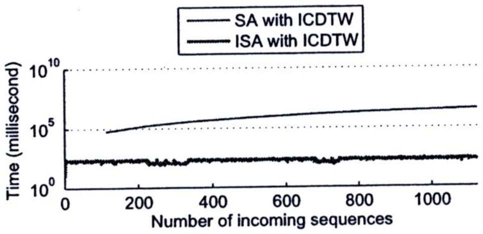
Lighting-7



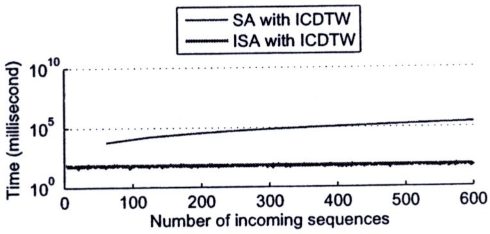
OliveOil



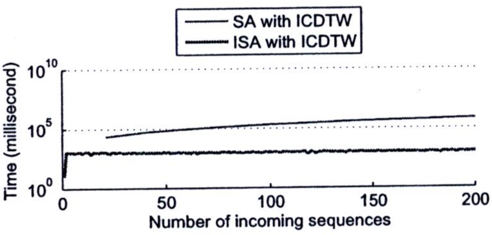
OSU Leaf



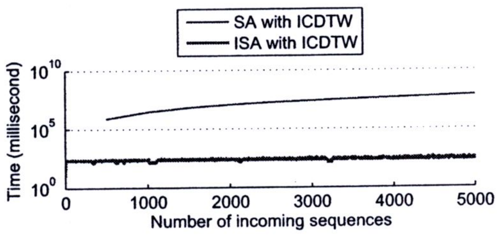
Swedish Leaf



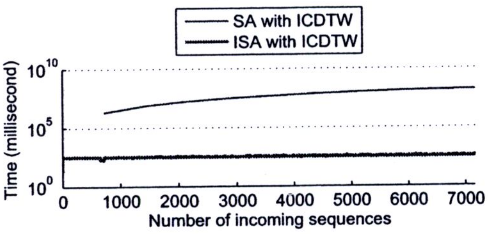
Synthetic Control



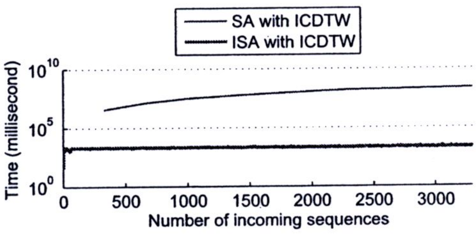
Trace



Two Patterns



Wafer



Yoga

Figure E.4: Computational time ofthan Shape-based Averaging around Incremental Shape-based Averaging and Shape-based Averaging with ICDTW function when a new incoming sequence arrives.

APPENDIX F

COMPLETE EXPERIMENTAL RESULTS OF THE SECOND EXPERIMENT ON CHAPTER V

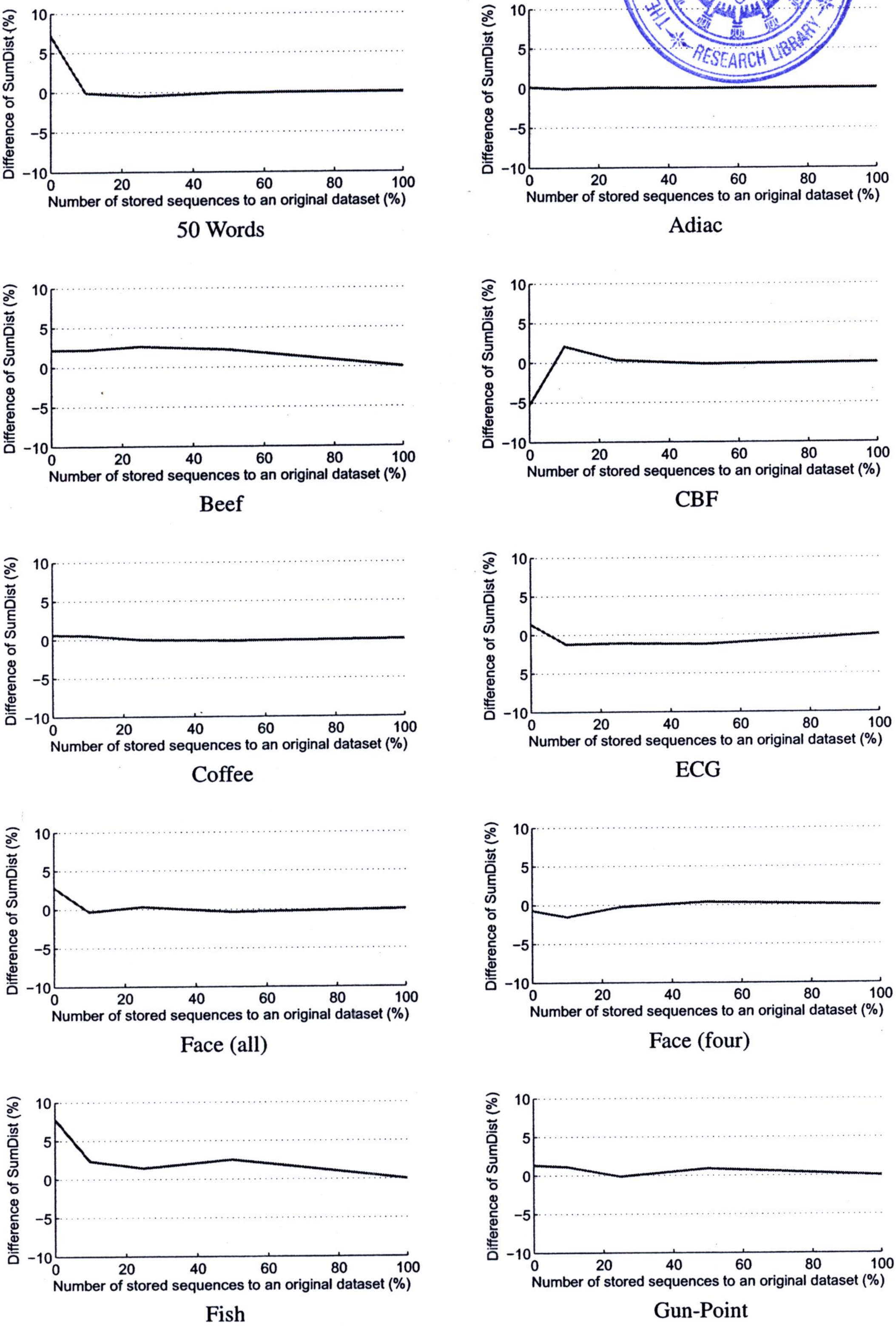


Figure F.1: Difference of SUMDIST of Incremental Shape-based Averaging with CDTW when the number of stored sequences to an original dataset is varied.

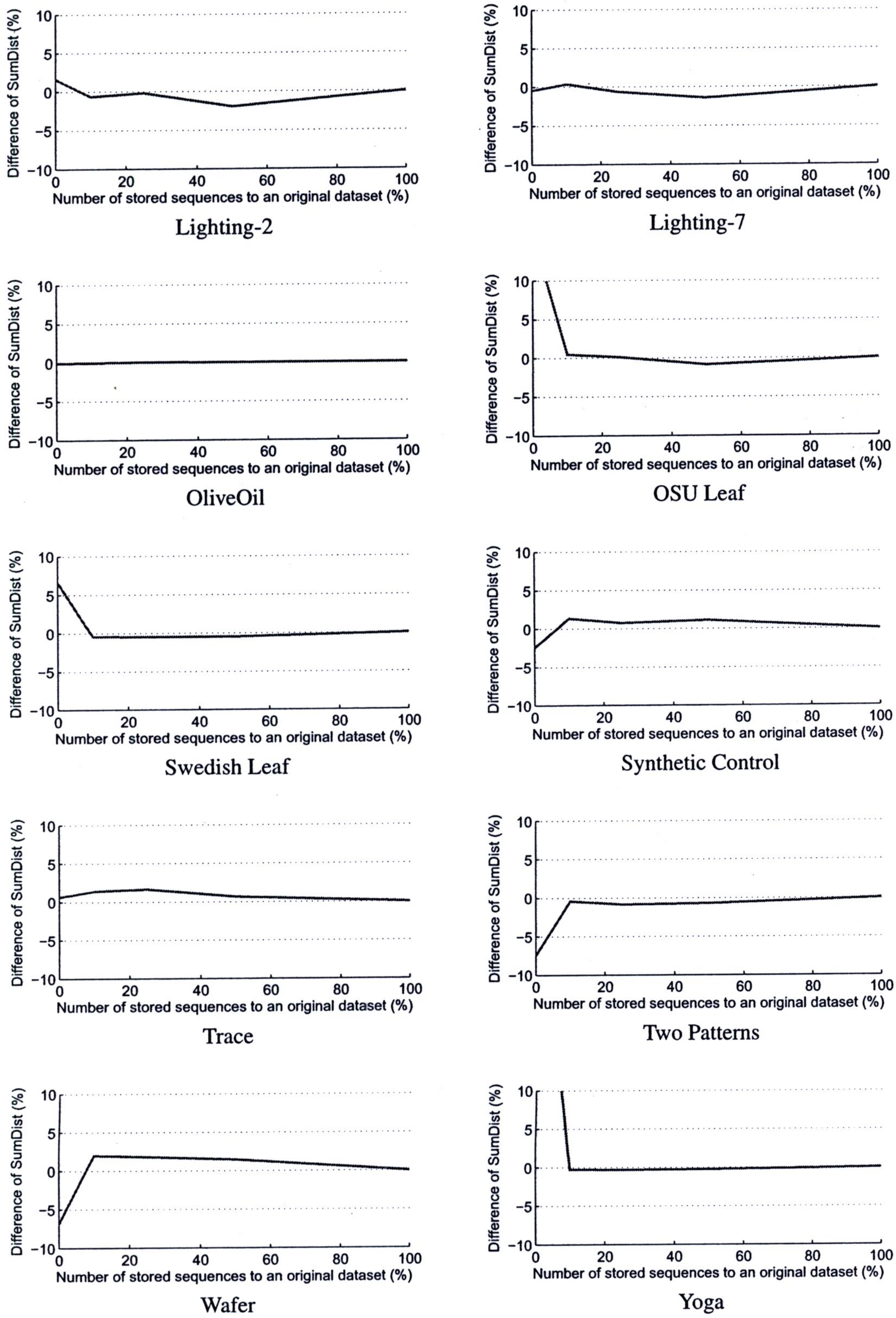


Figure F.2: Difference of SUMDIST of Incremental Shape-based Averaging with CDTW when the number of stored sequences to an original dataset is varied. (cont.)

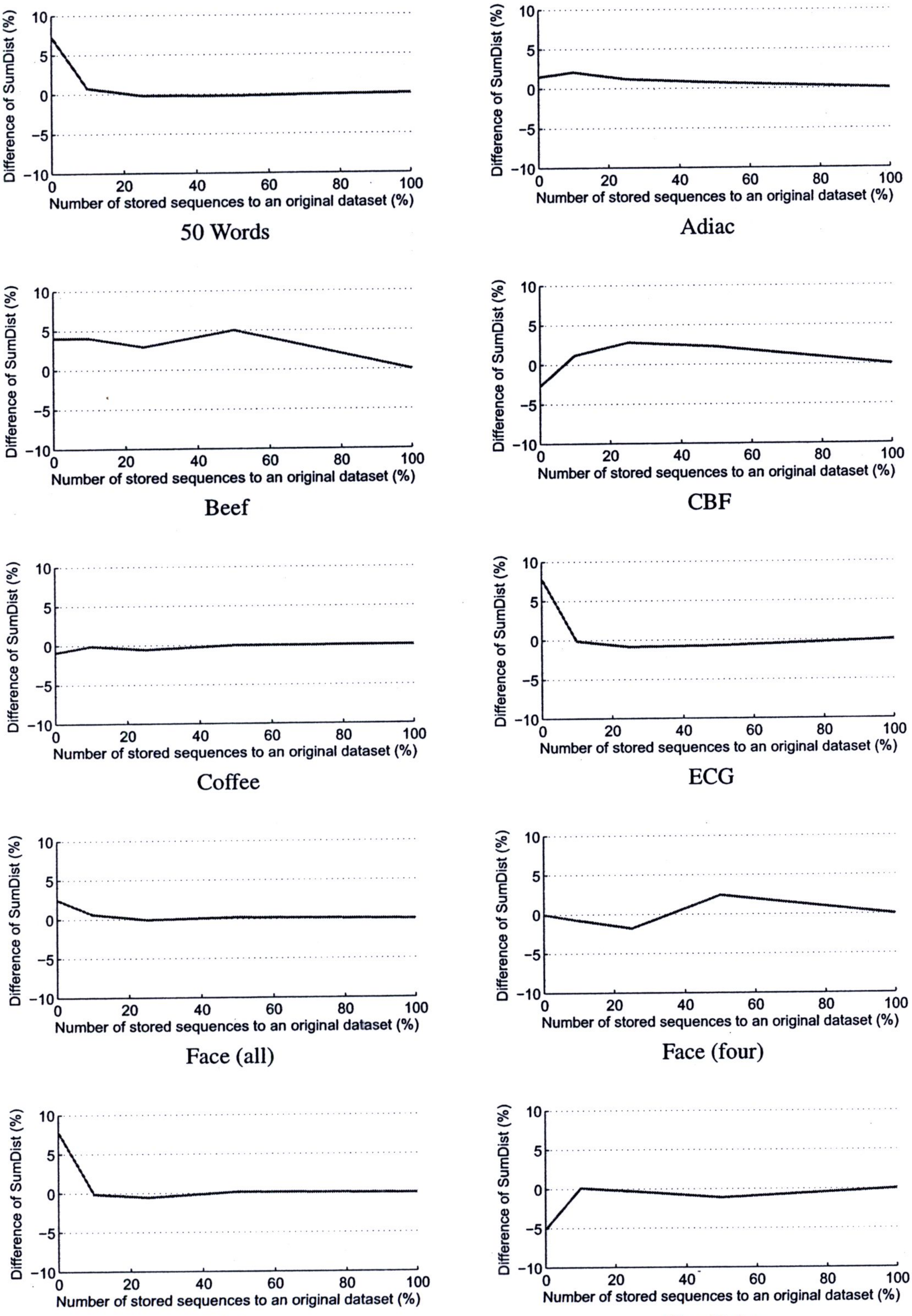
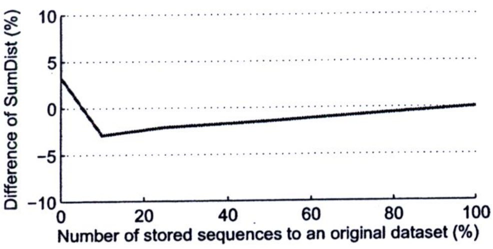
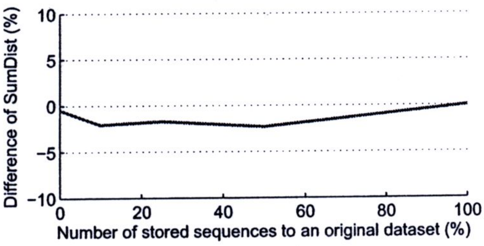


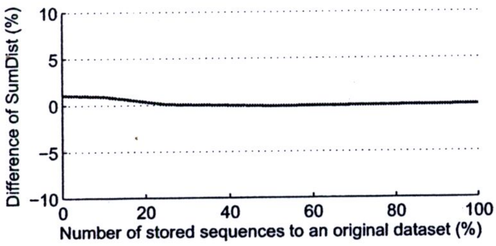
Figure F.3: Difference of SUMDIST of Incremental Shape-based Averaging with ICDTW when the number of stored sequences to an original dataset is varied.



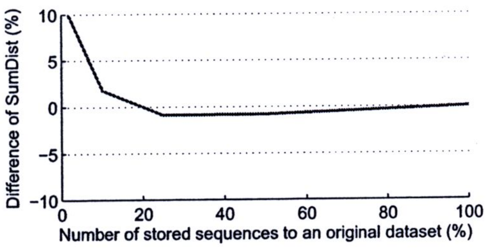
Lighting-2



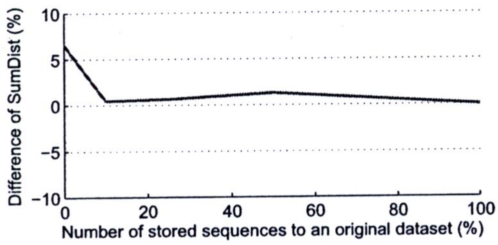
Lighting-7



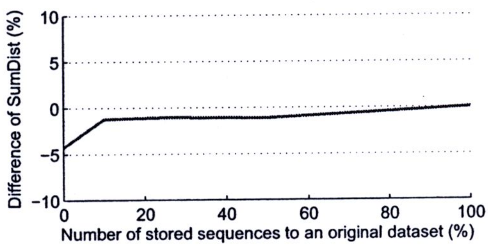
OliveOil



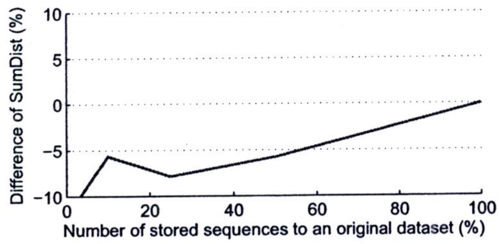
OSU Leaf



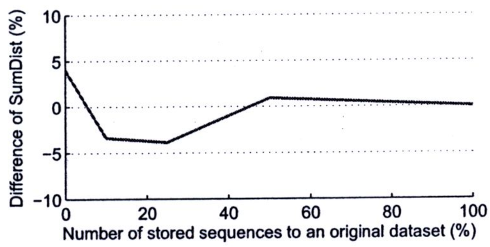
Swedish Leaf



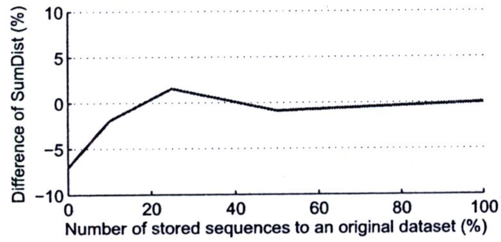
Synthetic Control



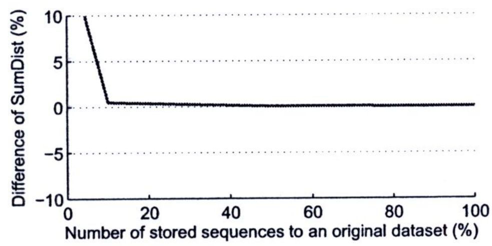
Trace



Two Patterns



Wafer



Yoga

Figure F.4: Difference of SUMDIST of Incremental Shape-based Averaging with ICDTW when the number of stored sequences to an original dataset is varied. (cont.)

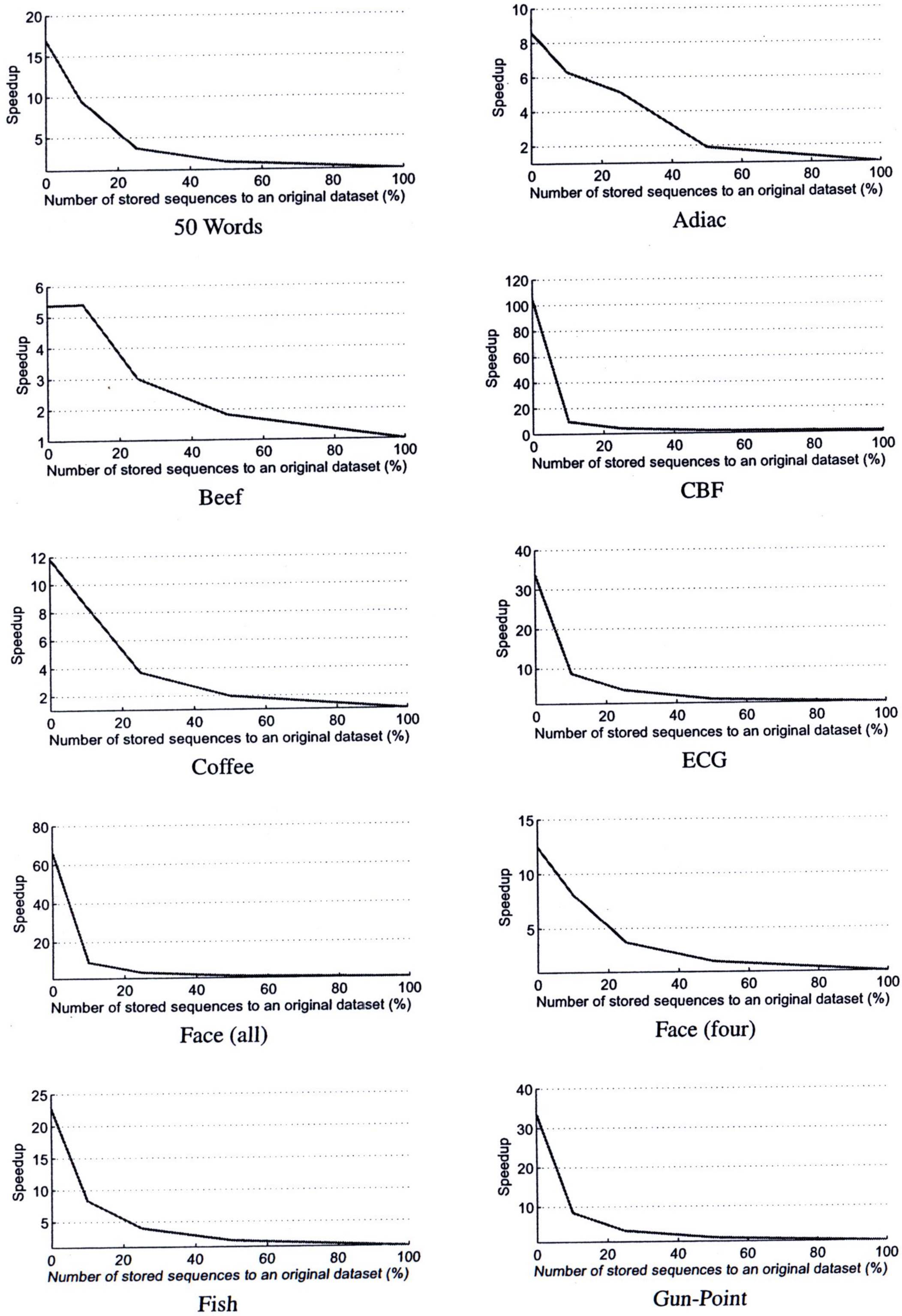


Figure F.5: Speedup of Incremental Shape-based Averaging with CDTW when the number of stored sequences to an original dataset is varied.

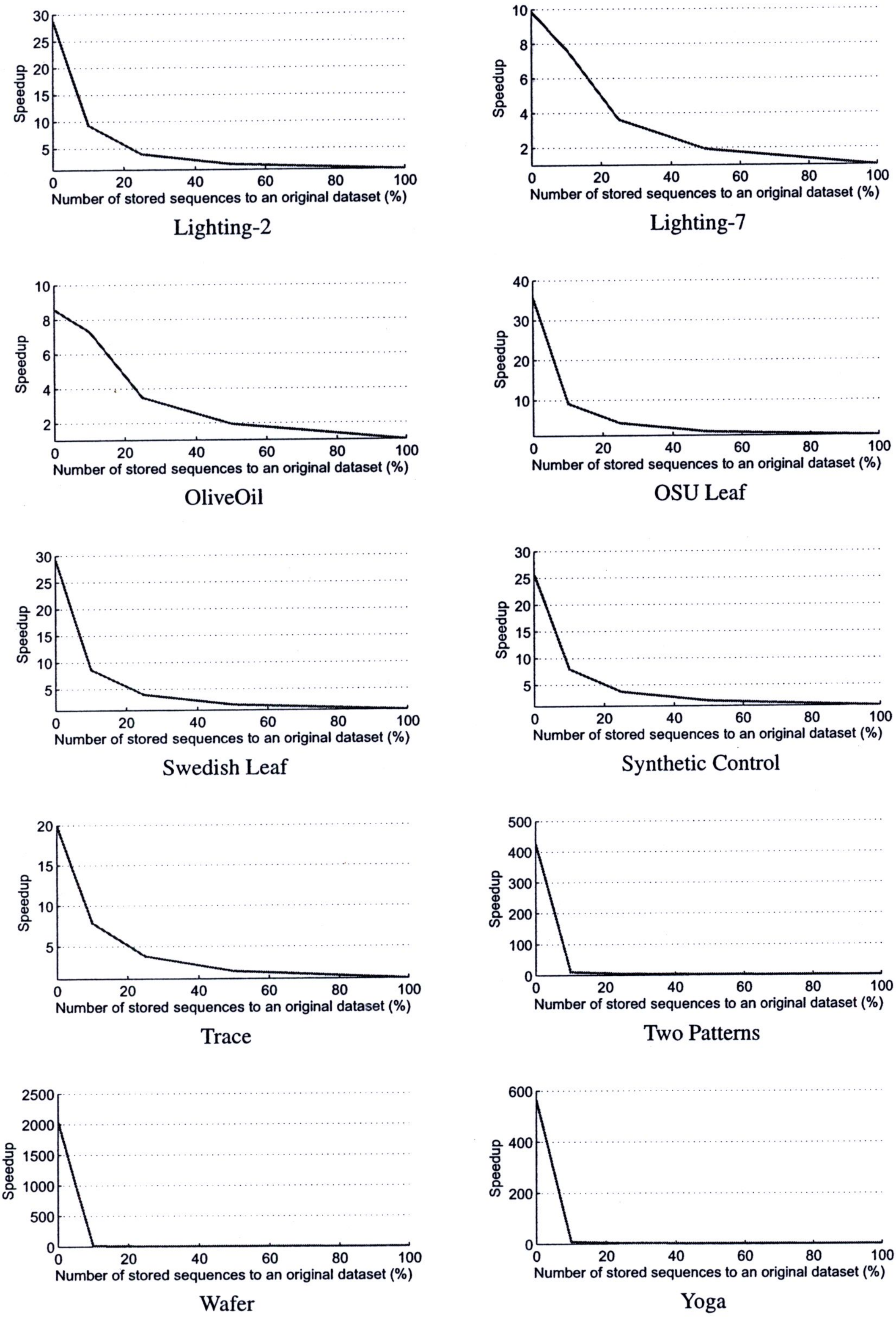


Figure F.6: Speedup of Incremental Shape-based Averaging with CDTW when the number of stored sequences to an original dataset is varied. (cont.)

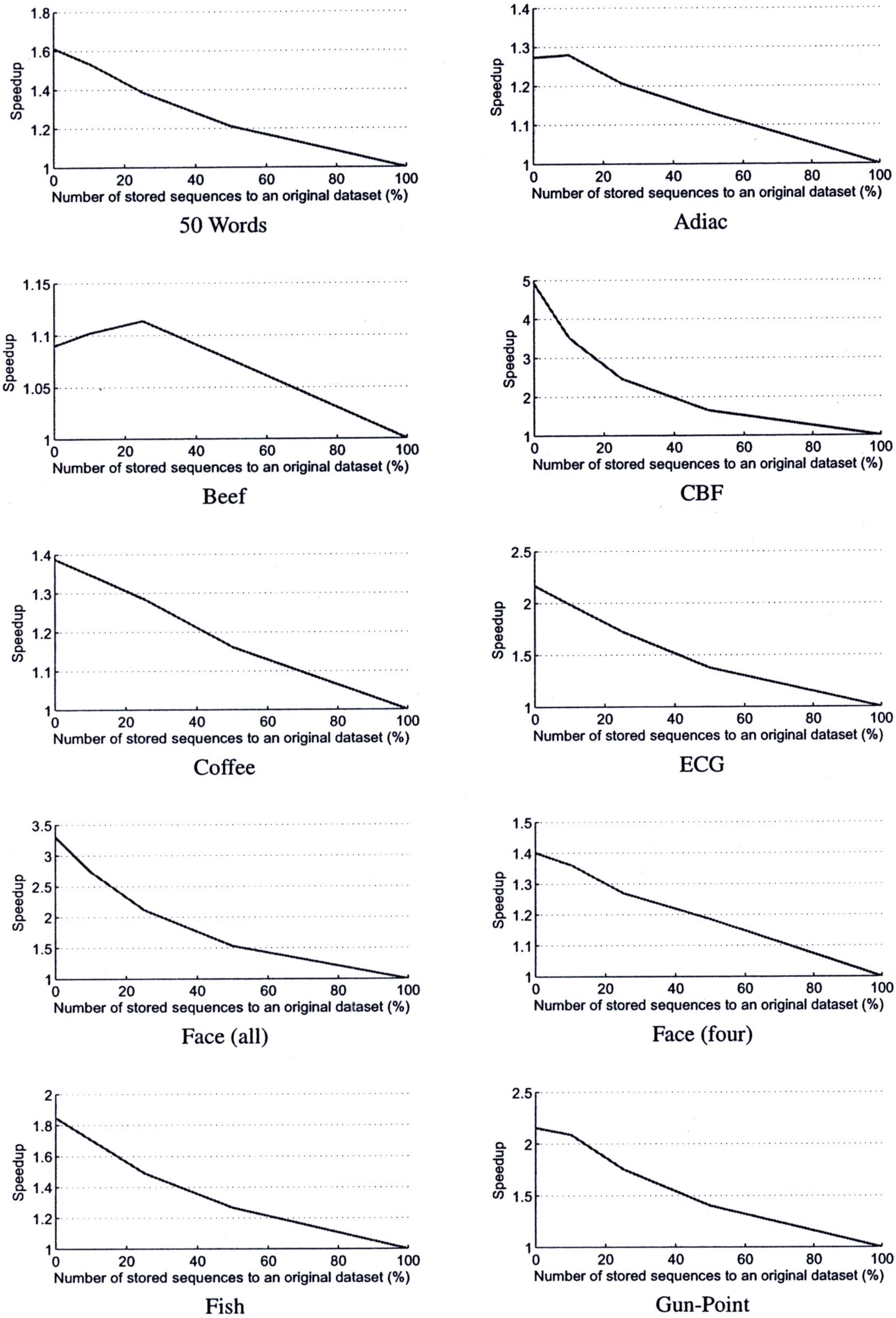
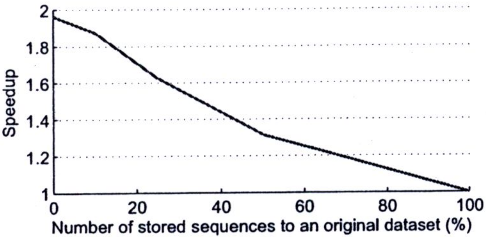
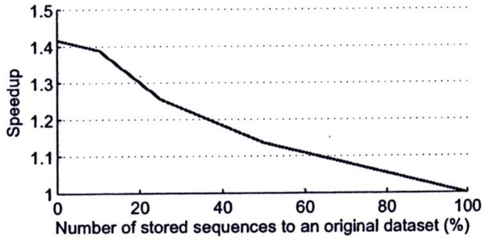


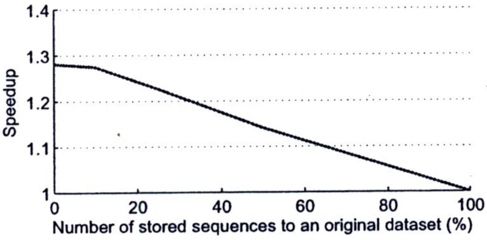
Figure F.7: Speedup of Incremental Shape-based Averaging with ICDTW when the number of stored sequences to an original dataset is varied.



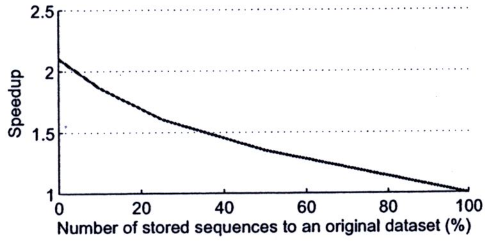
Lighting-2



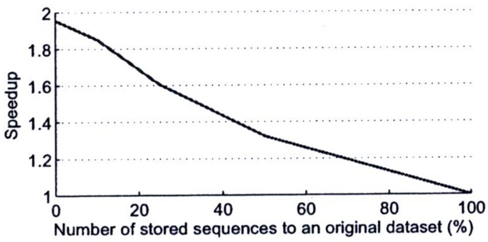
Lighting-7



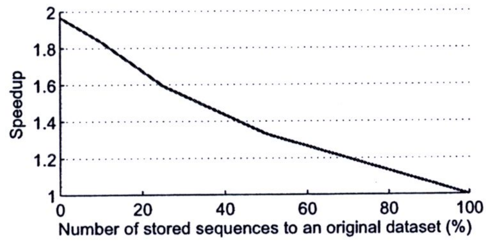
OliveOil



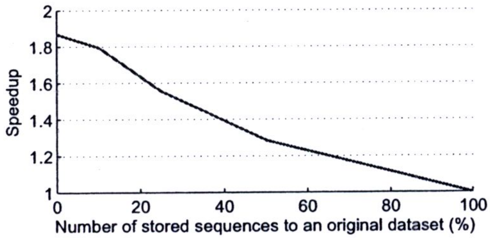
OSU Leaf



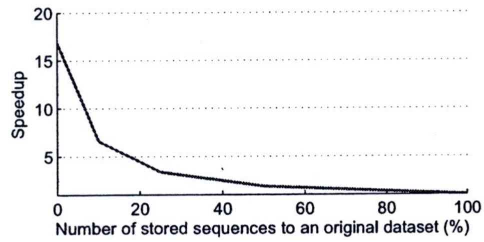
Swedish Leaf



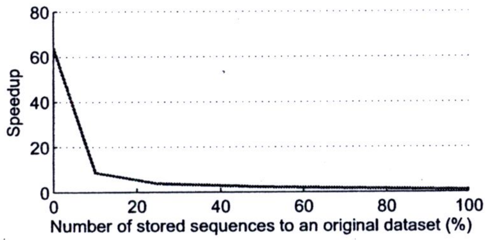
Synthetic Control



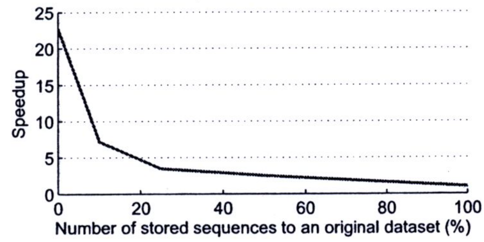
Trace



Two Patterns



Wafer



Yoga

Figure F.8: Speedup of Incremental Shape-based Averaging with CDTW when the number of stored sequences to an original dataset is varied. (cont.)

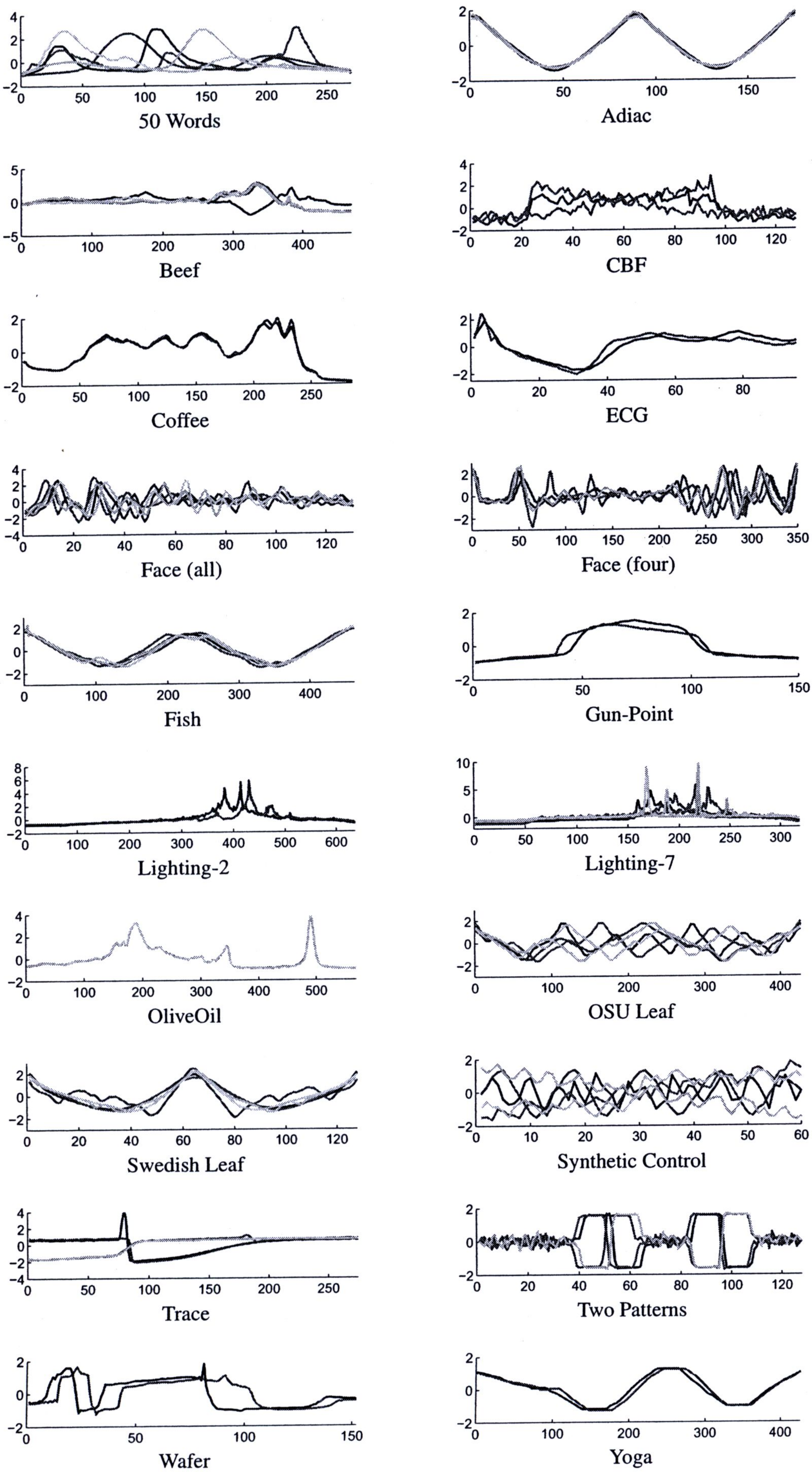


Figure F.9: Averaged results of some classes from Incremental Shape-based Averaging with CDTW when $\alpha = 1$.

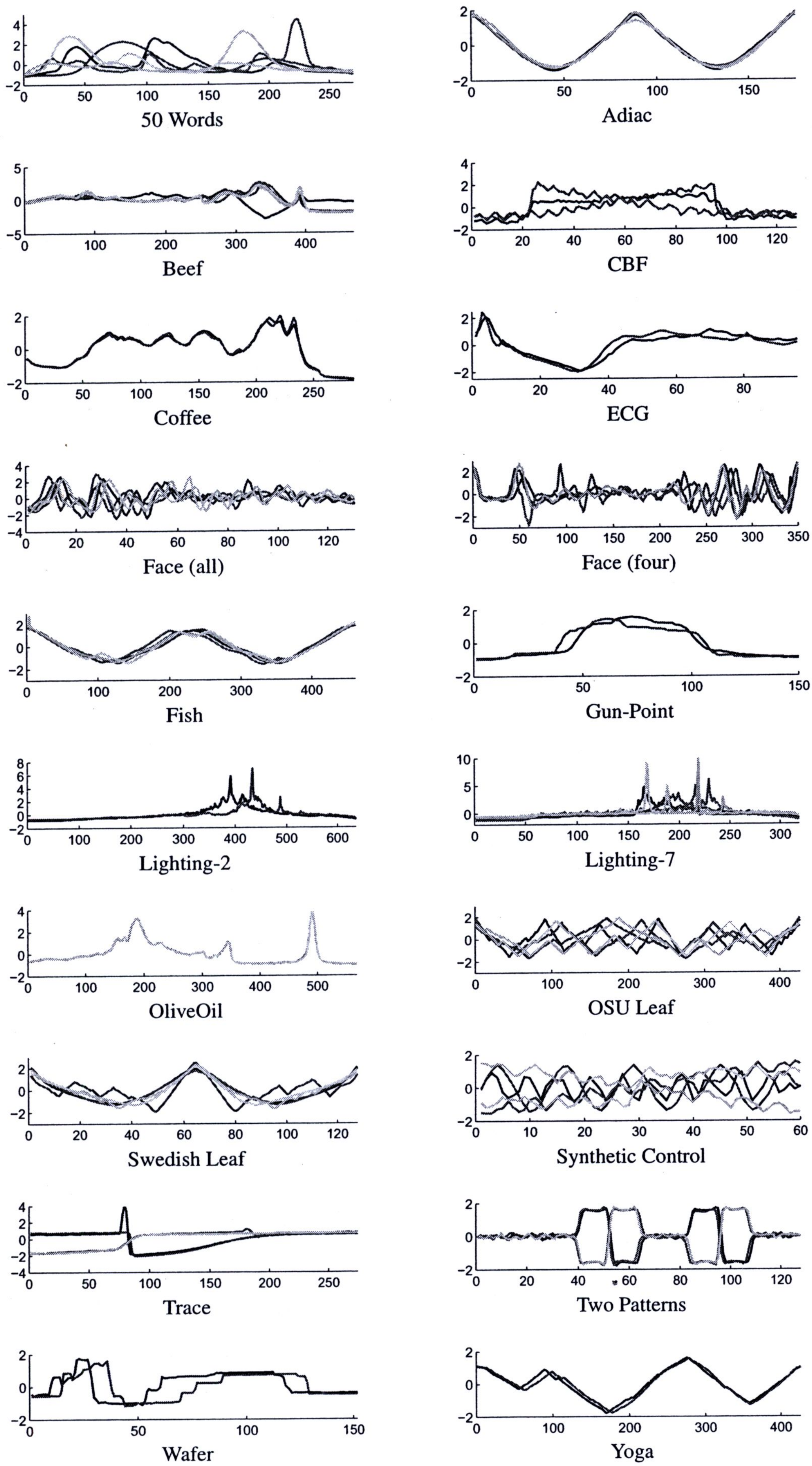


Figure F.10: Averaged results of some classes from Incremental Shape-based Averaging with CDTW when α is 25% of total number of each class.

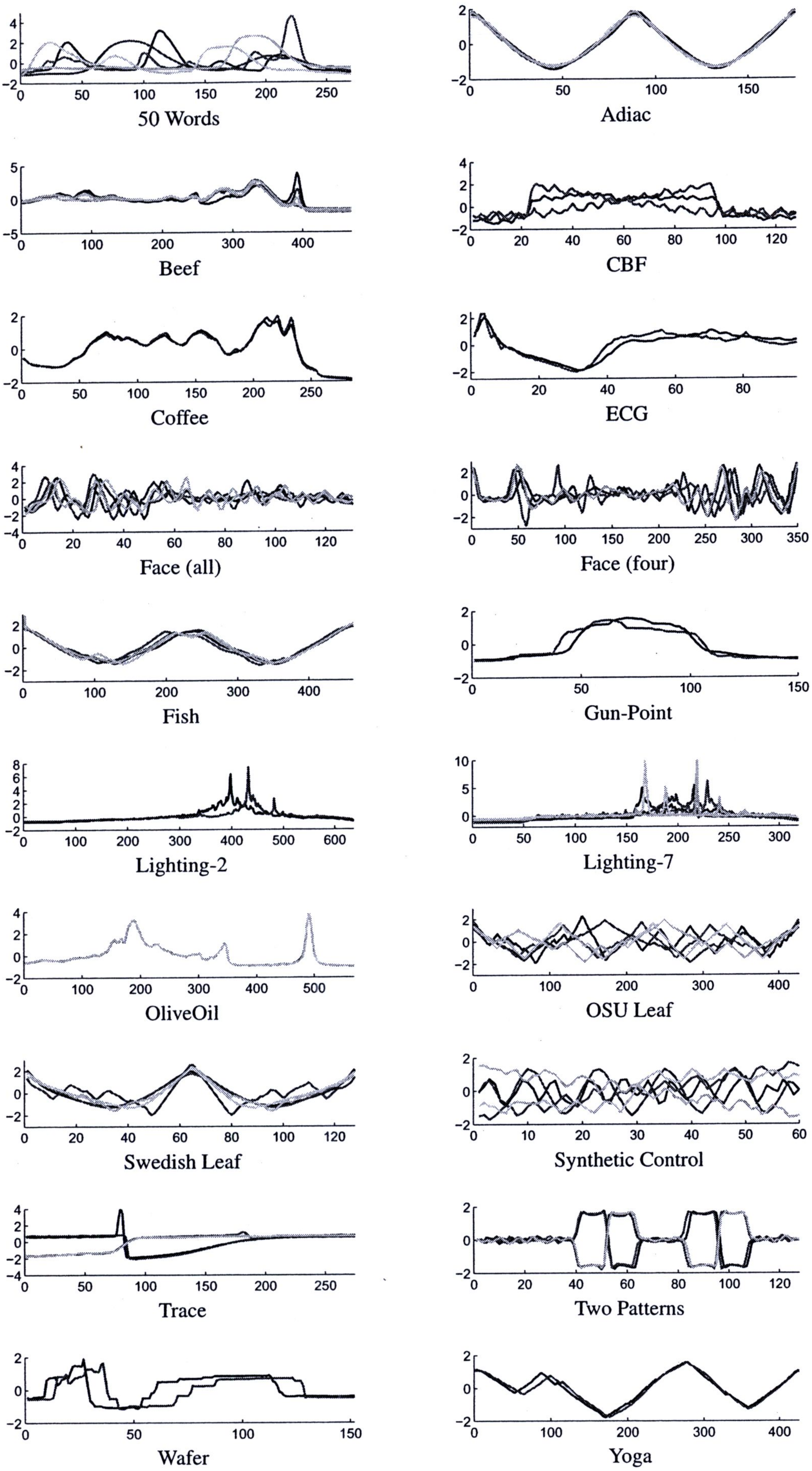


Figure F.11: Averaged results of some classes from Incremental Shape-based Averaging with CDTW when α is 50% of total number of each class.

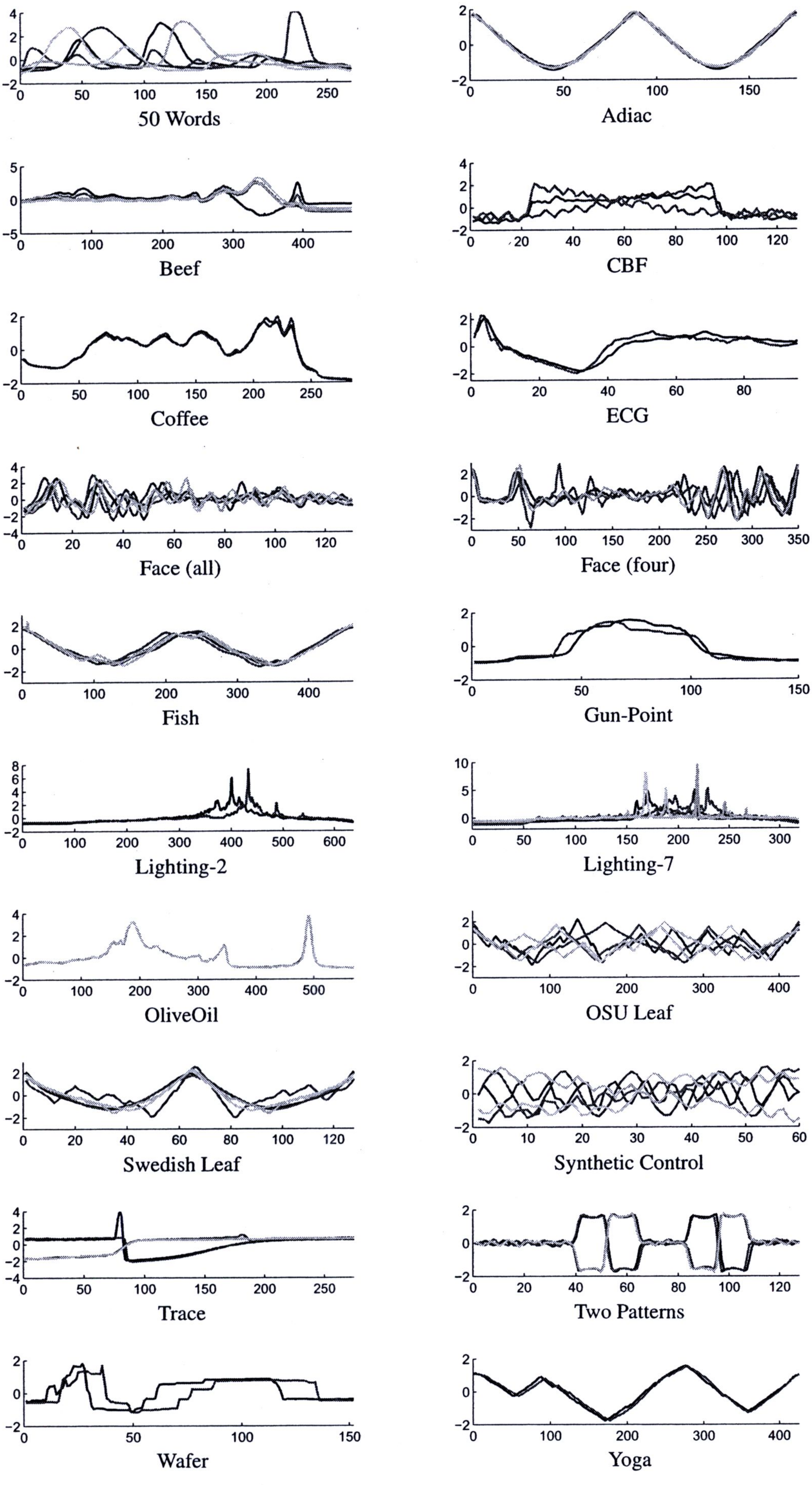


Figure F.12: Averaged results of some classes from Incremental Shape-based Averaging with CDTW when α is 100% of total number of each class.

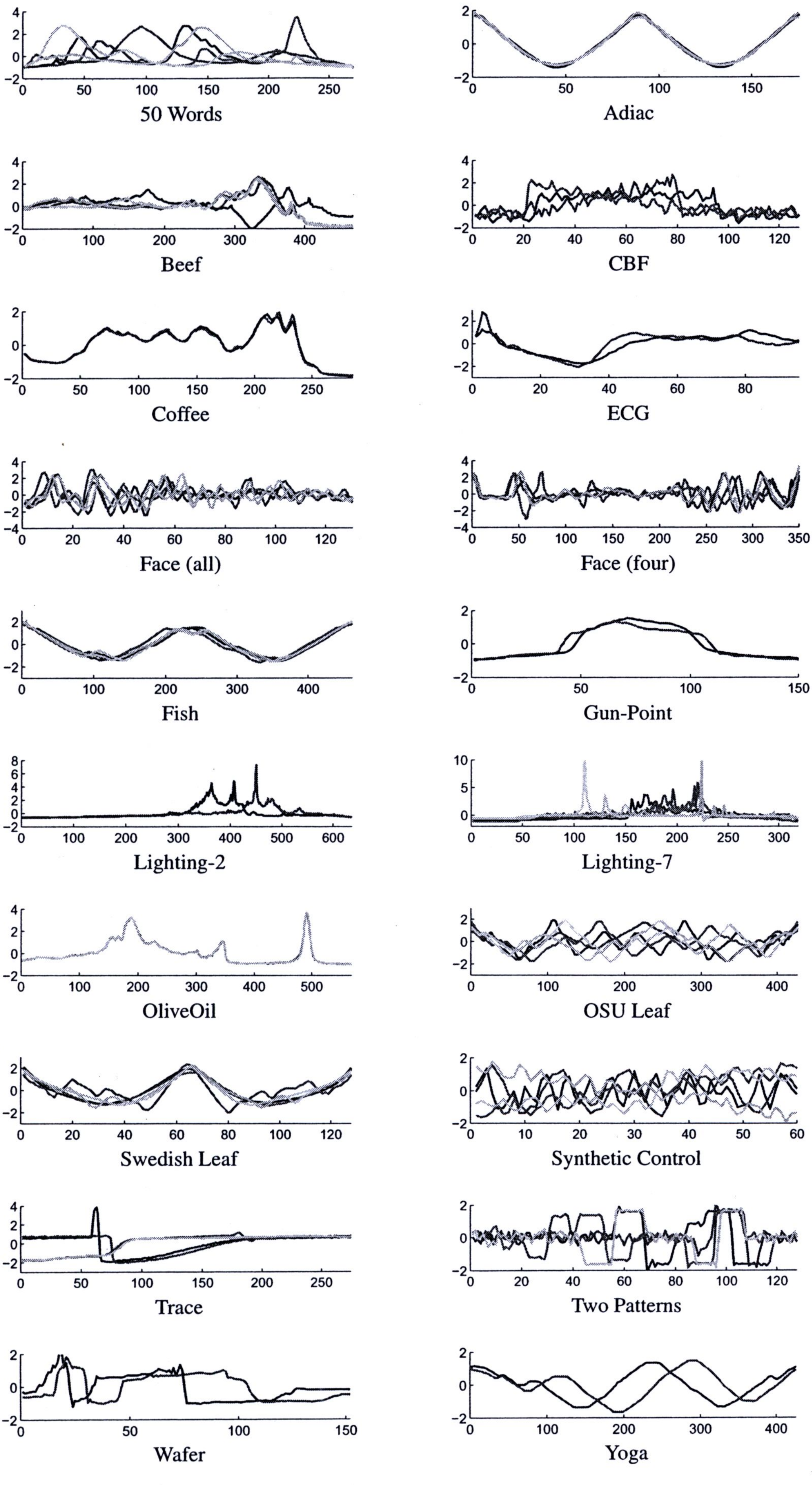


Figure F.13: Averaged results of some classes from Incremental Shape-based Averaging with ICDTW when $\alpha = 1$.

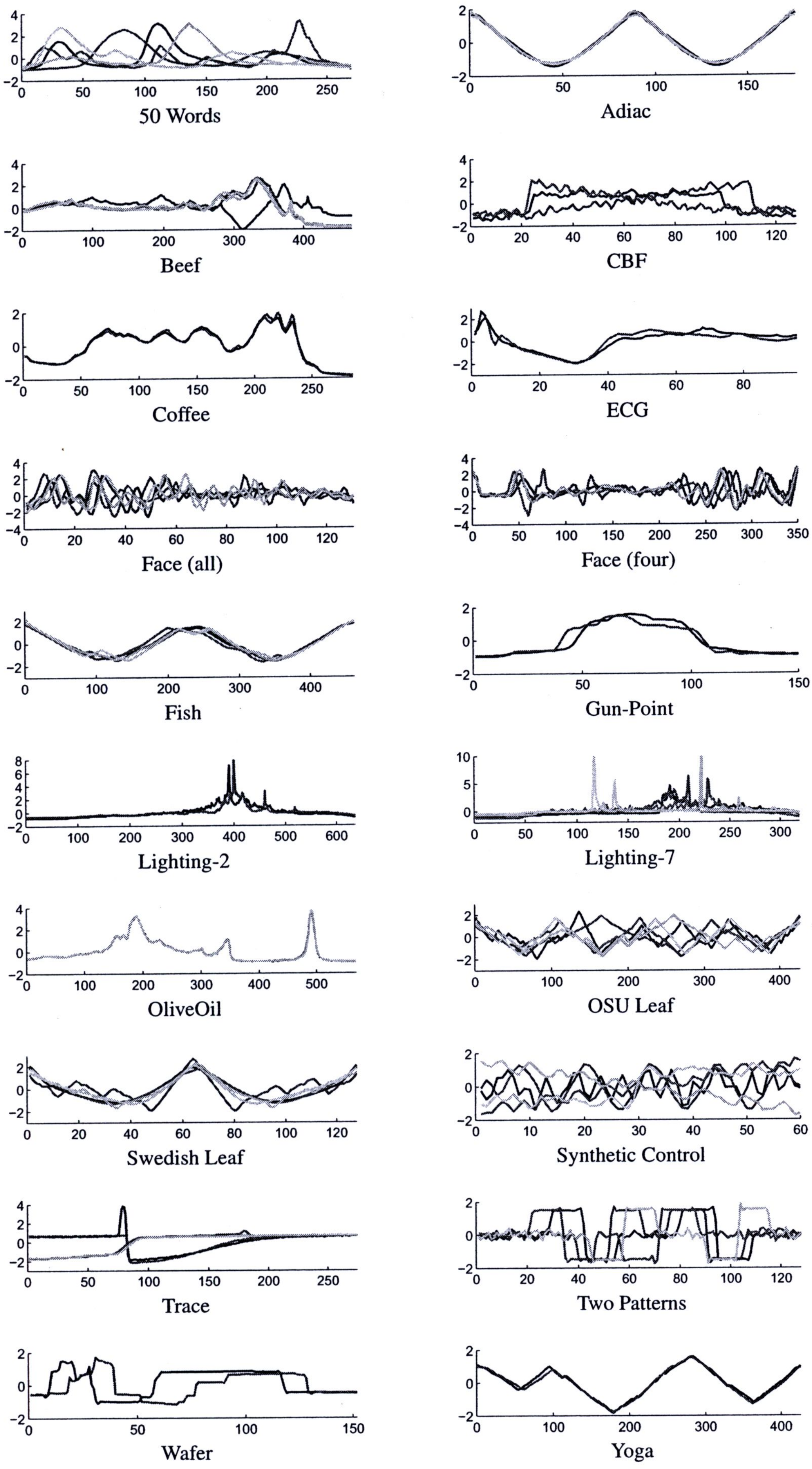


Figure F.14: Averaged results of some classes from Incremental Shape-based Averaging with ICDTW when α is 25% of total number of each class.

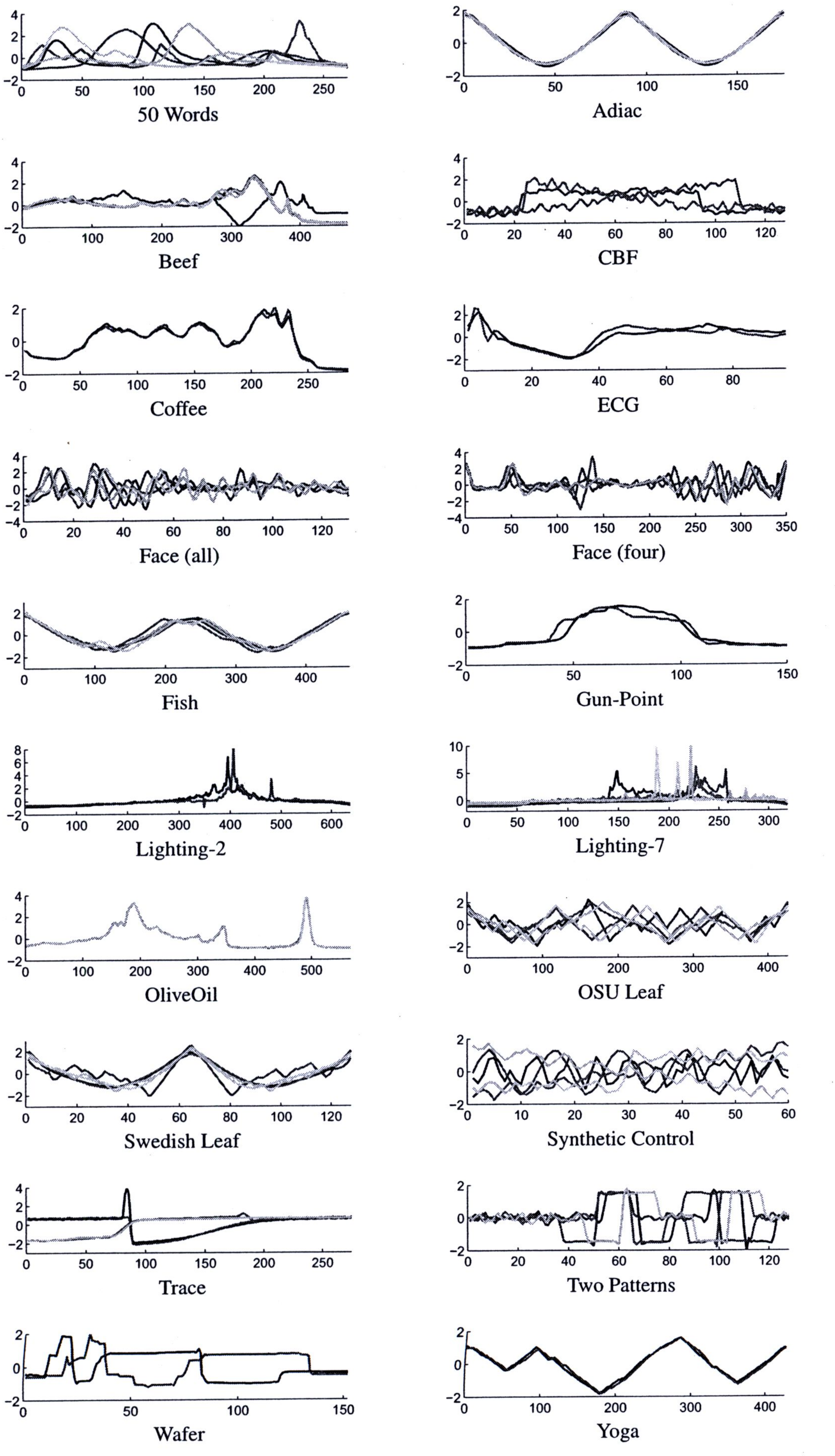


Figure F.15: Averaged results of some classes from Incremental Shape-based Averaging with ICDTW when α is 50% of total number of each class.

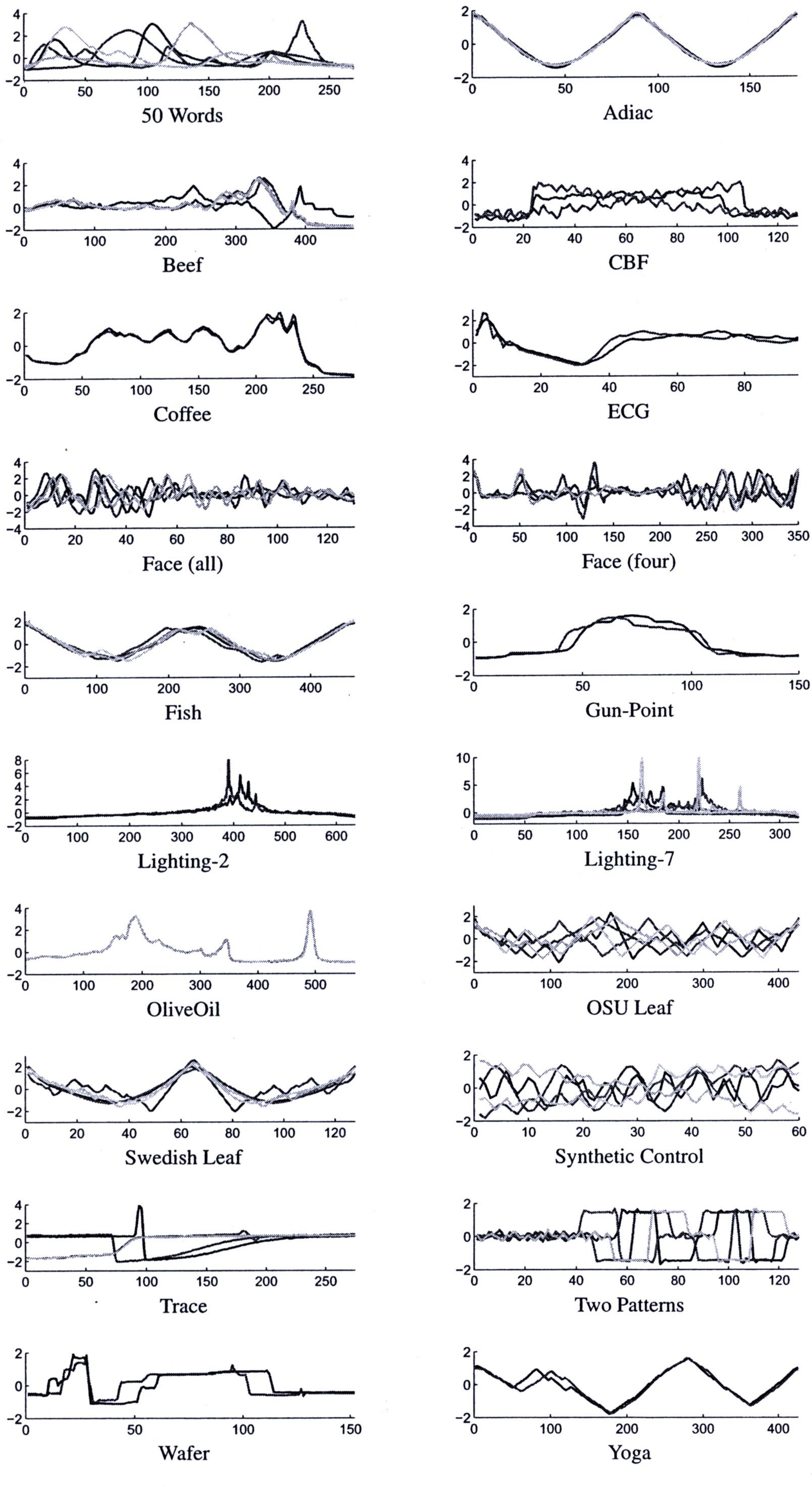


Figure F.16: Averaged results of some classes from Incremental Shape-based Averaging with ICDTW when α is 100% of total number of each class.

APPENDIX G

COMPLETE EXPERIMENTAL RESULTS OF THE FIRST EXPERIMENT IN CHAPTER VI

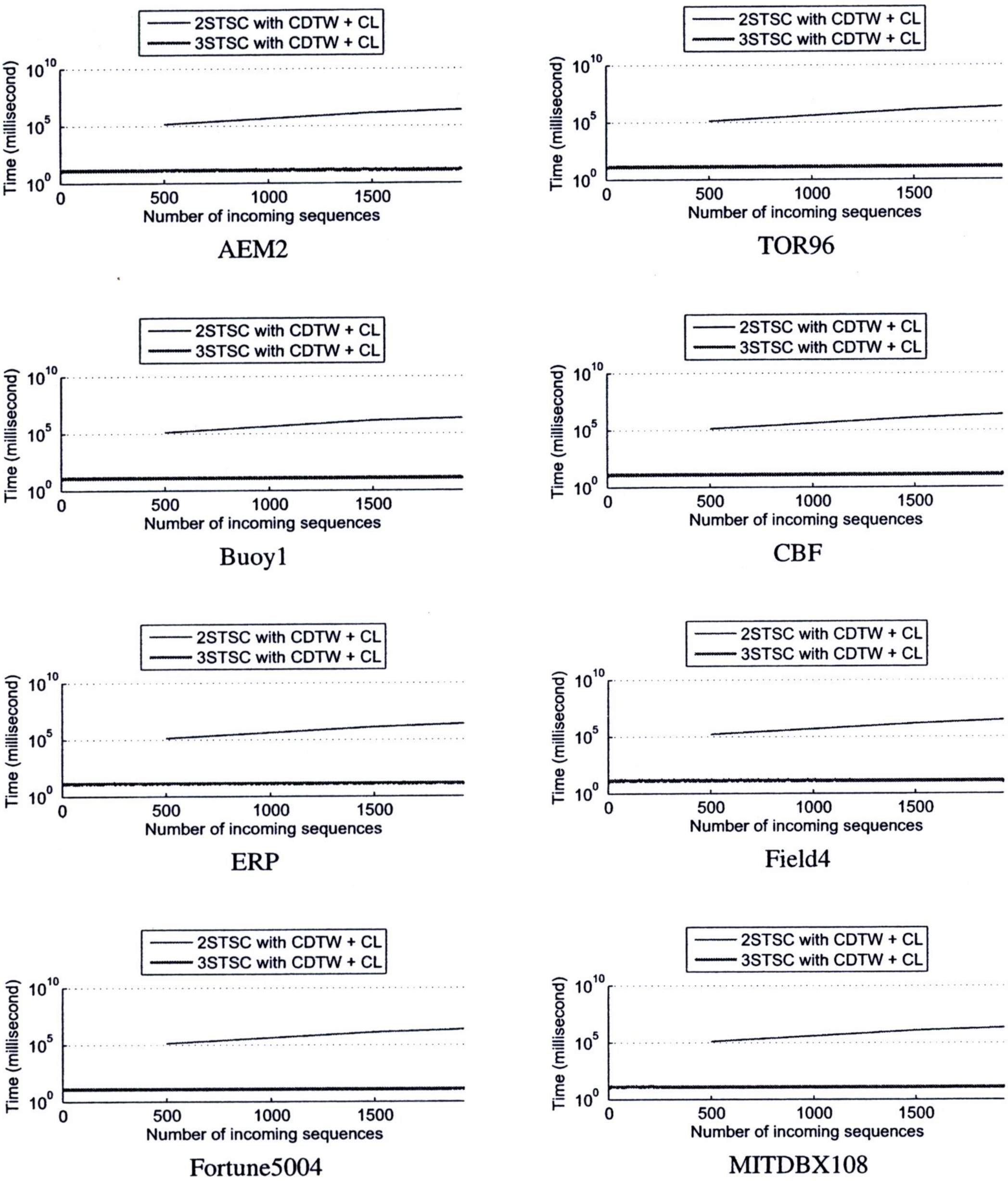


Figure G.1: Computational time of 3STSC and 2STSC with CDTW function and complete linkage when a new incoming sequence arrives, where $k = 3$ and $w = 64$.

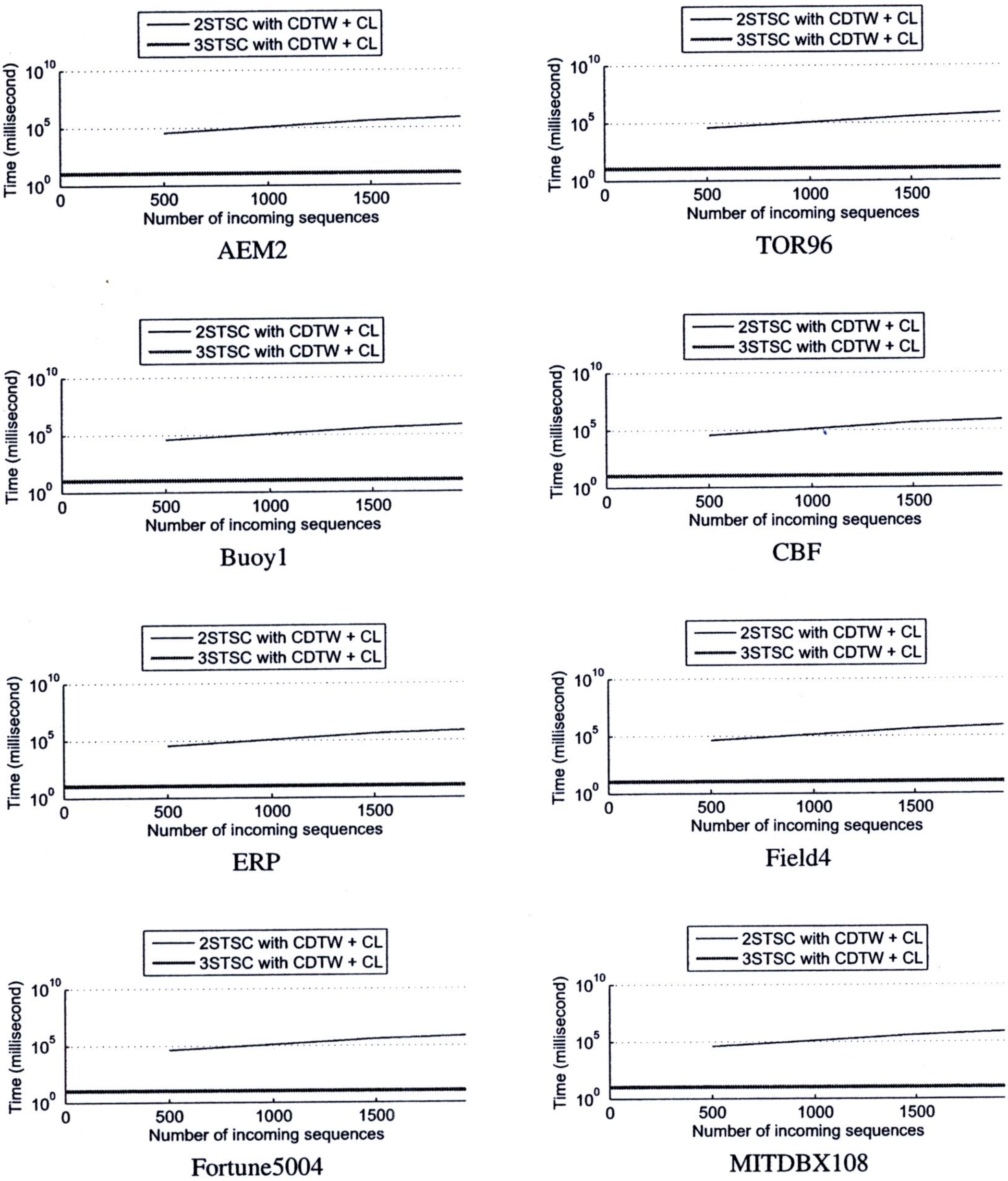


Figure G.2: Computational time of 3STSC and 2STSC with CDTW function and complete linkage when a new incoming sequence arrives, where $k = 3$ and $w = 32$

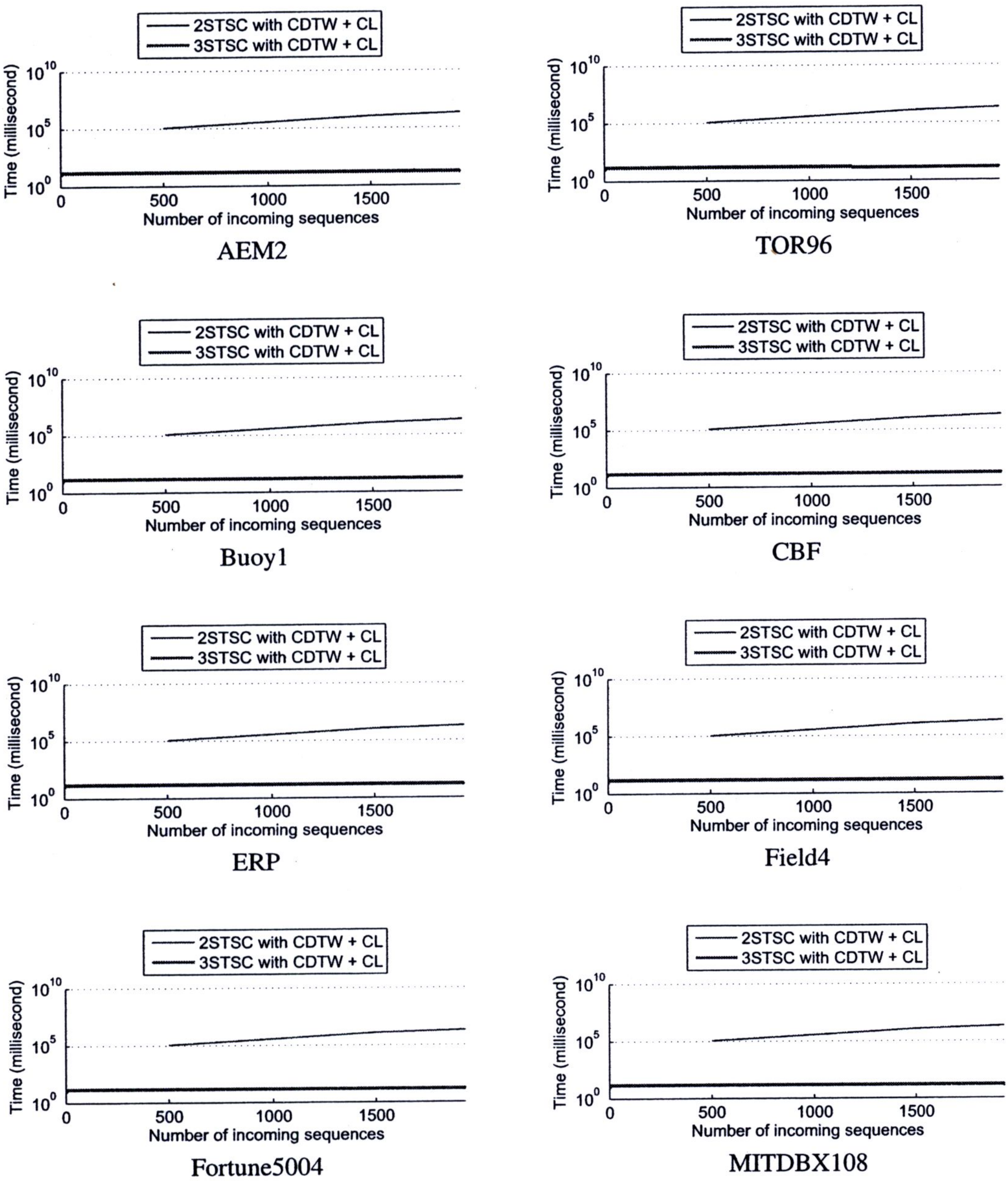


Figure G.3: Computational time of 3STSC and 2STSC with CDTW function and complete linkage when a new incoming sequence arrives, where $k = 5$ and $w = 64$.

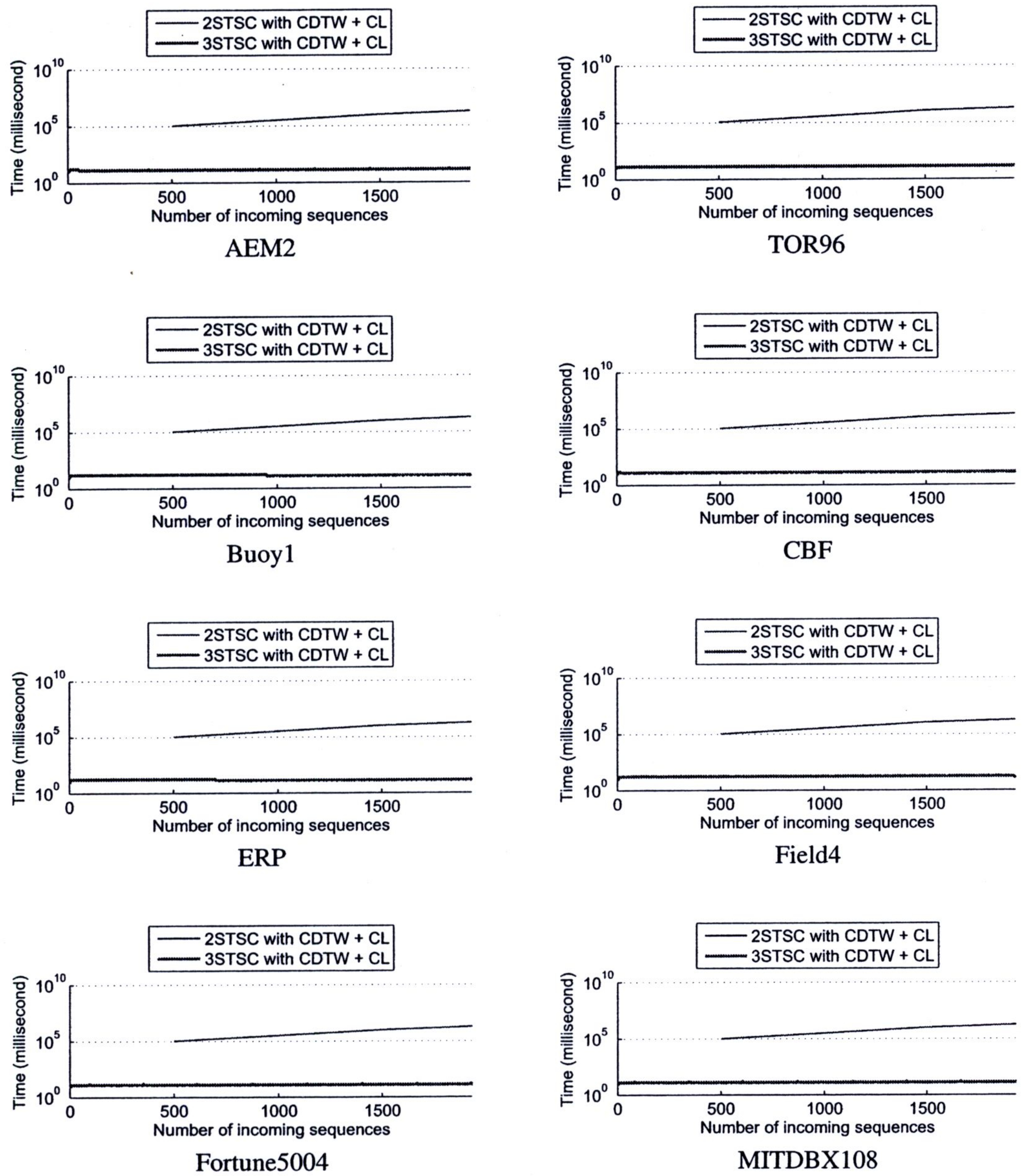


Figure G.4: Computational time of 3STSC and 2STSC with CDTW function and complete linkage when a new incoming sequence arrives, where $k = 7$ and $w = 64$.

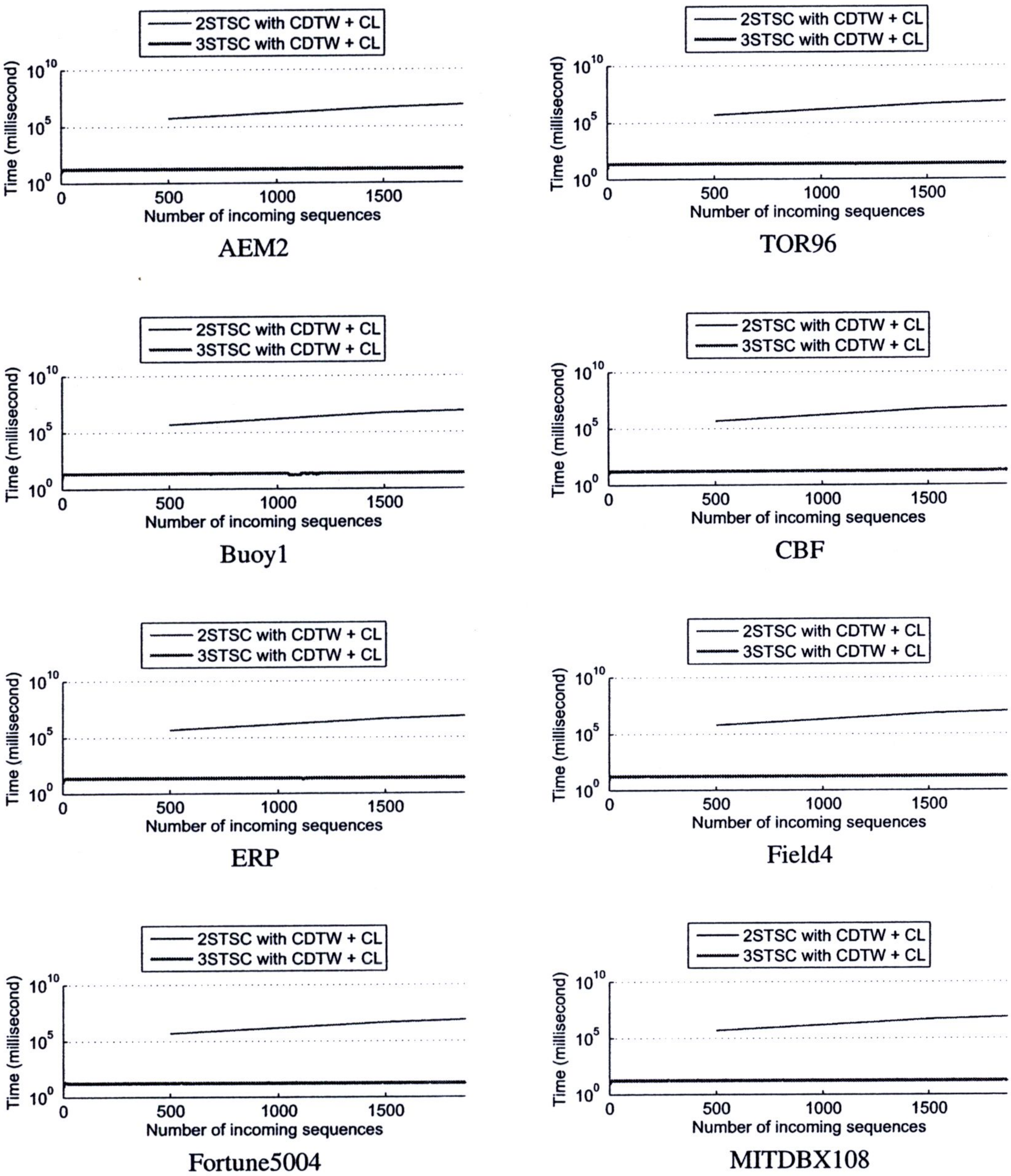


Figure G.5: Computational time of 3STSC and 2STSC with CDTW function and complete linkage when a new incoming sequence arrives, where $k = 3$ and $w = 128$.

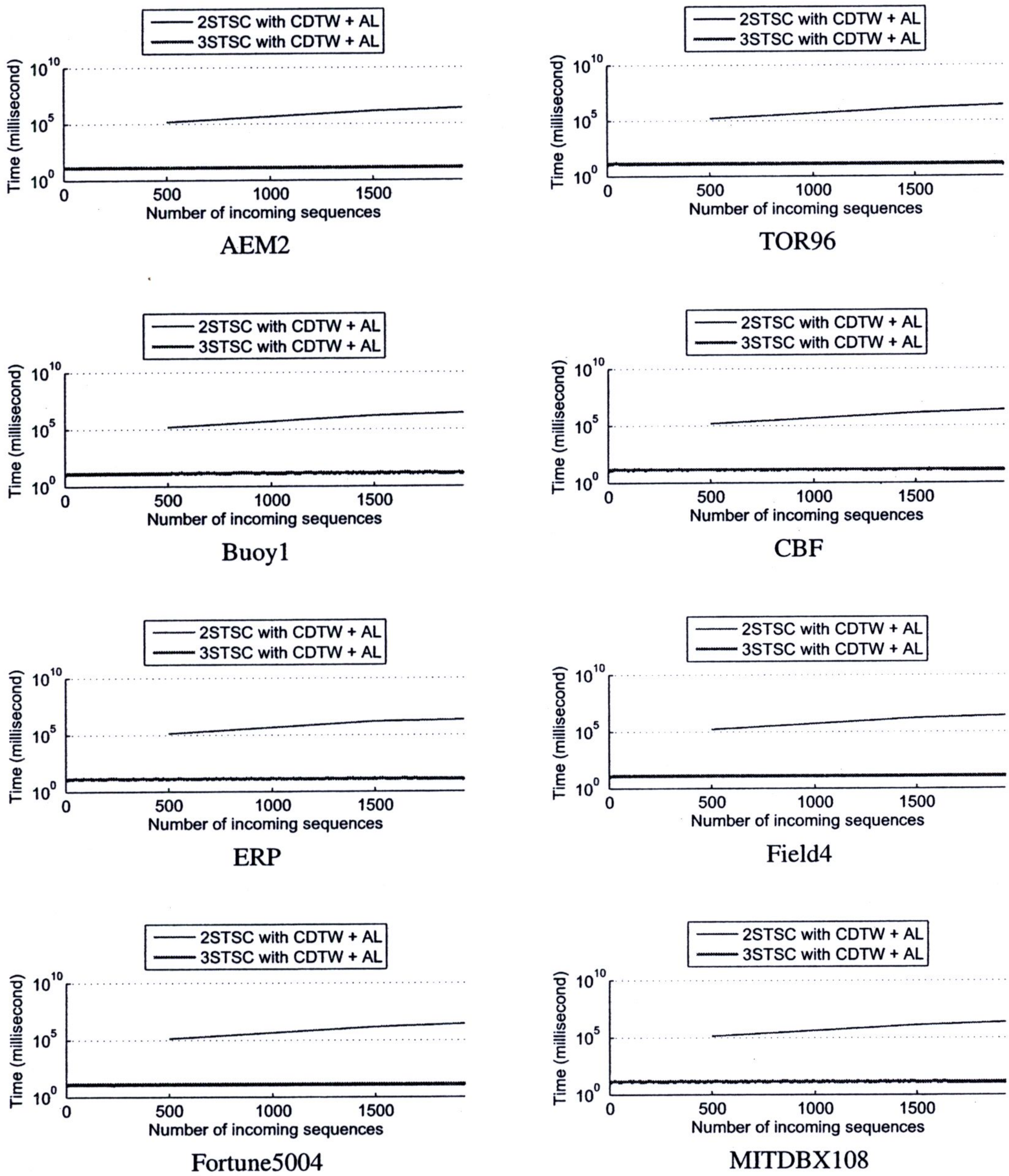


Figure G.6: Computational time of 3STSC and 2STSC with CDTW function and average linkage when a new incoming sequence arrives, where $k = 3$ and $w = 64$.

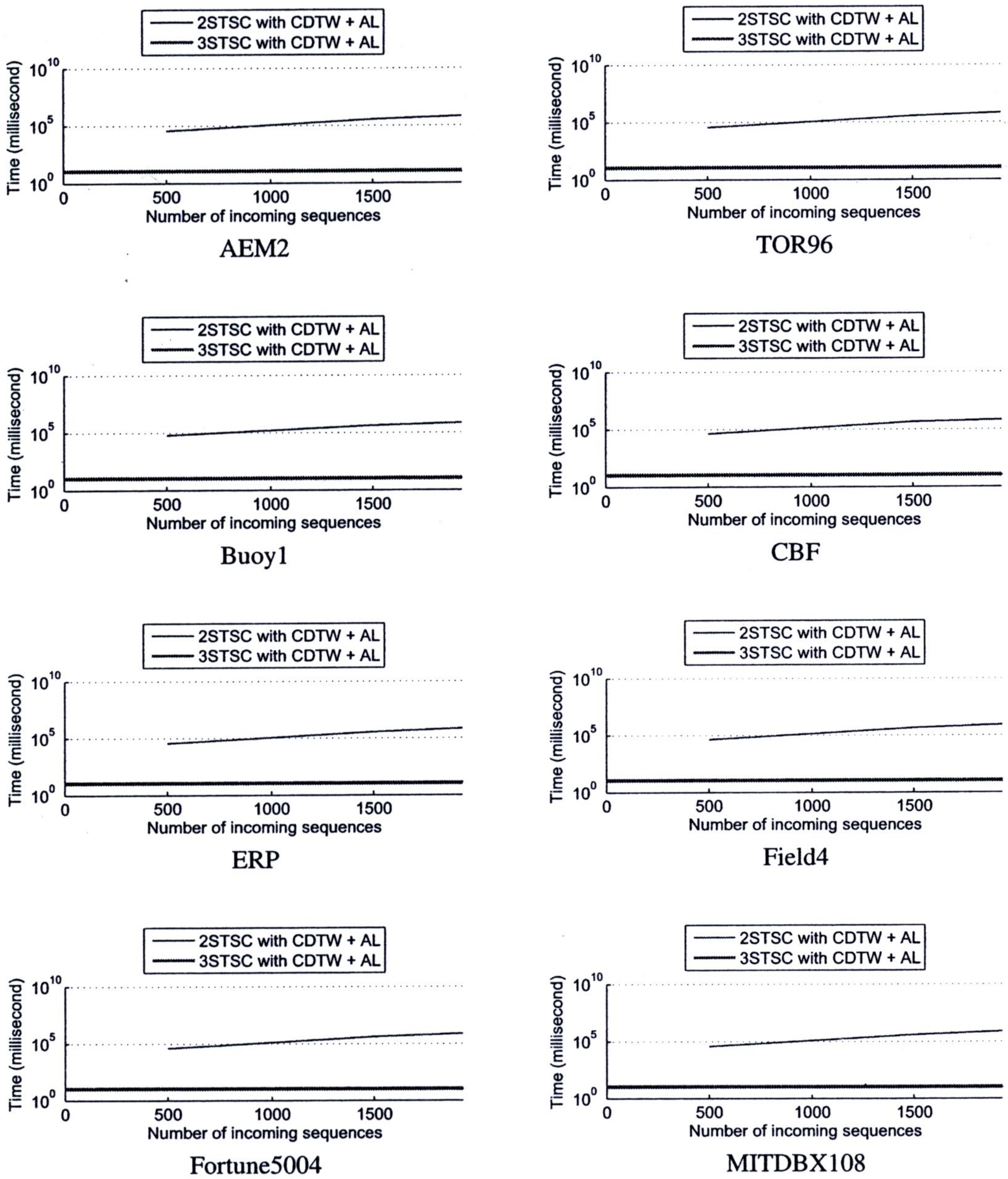


Figure G.7: Computational time of 3STSC and 2STSC with CDTW function and average linkage when a new incoming sequence arrives, where $k = 3$ and $w = 32$.

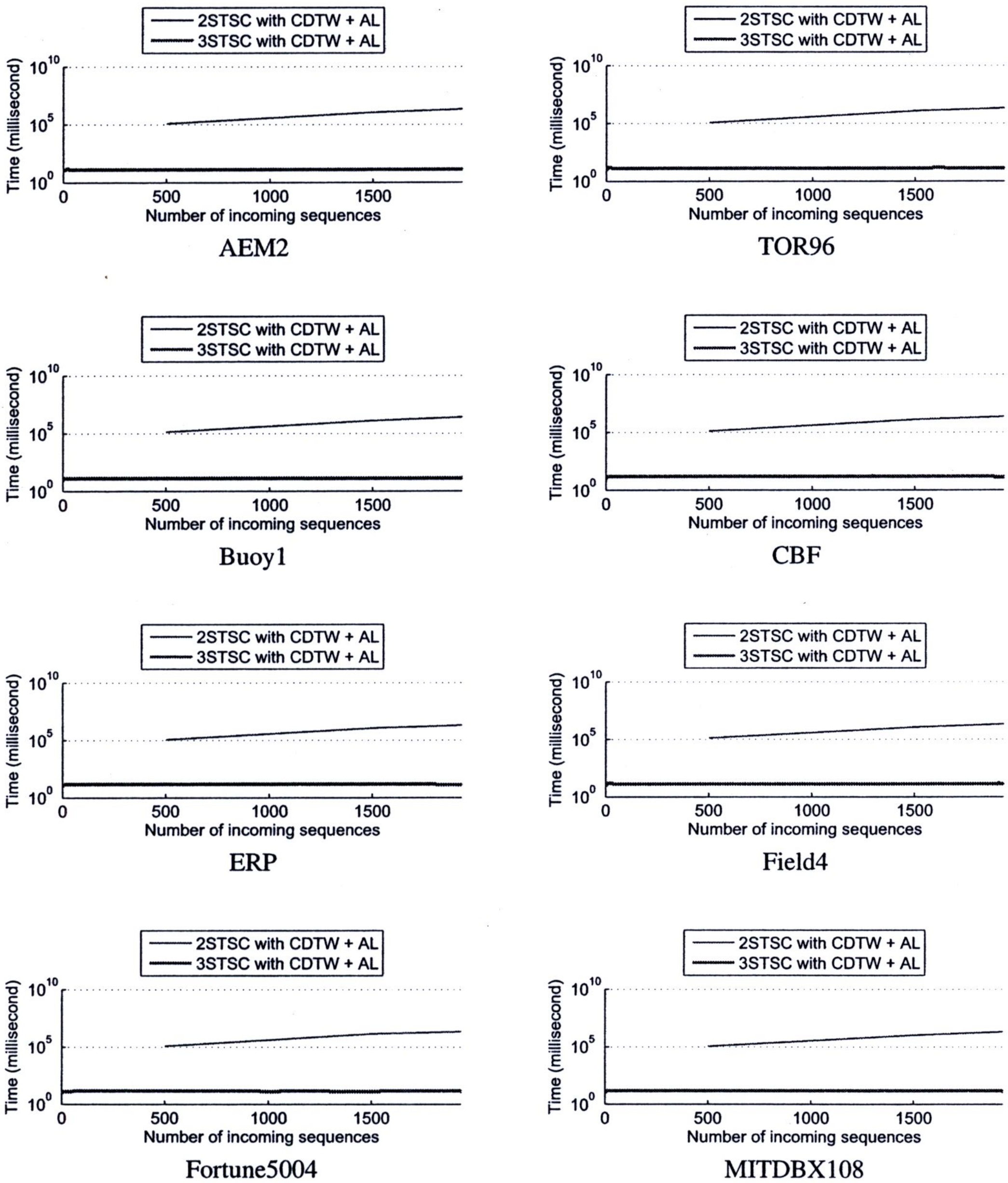


Figure G.8: Computational time of 3STSC and 2STSC with CDTW function and average linkage when a new incoming sequence arrives, where $k = 5$ and $w = 64$.

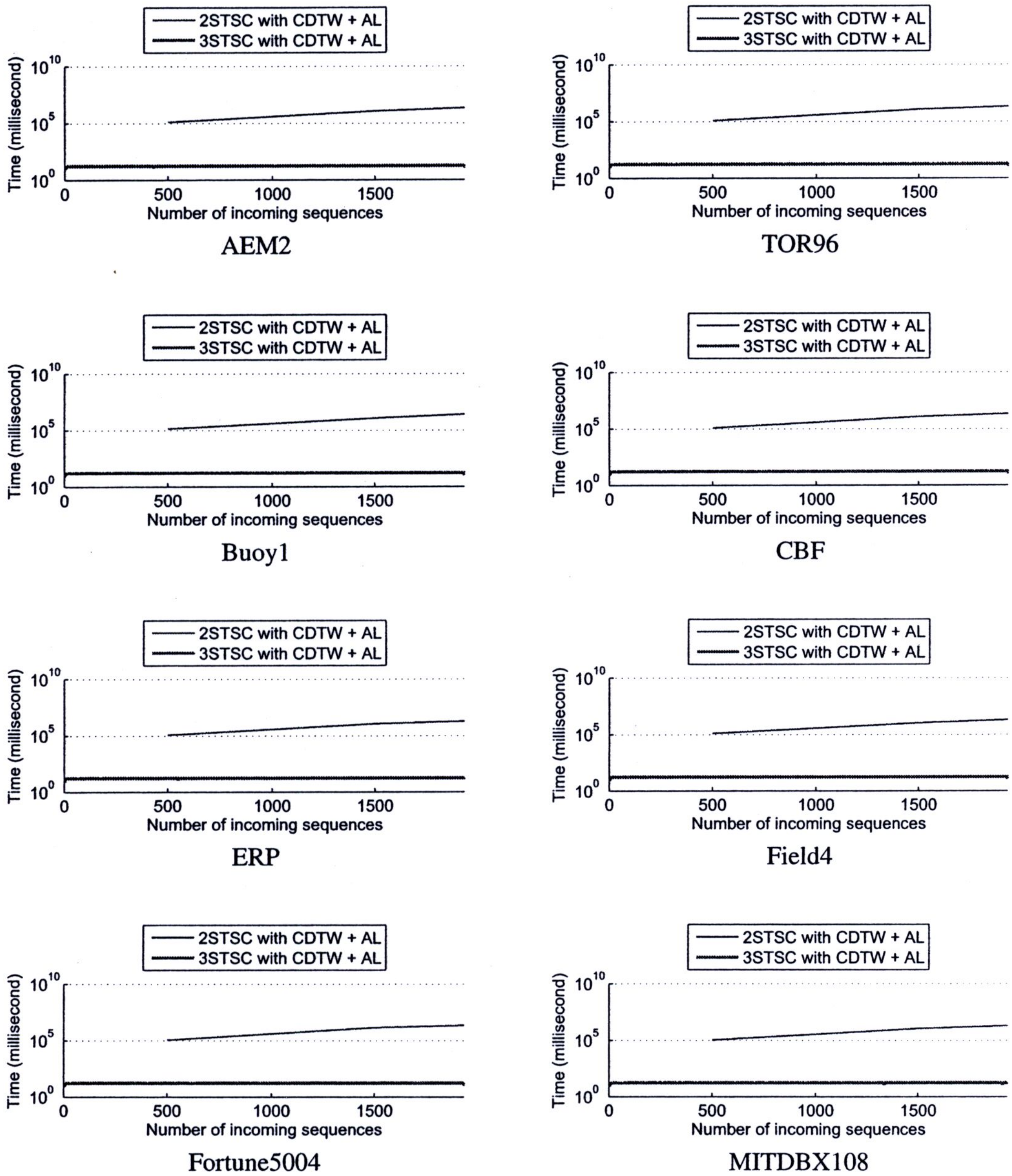


Figure G.9: Computational time of 3STSC and 2STSC with CDTW function and average linkage when a new incoming sequence arrives, where $k = 7$ and $w = 64$.

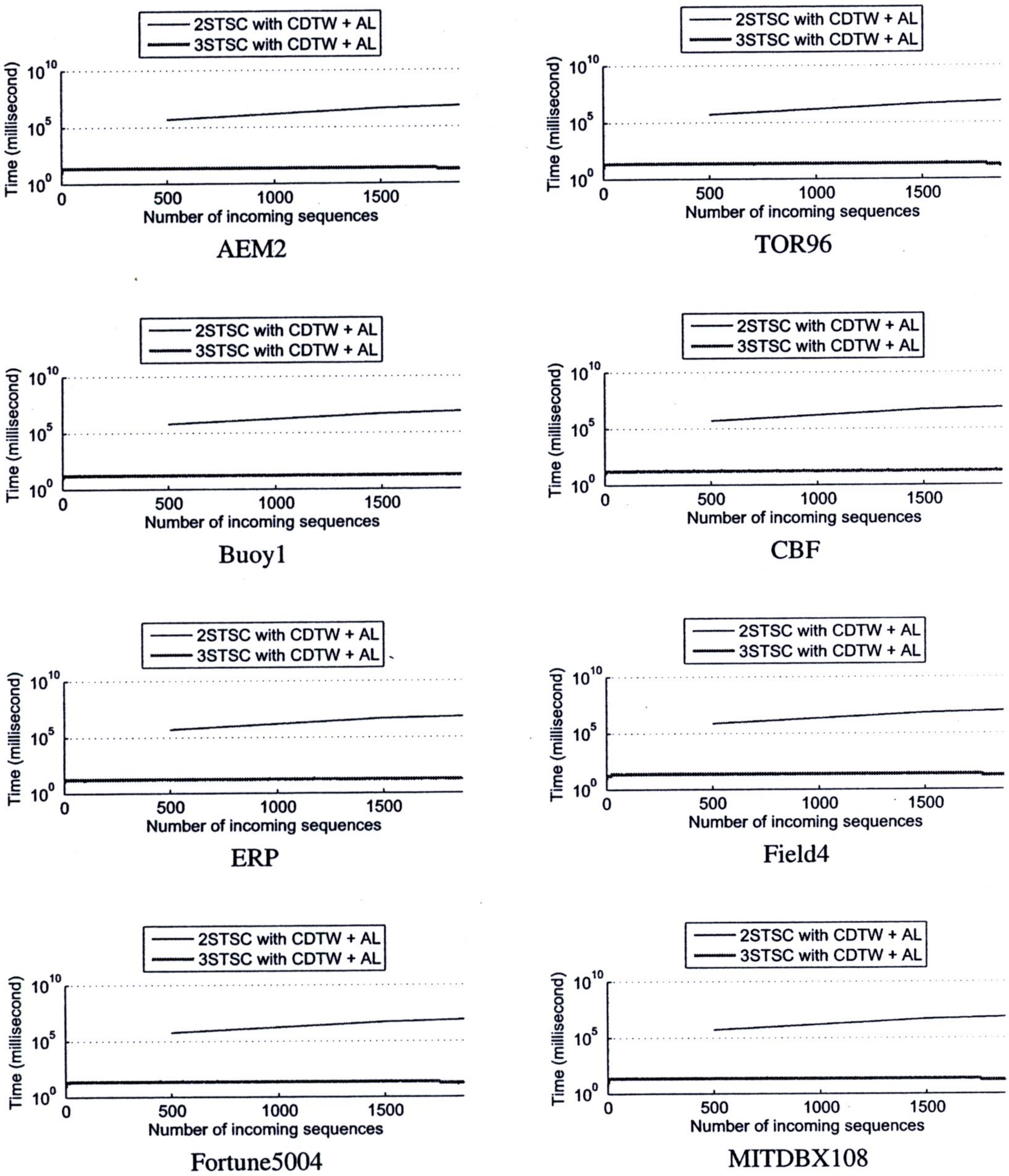
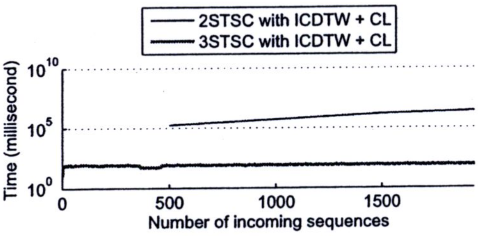
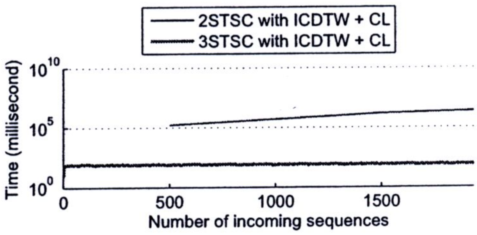


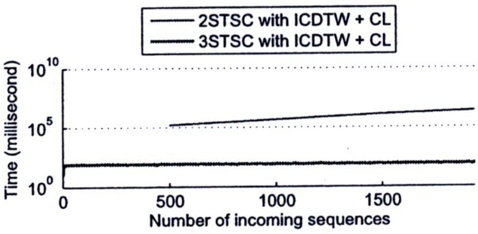
Figure G.10: Computational time of 3STSC and 2STSC with CDTW function and average linkage when a new incoming sequence arrives, where $k = 3$ and $w = 128$.



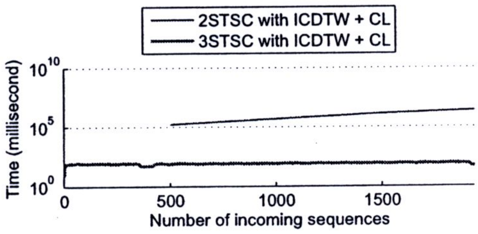
AEM2



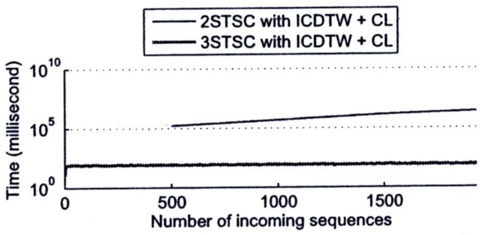
TOR96



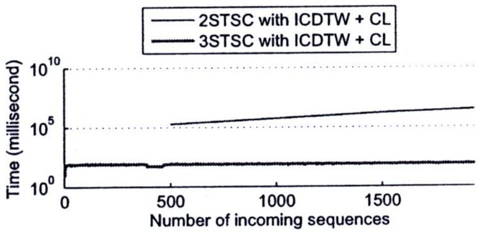
Buoy1



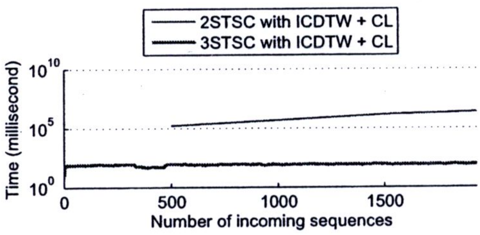
CBF



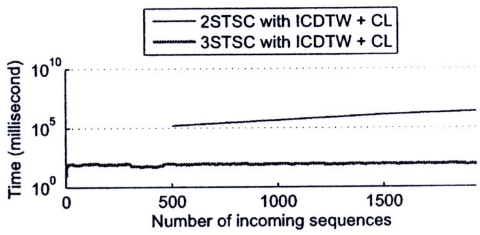
ERP



Field4



Fortune5004



MITDBX108

Figure G.11: Computational time of 3STSC and 2STSC with CDTW function and complete linkage when a new incoming sequence arrives, where $k = 3$ and $w = 64$.

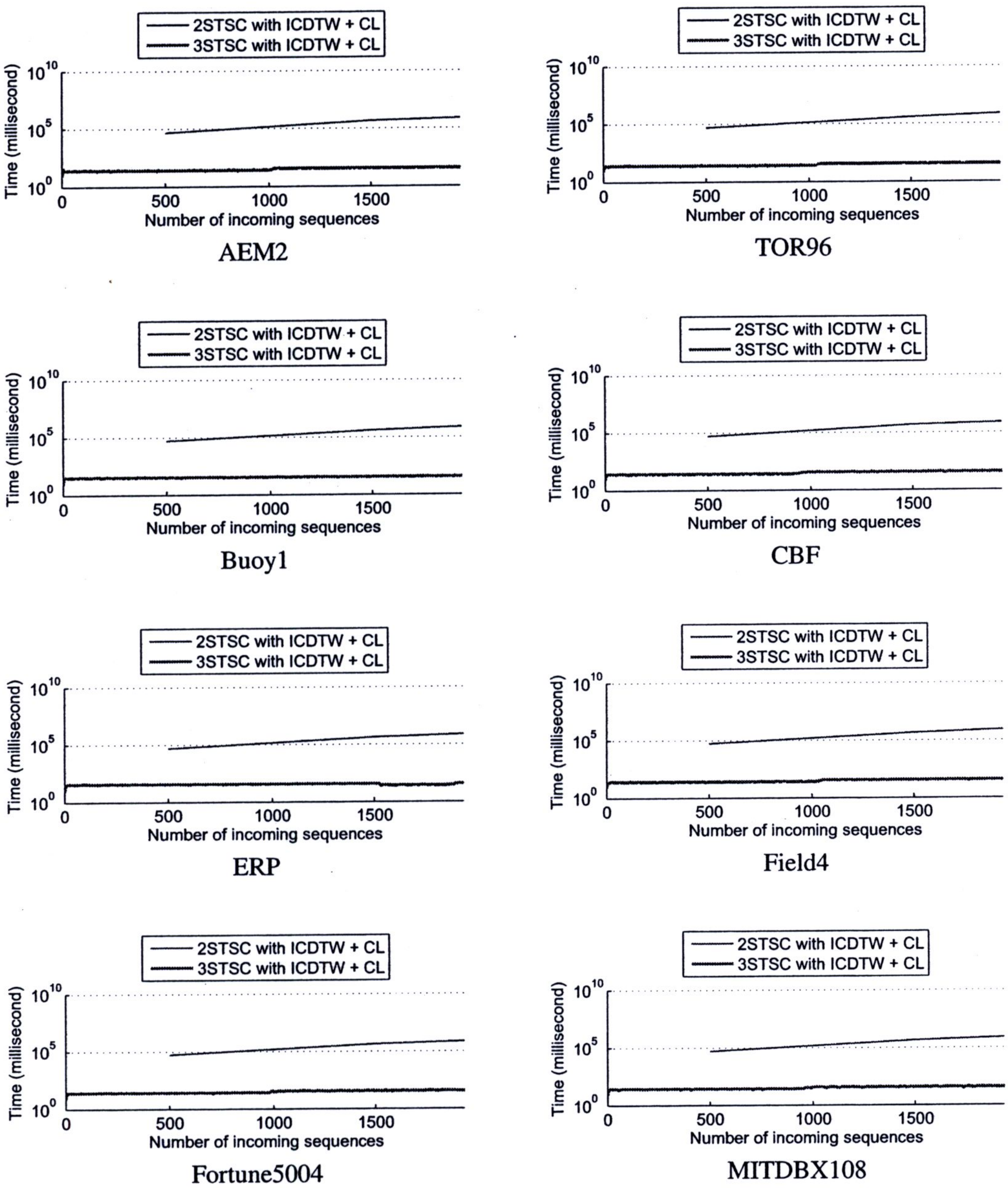
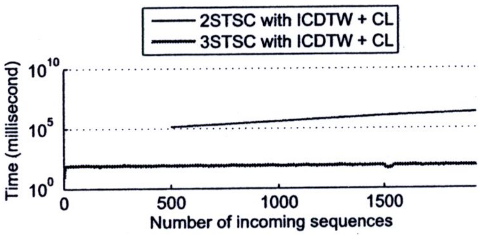


Figure G.12: Computational time of 3STSC and 2STSC with CDTW function and complete linkage when a new incoming sequence arrives, where $k = 3$ and $w = 32$.



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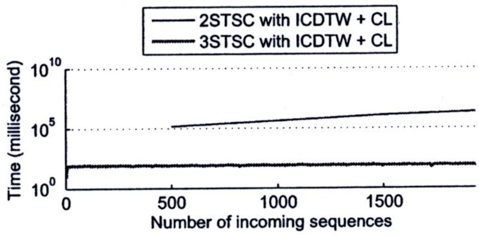
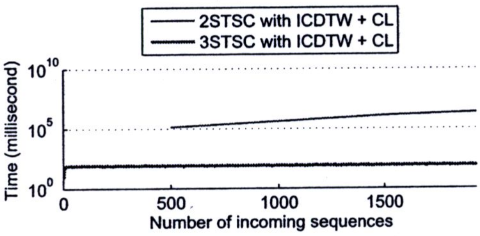
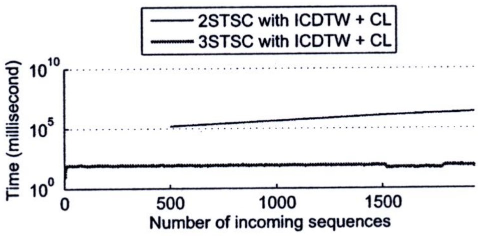


TOR96



Buoy1



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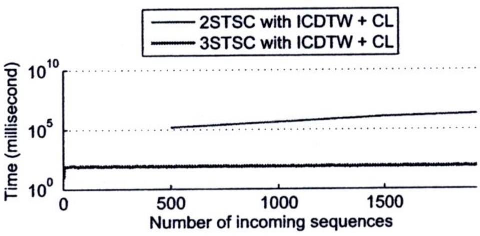
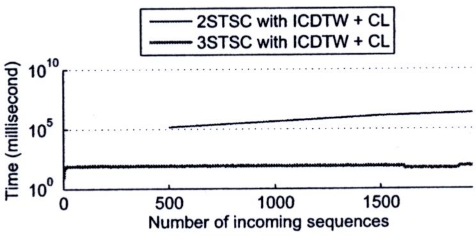
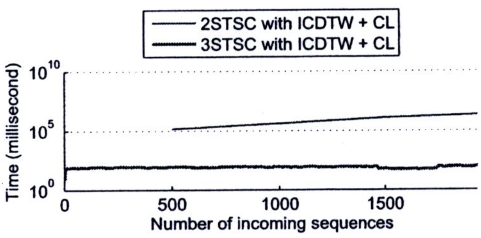


ERP



Field4



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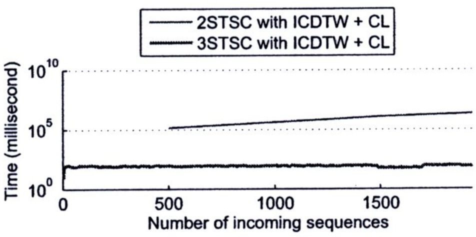


MITDBX108

Figure G.13: Computational time of 3STSC and 2STSC with CDTW function and complete linkage when a new incoming sequence arrives, where $k = 5$ and $w = 64$.

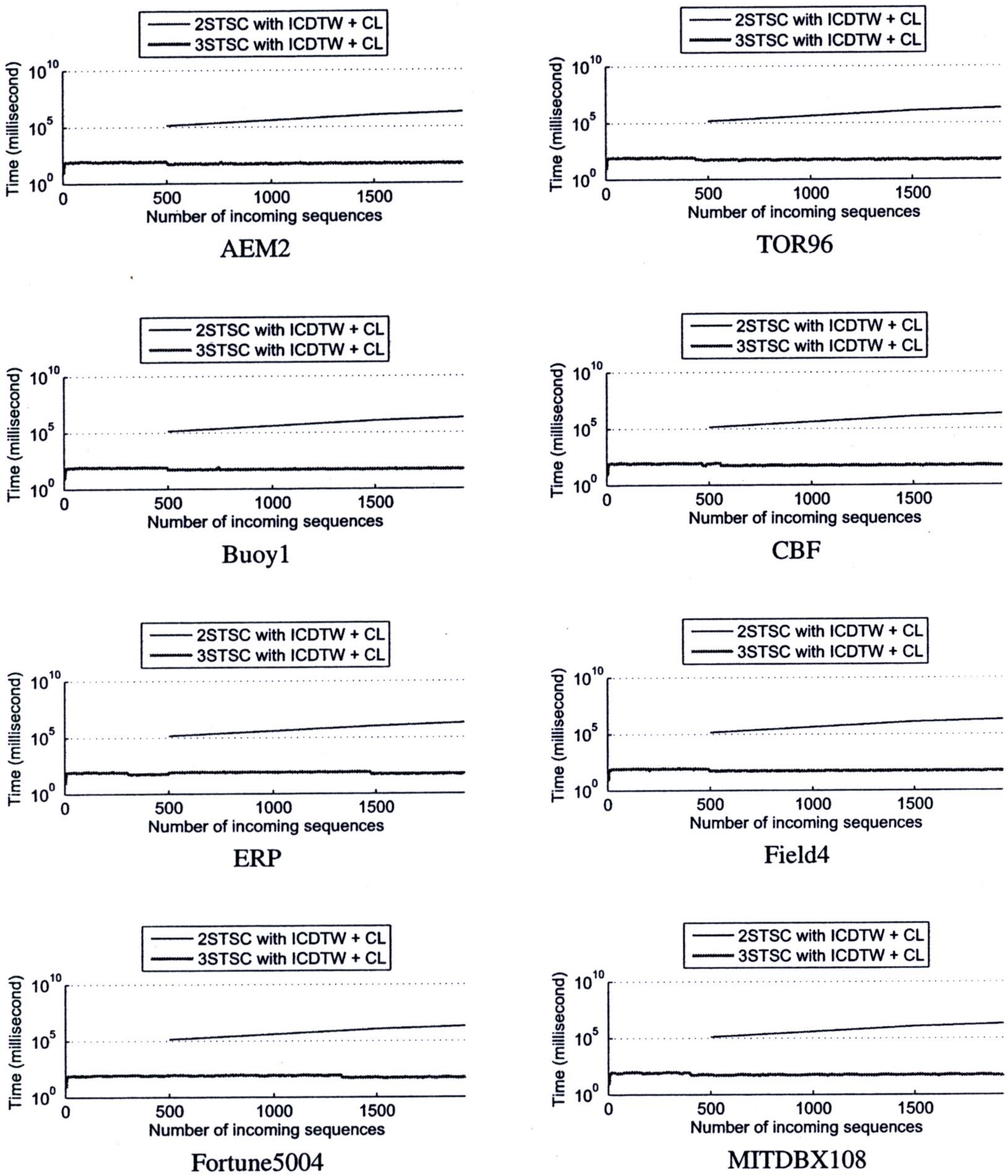
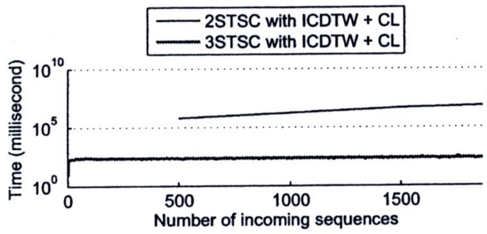
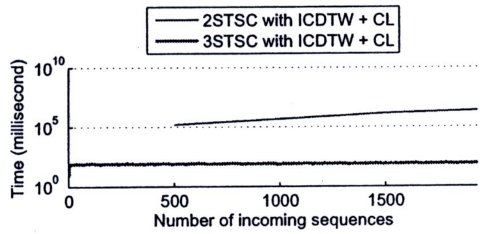


Figure G.14: Computational time of 3STSC and 2STSC with CDTW function and complete linkage when a new incoming sequence arrives, where $k = 7$ and $w = 64$.



AEM2



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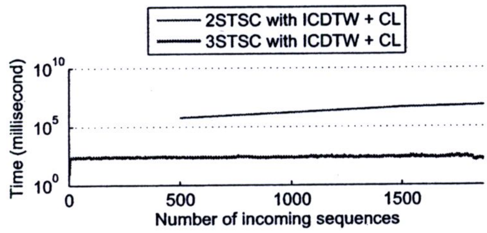
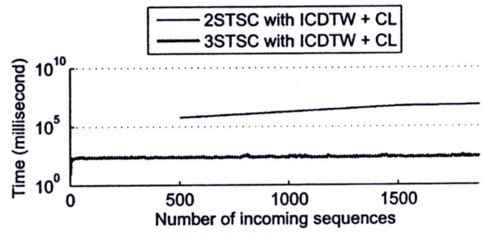
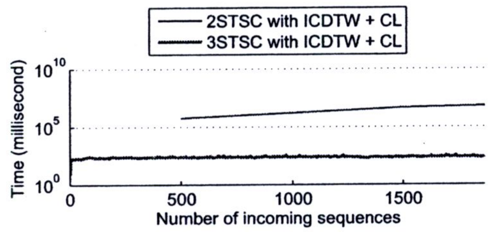


Buoy1



CBF



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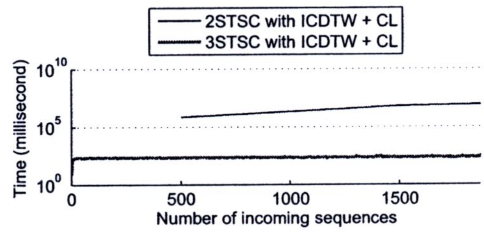
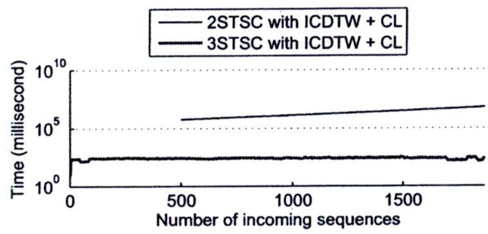
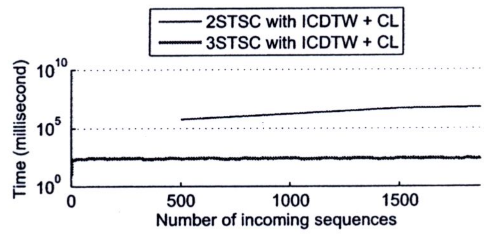


Field4



Fortune5004



MITDBX108

Figure G.15: Computational time of 3STSC and 2STSC with CDTW function and complete linkage when a new incoming sequence arrives, where $k = 3$ and $w = 128$.

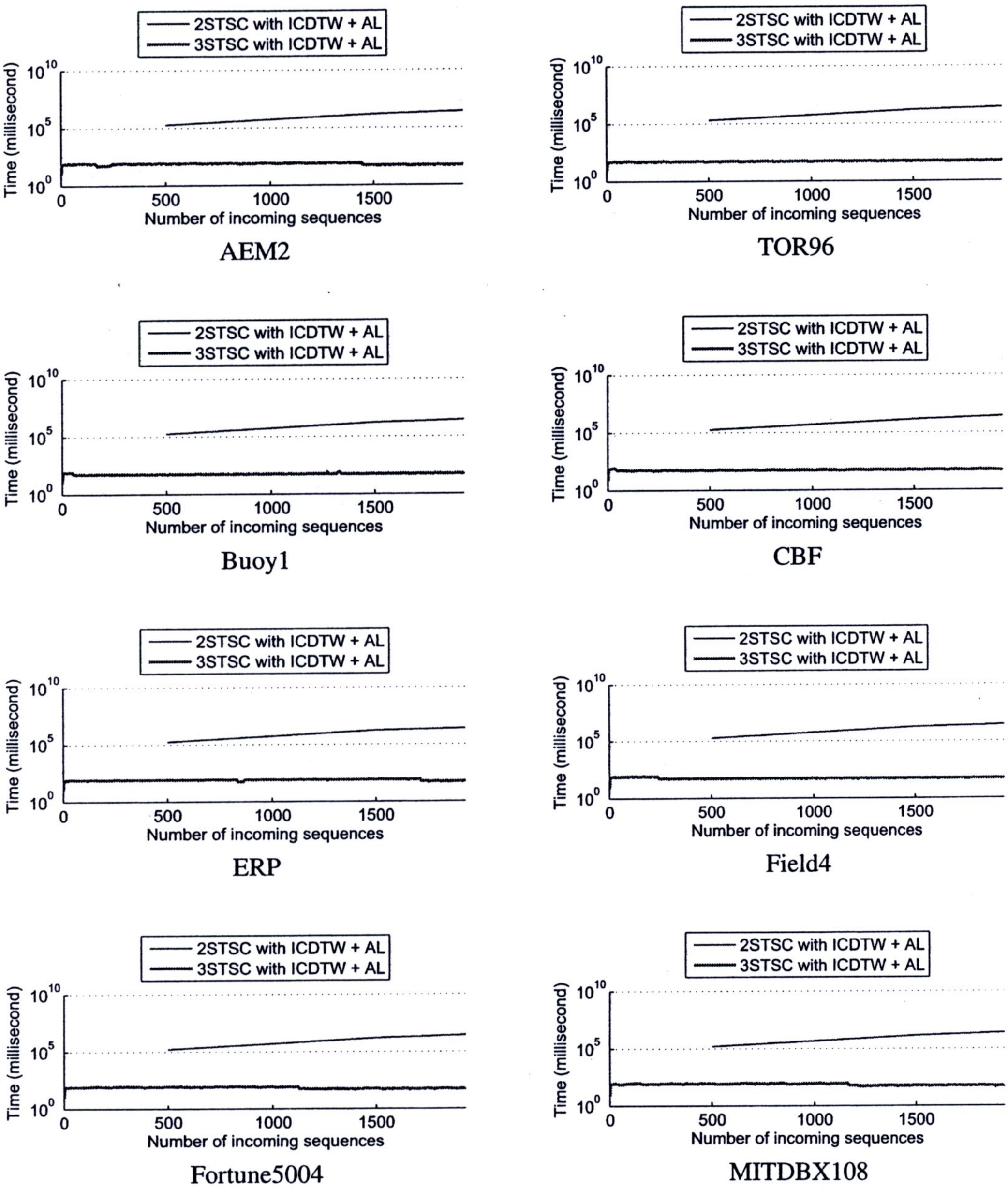
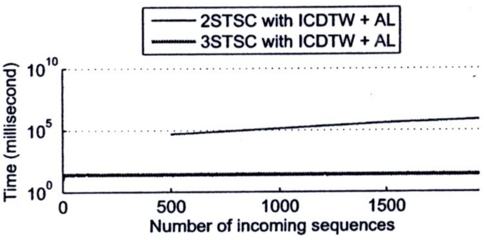
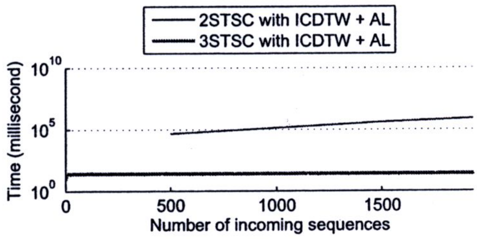


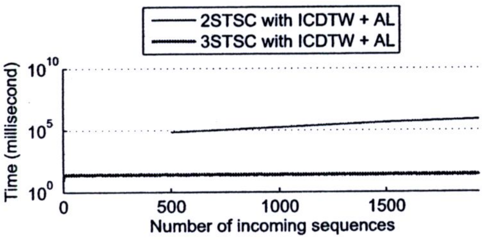
Figure G.16: Computational time of 3STSC and 2STSC with CDTW function and average linkage when a new incoming sequence arrives, where $k = 3$ and $w = 64$



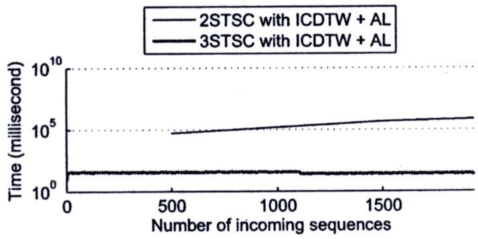
AEM2



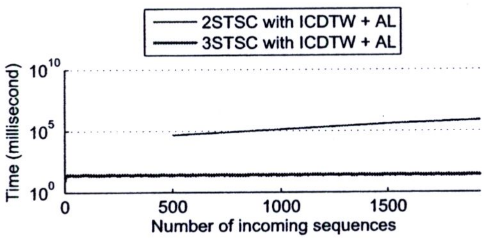
TOR96



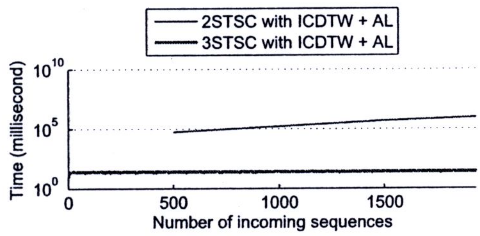
Buoy1



CBF



ERP



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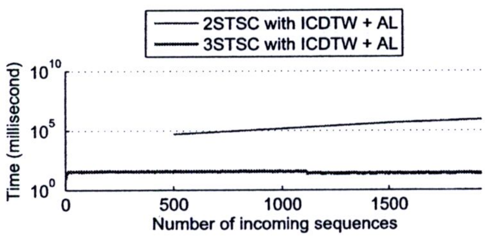
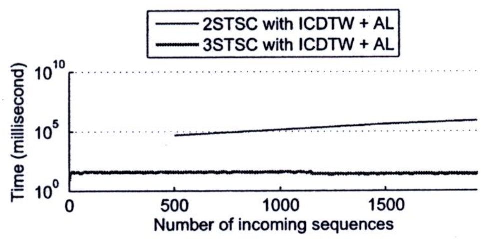


Fortune5004



MITDBX108

Figure G.17: Computational time of 3STSC and 2STSC with CDTW function and average linkage when a new incoming sequence arrives, where $k = 3$ and $w = 32$.

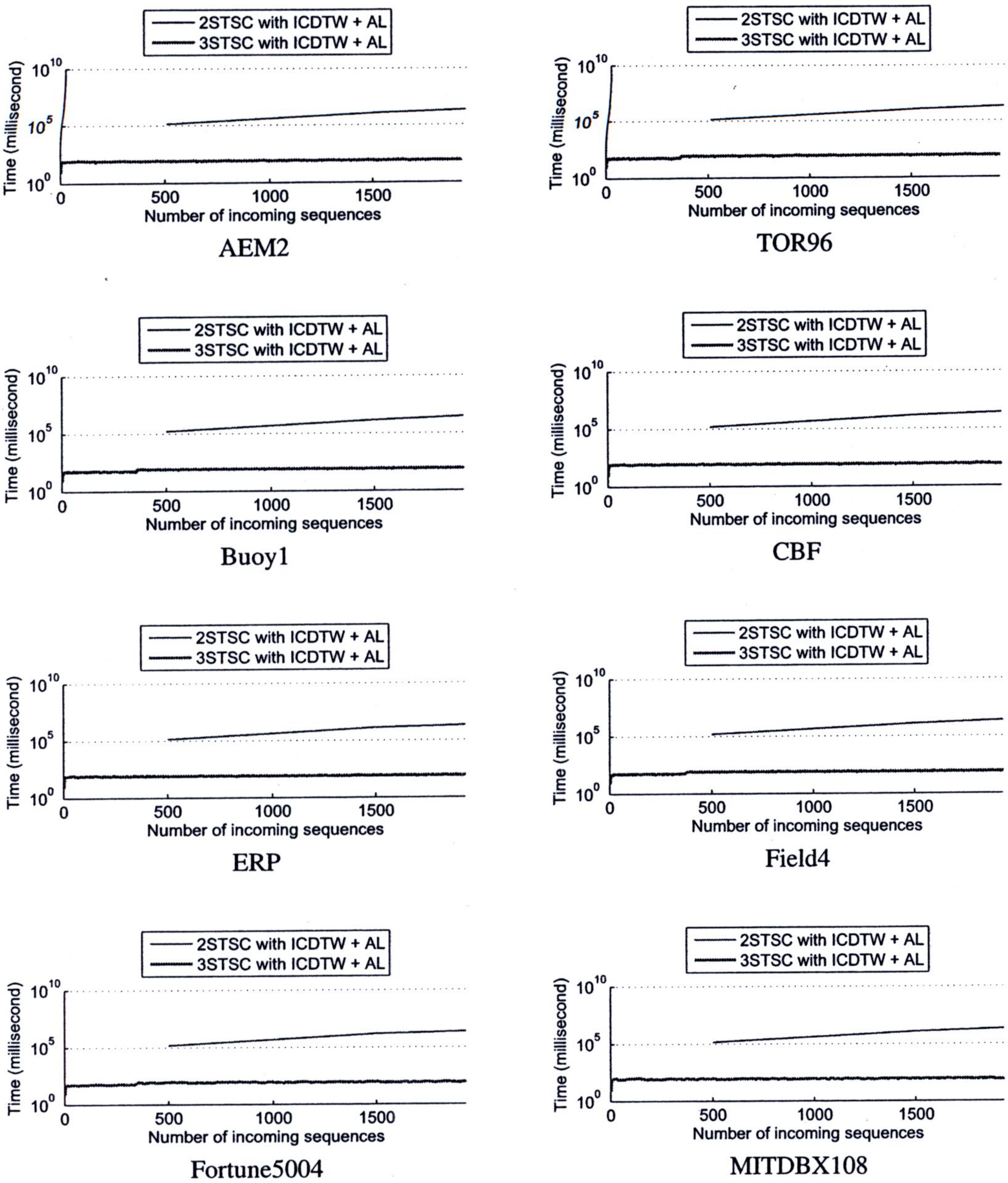


Figure G.18: Computational time of 3STSC and 2STSC with CDTW function and average linkage when a new incoming sequence arrives, where $k = 5$ and $w = 64$.

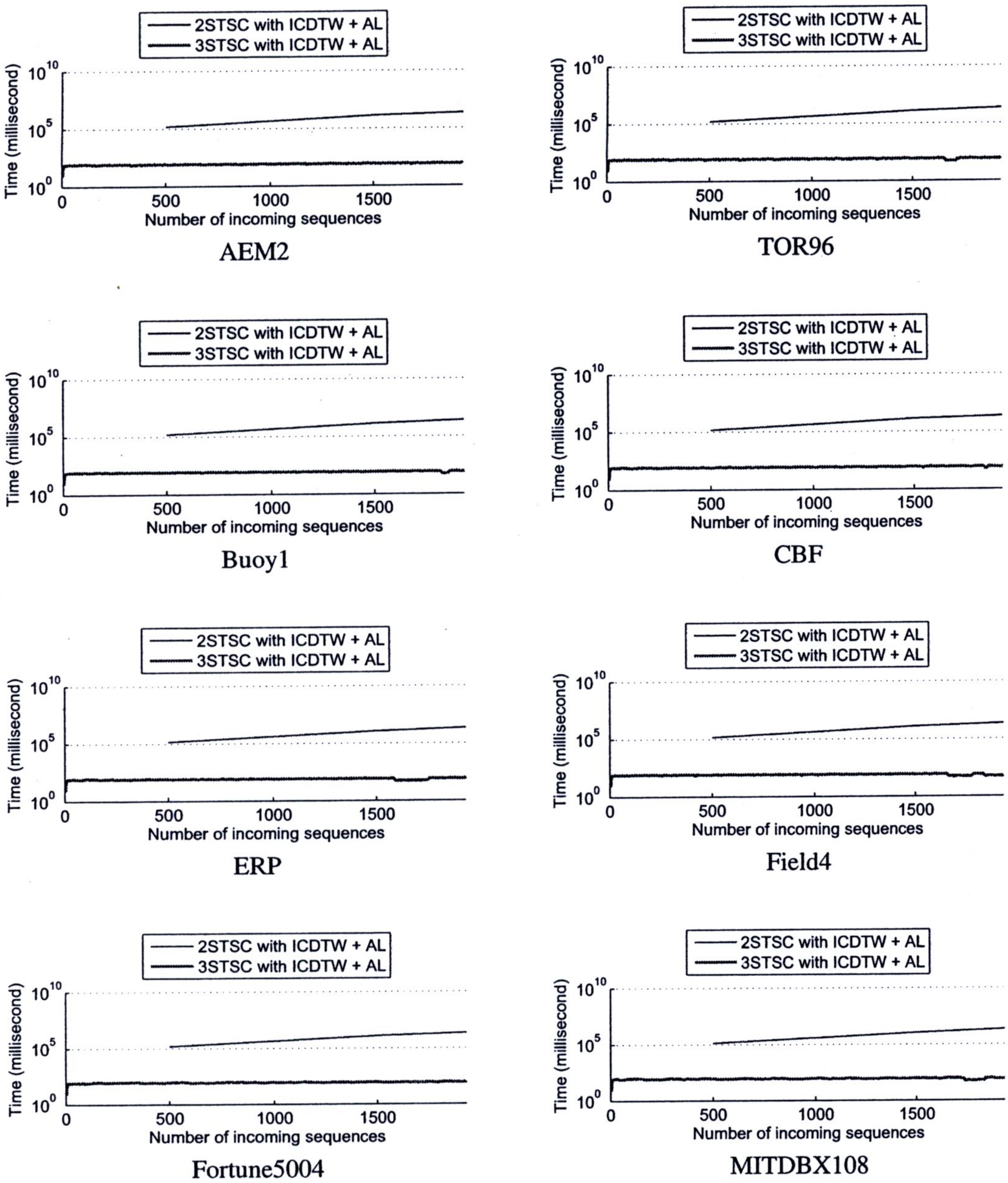
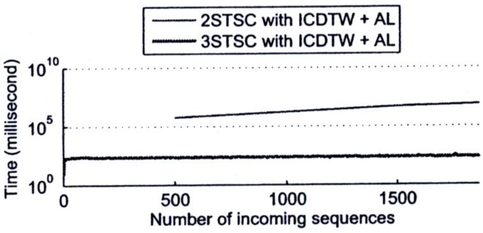
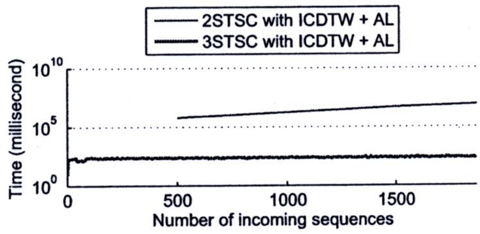


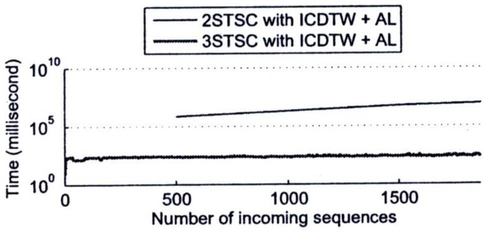
Figure G.19: Computational time of 3STSC and 2STSC with CDTW function and average linkage when a new incoming sequence arrives, where $k = 7$ and $w = 64$.



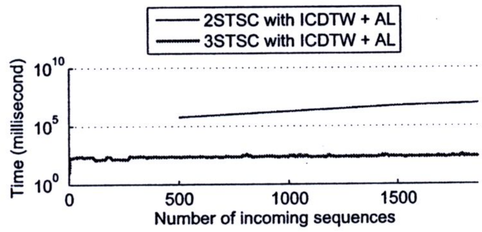
AEM2



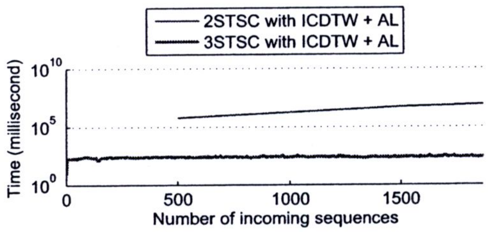
TOR96



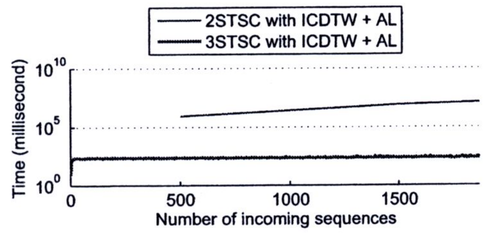
Buoy1



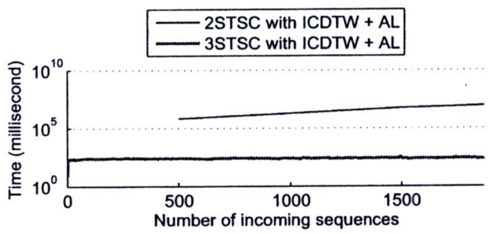
CBF



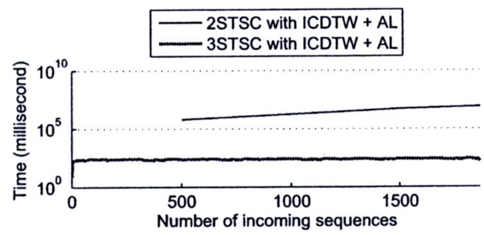
ERP



Field4



Fortune5004



MITDBX108

Figure G.20: Computational time of 3STSC and 2STSC with CDTW function and average linkage when a new incoming sequence arrives, where $k = 3$ and $w = 128$.

APPENDIX H

COMPLETE EXPERIMENTAL RESULTS OF THE SECOND EXPERIMENT IN CHAPTER VI

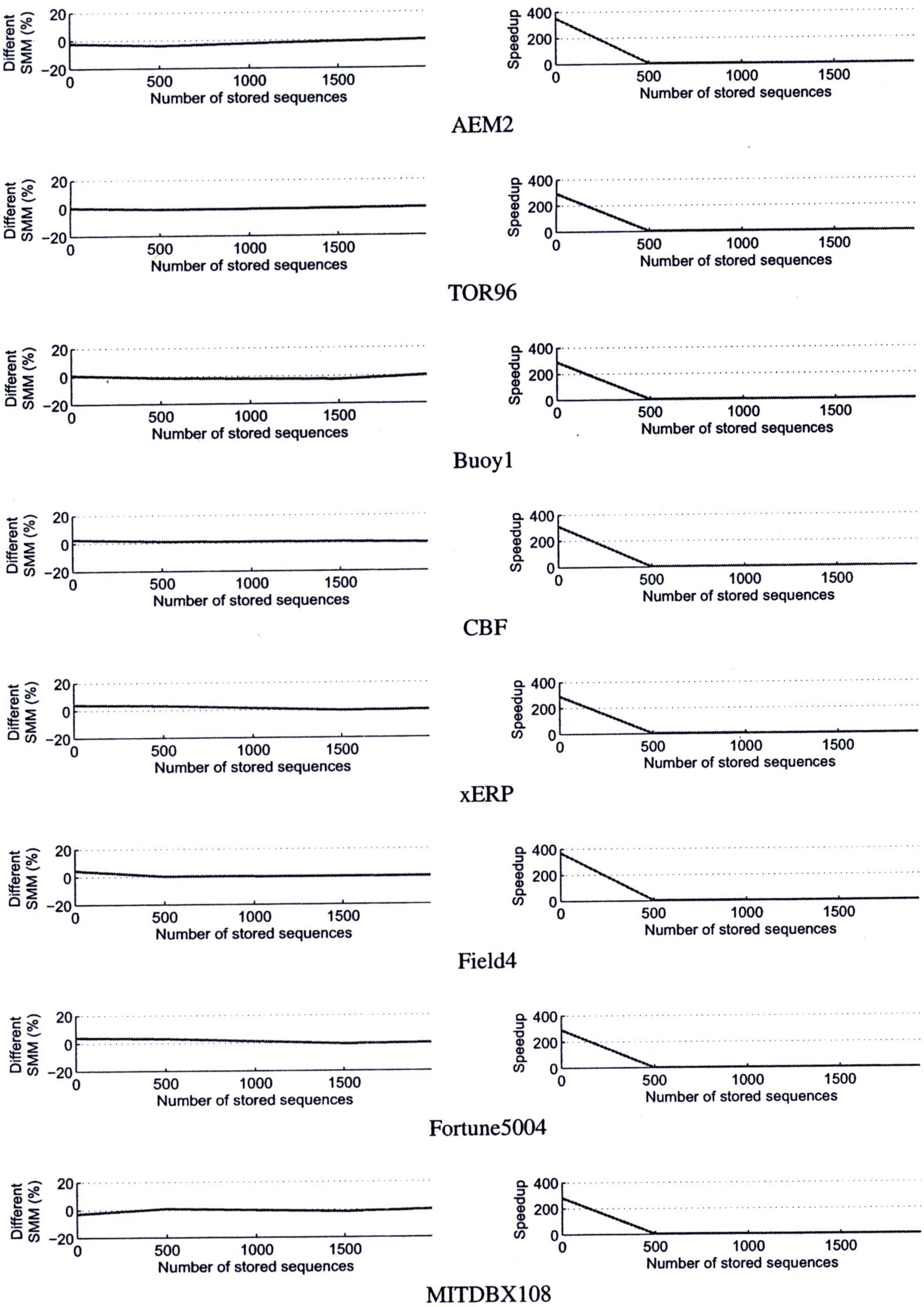


Figure H.1: Percentage difference of SMM and speedup of 3STSC with CDTW function and complete linkage when $k = 3$, $w = 64$, and number of stored sequences are varied.

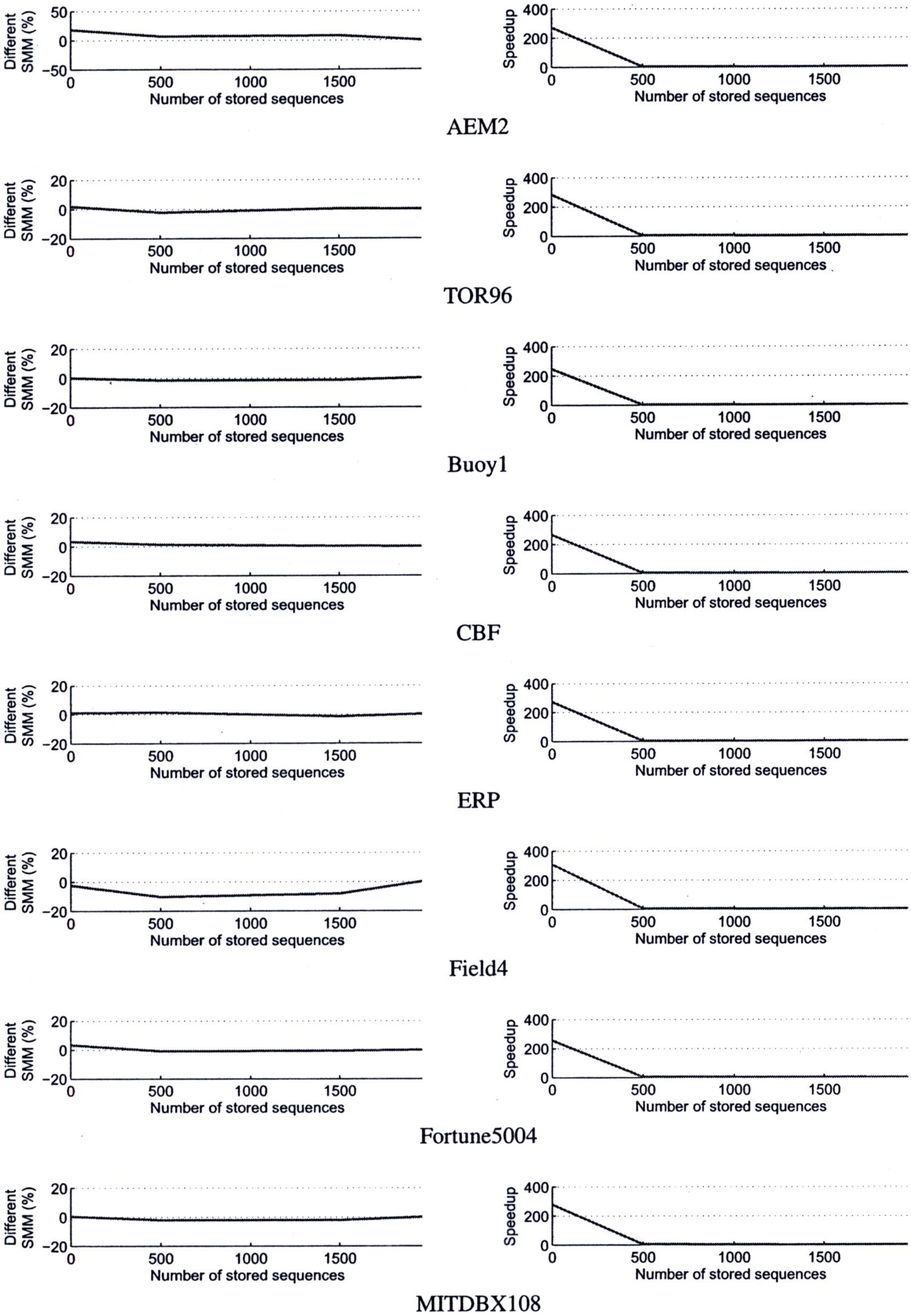


Figure H.2: Percentage difference of SMM and speedup of 3STSC with CDTW function and complete linkage when $k = 3$, $w = 32$, and number of stored sequences are varied.

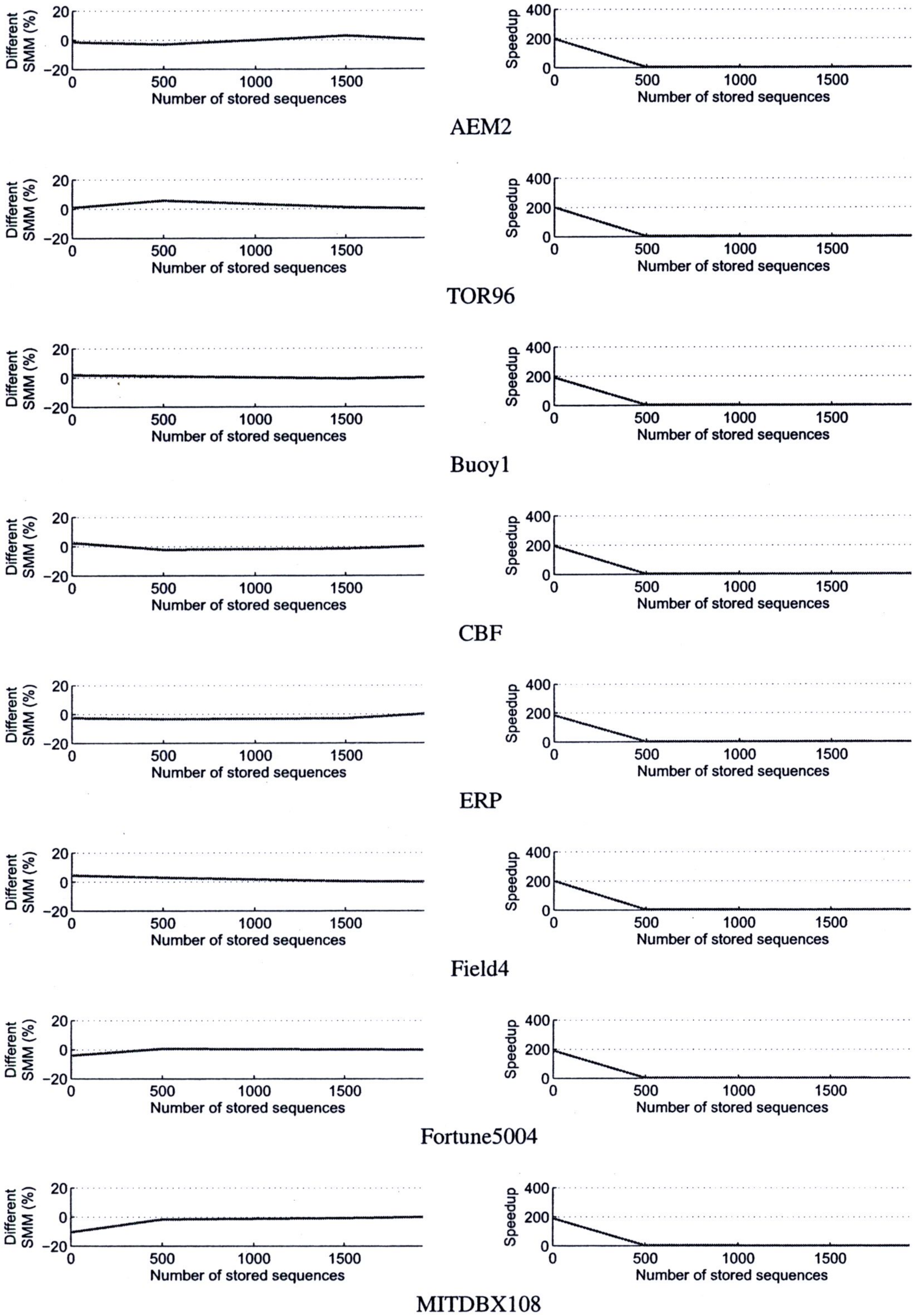


Figure H.3: Percentage difference of SMM and speedup of 3STSC with CDTW function and complete linkage when $k = 5$, $w = 64$, and number of stored sequences are varied.

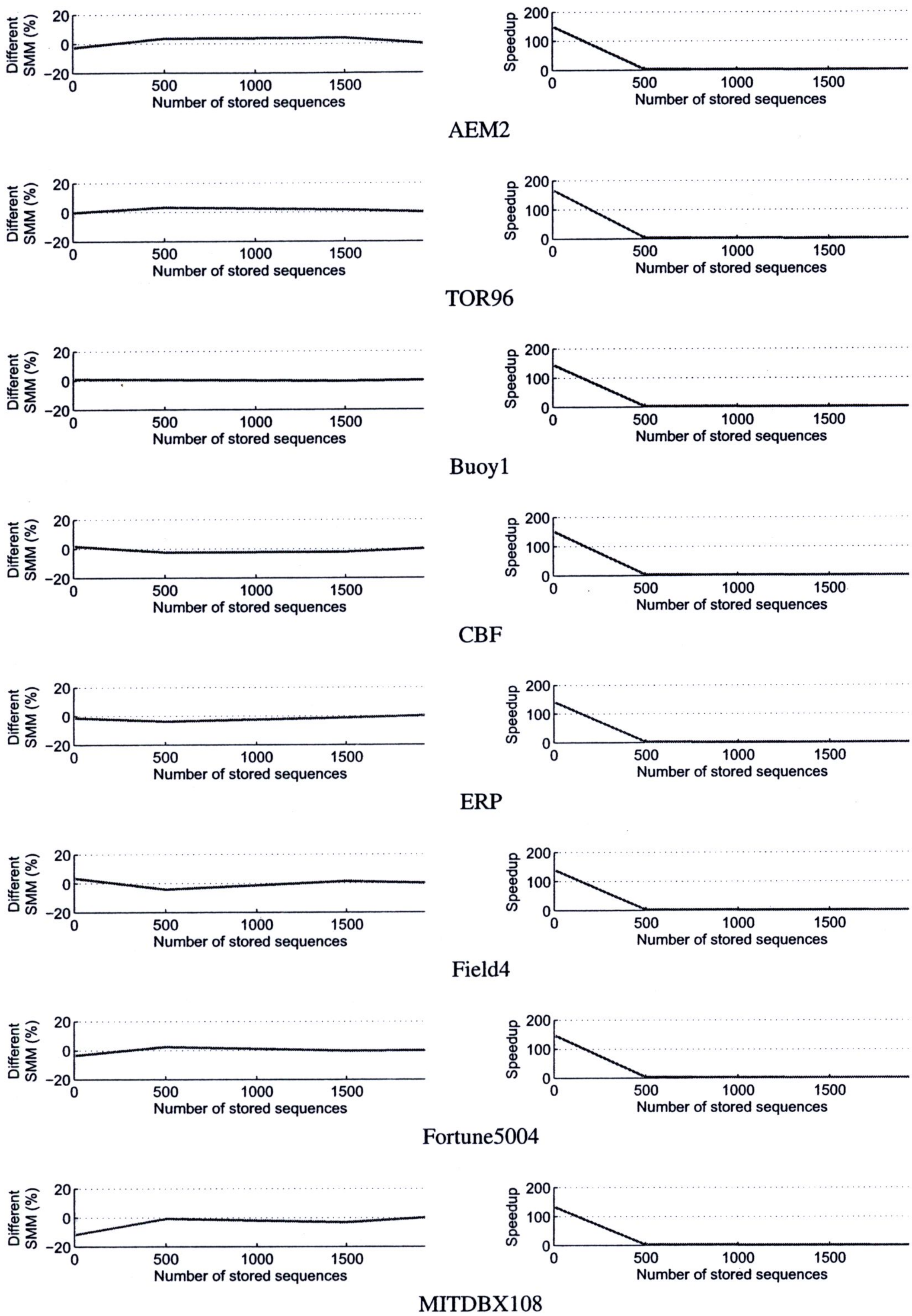
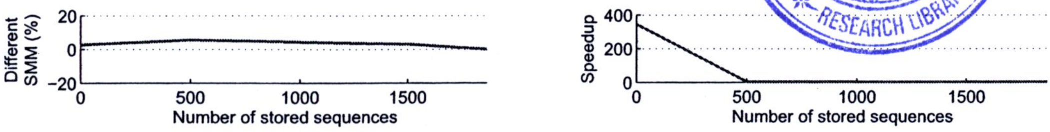
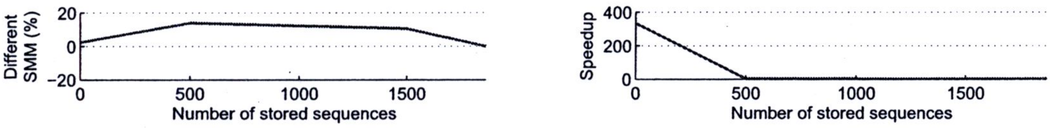


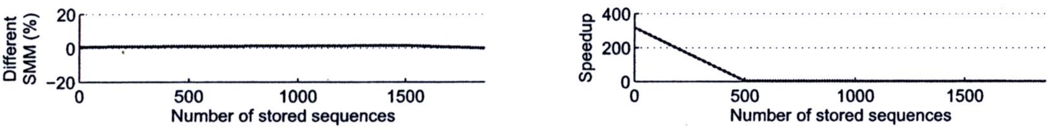
Figure H.4: Percentage difference of SMM and speedup of 3STSC with CDTW function and complete linkage when $k = 7$, $w = 64$, and number of stored sequences are varied.



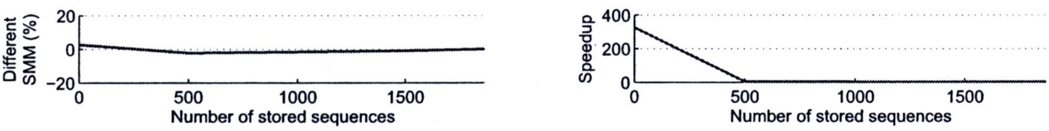
AEM2



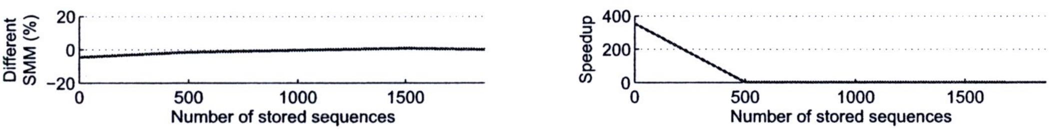
TOR96



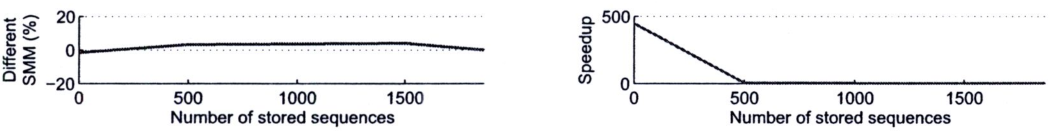
Buoy1



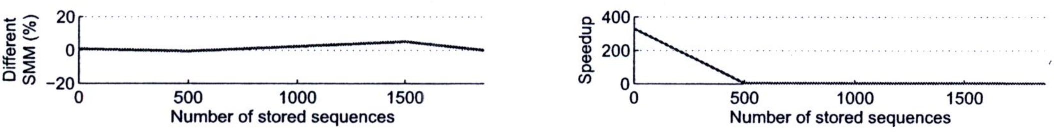
CBF



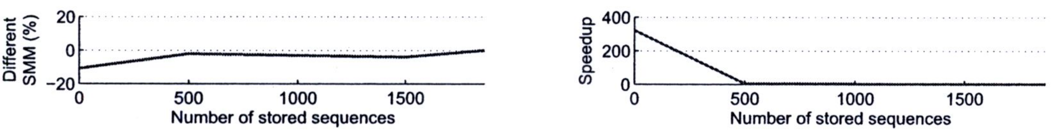
ERP



Field4

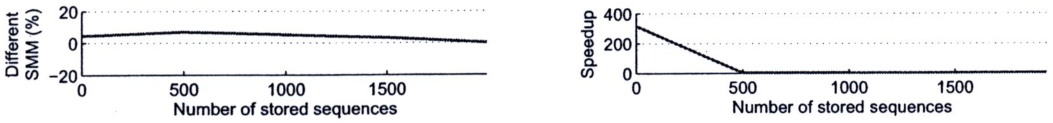


Fortune5004

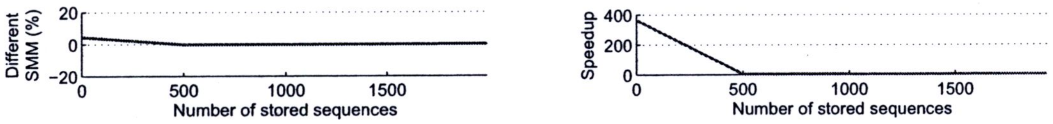


MITDBX108

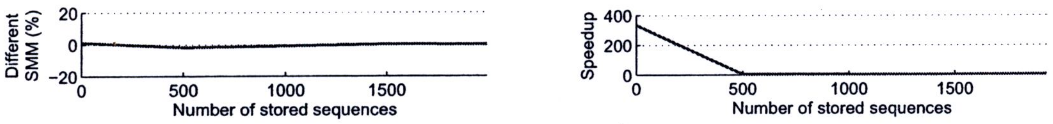
Figure H.5: Percentage difference of SMM and speedup of 3STSC with CDTW function and complete linkage when $k = 3$, $w = 128$, and number of stored sequences are varied.



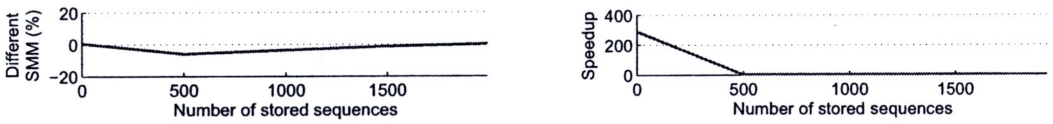
AEM2



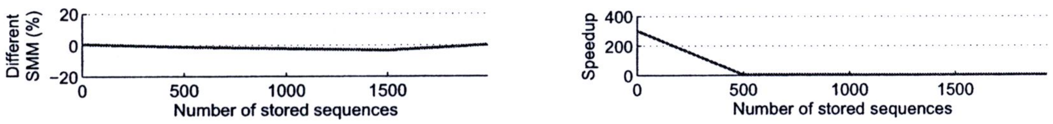
TOR96



Buoy1

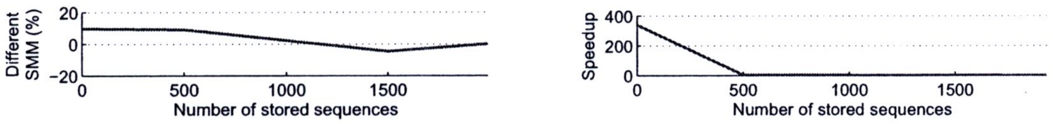


CBF

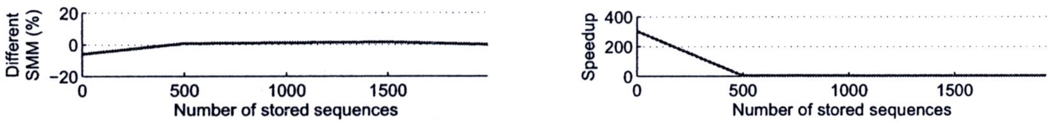


ERP

Field4



Fortune5004



MITDBX108

Figure H.6: Percentage difference of SMM and speedup of 3STSC with CDTW function and average linkage when $k = 3$, $w = 64$, and number of stored sequences are varied.

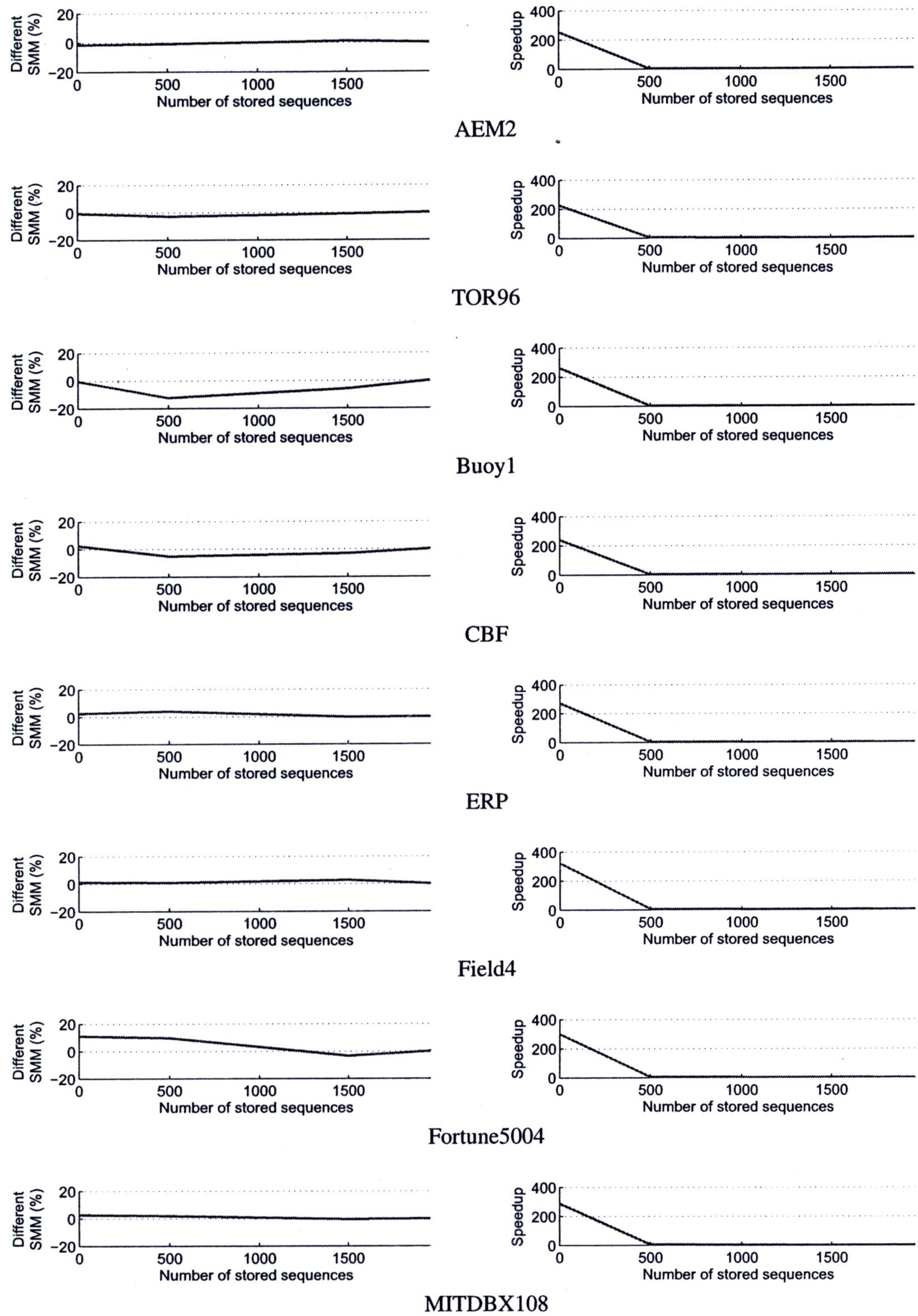


Figure H.7: Percentage difference of SMM and speedup of 3STSC with CDTW function and average linkage when $k = 3$, $w = 64$, and number of stored sequences are varied.

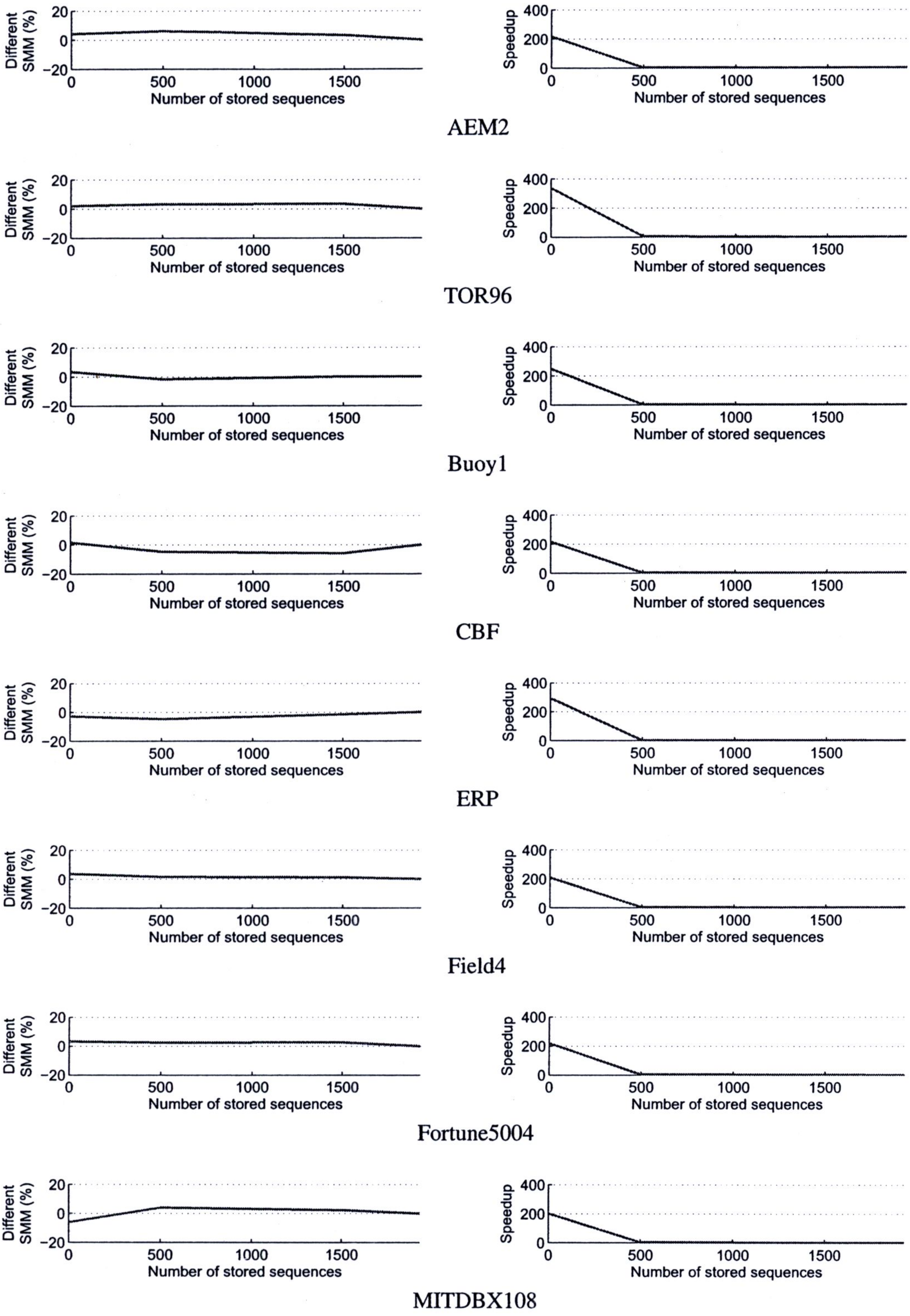


Figure H.8: Percentage difference of SMM and speedup of 3STSC with CDTW function and average linkage when $k = 5$, $w = 64$, and number of stored sequences are varied.

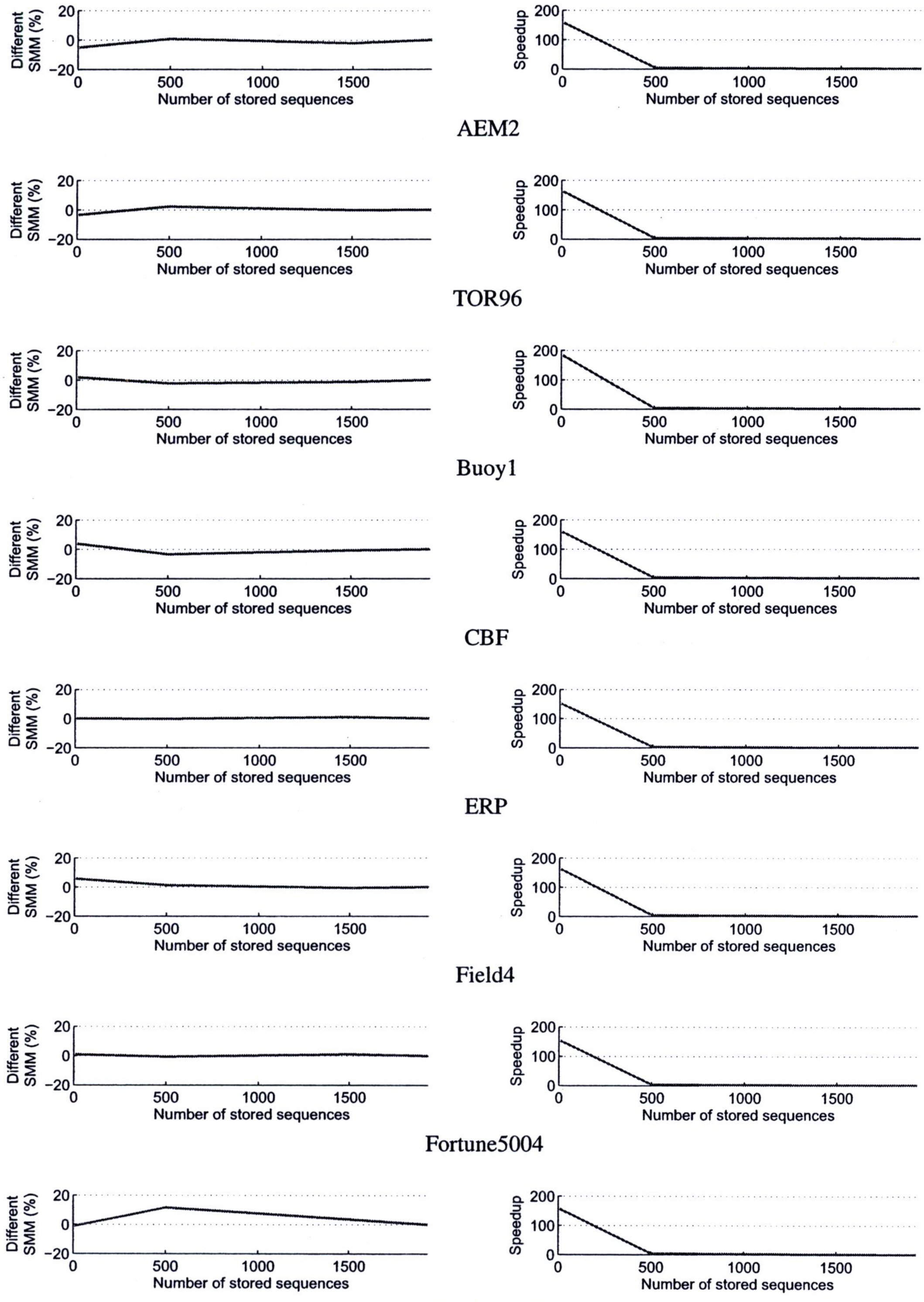


Figure H.9: Percentage difference of SMM and speedup of 3STSC with CDTW function and average linkage when $k = 7$, $w = 64$, and number of stored sequences are varied.

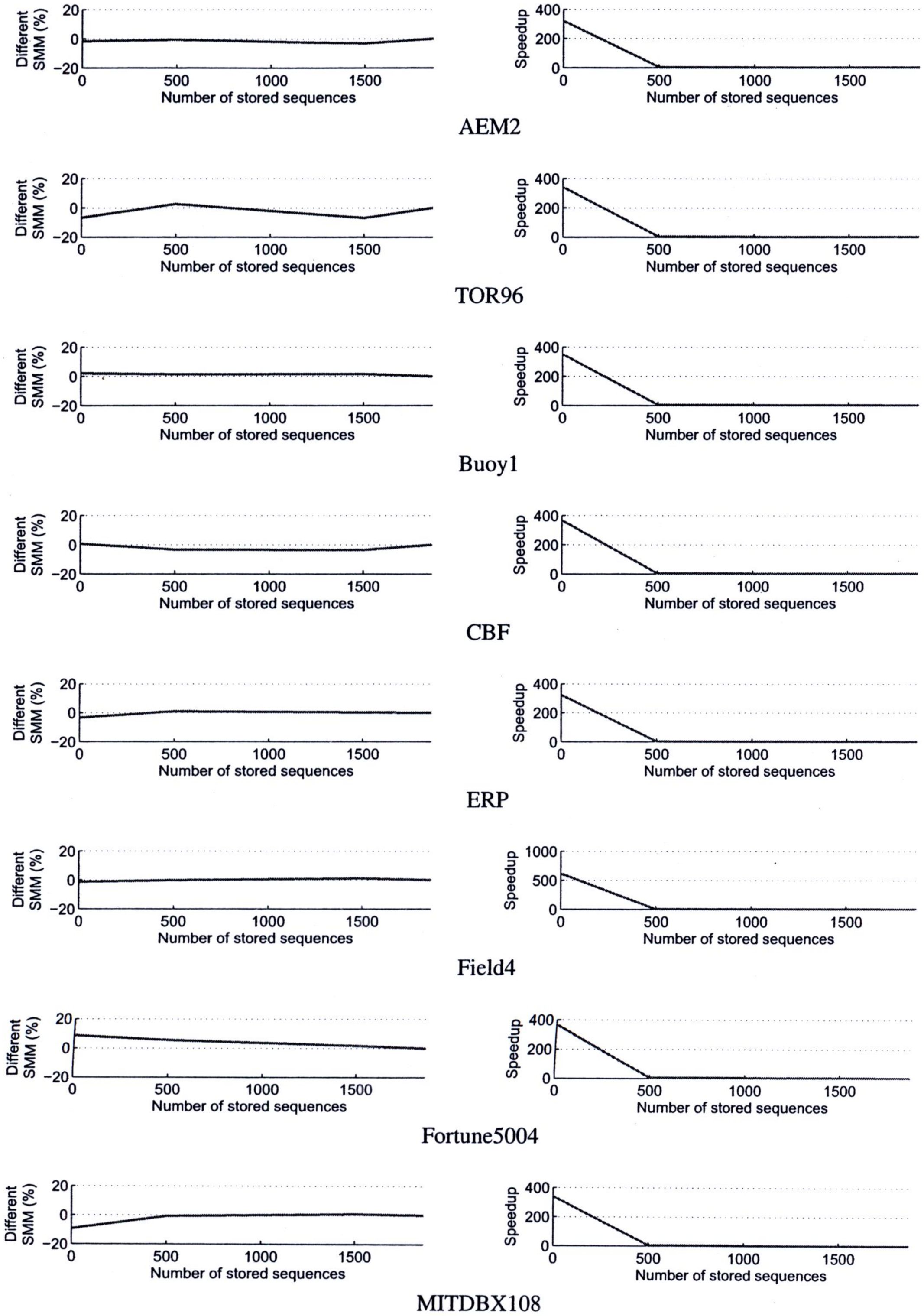
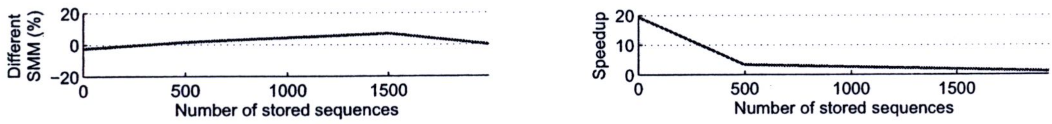
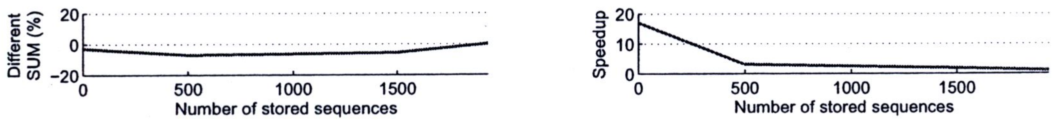


Figure H.10: Percentage difference of SMM and speedup of 3STSC with CDTW function and average linkage when $k = 3$, $w = 128$, and number of stored sequences are varied.



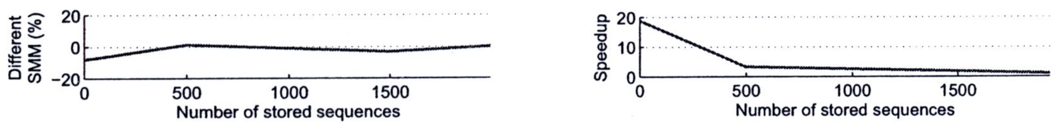
AEM2



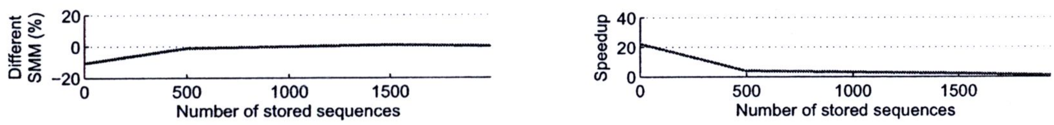
TOR96

Buoy1

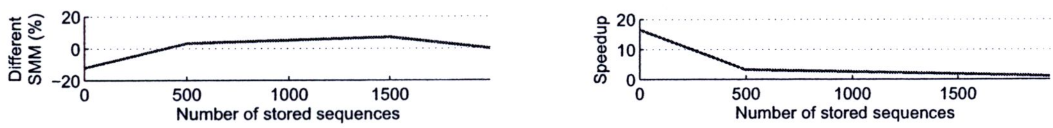
CBF



ERP



Field4



Fortune5004

MITDBX108

Figure H.11: Percentage difference of SMM and speedup of 3STSC with ICDTW function and complete linkage when $k = 3$, $w = 64$, and number of stored sequences are varied.

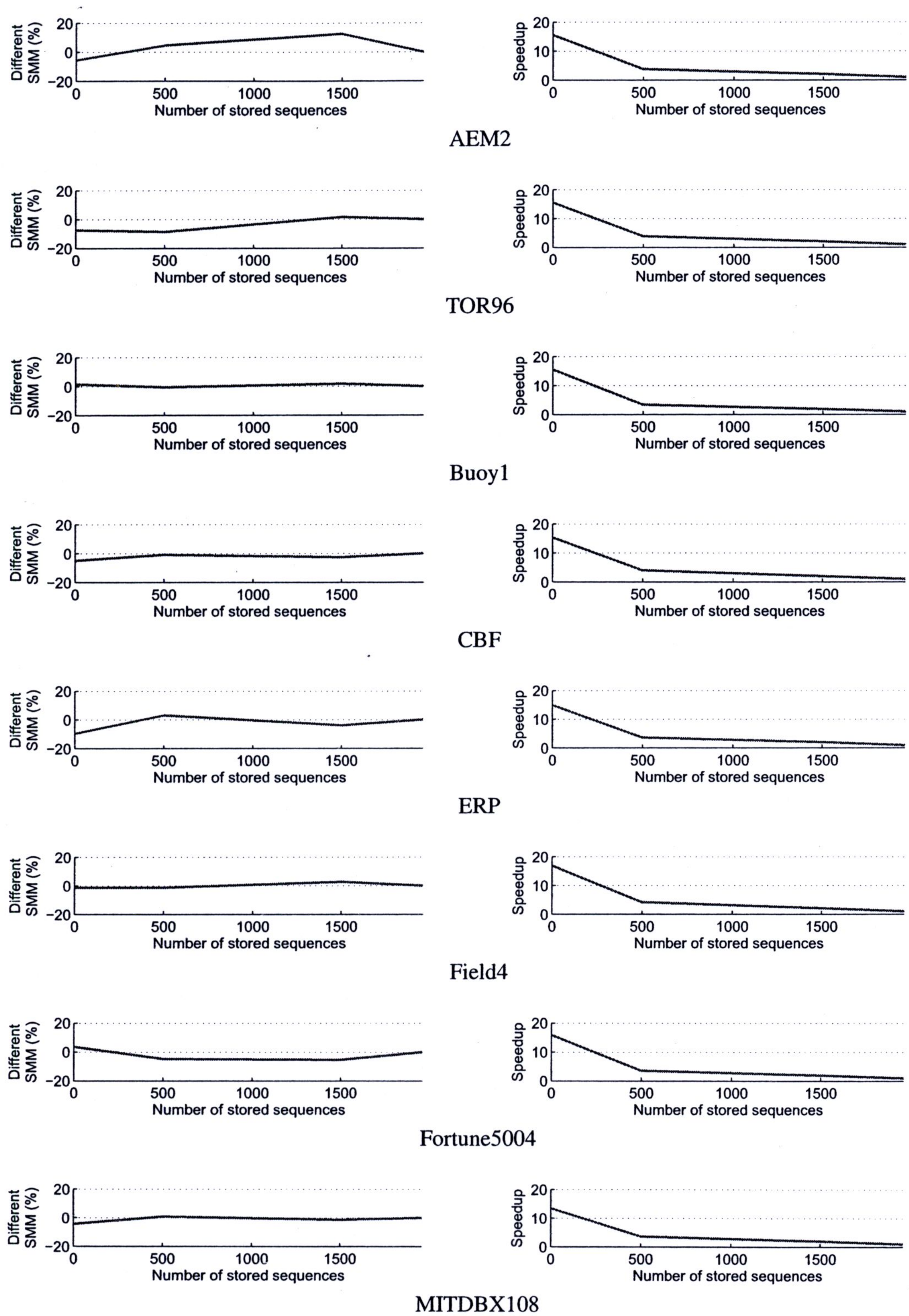


Figure H.12: Percentage difference of SMM and speedup of 3STSC with ICDTW function and complete linkage when $k = 3$, $w = 32$, and number of stored sequences are varied.

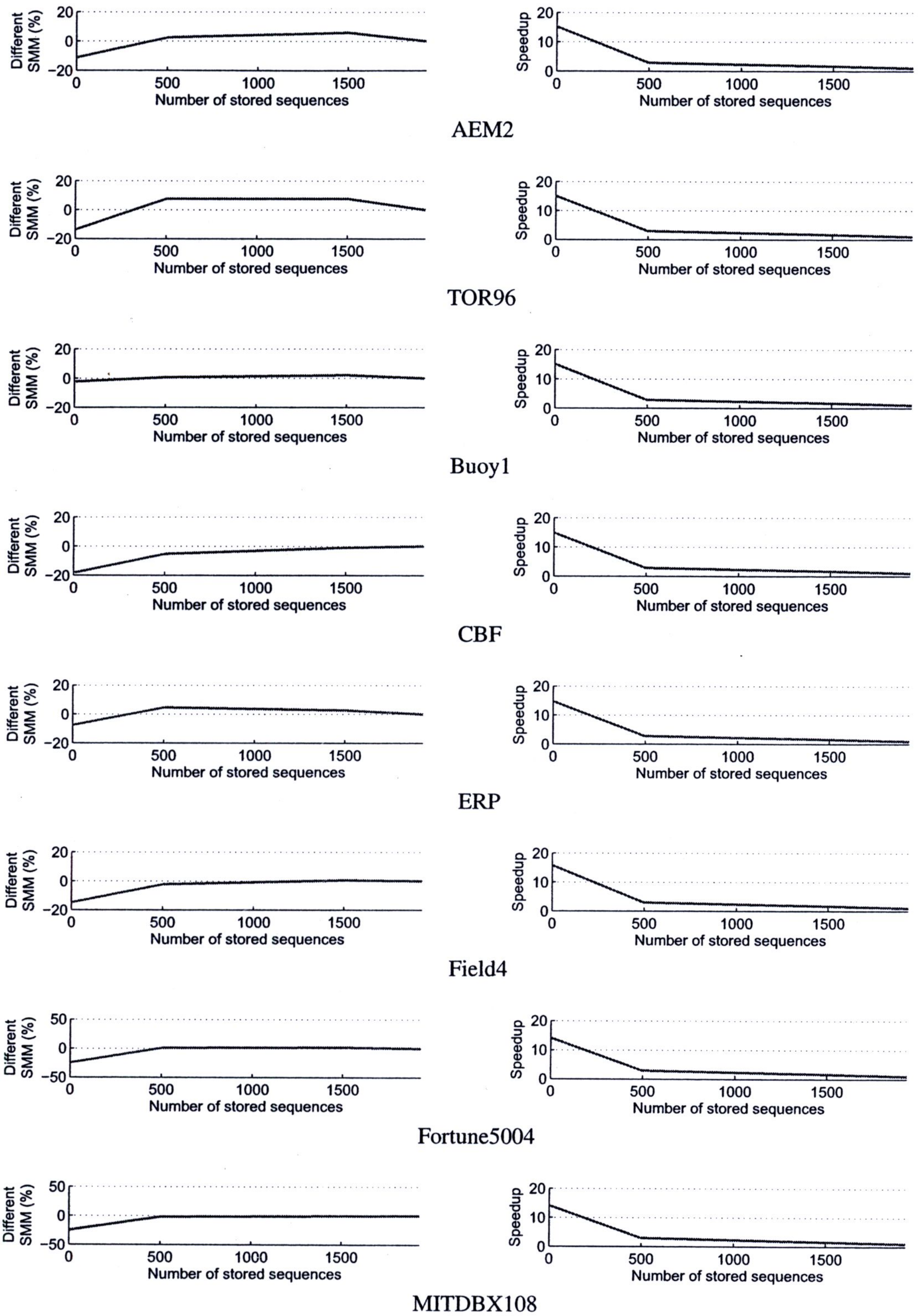
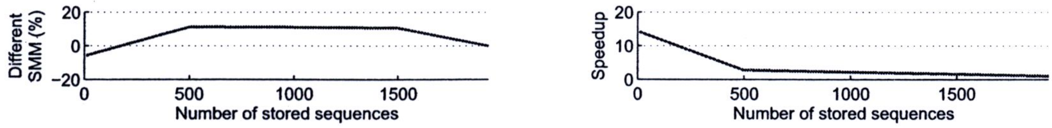


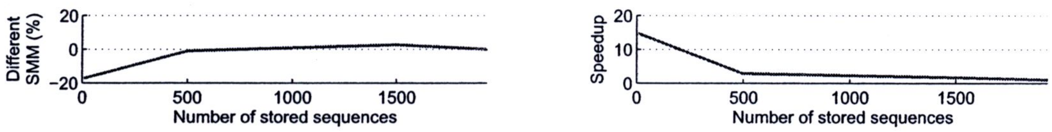
Figure H.13: Percentage difference of SMM and speedup of 3STSC with ICDTW function and complete linkage when $k = 5$, $w = 64$, and number of stored sequences are varied.



AEM2

TOR96

Buoy1

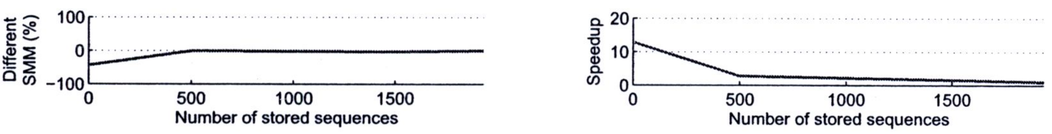


CBF

ERP

Field4

Fortune5004



MITDBX108

Figure H.14: Percentage difference of SMM and speedup of 3STSC with ICDTW function and complete linkage when $k = 7$, $w = 64$, and number of stored sequences are varied.

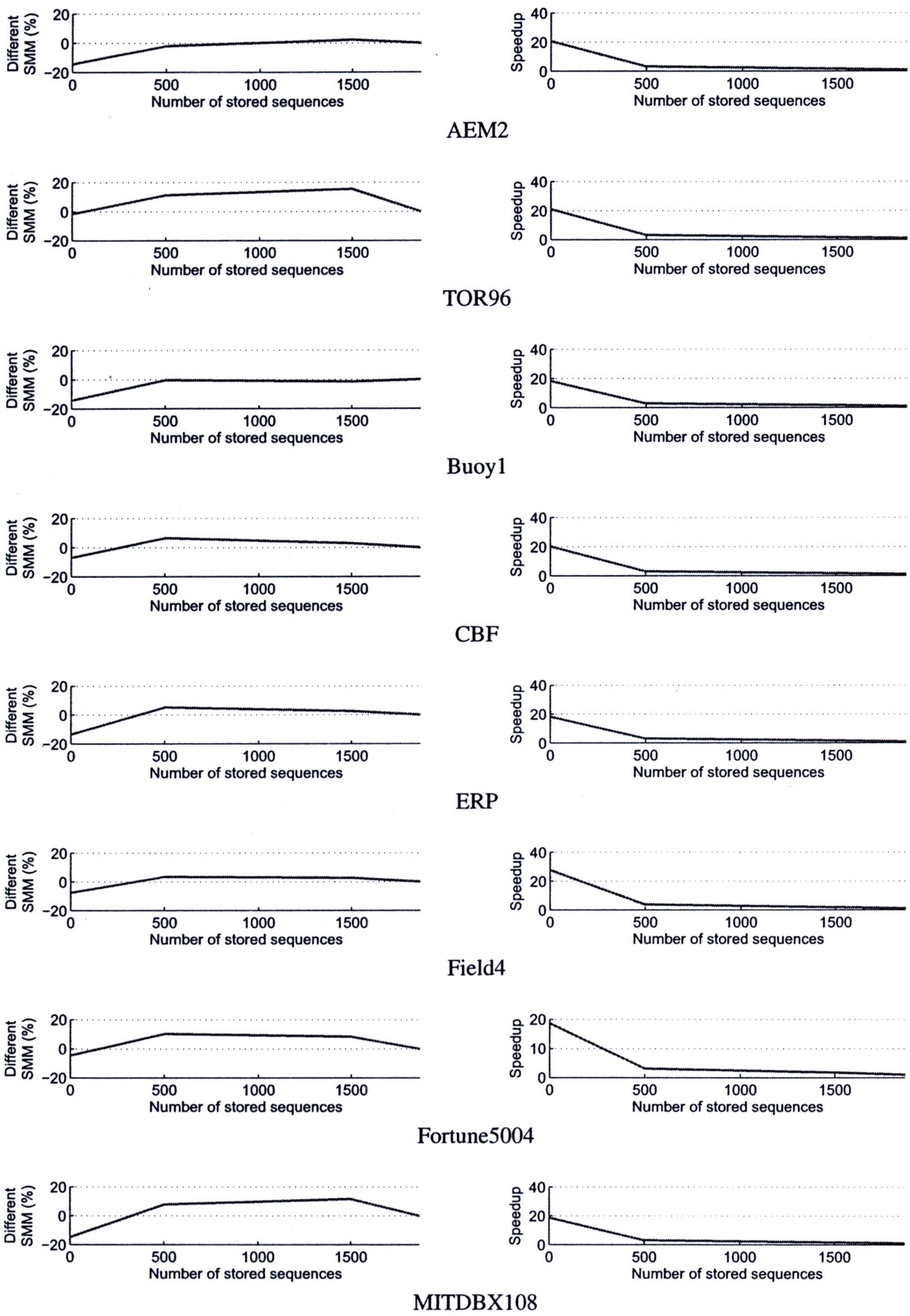


Figure H.15: Percentage difference of SMM and speedup of 3STSC with ICDTW function and complete linkage when $k = 3$, $w = 128$, and number of stored sequences are varied.

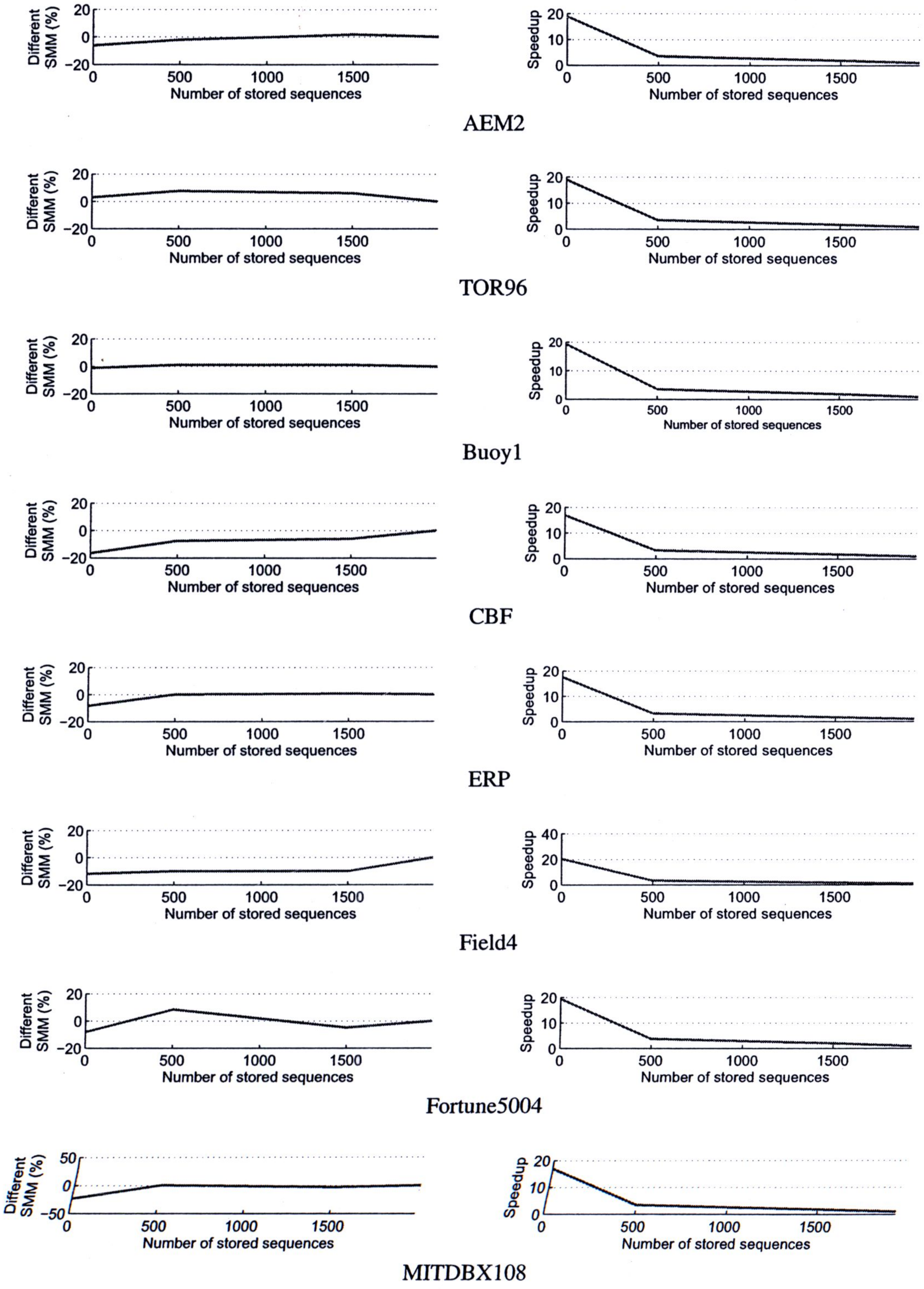


Figure H.16: Percentage difference of SMM and speedup of 3STSC with ICDTW function and average linkage when $k = 3$, $w = 64$, and number of stored sequences are varied.

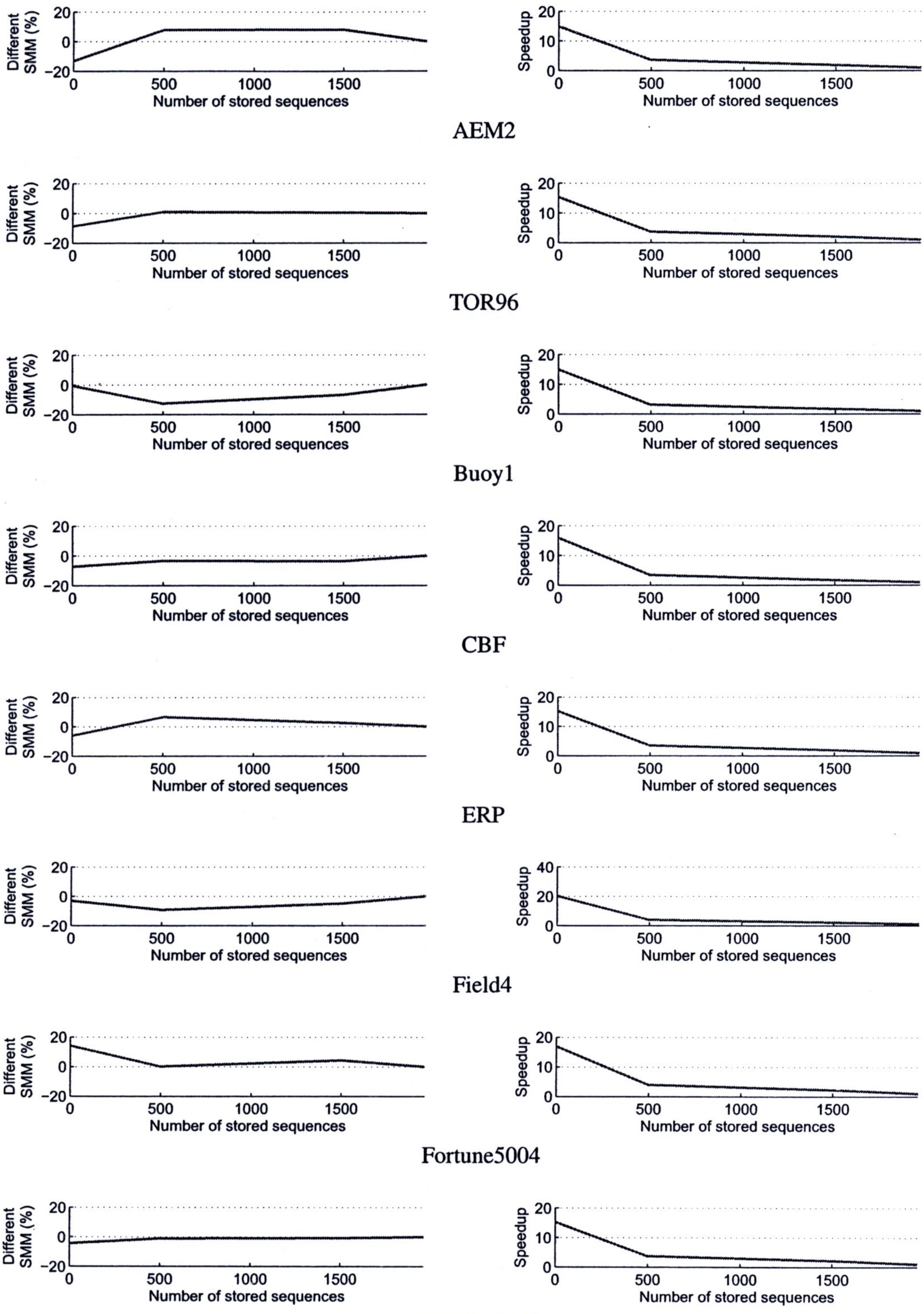
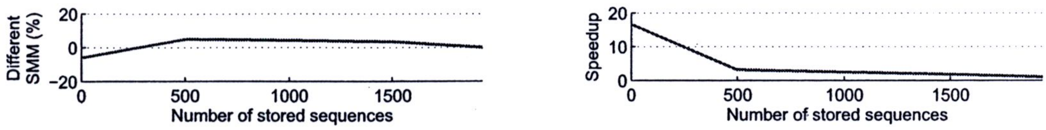
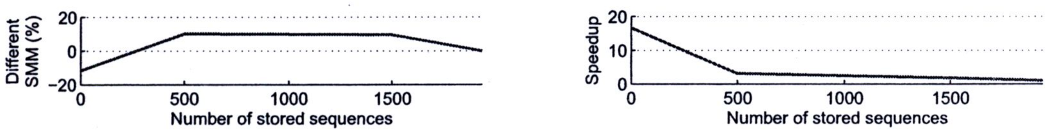


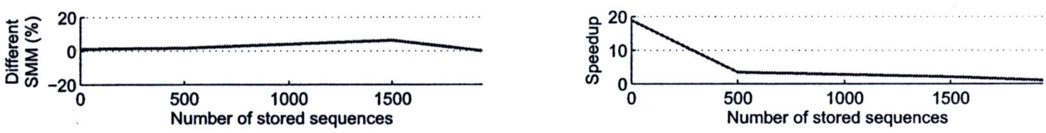
Figure H.17: Percentage difference of SMM and speedup of 3STSC with ICDTW function and average linkage when $k = 3$, $w = 32$, and number of stored sequences are varied.



AEM2

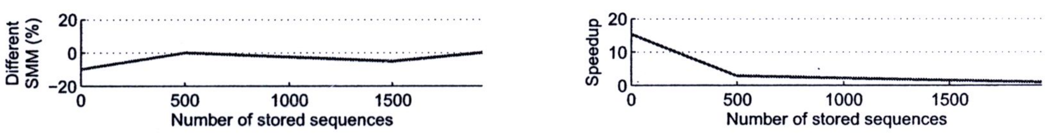


TOR96



Buoy1

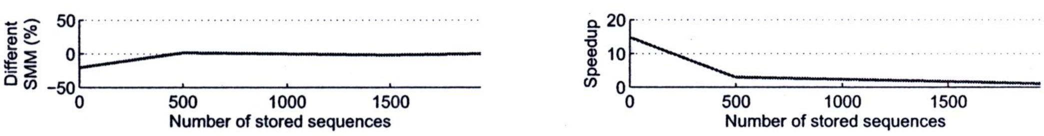
CBF



ERP

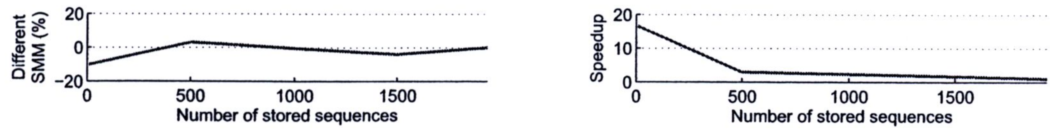
Field4

Fortune5004

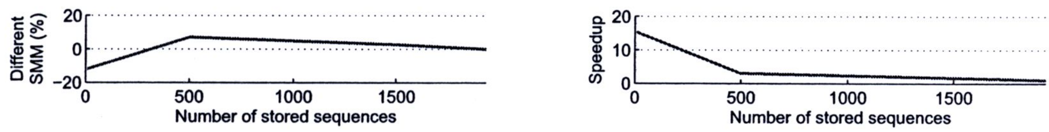


MITDBX108

Figure H.18: Percentage difference of SMM and speedup of 3STSC with ICDTW function and average linkage when $k = 3$, $w = 64$, and number of stored sequences are varied.



AEM2



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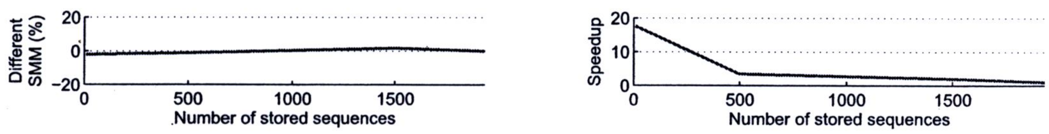
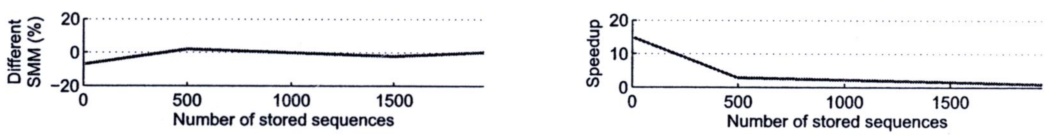
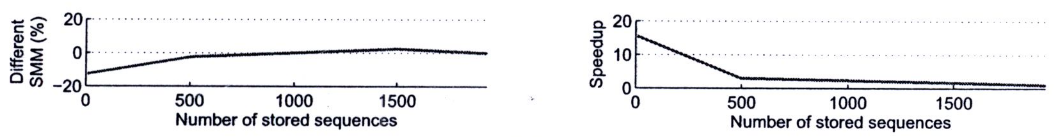


Buoy1

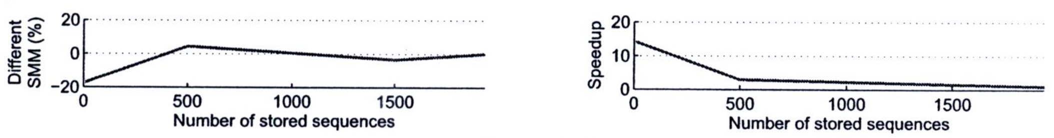
CBF



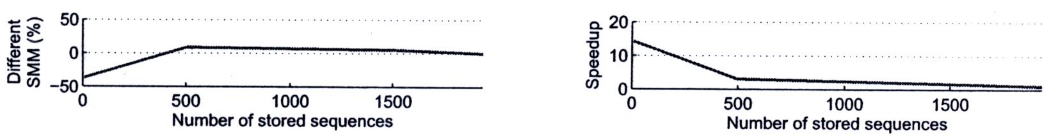
ERP



Field4



Fortune5004



MITDBX108

Figure H.19: Percentage difference of SMM and speedup of 3STSC with ICDTW function and average linkage when $k = 7$, $w = 64$, and number of stored sequences are varied.

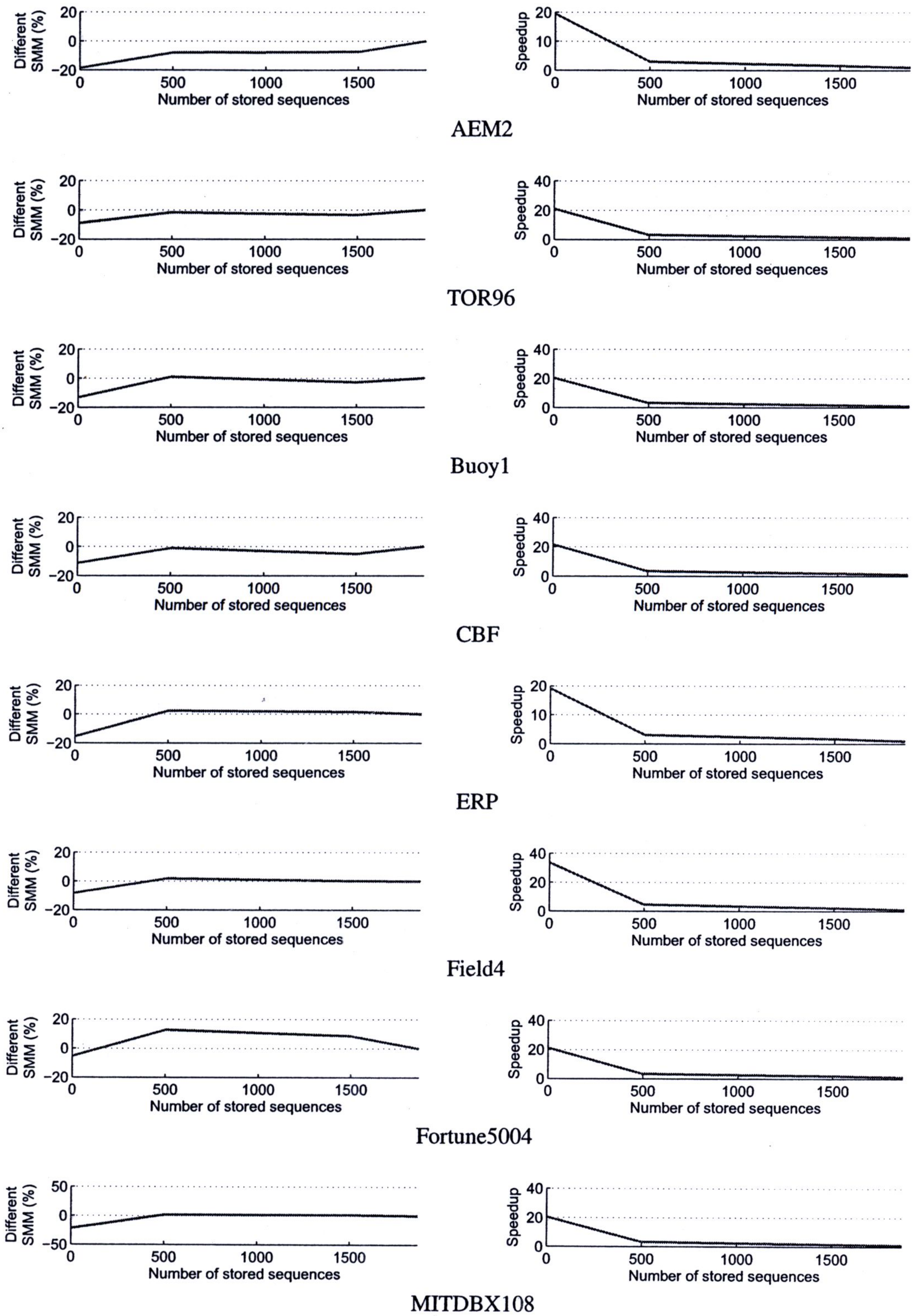


Figure H.20: Percentage difference of SMM and speedup of 3STSC with ICDTW function and average linkage when $k = 3$, $w = 128$, and number of stored sequences are varied.

Biography

Vit Niennattrakul was born in Bangkok, Thailand, on September 8, 1984. He received his B.Eng. in Computer Engineering from Chulalongkorn University in 2006. His doctorate has been under supervision of Asst. Prof. Dr. Chotirat Ann Ratanamahatana. During his Ph.D. study, he was a junior specialist at the University of California, Riverside under supervision of Prof. Eamonn J. Keogh for one year (September 2009 to August 2010), and he was granted scholarships from the Thailand Research Fund through the Royal Golden Jubilee Ph.D. Program (June 2007 to May 2011), Chulalongkorn University Graduate Scholarship to Commemorate the 72nd Anniversary of His Majesty King Bhumibol Adulyadej (June 2006 to May 2007), and the 90th Anniversary of Chulalongkorn University Fund (Ratchadaphiseksomphot Endowment Fund) (September 2009). He also was reviewers of many well-known journals including Knowledge and Information System (KAIS) and Data Mining and Knowledge Discovery (DMKD). His research interests include but not limited to time series data mining, machine learning, and natural language processing.