Efficient Temporal Kernels between Feature Sets for Time Series Classification *Supplementary material*

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1 Full results table

The performance in terms of classification error rate of the proposed method (K_{FS}) is given in Table 1, together with competing methods.

Dataset	BOSS [5]	DTD$_C$ [3]	LS [4]	TSBF[2]	BoW[1]	K_{FS}
Adiac *	0.235	0.299	0.478	0.230	0.248	**0.179**
ArrowHead *	0.166	0.280	**0.154**	0.246	0.194	0.246
Beef *	0.200	0.333	**0.133**	0.433	0.267	0.200
BeetleFly	0.100	0.350	0.200	0.200	0.100	**0.000**
BirdChicken	**0.050**	0.200	0.200	0.100	0.200	0.200
CBF *	0.002	0.020	0.009	0.012	**0.000**	**0.000**
Car *	0.167	0.217	0.233	0.217	0.083	**0.067**
ChlorineConcentration *	0.339	0.287	0.408	0.308	0.442	**0.135**
CinCECGtorso	0.113	0.148	0.130	0.288	0.180	**0.013**
Coffee *	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**
Computers	**0.244**	0.284	0.416	**0.244**	0.328	0.296
CricketX	0.264	0.246	0.259	0.295	0.236	**0.233**
CricketY	0.246	**0.226**	0.282	0.264	**0.226**	0.236
CricketZ	0.254	0.226	0.259	0.285	**0.203**	0.215
DiatomSizeReduction *	0.069	0.085	**0.020**	0.101	0.111	0.046
Distal[...]AgeGroup *	0.252	0.338	0.281	0.288	**0.147**	0.175
Distal[...]Correct *	0.272	0.275	0.221	0.217	**0.178**	0.180
DistalPhalanxTW	0.324	0.424	0.374	0.324	**0.210**	0.215
ECG200 *	0.130	0.160	0.120	0.160	**0.100**	**0.100**
ECG5000 *	0.059	0.076	0.068	0.060	**0.051**	0.060
ECGFiveDays *	**0.000**	0.178	**0.000**	0.123	**0.000**	0.055
Earthquakes *	0.252	0.295	0.259	0.252	0.202	**0.199**
ElectricDevices *	**0.201**	0.406	0.413	0.297	0.361	0.340
FaceAll *	0.218	**0.101**	0.251	0.256	0.226	0.198
FaceFour *	**0.000**	0.182	0.034	**0.000**	0.023	0.045
FacesUCR *	**0.043**	0.092	0.061	0.133	0.054	0.075

FiftyWords	0.295	0.246	0.270	0.242	0.266	**0.198**
Fish	**0.011**	0.074	0.040	0.166	0.023	0.023
FordA	0.070	0.235	**0.043**	0.150	0.085	0.070
FordB	0.289	0.347	0.083	0.401	0.111	**0.082**
GunPoint	**0.000**	0.013	**0.000**	0.013	0.020	0.020
Ham *	0.333	0.448	0.333	**0.238**	0.352	0.276
HandOutlines *	**0.097**	0.135	0.519	0.146	0.137	0.119
Haptics *	0.539	0.601	0.532	0.510	**0.490**	0.506
Herring *	0.453	0.453	0.375	**0.359**	0.438	0.391
InlineSkate *	**0.484**	0.491	0.562	0.615	0.591	0.629
InsectWingbeatSound *	0.477	0.527	0.394	0.375	0.426	**0.372**
ItalyPowerDemand *	0.091	0.049	**0.040**	0.117	0.056	0.050
LargeKitchenAppliances	0.235	0.205	0.299	0.472	0.163	**0.136**
Lightning2 *	0.164	**0.131**	0.180	0.262	0.164	0.246
Lightning7	0.315	0.342	**0.205**	0.274	0.288	0.260
Mallat	0.062	0.073	0.050	**0.040**	0.146	0.068
Meat *	0.100	**0.067**	0.267	**0.067**	0.117	0.100
MedicalImages *	0.282	0.255	0.336	0.295	0.253	**0.246**
Middle[...]AgeGroup *	0.455	0.500	0.429	0.422	**0.200**	0.215
Middle[...]Correct *	0.220	0.258	0.220	**0.186**	0.312	0.318
MiddlePhalanxTW *	0.455	0.500	0.494	0.403	0.386	**0.358**
MoteStrain	0.121	0.232	0.117	**0.097**	0.169	0.179
NonInvasiveFatalECGThorax1	0.162	0.159	0.741	0.158	0.076	**0.045**
NonInvasiveFatalECGThorax2	0.099	0.110	0.230	0.138	0.061	**0.042**
OSULeaf	**0.045**	0.116	0.223	0.240	0.087	0.145
OliveOil *	**0.133**	**0.133**	0.833	0.167	0.167	**0.133**
PhalangesOutlinesCorrect *	0.228	0.239	0.235	**0.170**	0.219	0.179
Phoneme *	0.735	0.732	0.782	**0.724**	0.731	0.752
Plane	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**
Proximal[...]AgeGroup *	0.166	0.205	0.166	0.151	**0.132**	0.180
Proximal[...]Correct *	0.151	0.206	0.151	**0.127**	0.192	0.131
ProximalPhalanxTW *	0.200	0.229	0.224	**0.190**	0.210	0.205
RefrigerationDevices	0.501	0.555	**0.485**	0.528	0.523	**0.485**
ScreenType *	0.536	0.563	0.571	**0.491**	0.525	0.523
ShapeletSim *	**0.000**	0.400	0.050	0.039	0.011	0.161
ShapesAll *	**0.092**	0.162	0.232	0.815	**0.092**	0.142
SmallKitchenAppliances *	0.275	0.352	0.336	0.328	0.285	**0.171**
SonyAIBORobotSurface1	0.368	0.290	0.190	0.205	**0.092**	0.218
SonyAIBORobotSurface2	0.141	**0.108**	0.125	0.222	0.179	0.153
StarlightCurves	0.022	0.038	0.053	0.023	**0.021**	0.022
Strawberry *	**0.024**	0.043	0.089	0.046	0.047	0.044
SwedishLeaf *	0.078	0.104	0.093	0.085	0.082	**0.061**
Symbols *	0.033	0.037	0.068	0.054	**0.017**	0.109
SyntheticControl	0.033	**0.003**	**0.003**	0.007	**0.003**	0.007
ToeSegmentation1	0.061	0.193	0.066	0.219	**0.026**	0.044
ToeSegmentation2	**0.038**	0.285	0.085	0.200	0.077	0.092
Trace	**0.000**	0.010	**0.000**	0.020	**0.000**	**0.000**

TwoLeadECG	0.019	0.015	**0.004**	0.134	0.024	0.040
TwoPatterns	0.007	**0.000**	0.007	0.024	0.007	**0.000**
UWaveGestureLibraryAll *	0.061	0.062	0.047	0.074	0.173	**0.029**
UWaveGestureLibraryX	0.238	0.225	0.209	**0.169**	0.231	0.171
UWaveGestureLibraryY	0.315	0.302	0.297	0.264	0.312	**0.246**
UWaveGestureLibraryZ	0.305	0.321	0.253	**0.228**	0.274	0.236
Wafer	0.005	0.007	**0.004**	0.005	0.008	0.005
Wine *	**0.259**	0.389	0.500	0.389	0.370	0.352
WordSynonyms *	0.362	**0.270**	0.393	0.312	0.365	0.281
Worms	0.442	0.351	0.390	0.312	0.343	**0.304**
WormsTwoClass	**0.169**	0.377	0.273	0.247	0.271	0.265
Yoga	0.082	0.144	0.166	0.181	0.131	**0.077**
Average rank	3.165	4.371	3.912	3.753	3.176	**2.624**

Table 1: Comparison of error rates between our temporal feature set kernel ($D = 8192$) and local feature based state-of-the-art methods. Recall that BoW baseline operates on the exact same feature sets as our K_{FS}. Stars indicate datasets for which cross-validation leads to take temporal information into account ($\gamma_t > 0$).

2 Parameter ranges

Table 2 gives the search range of the different parameters used for cross-validation.

Parameter name	Kernels	Parameter range
C	All kernels	$10^0 - 10^6$
γ_K	All kernels	$10^{-1} - 10^5$
γ_f	All variants of K_{FS}	$10^0 - 10^6$
γ_t	All temporal variants of K_{FS}	$10^0 - 10^6$

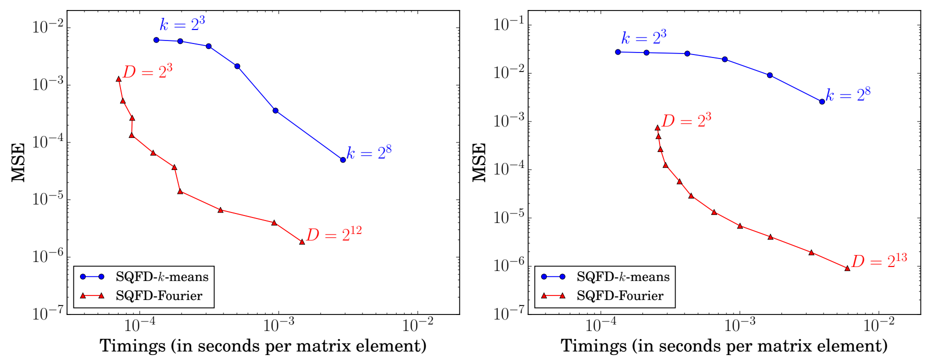
Table 2: Parameter grids for all kernels used in the paper. For all parameters, 5 values are selected at regular logscale locations in the range.

3 Timing experiments on more datasets

Fig. 1 represents the mean square error approximation of the approximated kernel matrix versus the timing for two datasets: *Adiac* and *Ham*. These datasets have been chosen so as to complement conclusions drawn in the paper for *ECG200* dataset. Indeed, *Ham* corresponds to a long time series case while *Adiac* has more training time series than *ECG200*. This figure matches Figure 2 of the paper and confirms that a good trade-off is obtained by the Fourier approximation.

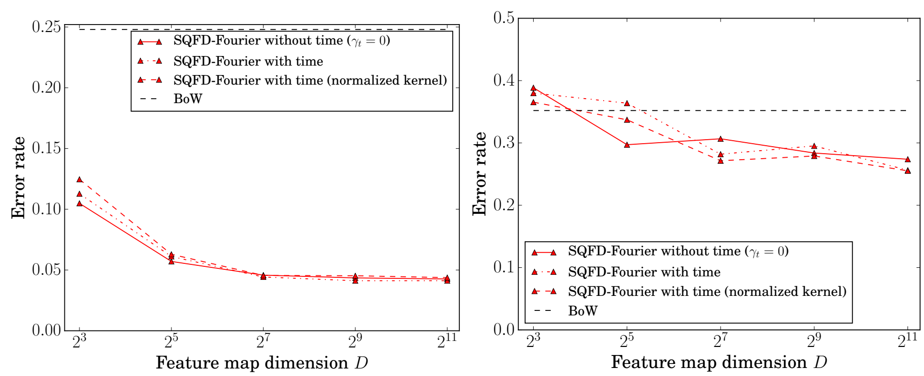
Fig. 2 shows the error rate versus the feature map dimension for *Adiac* and *Ham* datasets. It confirms the statements made in the paper (Figure 4) about the benefits of taking temporal information into account and of the kernel normalization.

Fig. 3 depicts the training and testing time of BoW, SQFD-k-means and SQFD-Fourier as a function of the size of the training set for the same datasets. This figure matches Figure 3 of the paper, and identical conclusions can be drawn. The Fourier approximation leads to lower execution times than k-means approximation. Compared to BOW, training time is reduced, especially for large training sets.



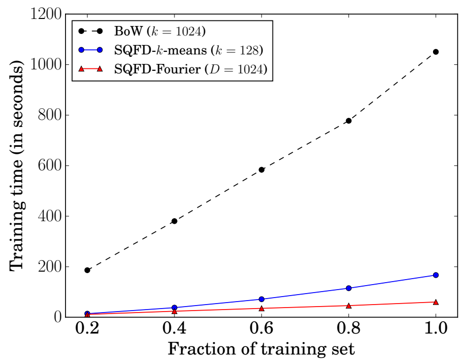
(a) *Adiac* (b) *Ham*

Fig. 1: Mean Squared Error (MSE) *vs* timings of the approximated kernel matrix (*Adiac* and *Ham*).

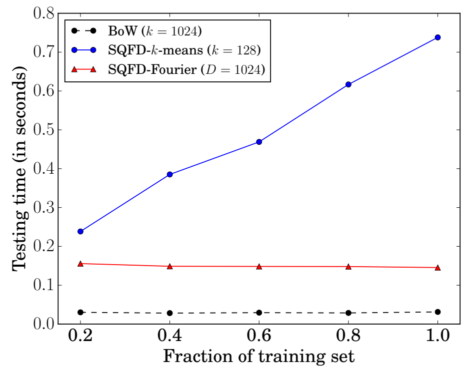


(a) Adiac (b) Ham

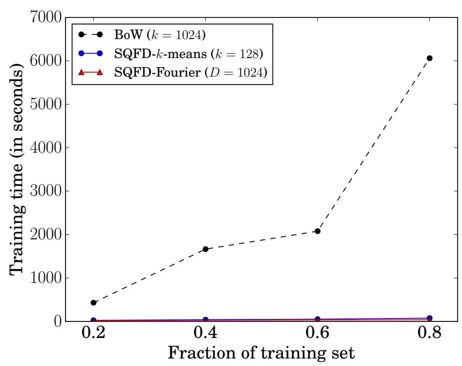
Fig. 2: Error rates as a function of the feature map dimension (*Adiac* and *Ham*).



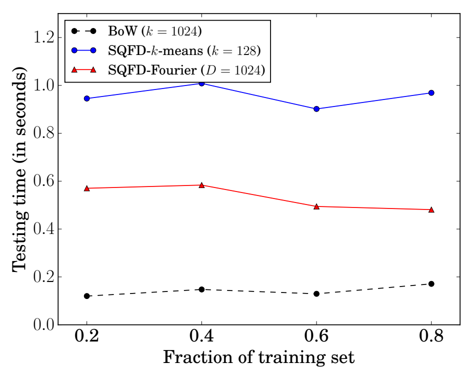
(a) Training time (*Adiac*)



(b) Testing time (*Adiac*)



(c) Training time (*Ham*)



(d) Testing time (*Ham*)

Fig. 3: Training and testing times as a function of the amount of training data (*Adiac* and *Ham*).

4 Pairwise comparisons

Figure 4 compares the performance of the proposed approach with two competing approaches : 1-nearest-neighbour (1NN) combined with DTW and BOSS-VS [6]. Classification error rates on the 85 datasets of the UCR-UEA repository are depicted, together with the Win/Tie/Lose scores and the p-values corresponding to one-sided Wilcoxon signed rank tests.

References

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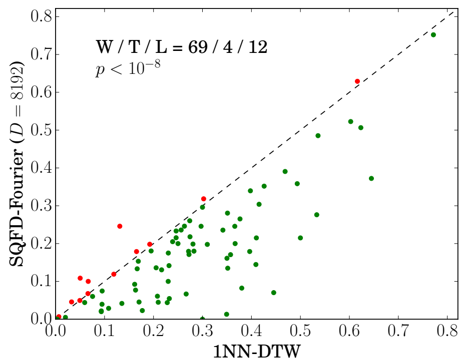
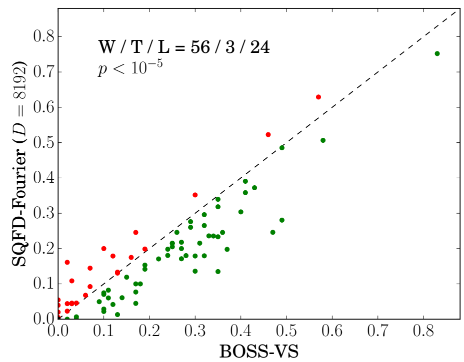


(a) SQFD *vs*1 NN-DTW



(b) SQFD *vs* BOSS-VS

Fig. 4: Pairwise performance comparisons.

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