Classification of Signatures of Aircraft Prototypes using Support Vector Machine

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Abstract:This paper focus on classification of signatures of four different types of aircraft prototypes. In order to classify the signatures, Support Vector Machinemethod is proposed. This procedure is designed to pair wise generate optimally aligned signatures by back tracking along the optimal alignment path. Classification results on these prototype signatures show that this method is quite robust in classifying the signals with unequal duration, compared to nearest mean classifier and Dynamic Time Wrapping method. Classification results were observed for different MSSNR for both classification methods. This paper also focused on reconstructing signatures based on the alignment path.

IndexTerms **- Nonlinear alignment; optimal alignment, Nearest-mean classification, Support Vector Machine.**

I. INTRODUCTION

This paper focuses on classifying four different types of aircraft prototype pictures taken under controlled light and background conditions. As a part of pre-processing the RGB images were converted into binary images by using different thresholds for all four images to make sure the shadow of the image is not included in the obtained binary image. If found any shadow region in the binary image, histogram equalization is applied locally near the shadow region on the gray scale prototype image to remove the shadow region and to ensure the quality of data.Ordered boundary for all the four binary images were found starting from the first top left pixel which is separating from the background. The signature for a particular prototype is generated by taking the Euclidian distance to each and every pixel in the ordered boundary [1]. In order to apply this method in real time problem, Gaussian noise is added to the signature and 100 random signals are generated.Nearest mean classifier is the general and common method for classifying the signals of this sort which compares the test signal mean to the means of different available classes of signals and chooses the class which is separated by lesser Euclidean distance. For using this method one needs to have the same signal length for all the signals which are meant for classification and which is not the case here. Re-sampling the signatures to make the number of sampling points constant is the only way to make the nearest mean classifier work. Re-sampling data may include under sampling or over sampling the signatures and they have their own limitations such as aliasing and loss of some crucial peaks in the signature due to under sampling the data. This is a major problem in classification of EEG (Electroencephalogram) signals which has very low amplitude signals. The need to overcome this kind of problem is the main reason to go for the nonlinear alignment. regions.

II. NONLINEAR ALIGNMENT

Nonlinear alignment [Dynamic Time Wrapping (DTW)] was initially proposed to solve the time registration problem between a test pattern and reference pattern in speech recognition problems [2]. The simplest way to recognize the isolated word or a signal is to compare it with the available reference signals and find the best match. This theory has a few limitations such as different samples will have different durations and the rate of speech may not be constant throughout. So the optimal alignment between the reference signal and the test signal is nonlinear. DTW typically used to measure the dissimilarities between different patterns in applications such as such as ERP signal classification [3], tongue movement ear pressure signals [4], and target recognition problems [1]. Ref [5] –[8] focused on different application of dynamic alignment. Though the classification problem considered here is not related to speech recognition, considered the fact that nonlinear alignment schemes compensate for local expansions and compressions as well as duration differences, this is used in rather unconventional way to separate different classes of test signals when compared to different reference signals.Let R (m) be the reference signal which has M number of sampling points and T (n) be the test signal which has N number of sampling points. Local distance matrix d (n, m) is calculated by finding the Euclidean distance from each and every sample in the reference signal to every sample in the test signal. This is given by the equation

$$d[n, m] = |T(n) - R(m)| \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \text{(1)}$$

From the local distance matrix, over all accumulated distance matrix D [n, m] is calculated by using the following equation

$$D[n, m] = d[n, m] + \min\{D(n-1, m), D(n-1, m-1), D(n, m-1)\} \ \ldots\ldots\ldots \text{(2)}$$

The first row and first column of the accumulated distance matrix is the accumulated sum of the previous sample value and the current sample value in the local distance matrix. This is given by

$$D[1, 1] = d[1, 1] \ \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \text{(3)}$$

$$D[1, m] = \sum d[1, p] \qquad p=1, 2 \ldots\ldots m \quad \ldots\ldots\ldots \text{(4)}$$

$$D[n, 1] = \sum d[q, 1] \qquad q = 1, 2\ldots\ldots n \quad \ldots\ldots\ldots \text{(5)}$$

D [n, m] is computed only for [n, m] values in a band across the diagonal because the optimal alignment path tends to fluctuate in the neighborhood of the diagonal. This will restrict the optimal search path and also reduce the number of computations required. Backtrack the values from D[N, M] choosing the minimum value from one of the three neighborhood of D[n-1, m], D[n-1, m-1], D[n, m-1] for D[n, m].This backtracking is continued till the path reaches D[1, 1]. This path is the optimal aligned path for the given reference and test signal. The number of points in this path gives penalizing factor for extra number of points added. Discrepancy (D) is calculated between the test signal and all the references and is given by

$$D = 1/K \{D[N, M]\} \quad \ldots\ldots\ldots (6)$$

The test pattern is then assigned to the class of the pattern that gives minimum discrepancy.

C* = ArgMINc {Dc}; c= 1, 2……C ……… (7) found within the lesion region.

III. SUPPORT VECTOR MACHINE

The support vector machine (SVM) based on statistical learning theory, is presented by Vapnik [9]. SVM tends to determine a hyperplane that can isolate the input samples. For the situation that the original data cannot be isolated by a hyperplane, SVM will transform the original data into a feature space of higher dimension by utilizing the kernel function. The well-known kernels are Linear kernel, Polynomial kernel of degree'd', Gaussian radial basis function (RBF), Neural nets (sigmoid). In this work, we utilized linear kernel. The Linear kernel is the least difficult kernel function.

$$S(x, y) = x^T y + c \ldots\ldots\ldots\ldots\ldots\ldots(7)$$

In this paper, the polynomial kernel is used. A training set S contains n labeled samples $(x_1, y_2),\ldots,(x_n, y_n)$ where $x_i \in R^N$ and $y_i \in \{-1,1\}$, $i = 1,\ldots,n$. $\phi(x)$ denotes the mapping from R^N to the feature space Z. It needs to find the hyper plane with the maximum margin as

$w \cdot z + b = 0$ (8)

such that for each point (z_i, y_i) where $z_i = \phi(x_i)$

$y_i (w \cdot z_i + b) \geq 1,\ i=1,\ldots,n.$ (9)

When the dataset is not linearly separable, the soft margin is allowed by introducing non-negative variables, denoted by $\varepsilon = (\varepsilon_1, \varepsilon_2, \ldots\ldots, \varepsilon_n)$, such that the constraint for each sample in Eq. (15) is rewritten as

$y_i (w \cdot z_i + b) \geq 1 - \varepsilon_i,\ i=1,\ldots,n.$ (10)

The optimal hyper plane problem is to solve

Minimize $\frac{1}{2} w.w + C\sum_{i=1}^{k} \varepsilon_i$ (11)

subject to $y_i (w \cdot z_i + b) \geq 1 - \varepsilon_i,\ i=1,\ldots,n.$ (12)

where the first term in Eq. (17) measures the margin between the support vectors and the second term measures the amount of misclassifications. C is a constant parameter that tunes the balance between the maximum margin and the minimum classification error.

IV. RESULTS AND DISCUSSION

Signatures for each prototype shown in Figure. 1 are generated by finding the distance from center of gravity co-ordinate of the plane to the ordered boundary co-ordinate points.

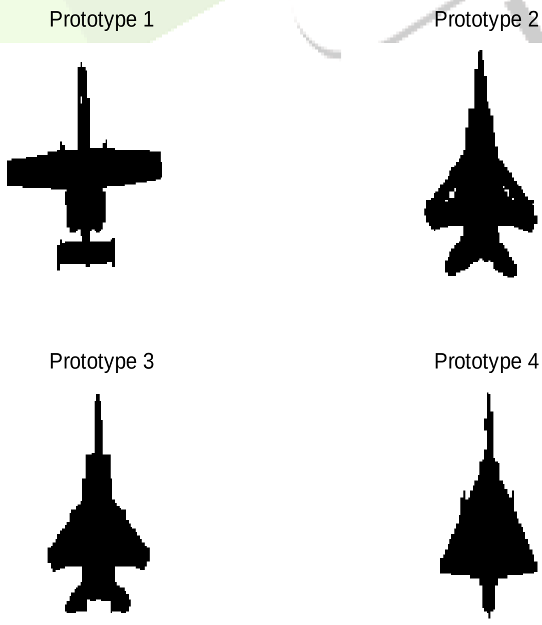

Fig 1. Aircraft prototypes used for classification

. The signatures are subtracted from the mean of the respective signatures to get the base line correction and 100 samples of Gaussian noise with zero mean and seven different SNR are generated and added to original prototype to generate noisy signatures. These assumptions are made realistically as the goal of this paper is to estimate the signatures as accuratelyNoisy signatures shown in Figure 3, are down sampled 10 times to decrease computational complexity.

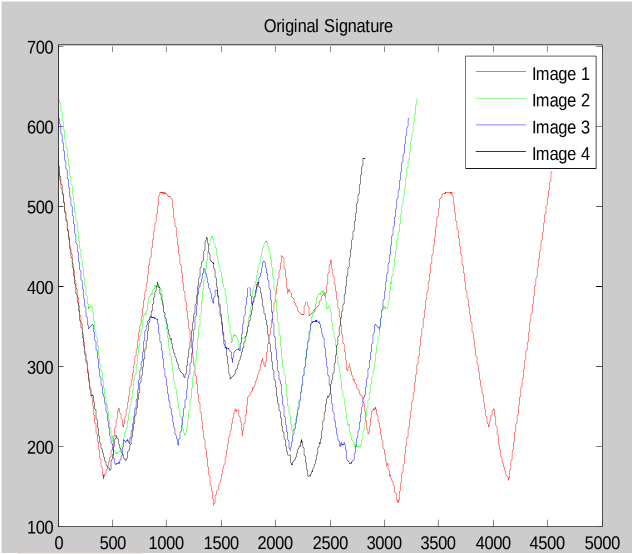

Fig 2. Original signatures of the aircraft prototypes

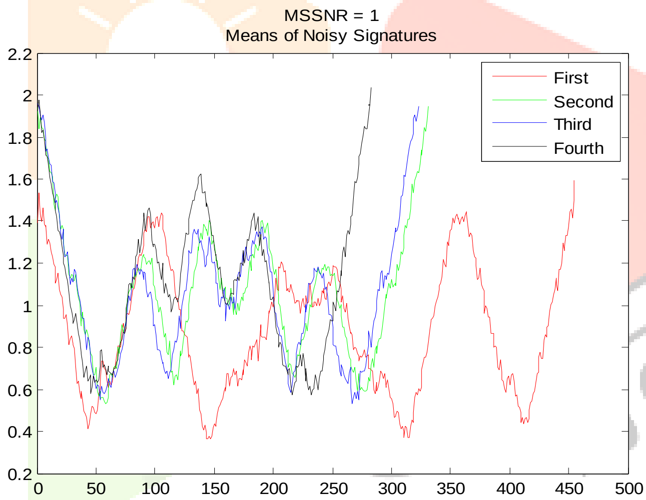

Fig 3. Means of noisy signatures with MSSNR = 1

For all the four different plane prototypes and for the given SNR half of the signals at random are taken as training signals and the rest of the signals as test signals. Mean signal of the training signals for each plane is computed to get reference signal for each plane type.The Nonlinear alignment method is applied for classifying the test signals. The test signal is taken on the Y axis and the reference is taken on the X axis. The local distance table *d* is calculated by subtracting the test signal from each frame of the reference signal one at a time. A band is considered around the neighborhood of the diagonal elements to confine the optimal path.All other values outside the band are set to Infinity so that while back tracking the path, the path should not go outsidethe accumulated distance matrix *D* is computed form the local distance matrix from the equations provided above. The first row and first column of this matrix at any point is the accumulated distance from the first point to the *D [n, m]* point where n, m is greater than one. From D *[N, M]* back track the path of the accumulated distance matrix *D* till reaching *D [1, 1]* and the path is given bythe band region and this path should be same for all the test signals and reference signal comparisons.

$$X[n, m] = D[N, M] \quad \ldots\ldots \qquad (12)$$

$$X[n, m] = \min\{D(n-1, m), D(n-1, m-1), D(n, m-1)\} \quad \ldots\ldots \quad (13)$$

X [n, m] has the indices of the back tracked signal and the length of which is the penalizing factor. Dividing the *D[N, M]* with the penalizing factor gives the discrepancy factor for the reference and the test signal. The discrepancy factor is obtained for each test and all four reference patterns. The test pattern will be of class which has the less discrepancy factor when compared with the reference. This process is repeated by changing the all the reference signals for each of the test signal provided.

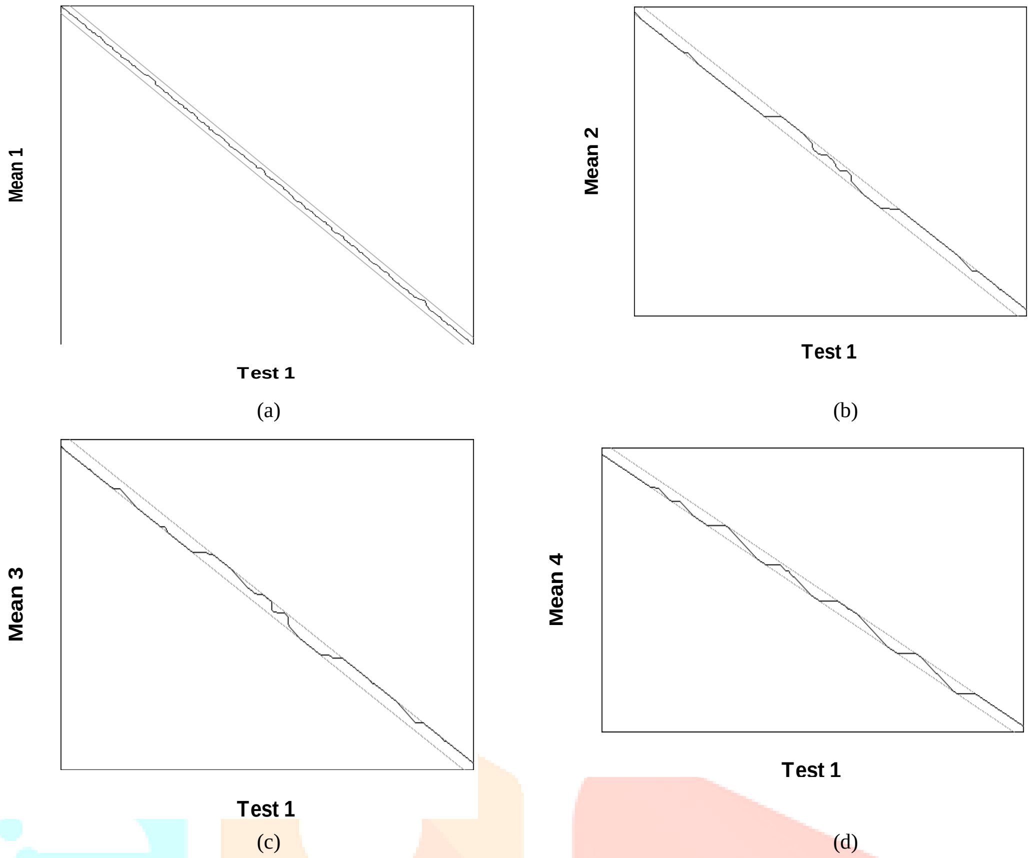

Figure 4. Alignment paths between test signal of class 1 with means from all classes

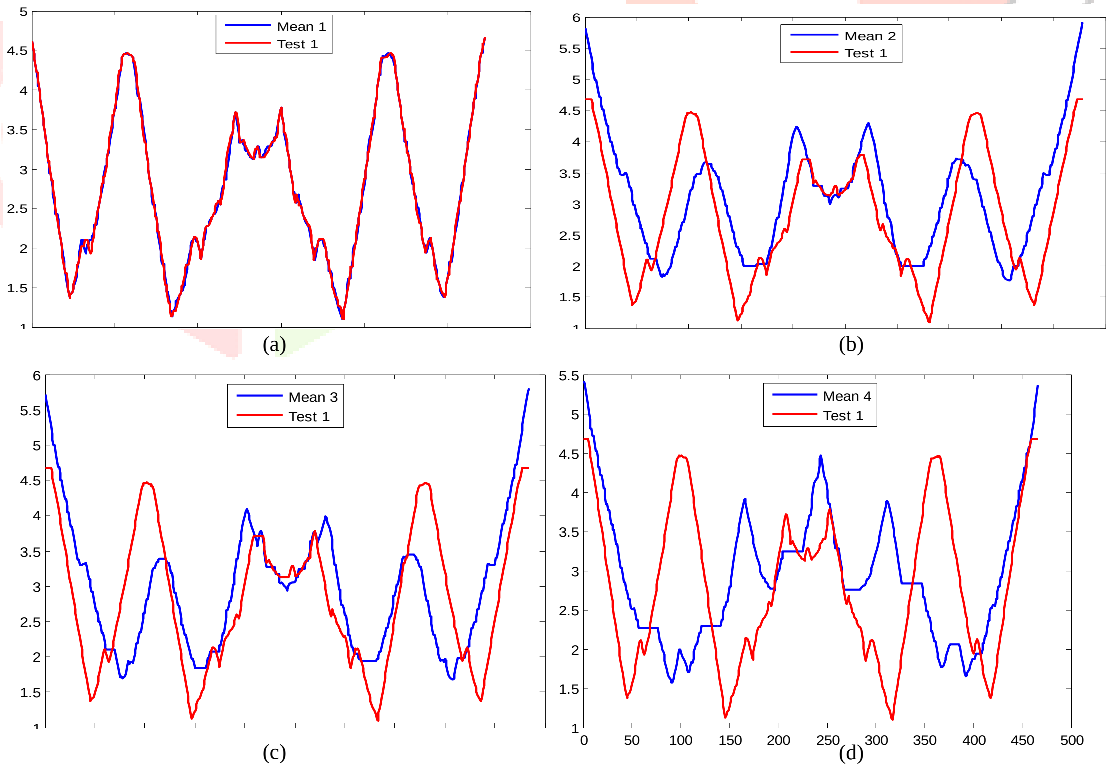

Figure 5. Reconstruction of test signal and mean signals based alignment paths shown in Figure 4

V. RESULTS

Figure 4 shows the alignment path of test signature belong to prototype image of class 1 with mean signatures from all classes. Figure 5 shows the reconstructed test signal of class 1 and mean signals from all classes based on corresponding alignment paths.

TABLE. I. Classification Accuracies

MSSNR	**Classifiers**		
	Nearest Mean	***Nonlinear Alignment***	***Support Vector Machine (SVM)***
0.01	0.2577	0.3500	0.4800
0.1	0.2736	0.5000	0.6500
1	0.2995	0.7000	0.8500
4	0.3812	0.9750	1
5	0.4122	1	1
10	0.4995	1	1
100	0.9927	1	1

Comparison between the nearest mean classifier, Nonlinear alignment classification and Support Vector Machine is performed. Results shown in Table 1 clearly results show that SVM classification works better than nearest mean classifier and Nonlinear Alignment where the signatures duration is maintained constant by under sampling the signatures. Table shows the difference between the two classification accuracies one above the other. The accuracies are calculated using all the four reference signatures and available test signals calculated at a particular SNR and tested taking 200 combinations of random signatures for both testing and references.

VI. CONCLUSION

This paper focused on solving alignment problem in classifying the closed planar signatures without compromising in loss of peaks (amplitude) due to under sampling. To achieve this, the unconventional method of Support vector machine method is used which initially proposed to solve time registration problem in speech recognition. The results of this method are compared with the conventional nearest mean classifier and then the results are tabulated. Results show that the proposed method gets more classification accuracy over the nearest mean classifier and Nonlinear Alignment.

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