EVALUATION OF PROPOSED ADMISSIBLE KERNEL FUNCTION ON A REAL TIME APPLICATION

7.1 Data Validation

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7.4 Chapter Summary
7.1 DATA VALIDATION

Data validation is a process that assesses the performance of the data mining techniques in real time data. Before validating a data mining technique, it is important to understand their characteristics and quality so that it can be easily deployed in the real time environment. The two steps involved in the data validation process are (i) fault data detection and (ii) fault data correction. Fault data detection finds the error values in the dataset and fault data correction helps to deal with the complicated dataset. Fault diagnosis can be measured by the data validation measures and they are given below:

✓ Accuracy
✓ Reliability
✓ Usefulness

Accuracy

Accuracy is a metric that helps to correlate the result with the features that are given in the dataset. This measure is always dependent on the empirical datasets that are taken for experimentation. Mainly, in the case of expansion and exploration of mining the classification model, accuracy should be balanced by the reliability measure.

Reliability

Reliability is a measure that analyzes and checks how well the data mining techniques perform on various datasets. A data mining technique is said to be reliable, when it generates the similar type of prediction results. Thus, the data mining techniques must generalize well to satisfy the reliability metric.

Usefulness

Usefulness consists of various measures that updates whether the particular mining technique provides any useful information or not. If a data mining technique is examined without the usefulness measure then it appears to be a meaningless task.
7.2 TARGET CLASSIFICATION

Currently, a number of powerful kernel based learning algorithms like SVM, KPCA, relevance vector machines, kernel fisher discriminant analysis and sparse kernels have been reporting their success in many real time domains like signal processing, image processing, estimation theory and pattern classification. In a nutshell, a kernel-based algorithm is a nonlinear version of a linear algorithm where the data has been non-linearly transformed to a higher dimensional space, in which the kernel functions are computed using inner products (Müller et al. 2001). The attractiveness of such an algorithm stems from their elegant treatment of nonlinear problems and their efficacy in high dimensional feature space.

To validate the proposed classification framework, the real time application considered is target classification in multitarget tracking and detection. Target classification is one of the key steps in tracking procedure, where it helps to classify and predict the target and its location accurately. Even though various classification algorithms are emerging in this field, still there is a necessity to develop a new algorithm that can classify the multiple targets efficiently.

**Dynamic model for Target and Sensor data (Sangeetha and Kalpana, 2012)**

The main objective of the tracking and estimation is to locate and classify a target in the wireless sensor network. The targets can be ground based, air based or sea based. In this research work, the ground based target is considered for classification. This section discusses a dynamic model of a ground based target and sensor in a tracking field.

First, the process model for the target state estimation is described. The acquaintance of the target’s current state and its transition matrix determine the next state of the target. The observation model helps to simulate the sensor behavior when target’s existence is known. The observable state of the target depends on the sensing mode employed by the sensor. Here, it is assumed that there exists a range,
where it comes under surveillance with a total of $N_T$ sensors and $S_m(t)$ are the set of nodes that are neighbors with $S_m$ (an arbitrary sensor node) at time $t$ for $i^{th}$ target.

**Process Model**

The process model finds the state of the target at time instant $t$ given the state of the target at time instant $t-1$. Let us consider a target state vector based on piecewise constant acceleration model with $M$ number of targets. The target process state vector is defined

$$ X = [x \ y \ z \ x \ y \ z \ x \ y \ z]^T, $$

and it evolves in time according to

$$ X_i^t = F X_i^t + V_i^t, \ \forall \ i = 1,2,\ldots,M $$  \hspace{1cm} (7.1)$$

where $F = \begin{bmatrix} I & TI & (T^2/2)I \\ 0 & I & TI \\ 0 & 0 & I \end{bmatrix}_{9 \times 9}$, $V_i^t = [V_i^x \ V_i^y \ V_i^z]$

In the above equations, the subscript $t$ denotes the time index, superscript ‘$T$’ represents the transpose, $X$ is the real target state vector, $F$ is the target state transition matrix, $V$ is the Gaussian-distributed process noise vector assumed to be zero mean in the $x$, $y$, $z$ directions respectively, $I$ is the identity matrix of order $3 \times 3$, $0$ is the null matrix of order $3 \times 3$ and $T$ is the sampling time. The maneuver variance of $i^{th}$ target $V_i$ can be measured by $(Q\delta)^{mc}$, where $\delta$ is the Dirac delta function and $Q$ is the process noise covariance

$$ Q = 2\alpha \sigma_m^2 \begin{bmatrix} (T^5/20)I & (T^4/8)I & (T^3/6)I \\ (T^4/8)I & (T^3/3)I & (T^2/2)I \\ (T^3/6)I & (T^2/2)I & TI \end{bmatrix}_{9 \times 9}, $$

where $\alpha$ is the reciprocal of the constant time and $\sigma_m^2$ is the variance assumed equal along the three axes.
equation (2) represents the target acceleration with uniform distribution, between
the limits $A_{\text{max}}$ to $A_{\text{max}}$ and probability varies from $P_o$ to $P_{\text{max}}$.

**Observation Model**

To model the sensor observation uncertainties, noise is added to the real
target state vector. Sensor nodes can only observe the two dimensions of the target
state, velocity and acceleration of the target state are not observable. But the
measurement of the target state location is available in spherical coordinates.
Moreover, sensor nodes collect range, bearing and elevation data, since they do not
observe the target coordinates directly.

The $i^{th}$ targets range $r_{m,d}^i$, bearing $\theta_{m,d}^i$ and elevation $\phi_{m,d}^i$ measured by $S_m$ are
defined with the respect to the true range $r_m^i$, bearing $\theta_m^i$ and elevation $\phi_m^i$ as

$$ r_{m,d}^i = r_m^i + n_r^i, \quad \theta_{m,d}^i = \theta_m^i + n_{\theta}^i, \quad \phi_{m,d}^i = \phi_m^i + n_{\phi}^i $$

where range $r_m^i$, bearing $\theta_m^i$ and elevation $\phi_m^i$ denote the radar measurements. The
original values $r$, $b$ and $e$ can be expressed as

$$ r = \sqrt{x^2 + y^2 + z^2}, \quad b = \tan^{-1}(y/z), \quad e = \tan^{-1}(z/\sqrt{x^2 + y^2}) $$

The errors in range $n_r^i$, bearing $n_{\theta}^i$ and elevation $n_{\phi}^i$ are assumed to be
independent and moments of Gaussian distribution:

$$ \mathbb{E}\left[n_{r,m}^i\right] = \mathbb{E}\left[n_{\theta,m}^i\right] = \mathbb{E}\left[n_{\phi,m}^i\right] = 0 $$

$$ \mathbb{E}\left[(n_{r,m}^i)^2\right] = \sigma_{r,m}^2, \quad \mathbb{E}\left[(n_{\theta,m}^i)^2\right] = \sigma_{\theta,m}^2, \quad \mathbb{E}\left[(n_{\phi,m}^i)^2\right] = \sigma_{\phi,m}^2 $$

where the $i^{th}$ targets time dependence is implicit. The mean target state vector
observed after the unbiased spherical to cartesian coordinates is given as follows

$$ \varphi_m^i = \begin{bmatrix} x_{m,d}^i \\ y_{m,d}^i \\ z_{m,d}^i \end{bmatrix} = \begin{bmatrix} r_{m,d}^i \cos \theta_{m,d}^i \cos \phi_{m,d}^i \\ r_{m,d}^i \sin \theta_{m,d}^i \cos \phi_{m,d}^i \\ r_{m,d}^i \sin \phi_{m,d}^i \end{bmatrix} - \mu_m $$
where $\mu_m$ is average true bias and

$$
\mu_m = \begin{bmatrix}
    r_{m,d}^i \cos \theta_{m,d}^i \cos \phi_{m,d}^i (e^{-\sigma_{m}^2} e^{-\sigma_m^2} - e^{-\sigma_{m}^2/2} e^{-\sigma_m^2/2}) \\
    r_{m,d}^i \sin \theta_{m,d}^i \cos \phi_{m,d}^i (e^{-\sigma_{m}^2} e^{-\sigma_m^2} - e^{-\sigma_{m}^2/2} e^{-\sigma_m^2/2}) \\
    r_{m,d}^i \sin \phi_{m,d}^i (e^{-\sigma_m^2} - e^{-\sigma_{m}^2/2})
\end{bmatrix}
$$

The covariance matrix $R_m^i$ of the observation errors in $\phi_m$ is

$$
R_m^i = \begin{bmatrix}
    R_{m1}^i & R_{m12}^i & R_{m13}^i \\
    R_{m21}^i & R_{m22}^i & R_{m23}^i \\
    R_{m31}^i & R_{m32}^i & R_{m33}^i
\end{bmatrix}
$$

**Dataset Description**

Since it is not practical to collect the data from the sensor field directly, the ground based target i.e. vehicle dataset is taken from the Statlog project repository. The Statlog project repository is a benchmark repository which contains the real time datasets for the classification/prediction purpose. The description of the vehicle dataset is given below:

**Vehicle dataset**

Vehicle identification dataset (Siebert, 1987) is a multiclass datasets that classifies the different types of vehicles based on silhouette information. It has 945 instances, 18 features and 4 classes. The attribute characteristics are integer valued and the values are compactness, circularity, distance circularity, scatter ratio, radius ratio and so on.

**7.3 EXPERIMENTAL RESULTS**

In this section, the proposed kernel and hybrid kernel functions for SVM classifier are validated using the real time vehicle dataset which is taken from the Statlog project repository. Primarily, the vehicle dataset is preprocessed and dimension reduced using the proposed techniques. After that the preprocessed and
dimension reduced vehicle dataset is classified by the proposed admissible kernel and hybrid kernel. As discussed earlier, the empirical results obtained from the kernel functions are evaluated using the three validation measures i.e. accuracy, reliability and usefulness.

**Figure 7.1 Comparison of Proposed Kernel and Hybrid Kernel using Accuracy, Support Vectors for Vehicle dataset**

**Figure 7.2 Comparison of Proposed Kernel and Hybrid Kernel using Error Rate, Time for Vehicle dataset**
Figures 7.1 and 7.2 depict the performance of proposed kernel and hybrid kernel function for vehicle dataset. The metrics used to compare the performance of SVM classifier are accuracy, support vectors and error rate. From the Figures, it is inferred that the proposed kernel function performs better for vehicle dataset when compared to the hybrid kernel function. The proposed kernel function increases the accuracy by 7% and decreases 17.16% of support vectors for vehicle dataset. It shows that the proposed kernel is an optimal and admissible kernel which reduces memory usage due to a minimum number of support vectors, improves the accuracy and generalizes well for various domains.

7.4 CHAPTER SUMMARY

This chapter presents the overall evaluation of the proposed classification framework using the vehicle dataset. From the observed results, it is revealed that the proposed preprocessing technique, dimensionality reduction technique and kernel function in Banach space have enhanced the performance of the support vector classifier by achieving improved accuracy, reliability and generalization. In future, this research framework can be considered as a robust classifier for different domains.