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A Novel SVM-Based OOK Detector in Low SNR Infrared Channels

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***Abstract*—**Support Vector Machine (SVM) is a recent class of statistical classification and regression techniques playing an increasing role in applications to detection problems in various engineering problems, notably in statistical signal processing, pattern recognition, image analysis, and communication systems. In this paper, SVM is applied to an infrared (IR) binary communication system with different types of channel models including Ricean multipath fading and *partially developed* scattering channel with additive white Gaussian noise (AWGN) at the receiver. The structure and performance of SVM in terms of the bit error rate (BER) metric is derived and simulated for these channel stochastic models and the computational complexity of the implementation, in terms of average computational time per bit, is also presented. The performance of SVM is then compared to classical binary signal maximum likelihood detection using a matched filter driven by On-Off keying (OOK) modulation. We found that the performance of SVM is superior to that of the traditional optimal detection schemes used in statistical communication, especially for very low signal-to-noise ratio (SNR) ranges. For large SNR, the performance of the SVM is similar to that of the classical detectors. The implication of these results is that SVM can prove very beneficial to IR communication systems that notoriously suffer from low SNR at the cost of increased computational complexity.

***Keywords*—**Least Square–Support Vector Machine, On-Off Keying, Matched Filter, Maximum Likelihood Detector, Wireless Infrared Communication.

I. Introduction

SVM is based on the statistical learning theory initially developed by Vapnik [1] in 1979 and later developed to a more complex concept of structural risk minimization (SRM). SVM is formulated on the structural risk minimization (SRM) principle which minimizes an upper bound on the generalization error, as opposed to the classical empirical risk minimization (ERM) approach which minimizes the error on the training data and is embodied in statistical learning. The quality and complexity of the SVM solution does not depend directly on the dimensionality of the input space.

The SVM theory starts from simple ideas on linear separable classes, then progresses into studying the case of linear non-separable classes. The separation of classes using linear separation functions is extended to the nonlinear case. The derivation of SVM is based on constructing an optimal separating hyperplane after nonlinearly mapping the input space into a high-dimensional feature space via simple kernel representations using linear separation functions. The classification problem is solved in the higher dimension space by constructing a linear classifier with maximum margin. We note that the dimension of the higher space is not needed and the explicit construction of this mapping function is avoided by the application of Mercer's condition [2]. Kernels that satisfy this condition and can be employed for SVM's are polynomials, splines, radial basis functions, and multilayer perceptrons with one hidden layer. For classification problems the parameters which are related to these kernel functions are chosen so as to minimize an upper bound on the Vapnik–Chervonenkis (VC) dimension of the SVM [2]. The training of SVM's with Vapnik's epsilon insensitive loss function is done by quadratic programming.

Only a sparse set of support vectors (SVs) determine the SVM classifier, and these SVs are automatically chosen from the training data during the learning process.

Support vector machines have been widely used in solving classification and function estimation problems due to its many attractive features and promising empirical performance with many successful applications in synthetic aperture radar image classification and pattern recognition [3]. Recently, SVM has been introduced to digital communication systems as a new method for *channel equalization* [4] – [6] and has proved to be very effective in overcoming intersymbol interference (ISI) and co-channel interference (CCI). SVM was also applied for the equalization of burst time division multiple access (TDMA) transmission [7]. To the best of our knowledge, SVM has not been implemented yet for *receiver detection* in digital communication systems in the presence of multiplicative *partially fading* channel noise and additive receiver noise. A notable exception is the initial work of Mokbel and Hashem [8] who applied SVM to a bipolar non-return to zero (BNRZ) digital communication detector based on a cascade of sampler and comparator using multiple samples per binary period (termed *dimension*) in the presence of additive white Gaussian noise in wire-line communication systems. Their work showed that the SVM-based detector outperformed the classical detector for low SNR and that the SVM performance improved (with a law-of diminishing return taking place) as the dimension increased with no practical improvement noticed after 10 samples per bit. The authors in [8] did not conduct further research to study SVM in wireless multipath fading channels.

II. Binary Wireless Infrared Communication

Wireless infrared communications refers to the use of free-space propagation of light waves in the near infrared band as a transmission medium for telecommunication applications. IR radiation (nondirected) has been shown to be a viable alternative to radio transmission for indoor wireless communication but it requires a high average power efficiency [9]. On-Off Keying is the simplest modulation techniques

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implemented in the physical link of general binary systems. Beside its simplicity, OOK is characterized by the ease of its clock recovery.

Another popular modulation technique for IR communication is L-pulse-position modulation (L-PPM). PPM is an effective modulation scheme for nondirected IR because of its high average power efficiency, which increases with an increase in L. However, the drawback of L-PPM is its poor bandwidth efficiency. As a result, L-PPM suffers from severe ISI in high speed indoor IR systems (> 10 Mbps) caused by the multipath fading channel's scatterers. OOK, on the other hand, does not suffer severely from ISI. For this reason, in addition to its simplicity, OOK is chosen as the modulation technique of the IR communication system analysed in this work.

Considering the receiver side of an OOK modulated signal, and assuming a distortionless channel, the ideal maximum likelihood (ML) detector is composed of a filter matched to the transmitted pulse shape, and a threshold detector equal to half the amplitude of a "high" pulse. The theoretical power requirements of unequalized OOK links computed on multipath channels including non-directed line-of-sight and diffuse configurations, with and without shadowing [10], show that the optical power requirement depends essentially on the normalized delay spread (the delay spread normalized to the it duration). Also it shows that for links operating at 100 Mbps unequalized, OOK faces a very large power drop and encounters an irreducible BER, which implies that unequalized OOK reception on multipath channels is not feasible. This triggers the need for a detector other than classical model-based ones.

III. Support Vector Machine

Since the idea of SVM emanates from determining an optimal hyperplane for separating two classes with maximum margin, it is logically very relevant to binary detection in communication systems.

In this section, we provide a succinct introduction to the SVM approach. The reader is referred to the initial work of Vapnik [1] and the tutorial paper of Burges [2] for more in-depth treatment of the SVM theory and the concepts of VC dimension and the structural risk minimization. These references also study the use of linear functions to classify data in both cases of separable data and non-separable data. A thorough coverage of the generalization to non-linear cases through the mapping to a higher-dimension space is also presented in these references in addition to the kernel mapping techniques.

Many reasons could be stated for preferring Least Square–Support Vector Machine (LS-SVM) over other methods and models of SVM, yet the most important reason is that LS-SVM is an iterative method that could be used to solve large scale problems with robustness in the sense of the choice of the regularization and smoothing parameters [11].

Moreover, in many real life applications it offers a fast method for obtaining classifiers with good generalization performance [12]. SVM is equipped with this intriguing potential to generalize mainly because its formulation embodies SRM as opposed to the ERM approach commonly employed in statistical learning.

Given a training set of N data points $\{y_k, x_k\}^N$, where x_k denotes the k^{th} input pattern and y_k the k^{th} output pattern, the support vector method approach aims at constructing a classifier of the form [13]:

$$\begin{aligned} f(x) &= sign\left[\boldsymbol{w}^T\ \varphi(x) + b\right] \\ &= sign\left[\sum_{k=1}^{N} \alpha_k y_k K(x, x_k) + b\right] \end{aligned} \tag{1}$$

where $\varphi(.)$ is a set of mapping functions that transform the input patterns into a high dimensional feature space termed the reproducing kernel Hilbert space (RKHS), $\boldsymbol{w}$ is the weight vector in the RKHS, α_k are support values (Lagrangian multipliers) and b is the bias term. The kernel function $K(x,x_k) = \exp\left(-\|x - x_k\|_2^2 / \sigma^2\right)$ for RBF (radial basic function) SVM, where σ is constant. For binary classification (separable data), we can assume

$$\begin{cases} \boldsymbol{w}^T\ \varphi(x_k) + b \geq +1, \text{ if } y_k = +1 \\ \boldsymbol{w}^T\ \varphi(x_k) + b \leq -1, \text{ if } y_k = -1 \end{cases} \tag{2}$$

Equivalently,

$$y_k\left[\boldsymbol{w}^T\ \varphi(x_k) + b\right] \geq 1,\ k = 1,\cdots,N \tag{3}$$

LS-SVM classifiers are obtained as a solution to the following optimization problem (non separable case):

$$\min_{w,b,\xi} \Im_{LS}(\boldsymbol{w}, b, \xi) = \frac{1}{2}\boldsymbol{w}^T\ \boldsymbol{w} + \gamma\sum_{k=1}^{N}\xi_k \tag{4}$$

subject to the equality constraint

$$y_k\left[\boldsymbol{w}^T\ \varphi(x_k) + b\right] = 1 - \xi_k,\ \xi_k \geq 0,\ k = 1, \cdots, N \tag{5}$$

where γ is the regularization factor and ξ_k is the difference between the output y_k and discriminant function $f(x_k)$.

The parameters of the kernels, such as σ for the RBF kernel, can be optimally chosen by optimizing an upper bound on the VC dimension, which involves solving a quadratic programming problem. The support values α_k are proportional to the errors at the data points in the LS-SVM case, while in the standard SVM case many support values are typically equal to zero [14].

IV. Stochastic Channel Modeling

The Rician fading channel model is widely used in the literature for wireless indoor IR systems [15-18]. We used for the SVM simulations a more accurate model for fading power in a local environment (small area), that of partially developed fading power whose probability density function (pdf) is formulated as a series of modified-Rician distributions weighted by orthogonal polynomials [19, 20]. Such pdf series model converges asymptotically to a modified-Ricean distribution. More models have been suggested in the literature, such as the WLAN IEEE 802.11 and the ultra wideband IEEE 802.12 standards and we leave this as an area of future investigation [21].

The partially developed fading envelope obeys the scattering stochastic model

$$\gamma_M = \left| \sum_{k=1}^{M} A_k e^{j\varphi_k} + V_0 \right|, \qquad (6)$$

with the partially developed fading power being $\nu_M = \gamma_M^2$. A_k is the random amplitude of the k^{th} scatterer, ϕ_k is the random phase of the k^{th} scatterer assumed to be uniformly distributed between $[0, 2\pi)$, V_0 is the amplitude strength of the direct line of sight (LOS), and M is the random number of scatterers in the channel assumed to obey a Poisson distribution, a valid assumption since the underlying random point process in space describing the spatial distribution of the channel scatterers satisfies a technical condition known as the *Khinchine orderliness* condition [22]. We note that as M approaches infinity, the stochastic model is termed fully-developed, the fading envelope γ_M is asympotically Rician, and the fading power ν_M obeys a modified-Rician distribution.

The received IR signal is corrupted by two types of noises: (1) channel fading *multiplicative* noise γ_M and (2) receiver *additive* white Gaussian noise (AWGN).

V. Simulation Results and Discussions

In this section all systems described earlier will be simulated and compared with their new SVM-based versions. The results of this section will cover the most widely used models of the wireless hostile channel. They could be thus considered as a corner stone for any future research in the field of SVM in comparison with conventional systems to give theoretically, not as accurately as in real time measurements with real systems, a clear insight of the performance of the new SVM-based system.

For simulation purposes, Matlab is used due to its enhanced mathematical capabilities and engineering based structure. The LS-SVM model was simulated using Matlab code downloaded from [23] on a 1.7 GHz Pentium IV computer with 256 MB RAM, to ensure that the comparison with classical detectors is fair since it is the main scope of this simulation. Without loss of generality (wlg) and for the purpose of simulation, we assumed $K = 3$ (the Rician K-factor defined as the ratio of diffuse power to coherent LOS power).

The classical infrared system detector was designed for directed LOS link using intensity modulation with direct detection (IM/DD). Then the SVM-based IR detector was also designed and simulated, yielding the graph of Fig. 1.

In order to take full advantage of the SVM technique, we considered several samples of the OOK signal in the bit period. This offers a generalization since the SVM classifier is applied in a wider space.

It is noticed from Fig. 1 that the SVM-based detector outperforms the classical ML-based detector for low SNR, while for high SNR, both systems seem to produce similar results and converge at 9.12 dB.

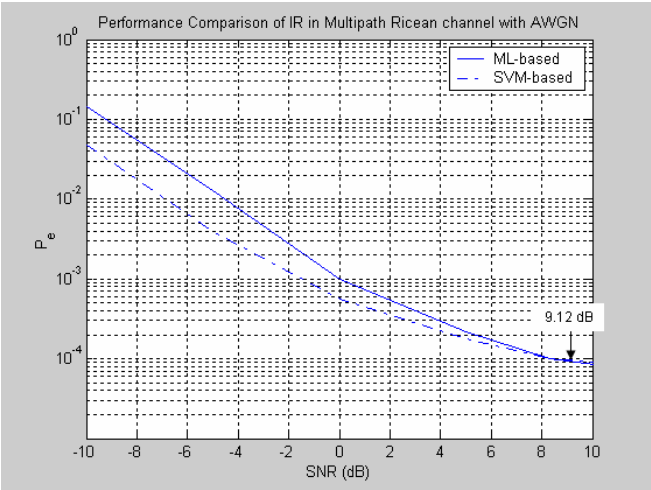

Fig. 1 Comparative performance of an IM/DD infrared communication system using OOK in fully developed multipath Ricean channel with AWGN

The results of the simulations for partially developed scattering noise are shown in Fig. 2 with the assumptions made in the stochastic model of (6) (wlg) as: $A_k = 1$ and $\Gamma = 1$ (the intensity of the Poisson distribution).

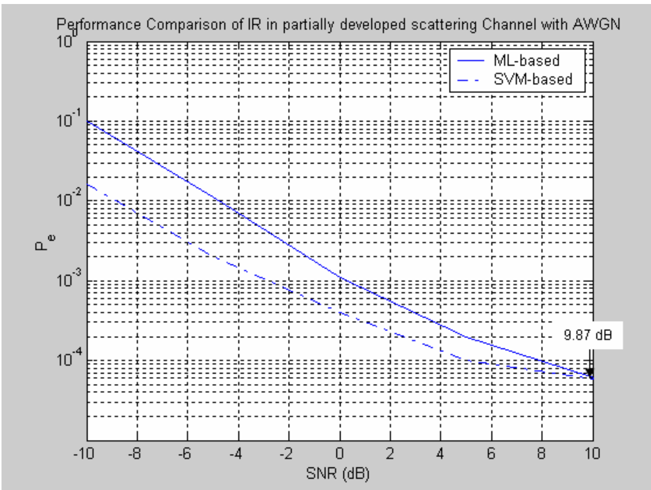

Fig. 2 Comparative performance of an IM/DD Infrared communication system using OOK in partially developed scattering channel with AWGN

Again, the SVM outperformed the ML detector for low SNR and it achieved the ML performance asymptotically at 9.87 dB. For very low SNR (-10 dB), the BER attempts 10% in the ML detector and 1.5% in the SVM detector, so the

SVM results present a significant improvement over the classical optimal ML-based detector for low SNR.

For very large SNR, there are no notable differences in the BER curves and the performance of SVM and ML are, in practice, almost identical. For high SNR, the BER is very weak and cannot be measured with sufficient precision for both methods, so a much larger training data block must be used.

In order to fully study the performance of the classical binary infrared system using a whitened Matched filter (WMF) and the new suggested SVM-based receiver, it is vital to study and compare the processing time for each system. These results are tabulated in Table I.

We note that the processing time is slightly smaller for partially developed fading for both WMF and SVM. This is expected because the partially developed model uses only a small number of scatterers. In both fading models, SVM was slower than WMF. In fact, the main drawback of SVM method is that it is a block-data based method.

TABLE I
PROCESSING TIME FOR THE DIFFERENT SCHEMES OF IR

	Adopted Scheme	Processing Time (micro secs/bit)
Fully Developed Ricean Fading	WMF	0.0852
	SVM	0.1054
Partially Developed Fading	WMF	0.0847
	SVM	0.1048

The results of this work are generated from simulation programs, which are not as accurate as the results that could be acquired from real-time physical systems. For this reason, the computational results of Table I remain rather inconclusive due to the subjectivity of the programming which is controllable in the sense of choosing the models parameters that may not meet the real-time characteristics of real physical systems. Moreover, the computation of the processing time is subjected to the processing time of the computer. Yet since all systems are written with the same programming methodology, the results are comparable in the sense that if one of the systems did give a better processing time than the other system, it is expected that it would give such difference in real time implementation.

To remedy this problem, we suggest, as future work, to adopt one of the many pre-designed SVM chips [24] and implement a real physical system and compare results with the simulation outputs. As processors technology becomes faster and cheaper, SVM's computational complexity disadvantage will be eliminated.

VI. CONCLUSION

In this paper, we applied SVM to binary OOK detection in IR systems in the presence of fading channel and AWGN receiver noise with various statistical characteristics. Two multipath fading channel models were considered: Fully-developed Rician and partially developed fading which is more practical for fading in a local environment with small area and is representative of a wide class of wireless communication systems, including IR, cellular (pico- and femto-cells), and WPAN (wireless personal area networks).

We found that the performance of SVM was superior to that of the traditional ML detector used in binary signalling, especially for very low SNR (below 9 dB). For large SNR, the performance of SVM was similar to that of the ML detector.

The implication of these results is that SVM can be applied to IR communication systems that notoriously suffer from low SNR at the cost of increased computational complexity. SVM can prove very beneficial to IR systems because it allows the transmission distance to increase without significant loss of detected signal quality. We thus expect this work to conceive a new generation of SVM-based IR systems. Since transmission range is also a major problem in deep space communication, such systems can also become SVM-based.

As perspective to this work, we propose to validate the conclusions on real data and to investigate the ability of the SVM-detector to generalize to new noise conditions. Moreover, since SVM is a boundary-based classifier, we propose to define a strategy to integrate in the decision samples from adjacent bits.

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