Defence Science Journal, Vol. 70, No. 1, January 2020, pp. 60-65, DOI : 10.14429/dsj.70.14687

A Robust Cooperative Modulation Classification Scheme with Intra-sensor Fusion for the Time-correlated Flat Fading Channels

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ABSTRACT

Networks with distributed sensors, e.g. cognitive radio networks or wireless sensor networks enable large-scale deployments of cooperative automatic modulation classification (AMC). Existing cooperative AMC schemes with centralised fusion offer considerable performance increase in comparison to single sensor reception. Previous studies were generally focused on AMC scenarios in which multipath channel is assumed to be static during a signal reception. However, in practical mobile environments, time-correlated multipath channels occur, which induce large negative influence on the existing cooperative AMC solutions. In this paper, we propose two novel cooperative AMC schemes with the additional intra-sensor fusion, and show that these offer significant performance improvements over the existing ones under given conditions.

Keywords: Automatic modulation classification; Multi-sensor fusion; Decision fusion; Time-correlated fading channels

1. INTRODUCTION

The wireless networks with spatially distributed nodes/sensors, e.g. cognitive radio networks (CRN) or wireless sensor networks (WSN), endorse viable application of cooperative concept, including the cooperative automatic modulation classification (AMC). The large-scale static or mobile (i.e. on drones) WSN/CRN, are envisioned to detect and analyse signals in security and military applications[1].

The AMC for signal emitted by unknown and uncooperative transmitter is a challenging problem[2]. The uncooperative nature of AMC precludes knowledge on signal and multipath fading (MPF) channel. Thus, classifiers solely rely on processing of small signal sample. So far, various AMC solutions with single sensor reception are proposed[2-5]. Thus, likelihood-based (LB) AMC[2,5] are complex solutions with optimal performance, while feature-based (FB), i.e. cumulant-based AMC[3] or Kolmogornov-Smirnov[4] present robust but sub-optimal solutions. Recently, cooperative AMC is proposed[6-10], and shown to offer potential gains through multi-sensor reception and fusion. However, all previous studies generally observe signal reception over static MPF channels. In practice, transmitter and/or sensors are mobile, and a reception over time-correlated MPF channels should be observed[10,11], with the performance loss reported for optimal maximum-likelihood classifier[11], or the cumulant-based one[10]. Reported performance loss occurs due to changes of channel during a signal reception, which causes variable statistic properties of feature used in AMC. This effect is enhanced as the length of signal sample increases, particularly for low symbol rates when flat-fading occurs.

In this paper, novel cooperative AMC with two-stage fusion is proposed, consisting of intra-sensor cumulant-based fusion and cooperative centralised decision fusion, designed particularly for application in time-correlated flat-fading channels. In order to design robust solution for PSK/QAM signals, suitable for the large-scale WSN deployment (i.e. with low complexity and communication demands), cumulant-based AMC is considered[3], since LB cooperative AMC have high communication burden.

2. THE CUMULANT-BASED AMC

The baseband symbol sequence received over the flat-fading channel is[3,10],

$$y(n) = h_{FF}(n) \times x(n) + g(n) \qquad (1)$$

where $x(n)$ is n-th symbol, $h_{FF}(n)$ is appropriate channel coefficient of an unknown MPF channel, $g(n)$ is the n-th sample of complex additive white Gaussian noise (AWGN) with a zero mean and variance σ_g^2, while a signal-to-noise ratio (SNR) is defined as $E\{x^2(n)\}/\sigma_g^2$ [3,6-10].

The AMC decisions are based on normalised fourth-order cumulant of emitted symbol sequence[3,6-10] (C_{42}), i.e. on the local cumulant estimate (C_{42}^{est}) calculated from the received symbol sequence of length N_{SS},

Received : 17 June 2019, Revised : 10 October 2019
Accepted : 30 December 2019, Online published : 10 February 2020

$$C_{42}^{est} = \frac{N_{SS} \times \sum_{k=1}^{N_{SS}} \left|y(k)\right|^4 - \left|\sum_{k=1}^{N_{SS}} y^2(k)\right|^2 - 2\left[\sum_{k=1}^{N_{SS}} \left|y(k)\right|^2\right]^2}{\left[\sum_{k=1}^{N_{SS}} \left|y(k)\right|^2 - N_{SS} \times \sigma_g^2\right]^2} \quad (2)$$

Due to uncooperative nature of AMC actual channel coefficients, $h_{FF}(n), n = 1,\ldots,N_{SS}$, are inherently unknown, as well as MPF channel type and properties, i.e. probability density function (pdf).

In Table 1, the theoretic means of fourth-order cumulant for some PSK and QAM signals are given[3], which present suitable reference means (to set decision threshold) for reception in AWGN channels[3,8-10]. The actual cumulant means for MPF channels strongly depend on MPF channel properties and SNR.

Table 1. The theoretic means of C_{42}

Signal	BPSK	QPSK	16QAM	64QAM
Mark	m_1	m_2	m_3	m_4
$C_{42}^{m_i}$	-2.0000	-1.0000	-0.6800	-0.6191

The common time-correlated MPF channels are observed[12]. A line-of-sight (LOS) and NLOS (non-LOS) reception is modelled with the Rician and Rayleigh flat-fading channel models, as defined in Table 2. Doppler frequency (B_{dop}) describes rate of channel change. Two B_{dop} values are observed: 4 *Hz* and 12 *Hz* corresponding to the pedestrian and slow vehicle speed[12], respectively. A number of symbols transmitted over the virtually unchanged channel, $N_{static} = 1/(100 \times B_{dop} \times T_S)$ as shown in Table 2, for symbol period T_S , define quasi-static channel[12].

Table 2. Parameters of considered LOS/NLOS MPF channel models

Channel Mark	σ_h^2	K	B_{dop}	N_{static}
CH#1 (NLOS)	0.3		4Hz	150
CH#2 (NLOS)			12Hz	50
CH#3 (LOS)	0.3	1	4Hz	150
CH#4 (LOS)			12Hz	50
CH#5 (LOS)	0.3	4	4Hz	150
CH#6 (LOS)			12Hz	50

2.1 The Single Sensor AMC

The cumulant estimate quality (CEQ) defines the AMC performance[6-10]. Hence, the actual cumulant means and variances are estimated for all channels as shown in Table 2, and chosen set of modulated signals $M_{\text{mod}} \in \{BPSK, QPSK, 16QAM, 64QAM\}$. Monte-Carlo trials to estimate these actual values for modulated signals modelled as random processes with randomly generated symbol sequences $x(n), n = 1,\ldots,N_{SS}$; $N_{SS} \in \{500, 1000, 2000, 4000\}$ and $snr[dB] \in [-5, 20]$ has been used.

Similar CEQ behaviour, regarding SNR and MPF channels, for all signals has been obtained. Thus, the actual cumulant means for QPSK signal and different channels are as given in Fig. 1, as an illustration.

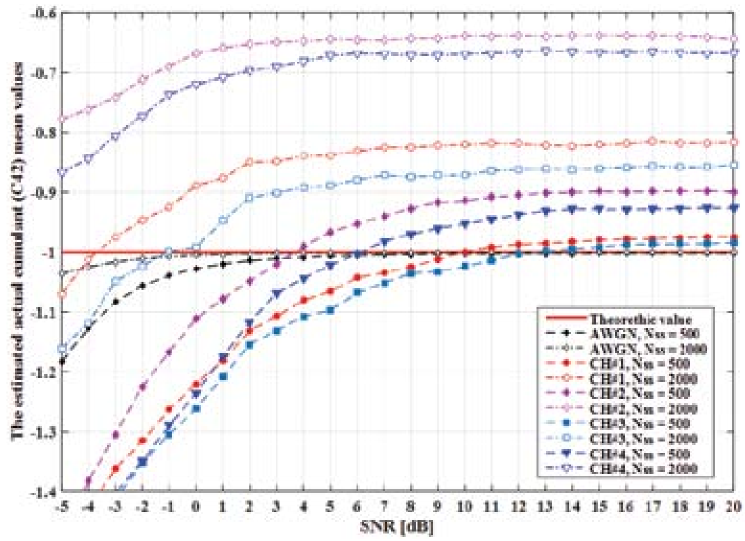

Figure 1. The actual cumulant means for QPSK and different MPF channels.

The general conclusions are:

- the actual cumulant means converge to theoretic means as SNR increases only for AWGN channel
- the actual cumulant means for MPF channels deviate from theoretic means, with a small shift for low B_{dop} and high SNR, and large shift towards zero for higher B_{dop} that increases with the sample length (N_{SS})
- CEQ does not improve as the sample length increases
- AWGN causes a significant decrease of CEQ for low SNR and the small sample lengths.

The standard measure of AMC performance is the average probability of correct classification $(P_{CC,avg})$ over equiprobable modulations under given conditions[2-11]. $P_{CC,avg}$ and confusion matrices (CMs), i.e. set of probabilities $p(m_j|(m_n, snr)), \forall (m_j, m_n) \in M_{\text{mod}}$ [8-10], when actual modulation is m_n , for $snr[dB] \in [0, 20]$ has been estimated.

The estimated $P_{CC,avg}$ for MPF channels are in agreement with the above conclusions regarding CEQ. The $P_{CC,avg}$ in Rician MPF channels for two Doppler frequency values are as given in Fig. 2. As expected, the AMC performance:

- increases as sample size rises only for AWGN channel
- increases as the SNR rises, but a much better performance is achieved for MPF channels with low B_{dop}
- strongly decreases as B_{dop} rises, especially for the bigger sample lengths
- small sample lengths $(N_{SS} = 500)$ are suitable for high SNR, while bigger lengths $(N_{SS} = 1000)$ suit only for low B_{dop} and poor SNR.

2.2 The Cooperative AMC

The cooperative AMC with centralised fusion is considered[6-10], in which N_{sen} sensors receive the same modulated signal, with an unidentified modulation type $m \in M_{\text{mod}} = \{m_1, m_2, m_3, m_4\}$, over uncorrelated channels and with sensor specific local SNR, $snr_i, i = 1,\ldots,N_{sen}$. Sensors collect sample sequence of N_{sl} symbols, $y_i(n), n = 1,\ldots,N_{sl}$. A cumulant-based AMC is used to produce local AMC results,

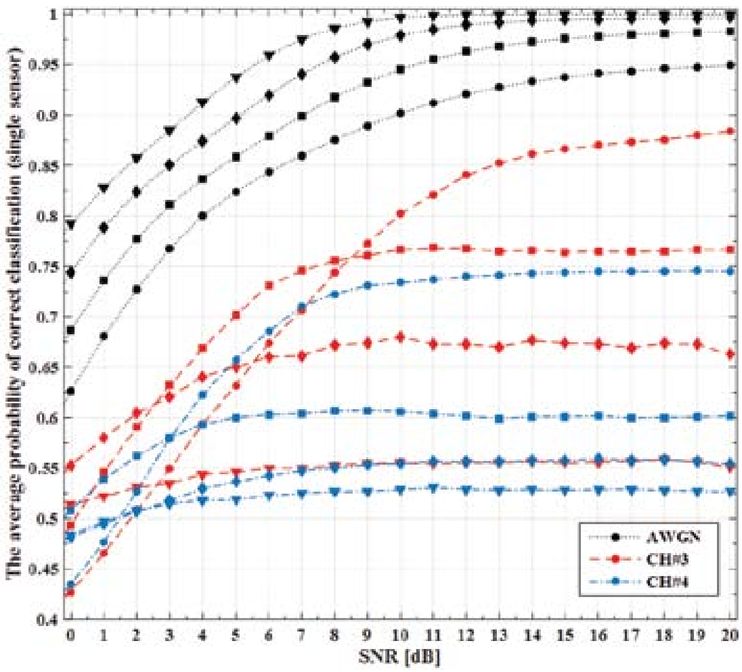

Figure 2. The $P_{CC,\,avg}$ for CH#3 and CH#4, and different N_{ss}: 500(●), 1000(■), 2000(♦) and 4000(▼).

i.e. local cumulant estimates, $C_{42,i}$, or decisions, $d_i, i = 1,\ldots,N_{sen}$ Fusion centre (FC) collects local AMC results and SNRs, and makes the final decision. Since MPF channel properties are unknown, local SNRs represent the sole quality measure of local AMC results.

2.3 Fusion Methods

Various fusion methods for cooperative AMC are proposed[5-10]. A data fusion (DaF)[9,10], is derived for high CEQ. Yet, it is shown[10] that DaF is not suitable for time-correlated flat-fading channels, since CEQ strongly depends on current channel state. Consequently, only the hard decision fusion (HDF), with reported fair behaviour in flat-fading channels[10] is considered. The other fusion methods[4-10] were also tested, but are omitted due to the poor performance in time-correlated MPF channels.

The optimal HDF (OHDF) is defined[8], with a decision rule,

$$M_{FC}^{OHDF} = \underbrace{\arg\max}_{m_n \in M_{mod}} \left\langle \prod_{i=1}^{N_{sen}} \frac{p\left(d_i \middle| \left(m_n, snr_i\right)\right)}{\sum_{k=1}^{M} p\left(d_i \middle| \left(m_k, snr_i\right)\right)} \right\rangle \qquad (4)$$

where $p\left(d_i \middle| \left(m_n, snr_i\right)\right)$ are the conditional probabilities of local decision d_i, made under the local SNRs, $snr_i = 1,\ldots,N_{sen}$, when the actual modulation is m_n. Thus, OHDF demands a priori knowledge of reference CMs, i.e. set of conditional probabilities $p\left(m_j \middle| \left(m_n, snr\right)\right), \forall \left(m_j, m_n\right) \in M_{mod}$[8-10].

Also, majority decision HDF (MDHDF) is considered, in which the final decision is chosen as the most frequent local decision.

2.4 The real-world application

The cooperative AMC achieves expected high performance only when the appropriate references (reference means, variances or CMs) estimated for the actual MPF channel and SNR are used[6-10]. In practice, actual MPF channel properties are unknown and cannot be reliably estimated from a short signal sample. Thus, mismatched references must be used with a considerable decrease in AMC performance[9,10]. In order to design a universal solution, we observed the worst case scenario of mismatched references (WCS), with the theoretic means chosen as reference means, and reference variances and CMs estimated for AWGN channel.

3. THE PROPOSED SOLUTION

In cooperative AMC, fusion methods exploit complete information about the unknown signal gathered by reception over the uncorrelated MPF channels. However, the unavailability of optimal references (estimated for the actual MPF channel), i.e. the mismatch of optimal and available WCS references, causes performance deterioration. This could be alleviated through CEQ improvement. However, as shown in Section 2 the increase of sample length causes degradation of CEQ for time-correlated MPF channels.

Two-stage fusion to overcome this problem is proposed. In the first stage, the intra-sensor fusion, symbol sequence of length N_{sl} is collected at each sensor. It is divided into several $\left(N_{seg}\right)$ segments of same length N_{ss} and the cumulant estimate is calculated for each segment.

The simplest approach to improve CEQ is to average cumulant estimates over segments and use that average to get local decisions, $d_i, i = 1,\ldots,N_{sen}$, used in the second stage at FC for cooperative HDF. We found that MDHDF presents a better solution than OHDF. Hence, average intra-sensor fusion with MDHDF (AisF+MDHDF) is defined.

For MPF channel with high Doppler frequency, averaging of cumulant estimates doesn't produce high CEQ due to the large cumulant estimate variance for small sample lengths (especially for low SNR). Thus, a solution is proposed in which AMC decisions are made for each segment and intra-sensor HDF is used to get local decisions, $d_i, i = 1,\ldots,N_{sen}$, which are used at FC for cooperative HDF (in the second stage). It is found that MDHDF presents a better solution for intra-sensor fusion, due to a substantial WCS reference mismatch in OHDF. Conversely, OHDF has better performance in the second stage. Thus, MDHDF intra-sensor fusion with OHDF (DisF+OHDF) is defined.

Reference CMs are needed in the second stage of DisF+OHDF. These can be estimated for any SNRs when MDHDF is applied for given segment number $\left(N_{seg}\right)$ and sample length $\left(N_{sl}\right)$, used with WCS references. Hence, a more suitable reference CMs than in cooperative AMC without intra-sensor fusion are used at FC, which allows optimal fusion with a small performance loss even for the low CEQ. So, DisF+OHDF should outperform AisF+MDHDF for the low CEQ (i.e. high B_{dop}).

4. NUMERICAL RESULTS

The comprehensive Monte-Carlo experiments were used to estimate the performance of cooperative AMC schemes. The network with up to 10 sensor and randomly generated channels, local SNR, input signals and AWGN is considered. The mixture of PSK/QAM signals $M_{\text{mod}} \in \{BPSK, QPSK, 16QAM, 64QAM\}$ is observed with randomly generated symbol sequences $x(n), n = 1,\ldots,N_{sl}$, with $N_{sl} \in \{500,1000,2000,4000\}$ for $snr_i[dB] \in [5,20]$. DisF+OHDF and AisF+MDHDF schemes are observed for sequences with 2000 and 4000 symbols, and division into segments with 500, 1000 or 2000 symbols. In all scenarios, sensors receive signal over MPF channels of the same type, which are independently generated.

Two scenarios regarding sensor placement are considered which are as follows:

- Spatially distributed sensors (SDS). Sensors are randomly placed around transmitter in different directions. The local SNRs are independent uniformly distributed random variables with $snr_i[dB] \in [5,20]$;
- Spatially grouped sensors (SGS). Sensors are grouped at similar distance from transmitter (but far enough to have uncorrelated reception). The local SNRs are independent uniformly distributed random variables with $snr_i[dB] \in [SNR-2, SNR+2]$, defined for $SNR = 7dB$ or $SNR = 15dB$ to model the low and high SNR reception.

The reference CMs used in the second stage of DisF+OHDF scheme are estimated for intra-sensor MDHDF for 1-8 segments with 500 or 1000 symbols and $snr_i[dB] \in [5,20]$. To get reference CMs that are not adjusted for the specific channels, MPF channels with variance σ_h^2 equal to 0.05, 0.1, 0.3, and 0.5 are used, and the resulting CMs are averaged. Thus, mismatch in reference CMs to model more realistic application conditions is introduced.

Due to a limited space only the most important results are presented. The results for DisF+OHDF and AisF+MDHDF are given for different number of segments (N_{seg}) and segment lengths (N_{ss}), when a whole sample length (N_{sl}) was 2000 or 4000 symbols. The cases with one segment represent cooperative AMC without intra-sensor fusion.

AMC performances of DisF+OHDF in SDS for CH#3 are as given in Fig. 3. As expected, intra-sensor fusion facilitates significant performance increase (compared to cooperative AMC without intra-sensor fusion), with the best results achieved for the shortest segment length $(N_{ss} = 500)$ when large input sample is divided into more segments.

Further results for DisF+OHDF in SDS with a small segment length $(N_{ss} = 500)$ and other MPF channels are as presented in Fig. 4. Clearly, the better performance is achieved for the larger input sequences (with more segments). As expected, better behaviour is achieved for MPF channels with lower Doppler frequency and for LOS (Rician) than for NLOS (Rayleigh) channels, due to higher CEQ. For higher Doppler frequency, the NLOS reception produces a larger performance loss than the LOS reception.

The performance of AisF+MDHDF in SDS for CH#5 and CH#6 is as presented in Fig. 5. Evidently, for lower

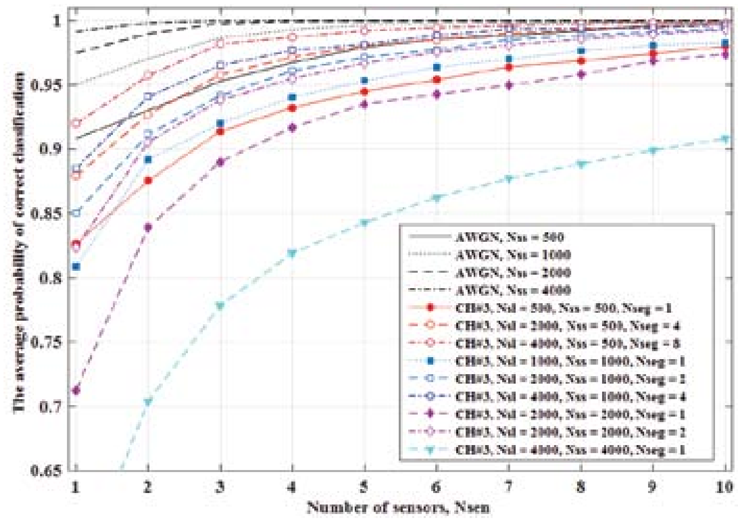

Figure 3. The DisF+OHDF performance in SDS for CH#3 and different segment number and lengths.

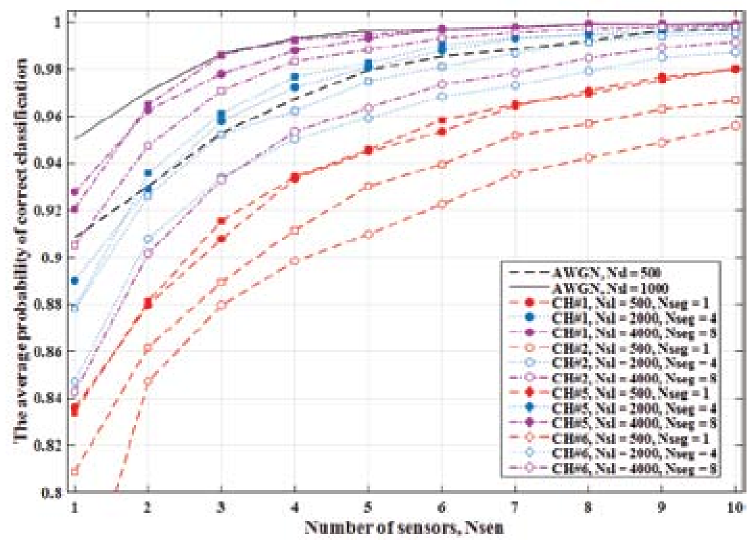

Figure 4. The DisF+OHDF performance in SDS for different MPF channels and N_{ss} = 500.

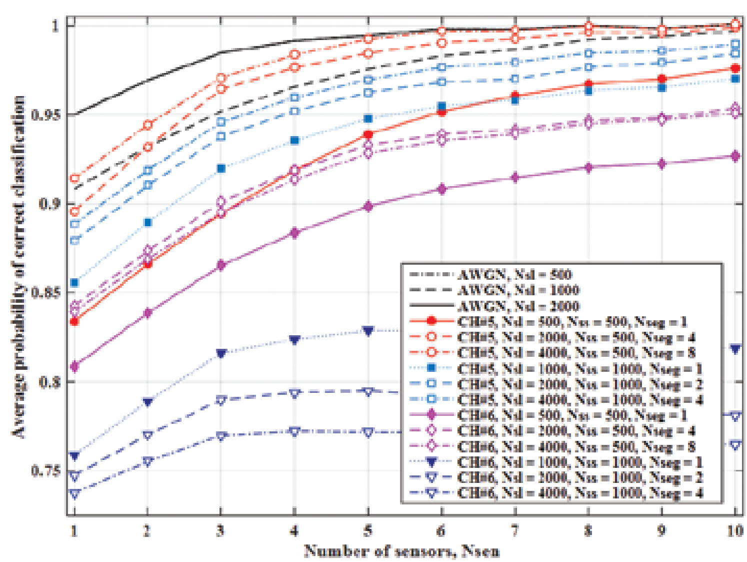

Figure 5 The AisF+MDHDF performance in SDS for CH#5 and CH#6, when $N_{ss} \in$ {500, 1000}.

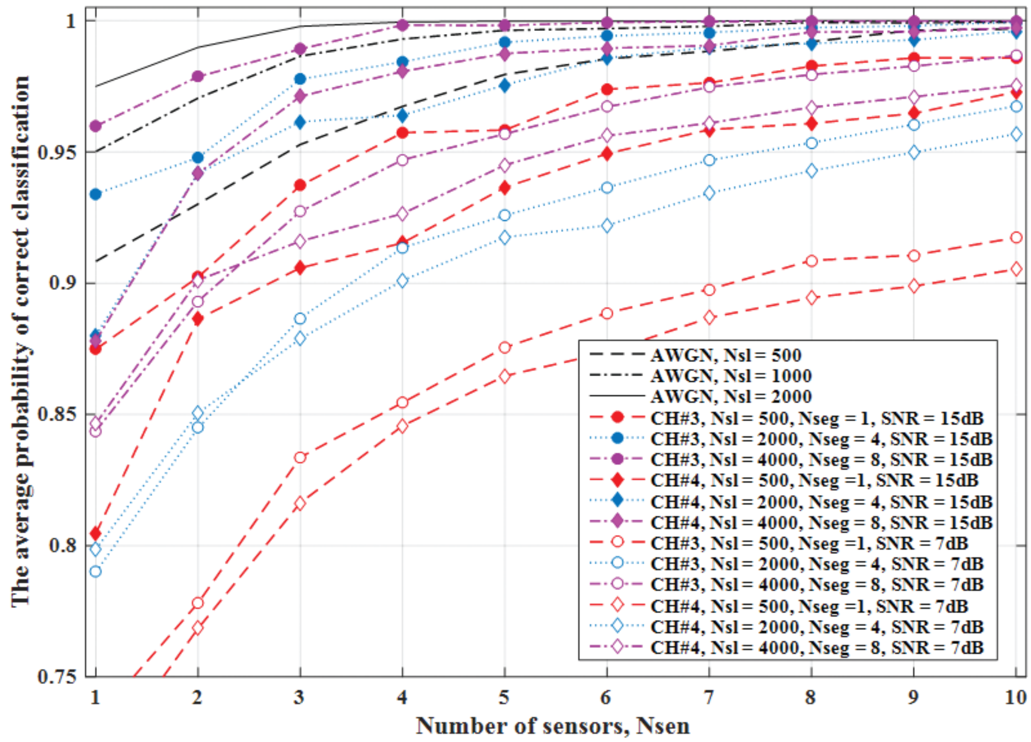

Figure 6. The DisF+OHDF performance in SGS for CH#3 and CH#4, when N_{ss}= 500.

Doppler frequency AisF+MDHDF achieves fair performance. The best option for larger input sample is shortest segment length $(N_{ss} = 500)$. For low Doppler frequency, due to a fair CEQ, AisF+MDHDF outperforms DisF+OHDF, but fails for channels with high Doppler frequency, particularly for long segments.

The performance of DisF+OHDF in SDS when local SNRs for all sensors are similar is as given in Fig. 6. For high SNR, lower Doppler frequency and large input sample, an almost ideal classification is noticed (for 4-5 sensor), but a performance loss occurs for higher Doppler frequency. For low SNR, i.e. low CEQ, there is a large decrease in performance. Therefore, sensors should be dispersed in space (as in SDS) to enable classification over wide spatial area, while closely placed sensors enable operation only in reduced area around transmitter.

5. CONCLUSIONS

The cooperative AMC presents feasible, natural and favourable solution for envisioned WSN/CRN based applications. Application of cooperative AMC should impose low communication and complexity burden in energy constrained WSN. As the most promising LB cooperative AMC solutions[5] have higher communication demands, FB solutions[4,6-10] seem to be more appropriate for the large-scale WSN, e.g. cumulant-based[6-10] classifiers.

In this paper, we studied highly important practical scenario with the signal reception over the time-correlated MPF channels (due to mobility) which was not addressed in literature. Based on the existing cooperative AMC with centralised fusion, which doesn't behave well under the given conditions[9,10], the two novel two-stage fusion solutions with the intra-sensor fusion are proposed. The cumulant feature aggregate and HDF were observed for intra-sensor fusion, to enable a more successful local AMC decision in all sensors. The results of numerical analysis confirm the main assumptions and expectations as given in section 3, and prove that the proposed solutions outperform those without intra-sensor fusion.

The proposed cumulant-based solutions are simple, robust and suitable for large-scale WSN. Their design could be applied to adjust existing LB[5] or other FB[4] AMC for application in time-correlated flat-fading channels and thus achieve even higher performance. Future studies should also present comprehensive analysis of communication and computation cost related to the existing and novel cooperative AMC solutions.

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In current study, he has contributed in conception and implementation of proposed solutions, validation and visualisation of results.

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In current study, he has contributed in conception of idea and simulations.