Single-mode optical fibre decoder using polarization and a KNN algorithm

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Abstract

It is shown experimentally a new digital optical decoding scheme based on the transmission or polarized light at p polarization planes using a K-Nearest Neighbor (KNN) algorithm through a single-mode optical fibre at 633 nm. The optical power signal is sent at p polarization planes which constitute p classes required for signal bit recognition. Results show that it is possible to recognize 32 polarizations planes, 5 bits, using 4 features corresponding to the measurement of optical power at 4 different angles at the photodetector side with an average assertiveness of 99.1%.

Single-mode optical fibre digital decoder based on polarization using a K-Nearest Neighbour algorithm

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Introduction: The use of artificial intelligence has recently increased in many areas of science and engineering, including wireless telecommunications , optical fibre communications and optical fibre sensor applications . In this paper we explore experimentally the use of the K-Nearest Neighbour algorithm (KNN) for the integration of a fibre optics digital decoder based on light polarization to estimate 32 angular positions of a device. According with , KNN is a supervised learning classification algorithm that uses the proximity of the data to classify with respect to a data base. For this reason, a data base has been created that stores information about the optical power pattern in the output of a single-mode optical fibre for each of the 32 transmitted signals encoded in polarization.

Experiment: Fig. 1 shows the elements required to generate a KNN database. Light from a He-Ne laser is coupled into a single mode fibre SM600 (Thorlabs) through a polarizer disk that has the function of modifying the polarization angle in which the light is launched into the optical fibre. For the transmission of 5 bits is necessary to control 32 polarization planes in 180° and each bit sequence has a specific polarization angle associated with it as shown in Table 1. The coding disk will take any of these 32 positions which are called "classes". On the other hand, with the analyzer disk, 4 "features" are obtained that characterize the optical power pattern received by the photodiode of the optical power meter at the output of the fibre. These features are records of the optical power measured for 4 positions of the analyzer disk (0°, 45°, 90° and 135°) for each one of the classes. Table 2 shows a section of the data base can be formed with 32 classes, 100 inputs per class and 4 features for each input.

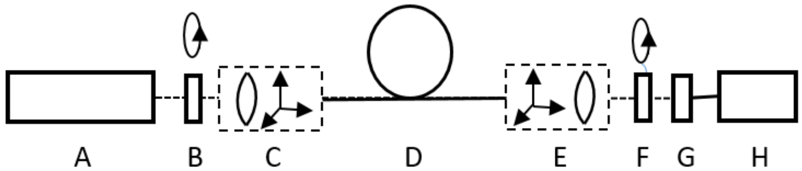

Fig. 1 Experimental setup A: He-Ne laser 633 nm, B: Polarizer disk (encoder), C: Single mode fibre launch XYZ with objective lens, D: Single mode optical fibre at 633 nm (50 m), E: XYZ translation stage, F: Analyzer disk, G: Silicon Photodiode, H: Optical Power Meter.

Table 1: Class number, 5-bit chain and equivalent polarization plane.

Bits	Polarization Plane		Bits	Polarization Plane		Bits	Polarization Plane		Bits	Polarization Plane	
a b c d e	Degrees	Class	a b c d e	Degrees	Class	a b c d e	Degrees	Class	a b c d e	Degrees	Class
0 0 0 0 0	0	0	0 1 1 0 0	45	8	1 1 0 0 0	90	16	1 0 1 0 0	135	24
0 0 0 0 1	5.625	1	0 1 1 0 1	50.625	9	1 1 0 0 1	95.625	17	1 0 1 0 1	140.625	25
0 0 0 1 1	11.25	2	0 1 1 1 1	56.25	10	1 1 0 1 1	101.25	18	1 0 1 1 1	146.25	26
0 0 0 1 0	16.875	3	0 1 1 1 0	61.875	11	1 1 0 1 0	106.875	19	1 0 1 1 0	151.875	27
0 0 1 1 0	22.5	4	0 1 0 1 0	67.5	12	1 1 1 1 0	112.5	20	1 0 0 1 0	157.5	28
0 0 1 1 1	28.125	5	0 1 0 1 1	73.125	13	1 1 1 1 1	118.125	21	1 0 0 1 1	163.125	29
0 0 1 0 1	33.75	6	0 1 0 0 1	78.75	14	1 1 1 0 1	123.75	22	1 0 0 0 1	168.75	30
0 0 1 0 0	39.375	7	0 1 0 0 0	84.375	15	1 1 1 0 0	129.375	23	1 0 0 0 0	174.375	31

Table 2: Example of a section of a database obtained with 32 classes and 4 features per class.

Polarization Plane		**Features (μW)**				**Polarization Plane**		**Features (μW)**			
Degrees	Class	**0°**	**45°**	**90°**	**135°**	Degrees	Class	**0°**	**45°**	**90°**	**135°**
0.00	0	7.9	21.03	21.01	8.28	90	16	16.15	6.62	7.16	16.9
5.63	1	5.82	19.8	22.16	8.05	95.625	17	18.7	7.02	5.74	17.5
11.25	2	3.82	18.93	23.28	8.37	101.25	18	20.55	7.14	3.92	17.78
16.88	3	2.8	17.4	23.84	9.2	106.88	19	22.1	7.43	2.515	17.5
22.50	4	1.7	16.67	24	9.55	112.5	20	24.17	8.3	1.86	17.84
28.13	5	1.21	15.28	23.67	9.97	118.13	21	25.17	9.2	1.575	17.77
33.75	6	1.13	14.33	23.4	10.6	123.75	22	25.56	10.04	1.56	16.86
39.38	7	1.515	12.71	21.81	11.5	129.38	23	25.58	11.45	1.88	16.73
45.00	8	1.99	11.5	20.7	11.73	135	24	25.06	12.74	3.16	15.68
50.63	9	2.83	10.92	19.44	12.2	140.63	25	23.67	14.35	5.13	15.65
56.25	10	4.43	9.77	17.95	12.78	146.25	26	23.06	14.75	5.98	14.4
61.88	11	6.43	8.98	16.13	13.56	151.88	27	21.33	16.25	8	13.23
67.50	12	8.01	7.78	13.83	14.01	157.5	28	19.09	17.24	10	11.67
73.13	13	9.8	7.07	11.84	14.79	163.13	29	16.55	18.37	12.24	10.48
78.75	14	12.22	6.9	10.66	15.3	168.75	30	14.52	18.95	13.93	9.76
84.38	15	14.12	6.88	8.86	16.17	174.38	31	11.75	20.21	16.95	8.48

KNN algorithm implementation: Tests were carried out with 11 distinct data bases. The first of these data bases had 3,200 inputs and 4 features for each input. Next, the other 10 databases were generated with the possible combinations of the 4 features to determine which of these provide the larger assertiveness index. This is because, usually, the KNN classification algorithm usually works better if there is a large separation between classes. This separation might be superior if 3 features are used instead of 4 or 2 features instead of 3. However, in our case 4 features provided the best result. Each one of these 11 databases has been processed in multiple occasions by the KNN algorithm varying the number of neighbours used to perform the classification from 3 to 99 neighbours.

A K fold cross validation (KFCV) has been utilized to evaluate the KNN model. Each of these 11 databases has been randomized in 10 distinct occasions. In each one of them, the first 80% of the elements has been chosen as a training set and the remaining 20% as the test set. The training set has been delivered to the KNN and the assertiveness index obtained with the classification of the test set varying from 3 to 99, with increments of 2 for the number of neighbours. The process described above has been repeated in 5 occasions, choosing in each of them a new 20% in each database as a test set and training the KNN with the remaining 80%.

Results: The results obtained for each of the databases applying KFCV in 10 occasions are shown in Fig. 3. The database that contains 4 features presents the larger assertiveness index with an average of 99.02%, which has been obtained when 13 neighbours are used to perform the classification of the test set. 10 iterations of KFVC have been made and in each one of them 5 different training sets and test sets have been chosen. Fig. 3 shows the assertiveness index for each of the 50 tests made on the databases that contain the 4 features varying the number of neighbours.

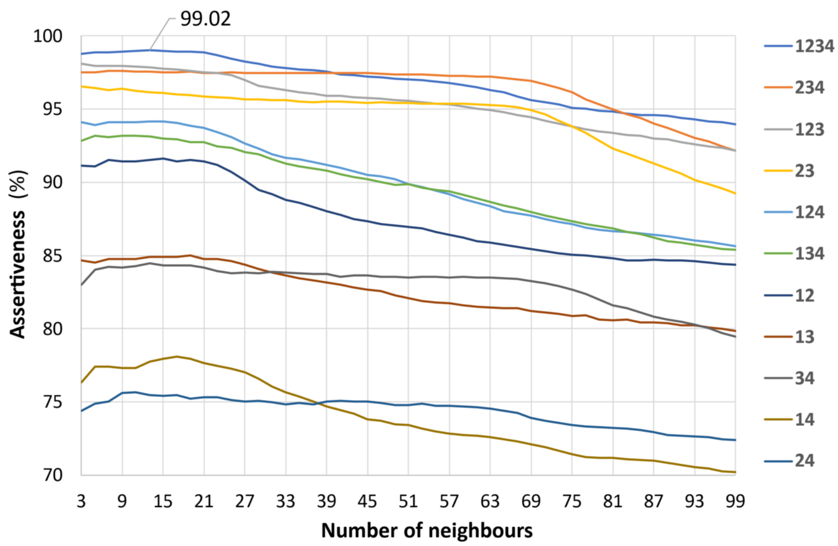

Fig. 2 Average value the assertiveness index in the classification of 11 databases varying the number of neighbours when KFCV is applied to 10 KFCV iterations.

Fig. 4 shows the confusion matrix for the KNN algorithm used in the decoder and it is another way of looking at its performance. For example, class 2 was sent and class 2 was obtained during all 200 trials but for class 5 the algorithm obtained 3 classes 4, 184 classes 5 and 13 classes 6. In this analysis, from a total of 6,400 signals sent, 102 were incorrect, alternatively it can be said that from a total of 32,000 bits coded, 102 bits were incorrectly decoded which represent a $3.2\text{x}10^{-3}$-bit error rate (BER). This BER is low for an optical fibre communication system if it were used as a modulation scheme, but it is an interesting result for applications in which the angular position of a device needs to be determined and the information transmitted through an optical fibre . The experiment was done using a specialty fibre single mode at 633 nm, but it can easily be replicated using a standard SMF-28 single mode fibre at 1550 nm, only the optical elements must be chosen for this wavelength. It is important to emphasize that 32 polarizations states have been sent through a non-polarizing optical fibre and estimated correctly 99.02 % of the time.

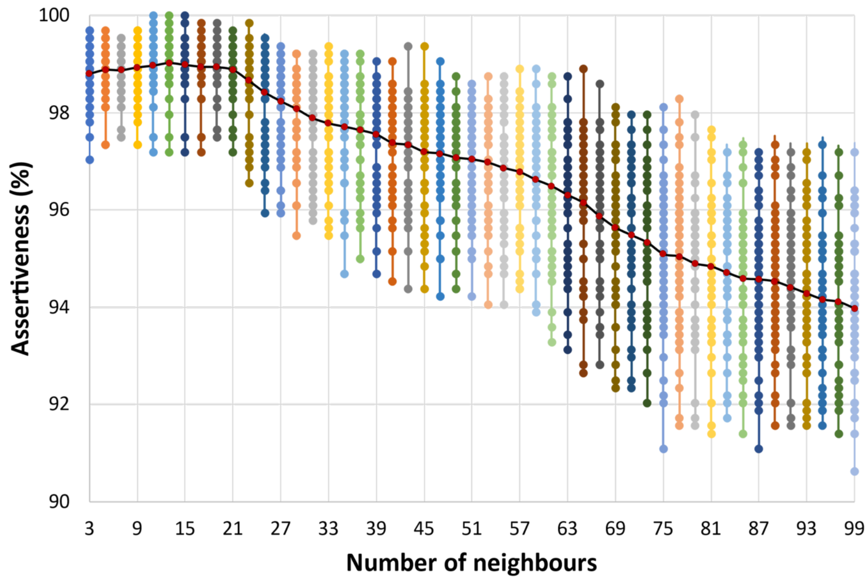

Fig. 3 Assertiveness index versus number of neighbours for the 50 tests made over the database with 4 features.

Class obtained

Class sent	0	1	2	3	4	5	6	7	18	19	20	21	22	23	24	25	26	27	28	29	30	31
0	200																					
1		200																				
2			200																			
3			2	191	7																	
4				5	175	20																
5					3	184	13															
6						1	194	5														
7								200														
18									200													
19									21	179												
20										23	177											
21											2	198										
22													200									
23														200								
24															200							
25																200						
26																	200					
27																		200				
28																			200			
29																				200		
30																					200	
31																						200

Fig. 4 A section of the confusion matrix for the KNN algorithm used in the decoder.

Conclusions : It is demonstrated that it is possible to code 32 polarizations states over a non-polarization maintaining single-mode fibre at 633 nm by using an artificial intelligence K-nearest neighbor algorithm with 4 features and 13 neighbours with an average assertiveness index of 99.02%. This is a good estimate for applications in which the angular position of a device needs to be determined and the information sent through a standard non polarizing fibre.

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