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Capturing correlations in vision parameters by artificial neural networks

A. Erculei([1]), V. Cimini([2])([1]), M. Barbieri([1])([3]) and A. Rotondi([1])

([1]) *Dipartimento di Scienze, Università degli Studi Roma Tre - Via della Vasca Navale 84, 00146 Rome, Italy*
([2]) *Dipartimento di Fisica, Sapienza Università di Roma - P.le Aldo Moro 5, 00185 Rome, Italy*
([3]) *Istituto Nazionale di Ottica, CNR - Largo E. Fermi 6, 50125 Florence, Italy*

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Summary. — Understanding the correlations between different visual functions is fundamental to ensure the right intervention to solve refractive problems. Existing studies are based on complex procedures, where it is possible to address analysis through empirical models. A different approach that has shown great functionality are neural networks, since they are able to find correlations within large collections of data with little assistance from the user. The present study stems from the desire to develop a prediction algorithm through Neural Networks by adopting a black-box approach. The objective is to design a network able to predict the values of visual acuity from the refractive errors and take into account correlation between the two quantities. For the construction of the network in questions, 136 eyes (68 subjects) were included, and, even using commercial, unsophisticated tools, the predictions for visual acuity remain close to the actual one. Our results give hope for the wide diffusion of this contact between optometry and neural networks.

1. – Introduction

In the analysis of vision, functions are often assessed as independent abilities, despite the fact that correlations are actually present. A more comprehensive view may assist practitioners in critically evaluating the outcomes of their measurements, as well as highlighting possible anomalies. Due to the natural variability of physiological data, these correlations are not expected to be sharp, and a model guiding our intuition can often be hard to find. This complicates the issue of evaluating what can be considered as the standard condition. In addition, a given parameter generally depends on many others. A case in point is visual acuity (VA): while it captures a specific aspect of vision, *i.e.*, spatial resolution and the ability of discriminating details [1], it is considered as a prominent function signalling issues with the integrity of the visual system. Hence, the attention to the measurement of VA as the main indicator of the quality of vision [2]. Measurements of VA adopt different standards: for instance, Snellen charts are the most popular choice in English-speaking countries, and Monoyer are more frequently adopted in continental Europe. Intrinsic limitations have been investigated and stem from factors including inconsistent progression in letter size, unequal legibility of letters, unequal and unrelated spacing between letters and rows [3]. Changes in background ambient illumination and contrast constitute an additional source of variability.

VA is influenced by multiple factors at once: optical aberrations in the eye, diameter of the pupil, transparency of the medium [4]. Crucially, refractive errors play a major role in determining the VA, and this link has been the subject of an intense research efforts over the last decades. Empirical studies have described the connection between VA and spherical and sphero-cylindrical errors [5-9], but the dependence of VA on multiple parameters at once makes it difficult to inspect data directly. The availability of phenomenological models allows reducing the dimensionality of the problem, making it tractable [6], but this is tantamount to assuming a specific functional dependence. In practice, the Emsleys relation ("one line of the Bailey-Lovie optotype corresponds to 0.25 D of spherical error" [1]) is frequently adopted as a guide by practitioners, but more general solutions going beyond this specific case would be highly desirable. These, however, need to be sufficiently flexible to be adapted to different situations and cannot demand too complex analysis, in order to be widely adopted.

Nowadays, machine learning(ML) techniques offer the possibility to inspect large sets of and to extract relevant information in a model-independent way [10-14]. These have found applications in ophthalmology, especially in image recognition for computer-assisted screening of pathological conditions of the retina, as well as of keratoconus [15-17]. In the light of the solid advantage demonstrated by ML in these cognate domains, these same methods are expected to provide support to optometrists in primary eye care. This requires applying them to cases that have received limited attention, such as magnitudes pertinent to vision.

In this article, the application of a prominent ML paradigm is presented: artificial neural networks (ANNs) are employed to successfully recover the correlation between VA and refractive errors with a simple algorithm. The optimisation of our network demonstrates that this operation can be performed with reduced complexity, despite the small size of our data sample. With the inception of these techniques beyond this well-known case, a path can be opened up in which more general correlations can be unveiled. While the experience of practitioners cannot be replaced by automated methods [18], they can nevertheless benefit from guidance obtained based on ANN analysis.

2. – Results

In this study, the correlations between VA and refractive errors are analyzed based uniquely on empirical grounds. Differently from previous studies [6], we do not attempt at capturing mutual dependence by means of a fitting curve: we rather rely on direct inspection of data assisted by ML.

2˙1. *What is an Artificial Neural Network*. – Algorithms can be generally described as sets of instructions that computers have to follow to provide responses. For instance, if the desired task is to compute the Pearson correlation coefficient between two sets of data X and Y, the machine should be previously instructed to compute the standard deviation of X, then the one of Y, then the covariance term, and, finally, take the appropriate ratio – the structure can be nested, as some of these subroutines are actually made of more elementary instructions.

A computer can then be asked to quantify the level of correlation, whenever it is expected to be present, however, in many cases, it would be handy to have the machine itself predict the presence and shape of correlations when our intuition provides no guidance: this is especially true for multiparameter problems, as visual inspection would offer little or no assistance. However, standard algorithms require detailed instructions to solve the demanded task. A different take to programming is thus necessary. Artificial intelligence takes this route, by avoiding giving instructions to the computer, while letting it learn the solution to the problem directly by inspecting data [11].

ANNs are a common solution in artificial intelligence, with an architecture inspired by that of biological neural connections [10]. The aim of this algorithm is to establish how variable Y depends on variable X: for these, auxiliary variables called neurons are introduced, and are arranged in layers, including the input layer containing X, the output layer containing Y, and a series of hidden layers which perform the association task. The value of each neuron is set by those of the previous layers by means of an appropriately chosen function; not all of these contribute equally to determine the new value, but a weight establishes the strength of the mutual connections. ANN can thus be pictured as a system that accepts X as an input, then its neurons fire accordingly, until they can produce outcome Y.

The key step is the process of training: examples of correlated pairs (X_i, Y_i) are given to the ANN, and the weights are varied starting from an initial random guess until the network is able to replicate the correct connections $X_i \to Y_i$. At this point, the ANN is able to accept a generic input X_j, and make a prediction of the value Y_j, even though the relation between the two variables was not previously explicitly coded. During the training stage, the ANN tries to minimise a specific loss function (the most basic example is represented by the mean squared error) in order to reduce the difference among its prediction and the target output. The quality of the trained ANN is then assessed by looking at the mean squared error $\epsilon_{\mathrm{MS}} = \sum_i (Y_i^{\mathrm{pr}} - Y_i)^2$, where Y_i^{pr} is the value predicted by the ANN.

2˙2. *Clinical data.* – The study was conducted on 88 subjects, both women (39) and men (49), with an average age of 32 years (min. 4, max. 86), of which 30 subjects were examined by retinoscopy, and the remaining 58 by means of an autorefractor. Inclusion criteria: no limits were imposed to high ametropia and low VA; all subjects reporting history of ocular trauma, ocular disease, amblyopia, aphakia or pseudophakia were excluded, as they could exhibit modifications of the VA beyond what is influenced only by refractive errors; all age groups were accepted. Measurements at the autorefractor were made available from an existing database, and they were performed by an experienced optometrist taking the average over three repeated measurements. VA was measured for distance, for both eyes, with a Rodenstock digital optotype at a fixed distance of 4.5 m with logarithmic scale. Objective refraction for distance was performed with the Nidek autorefractometer for both eyes. These data provided, present a good age and gender distribution, however, with very similar ametropia values.

After performing preliminary tests on this sample, we found it necessary to expand the database with additional measurements, although with different instrumentation. VA was then measured for distance with a Vision Chart digital optotype with logarithmic scale at a fixed distance of 4 m (maximum measurable VA −0.30 logMAR) for both eyes. Retinoscopy was performed using the Heine retinoscope. The working distance of retinoscopy was 50 cm. The illumination conditions were not measured, but kept consistent during the test and among measurements by recurring to artificial illumination only. Before measurements were taken, all subjects signed their informed consent, and the place was sanitized after every measurement against the risk of COVID-19 infection.

2˙3. *Building our ANN*. – There exist several software applications available to program ANNs. We chose to adopt the dedicated package in Matlab, as it offers simplicity of operation, while retaining good computational performance. An in-built function can be called, building one of the most basic network architectures composed by multiple layers, labelled by index l, each constituted of n_l neurons; these are connected each to one and only one neuron of the previous and successive layer. The dataset is randomly partitioned in three subset. The training set (70% of the total data) is used to adjust weights: in an epoch, *i.e.*, a single iteration of the training process, the weights are varied in order to improve the predictions on the training set. In order to minimise over-fitting effects, which occur whenever association is wrongly optimized on specific features within the data of the training set, the training proceeds until ϵ_{MS}, calculated on an independent validation set (15%, stops decreasing. For the purposes of our analysis, 136 eyes (68 subjects) were considered, since we are investigating correlations in monocular vision. In addition, we chose not to distinguish by biological gender or age, although these factors are prone to constitute confounding variables. The data discussed above was imported into Matlab in the form of a 2×136 input matrix, which contain the values of sphere and cylinder corrections and constitute independent variables X, and a 1×136 vector with the VA, representing dependent variables Y. In our study, we aim at understanding what is the complexity needed to build an efficient ANN for our data: if the network is too small or too simple, it would fail in its predictive capabilities, while too large architectures would result in significant overfitting. We chose to evaluate the performance of the network with only one hidden layer when the number of neurons is equal to $n_1 = 3$, 5 or 7; we also evaluated it with 2 hidden layers, while keeping the total number of neurons to $n_1 + n_2 = 5$: $n_1 = 3$, $n_2 = 2$ and $n_1 = 4$, $n_2 = 1$. This is commonly adopted in inspecting the performance of ANNs.

3. – Results

In all of the realisations of the ANNs we implemented, we have considered the variation of the mean square error as a function of the epoch, as a figure to capture the evolution of the training. To quantify the quality of the association, we have employed Pearson coefficient R, calculated between the predicted and observed values of VA for the three training, validation, and test data subsets. A characteristic behaviour is depicted in fig. 1(a), for the single layer case with $n_1 = 7$: the three curves show error ϵ_{MS} for the training set, the validation set and the test set. Notice how the curve for the training set keeps decreasing past epoch 18, which is taken as the training time. In fact, the computation is halted when the curve for the validation set stops improving, as it is the case. The further reduction in error for the training set at longer epochs is then attributed to overfitting. Similar curves are obtained for all ANNs. The reconstruction is assessed in fig. 1(b)–(e), in which the observed VAs in the abscissas, and the predicted output VAs in the ordinates are plotted: if the ANN was able of perfect predictions, these should lie on the diagonal, reported as a dashed line in the plots. The difference among the latter and the solid lines corresponding to a fit of the obtained result shows some discrepancy between the ANN predictions and the target outputs. Importantly, despite such a visible deviation, the R coefficients remain solidly above 0.90. A summarising table (table I) reports the values obtained for the five different configurations out of ANNs.

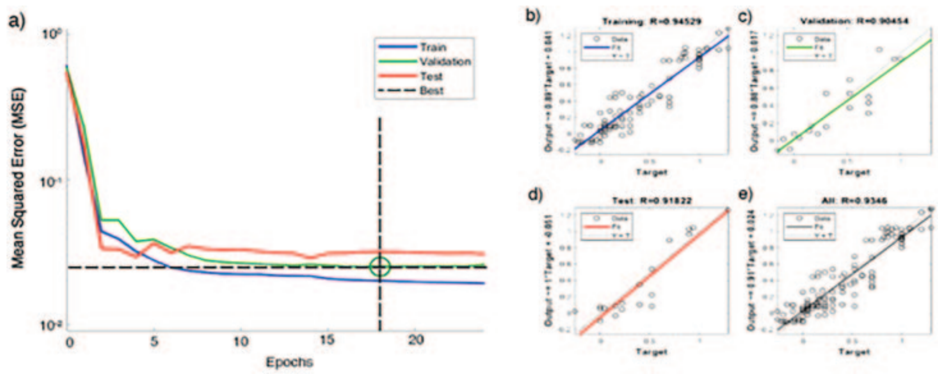

Fig. 1. – (a) Performances of the ANN training in terms of mean squared error for the single hidden-layer architecture. The results relative to the three data subset, *i.e.*, training, validation and test are reported as a function of the training epoch. Comparison of the ANN's predictions and the target output once the training is halted for (b) training, (c) validation, (d) test set and (e) when considering the overall set of available data.

TABLE I. – *Performance of the network.*

n_1, n_2	Final MSA	Halting epoch	R training	R validation	R test	R complete
3,0	0.041	13	0.916	0.876	0.907	0.909
5,0	0.039	6	0.928	0.903	0.910	0.920
7,0	0.025	18	0.945	0.905	0.918	0.935
4,1	0.034	15	0.892	0.876	0.653	0.854
3,2	0.030	13	0.922	0.907	0.882	0.914

For the single-layer networks, we notice that the performance is not severely influenced by its size, but the one with $n = 7$ works marginally better in terms of both mean-square error and coefficients. Introducing a further layer provides no advantages: the case with $n_1 = 3, n_2 = 2$ actually shows poor performance for the test set, a clear indication that overfitting is a prominent effect.

4. – Discussion

The demonstrated results show that simple neural networks can reliably identify correlations in vision parameters. Even if they are based on a simple, known instance, it is likely that this advantage may not be lost in extensions to other cases. This kind of model-independent approach suits well studies aiming at capturing difference in the correlations between AV and refractive errors accounting, *e.g.*, for age group, sex, ethnicity, for which a parametric description would enforce a bias in the description. At the same time, this method can also include systematic effects induced by the measurement conditions, such as those due to illumination or the kind of optotype: the simplicity of the NN algorithm suggests that applications can be elaborated providing a sort of calibration to the practitioner who can build or, more likely, refine an initial dataset based on their own actual data. Computational requirements are not heavy, thus the routine could be realistically made to run on a local machine, however cloud-computing solutions may also be considered.

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