

REMOTE DETECTION OF CEREBRAL PATHOLOGIES IN MAGNETIC RESONANCE IMAGERY: AN UNSUPERVISED HEURISTIC APPROACH

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ABSTRACT:

In this work, the attention has been focused to the field of "medical imaging". The problem of pattern recognition in remote sensing with medical application has been discussed in order to detect significant lesions in encephalic non-invasive diagnostics. In particular, Nuclear Magnetic Resonance analysis have been considered. The aim is to propose an automatic way to recognize encephalic pathologies in real imagery by using computer abilities. Because of problem solution has remarkable difficulties, proposed approach is based on heuristic unsupervised techniques. In this case, imagery have been evaluated by implementation of a particular Self-Organizing Map Neural Network with diagnostic purposes. The Self-Organizing Map receives as input different images of pathological encephala; the aim is to conjugate sensibility of medical imaging techniques with pattern recognition flexibility of Artificial Neural Networks. Retrieved results confirm reliability of proposed heuristic approach in medical application of remote sensing and imagery segmentation.

1. INTRODUCTION

Nuclear Magnetic Resonance (NMR) is a tomographic technique which allows to obtain imagery of multi-planar sections of body. NMR signals, retrieved by coils, are elaborated and codified as gray-scale images, in which contrast depends on correlation between excitation times and proton relaxing ones; usually they are called T1, T2, and Proton Density (PD). NMR and imagery interpretation are more complex than other diagnostic methods. In fact, NMR imagery is at least determined by about ten of physical parameter, which are a function of impulse sequence of used radiofrequency.

Electronic calculators are able to execute calculus, store data and learn new solutions by starting from experience. All of them are essential characteristics of "intelligence" concept. Artificial Intelligence cannot be considered as a "computer reproduction" of human mind, but a way to use calculators in order to improve the same human decisional abilities. Expert systems are a real and valid example of this kind of usage. They have to formalize, in any way, knowledge of a specific domain in order to make it storable by a calculator. On the other hand, Artificial Neural Networks (ANNs) can learn in an automatic way by means of a specific and internal representation of reality, based on the previously provided information set. In this paper, a particular interest has been given to an hybrid network composed by Fuzzy clustering and a Self-Organizing Map (SOM, unsupervised learning in order to classify in categories of similarity) for NMR imagery segmentation. Neural approach has been proposed because the inter-connectivity among intra-layer neurons is independent by absolute position of neurons, while it strongly depends on their distance on the simulated brain mantle. Moreover, distribution of lateral connections into the brain mantle is approximately the same around each neuron: thus, a spatially sorted network has been obtained. During the

phase of stimuli representation, it kept the spatial topology, in which the same stimuli are described, on the brain mantle. In other words, it has been observed how similar stimuli activated adjacent areas of the brain mantle. These characteristics allowed to use the specific SOM (Kohonen, 1987) into the medical imaging claw. The choice of a Fuzzy-SOM structure can be justified by an high presence of self-organizing structures into the brain mantle.

2. GENERAL FUNCTIONING OF NMR

In a general sense, it is possible to distinguish a set of "invisible" molecules (protein, cellular membranes, macromolecules) and a set of more-or-less "visible" molecules (fat and water) into the NMR. Whereas fat have not a tendency to interact with other molecules, water continuously interacts with macromolecules, with a temporal change from the "free" state to the "linked" state and vice versa (T1 and T2). For different tissues, T1 and T2, largely variable, have a critical dependence on the different representation of various molecular compartments. However, fat and free- or linked-water content influence the relaxing times in normal or pathological situations. In a data analysis, the most exploited method takes into account retrieved bi-dimensional slices and analyze them as x-rays. Improved results can be obtained by a 3D data reconstruction, by interacting with the model and eventually using the stereoscopic vision or generating animations. In NMR, information extraction about the kind of tissue and the pathological modification has a great interest. In fact, pathologies inducing modifications of content and distribution of tissular water have a particular influence on T1 and (more strongly) T2 values. Images highlight tissue nature by using a greater/smaller signal intensity into the single voxel. The output

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of a NMR tomographic instrument is built up by slices representing the scanned object. NMR retrieves images of structures and organs with an high content of mobile protons (such as weak-tissue, fat, bone-marrow), but it cannot observe solid structures as bones. The image in which contrast is prevalently caused by differences between tissular T1 is called T1-weighted (excellent anatomic details). Similarly, for T2 and Density of Proton (DP), images are called T2-weighted (optimal contrasts), and DP-weighted (weighted in proton density).

3. DATA ACQUISITION

When, in a Neural Network based approach, a supervised learning algorithm is used, data are collected in input/output pairs, in order to train the Neural Network for specific aims. On the other hand, working with an unsupervised approach, a sort of data clustering is applied and training data are a series of inputs only. In our case of study, Magnetic Resonance Images (MRIs) showing encephala affected by multiple sclerosis have been collected. In particular, T1-weighted, T2-weighted and PD-weighted images have been used (Brainweb, 2006). For each kind of imagery, 36 slices have been selected (total amount equal to 108 slices), collected in level of depths outdistanced each other by 1 mm, during 18 different time instant t_0, \dots, t_{17} , with ideal-supposed conditions (0% noise) and a resolution of 181x217 pixels (2^{12} gray levels).

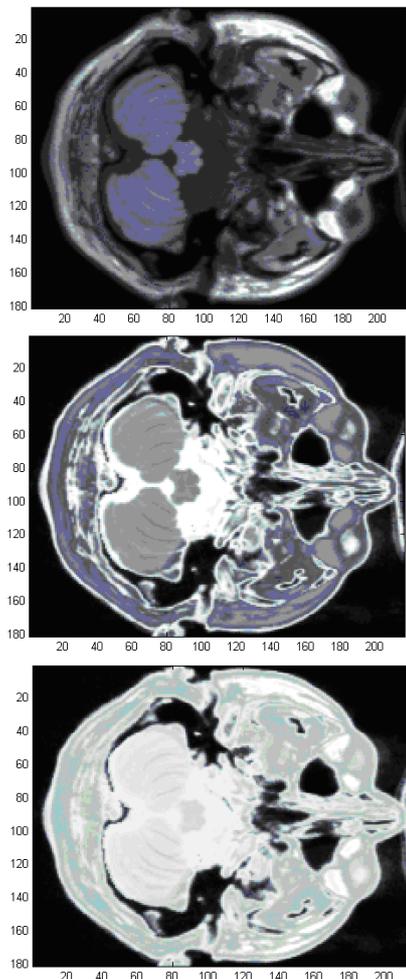


Figure 1. From top to bottom: T1-, T2-, PD-weighted images

In particular, each voxel has been assigned to a 5-dimensional feature vector (level gray intensity, average and standard deviation of intensity, minimum and maximum value of intensity calculated in a 3x3 pixel-square) chosen because it compensates random noise, minimizing loss of resolution into the images. Concerning feature selection problem, it has been carried out using a statistical-structural approach. In particular, used approach makes inquiries to arrange a training set statistically representative of data set considered in operative functioning of classifier. In fact, aim of training algorithms is to create decisional regions in order to minimize errors on training set: therefore, its representation is a necessary condition in order to make the recognition process efficient. Classification problem, mainly important in statistical approach, is considered subordinate to description problem in structural approach, because it supposes that an adequate description could allow to use simple classification techniques. Nevertheless, in real cases, this assumption is not always verified and then classification can become even more complex than in the case of statistical approach. Since that, feature vector has been obtained by considering a hybrid approach. It profits of advantages of both described approaches (i.e. statistical and structural approaches), allowing an almost optimal description of feature space in which the clustering has been carried out.

4. PIXEL VECTOR THEORY AND FEATURE EXTRACTION

Features extracted by each slices have been codified according to Pixel Vector Theory (PVT) (Semeion Research Centre, 1991). PVT represents an attempt to overcome limits of actual techniques, generally based on evolution of gray levels during the time of a “suspected” Region Of Interest (ROI), located by a technician through comparisons with a series of “prototypes” of temporal evolution. The process can be automated by giving the mean-temporal evolution of examined ROI to an inferential model. In spite of this, it is impossible to define a priori a ROI which could be examined during the operative phase of algorithm, as the average operation of ROI activation values. Therefore, PVT approach is based on analysis of value for each pixel relatively to a specific area around it. In fact, it is possible to establish the following information for each pixel: brightness and local characteristics of a pixel group. In the first case, the whole of original information selected by a priori hypothesis and given to induction algorithm is not sufficient to distinguish significant elements of images. In ideal conditions, it could be necessary to analyze brightness of the same pixel by a contrast medium and evaluate temporal evolution of pixel activation in order to identify the kind of tissue to whom pixel belongs. Nevertheless, also this approach does not remark significant presence of cluster (cluster overlapping).

4.1 The Feature Extraction Procedure

Used codify assumes that significant information for imagery segmentation and classification is based on local relationships between each pixel and an opportune area around it. It implies the necessary use of information about the area around each pixel (particularly the area dimension) as model input. Therefore, a single-gradient area into a two-dimensional space has been chosen. If considered area is a N-gradient square, codification of pixels consists of a $(2N+1)^2$ feature set in order to characterize each pixel belonging to analyzed image. Use of PVT notably increases information of input vector, in relation to the histological nature of tissue referred by considered pixel.

In conclusion, let us denote how it is possible to codify the difference between each pixel of each spatial range and the referring pixel. The procedure allows to link pixels having both similar brightness and similar variation into the area around them. Moreover, data has been normalized in order to increase the system efficiency.

5. DATA CLUSTERING AND SOM IMPLEMENTATION

Collected MRIs have been used in a first step in order to implement suitable and significant clusters. Each cluster groups patterns having similar features, in order to simplify the next steps of pattern classification. The aim is to obtain initial clusters which can group input data in a non-crisp way by using a relatively simple fuzzy clustering algorithm. Center of clusters will be used in a second step to implement the SOM.

5.1 Fuzzy C-means Clustering

It has been possible to determine clusters represented by fuzzy sets by means of C-means algorithm (Bezdec, 1981): each cluster is a fuzzy set and each pixel has a membership value corresponding to each cluster. In order to understand the C-means clustering, it is important to denote how, starting from an input dataset and a cluster number (with an initial random setting of cluster centers), the algorithm assigns a membership degree to each pixel belonging to a particular cluster. The algorithm iteratively updates centre positions and membership degrees of each point. In this way, cluster centers iteratively moves towards a position minimizing an objective function. It represents the distance of a considered point from the cluster center, weighted by using the membership degree (fuzzy clustering). Once obtained fuzzy data, "evaluation of rules" has been carried out by determination of particular fuzzy outputs for each specific input set. Substantially, a set of rules corresponding to the following template have been added to decisional module:

"IF (input n belongs to class k) THEN output m belongs to class j with a degree equal to membership degree of n to k "

Therefore, a number of fuzzy clusters corresponding to kind of considered cerebral tissues (background, cerebrospinal fluid, grey matter, white matter, fat, muscle/skin, skin, skull, glial matter, connective tissue, lesions) have been found out.

5.2 SOM Implementation

In order to refine classification results, a suitable SOM has been implemented starting from the centers of fuzzy clusters and using the same input data set above described. Generally, SOM architecture is similar to the diagram in Fig. 2.

Initially, neurons of a SOM are spatially disposed in an orderly way, according to a specific typology (hexagonal as default); it is obtained by means the so-called of *hextop* function. Typical dimensionality of a SOM layer is 2; this neuronal layer evolves during training phase, updating position of single neuron as marker of main characteristics of input stimuli. The *spatial organization* process of input data is also called *feature mapping*, and in our case study starts from neuronal configuration showed in Fig. 3.

Default function used to calculate the distance between i -th neuron and its neighbors is the so-called *linkdist* function: it calculates for i -th neuron the number of links (or the number of

steps) which connect the considered neuron to any other neuron into the SOM network.

In Fig. 2, the *||ndist||* block accepts the input vector \mathbf{P} and the weight set \mathbf{IW} and retrieves as output the vector \mathbf{S} . The i -th element of \mathbf{S} is so defined:

$$n_i = - \|\mathbf{IW}_i^{1,1} - \mathbf{P}\| \quad (1)$$

The mapping function retrieves 1 for the element a_i corresponding to i^* (i.e. the winning neuron), while the other outputs are set to 0.

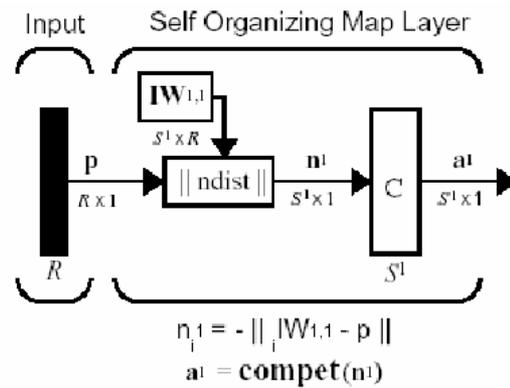


Figure 2. Architecture of a SOM

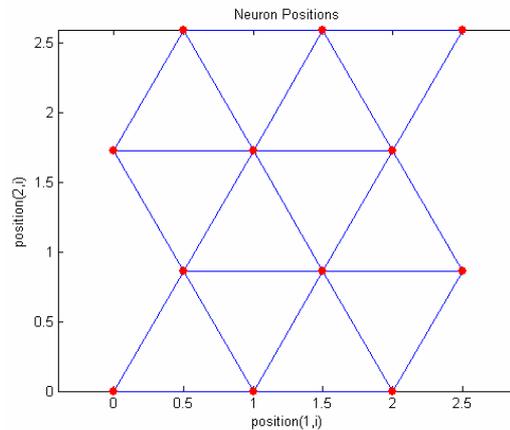


Figure 3. Starting hexagonal grid of SOM neurons

A SOM network has two layers, X (input layer) and Y (output layer) representing the classification results. There are two type of links: from X layer to Y layer (defined as \mathbf{W}) and among units of Y layer, known as lateral links; they are organized in a two-dimensional grid-like schema (each unit is linked only to its "neighbors"). Considering an input \mathbf{X} , the algorithm calculates euclidean distance between \mathbf{X} and each classification unit. Then, the algorithm chooses the unit with minimal distance as the best-representing class. During the training phase, the SOM repeatedly analyze the inputs and, for each new example, the winning unit is found; thus, only the weights which link the winning unit with its neighbors are updated according to a specific topology.

A weight variation increases the membership of input \mathbf{X} to the calculated winning class (\mathbf{Y}_v). At the end of training phase,

SOM neurons are disposed according to a well-defined spatial order; it is based on determination of weights of connections between classification units (Fig. 4).

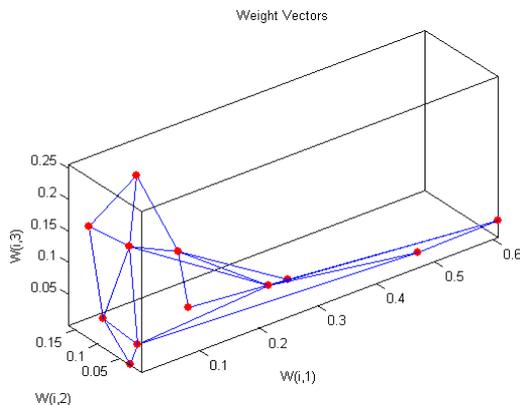


Figure 4. Final disposition of SOM neurons into the space of inputs after training phase

Therefore, it is possible to denote a spatial disposition of SOM neurons as similar as possible with the input space, so that inputs with similar features are rightly related to the same classification unit. In the analyzed case of study, it has been necessary to pursue a trade off between performances of trained SOM and its complexity.

In fact, classification performances of SOM increase if number of SOM neurons is comparable to the dimension of input space. On the other hand, a high number of neurons compromises the quick functioning of classifier in a real-time application. Therefore, a number of neurons equal to considered cerebral tissues has been used (i.e. 12 neurons). It is a restricted number if compared with the dimension of input space, but adequate to assure improved performances of a SOM-based segmentation (Kohonen, 1997).

6. ANALYSIS OF RESULTS

Image used in Fuzzy-SOM test (Fig. 5) has been downloaded from the same BrainWeb site (BrainWeb, 2006). In this image, it is possible to detect some damaged cerebral areas (i.e. areas interested by sclerosis), which are highlighted with white circles.

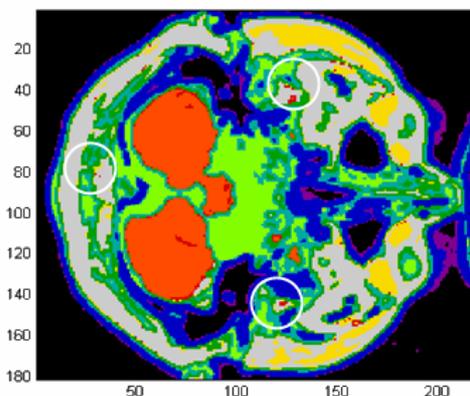


Figure 5. A view of cerebral damages into the test images: white circles focus areas interested by sclerosis

The proposed Fuzzy-SOM hybrid approach has been applied to this test image, in order to verify if the algorithm is able to distinguish damaged areas from the other biological tissues. Obtained results are reproduced in Fig. 6.

In order to improve the comparison between observed and simulated data, only damaged areas are depicted into observed test image. Moreover, for a first evaluation of proposed heuristic approach, Fuzzy-SOM structure classify the presence or absence of pathological damages.

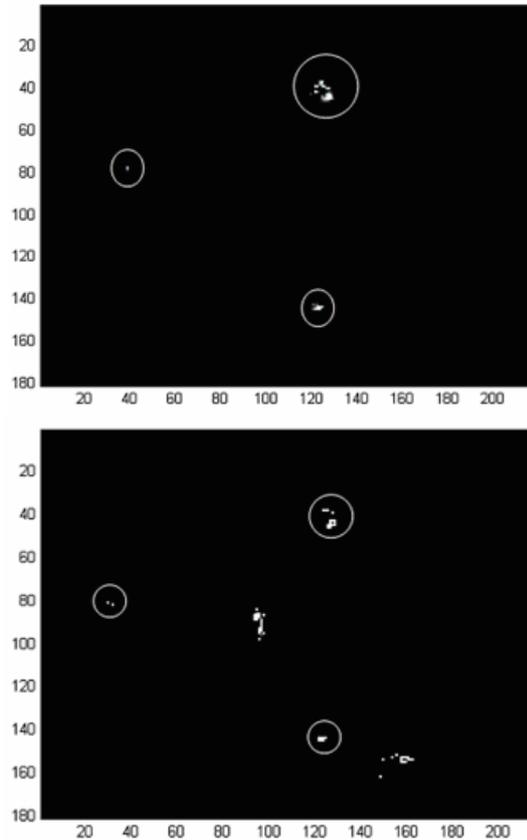


Figure 6. Reproduction of observed (top) and Fuzzy-SOM simulated (bottom) positions of damaged areas into test image; the uncircled white-coloured areas into simulated image are due to misclassification

From Fig. 6, it is possible to verify a good classification performance of proposed Fuzzy-SOM approach. Areas interested by sclerosis are all recognized; some misclassification are present, but they are negligible to diagnostic aims.

6.1 Tests on data acquired by NMR phantoms

In order to give a greater practical utility to proposed approach, a set of test images has been collected by using real NMR phantom of patients having cerebral damages of various nature and various extension. The new test set has been furnished by the Neuro-radiology Division of "Bianchi-Melacrino-Morelli" Hospital of Reggio Calabria, Italy. Since the hospital has not a digital version of database, phantoms have been digitalized by means of a specific scanner, having a double-illumination and a vertical-scanning: it is in equipment to the "Bone Marrow Transplant Center" of Reggio Calabria, Italy. Naturally, the acquisition process and the degradation of some phantoms

involves a remarkable informative loss in terms of resolution and details of considered test imageries. The collected test set has been submitted as inputs to the Fuzzy-SOM network, obtaining encouraging. In the following subsection, two examples are going to be described.

The first examined case concerns a NMR image with the following medical report: *in cortical area with a dural basis, a nodular damage corresponding to right occipital area exists. Damage is coupled with an extended hemispheric edema. It is most probably a secondary damage.*

The correspondent NMR has been passed to the trained Fuzzy-SOM classifier in order to obtain a segmented image and verify the abilities of heuristic classification, i.e. abilities of clustering of different tissues. Fig. 7 shows the classification result. It is evident how segmentation process carried out by proposed Fuzzy-SOM method has been able to recognize the damage, by evidencing interested area with a dark-green hue and distinguishing it into the context of the whole NMR phantom (Fig. 7).

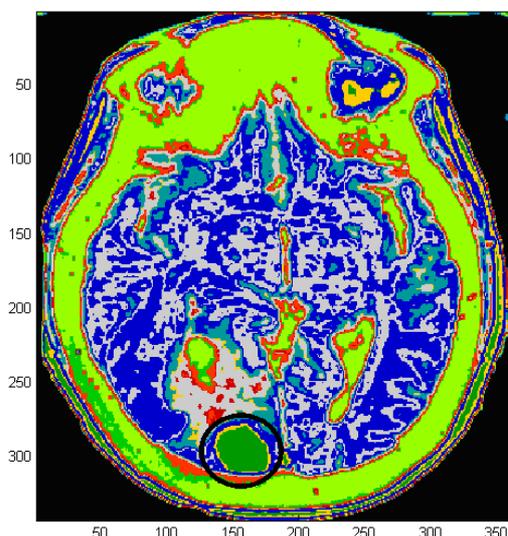


Figure 7. An overview of Fuzzy-SOM result by using a real NMR phantom: the dark-green black-circled area is a well-recognized cerebral nodular damage

A similar process has been carried out with a second NMR phantom. In this case, medical report is: *presence of a blastoma with an oval extension in cortical area.*

Fig. 8 shows result of classification carried out by Fuzzy-SOM network. Black-circled area depicts the blastoma lesion; it has been coloured with a dark-blue hue like the skull tissue because of NMR phantom degradation. In spite of this, result is a valid medical support, because blastoma has been distinguished from the rest of inner-cerebral tissues, whereas a doctor can excluding the black-circled area is skull for its same location.

Other real cases have been considered in order to validate the efficiency and performances of proposed approach. The new test set reveals that segmentation process is very able to detect different kinds of tissues in NMR images, with a particular interest for pathological events. Moreover, by means of NMR images furnished by "Bianchi-Melacrino-Morelli" hospital, it has been proved that Fuzzy-SOM network is able to detect cerebral areas interested by any pathologies even if the same pathologies are not represented in training pattern set.

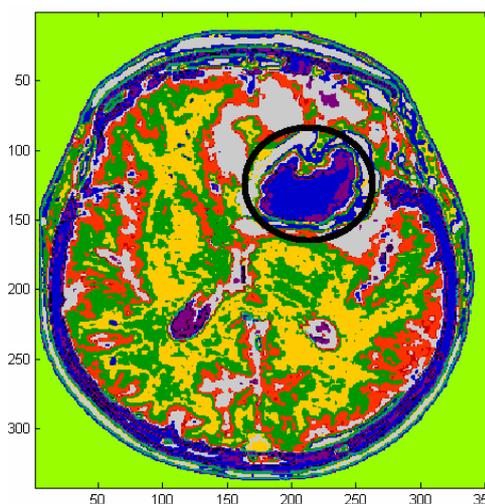


Figure 8. The second test using a scanning NMR phantom: the black-circled area is a blastoma

7. CONCLUSIONS

In this paper the problem of pattern recognition in remote sensing imagery with medical applications has been examined. In particular, the attention has been focused on cerebral pathologies detection from NMR phantoms. Since they are determined by about a ten of physical parameters changing with impulse sequence at used radiofrequency, imagery interpretation is more complex than other non-invasive medical diagnostic methods. In order to solve this inverse problem, an unsupervised heuristic approach has been proposed for pattern recognition; it is based on Fuzzy clustering and Self-Organizing Neural Networks. Fuzzy C-means has been used in order to retrieve cluster centers of various classes (i.e. kind of cerebral tissues showed in a MRI). In order to improve classification performances, a SOM network has been trained by a suitable data set, using the cluster centers obtained by Fuzzy C-Means as initial values of SOM's cluster centers. Fuzzy-SOM approach has been subsequently tested on a MRI available at BrainWeb site (BrainWeb, 2006) and on a set of NMR phantom images kindly provided by "Bianchi-Melacrino-Morelli" Hospital of Reggio Calabria, Italy.

By analyzing retrieved results, it is possible to affirm that proposed network can highlight different type of pathologies in an appreciable way, even if the actual pathology were not represented into the training set. In conclusion, let us remark the efficiency and reliability of proposed approach in imagery segmentation and classification; thanks to its flexibility and adaptation abilities, the Fuzzy-SOM network has been able to establish the complex linkages which exist into the input space, generally joining similar inputs to a same output class.

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