We propose a multimodal and multidiscipline data fusion strategy appropriate for automatic target recognition (ATR) on synthetic aperture radar imagery. Our architecture fuses a proposed clustered version of the AlexNet convolutional neural network with sparse coding theory that is extended to facilitate an adaptive elastic net optimization concept. Evaluation on the MST AR dataset yields the highest ATR performance reported yet, which is 99.33% and 99.86% for the three- and ten-class problems, respectively.

1. INTRODUCTION

Modern warfare requires high performing automatic target recognition (ATR) algorithms to avoid collateral damage and fratricide. During the last decades, both industry and academia have made several ATR attempts in various data domains such as two-dimensional (2-D) infrared [1], three-dimensional (3-D) light detection and ranging [2]–[4], and 2-D synthetic aperture radar [5]–[19] (SAR). Despite each data modality having its own advantages, SAR imagery is appealing because it can be obtained under all-weather night-and-day conditions extending considerably the operational capabilities in the battlefield. Due to these advantages, SAR ATR has been attempted using various techniques.

Suggested methods include feature-based solutions where the SAR image is described by a set of robust attributes capable of achieving target classification under various nuisance factors. Feature-based solutions may rely on Krawtchouk moments [20] where features are derived from the discrete-defined Krawtchouk polynomials or on biologically inspired features. The latter can rely on episodic and semantic features [21] or sparse robust filters [22] that originate from the human cognition process. Other methods include binary operations [23], using the target’s scattering centers [15], [24] or the azimuth and range target profiles fusion [25].

Another type of SAR ATR algorithms uses a stacked autoencoder (SA) that extracts features from SAR imagery and inputs them to an SA-type neural network. The latter is an unsupervised learning structure used in neural networks that can convert the input data into abstract expressions utilizing a nonlinear model. SA-type SAR ATR suggests either exploiting local binary features [18] or modifying the reconstruction error of the typical autoencoder scheme by adding a Euclidean distance restriction for the hidden layer features [17]. Other autoencoder-based solutions are influenced by the human visual cortical system [26] or are combined with a synergetic neural network concept [27].

Compressive sensing (CS) has also been used for SAR ATR to recover the SAR signal that has been remapped from the originating domain into a domain where the signal is sparse using a nonadaptive linear projection. Signal recovery is achieved via an $l_1$-norm optimization process. For example, multitask CS [28] exploits the statistical correlation among multiple target views to recover the target’s signature that is then used for target recognition under a CS scheme. Bayesian CS [14] relies on the scattering centers of the SAR image that are used as an input signal to the CS technique.

Sparse representation classification (SRC) or sparse coding (SC) type of solutions aim at recovering the SAR testing imagery out of a dictionary where the SAR training images are the dictionary’s base elements. SRC aims at identifying the sparsest representation of the testing imagery within the dictionary by employing an $l_1$-norm optimization scheme. The final classification decision mechanism matches the class that provides the smallest
residual error. Joint SRC [29], for example, exploits three target views to increase the completeness of the target’s SAR signature and a mixed $l_0/l_2$-norm. The reasoning of using multiple views is that these are highly correlated sharing the same response pattern within the dictionary, and thus this conciseness can enhance the overall ATR performance. In [19], Cui et al. suggest the $L_{1/2}$-NMF technique that combines the $l_{1/2}$-norm optimization to identify the sparsest solution, with a non-negative matrix factorization (NMF) scheme. The NMF features used as input to the SRC technique are the outcome of an NMF process that is applied on the SAR imagery. Dong et al. [11] use the monogenic signal of a SAR image as an input to the SRC process. This signal comprises the 2-D SAR image signal and its Riesz transformed representation.

Deep convolutional neural networks (CNNs) have also been suggested for SAR ATR. Literature proposes several CNN-based solutions that use handcrafted CNNs [5], [8], [12], [13], [30] that are trained on SAR template images. Recently, a recurrent neural network is also suggested [31].

In the context of SAR ATR, SC- and CNN-based methods have individually shown their strengths by achieving quite high recognition rates. However, these techniques have not been fused yet such as to complement their strengths and afford an even higher recognition rate. Most important reasons to fuse SC- and CNN-based ATR are as follows.

1) To extend the search space for the SAR ATR solution as SC and CNN ATR search for an ATR solution in different spaces. Indeed, SC ATR searches for linear projections between the target and the feature spaces, while CNN ATR for nonlinear projections. Hence, by fusing these two concepts, we essentially span a wider search area aiming a gaining higher ATR rates.

2) Combined classifiers can improve performance, as training a single classifier to work well for all test data is difficult. This multiclassifier strategy might not necessarily outperform a single best performing classifier, but on average, it will perform better.

Driven by these reasons, we fuse CNN and SC. Even though fusion, in general, can be at a data, feature, or decision level, in this paper we implement a decision-level fusion. This is because the data modality for both contributing ATR modules, i.e., CNN and SC, is the SAR, and therefore, a data fusion scheme is not applicable. Additionally, despite feature fusion could be an option, we neglected it as this would create an even larger feature encoding every SAR image, increasing the processing time needed to perform feature matching and neglecting it from military applications that require near-real-time performance.

Additionally, state-of-the-art CNNs such as AlexNet [32], VGG [33], GoogleNet [34], and ResNet [35] have not been used in the context of SAR ATR. Driven by that, we suggest a novel architecture dubbed $l_{1-2}$-CCNN that fuses an adaptive $l_1$-norm, $l_2$-norm SC scheme with a modified clustered AlexNet CNN (CCNN) that uses a multiclass support vectors machine (SVM) structure for final classification. The contributions of this paper can be summarized as follows.

1) In contrast to current SC-based applications that use a fixed $l_p$-norm, we propose a novel adaptive elastic net type optimization that balances the advantages $l_1$-norm and $l_2$-norm depending on the characteristics of each scene SAR imagery. It is worth noting, that in contrast to current SC SAR ATR solutions, we neglect using the scattering centers of the SAR imagery in order to reduce the additional processing cost.

2) We extend the usability of the AlexNet CNN from the visual domain to the SAR by introducing a hidden layer clustering technique. This modification is combined with a multiclass SVM classification module that bridges the visual-SAR modality gap.

3) We innovatively fuse these two multidiscipline solutions under a decision-level scheme that adaptively changes its fusion weights. Fusing these two techniques aims at expanding the search region of the SAR ATR solution and overcome the weaknesses of each of the two techniques.

The rest of the paper is organized in the following sections. Section II introduces the proposed $l_{1-2}$-CCNN architecture, while Section III evaluates our method on the MSTAR dataset. Finally, Section IV concludes the paper.

II. SAR ATR ARCHITECTURE

The suggested architecture relies on a weighted SC, a clustered AlexNet variant, and a decision-level fusion scheme aiming at exploiting the advantages of all three techniques, each of which will be analyzed in the following paragraphs.

A. Sparse Coding

Sparse representation or coding aims at recovering a sparse representation $x$ of a measured one-dimensional signal $y$ as a linear combination of a few atoms, i.e., entries of a dictionary $D$ [11], [29], [36], [37]

$$y = Dx \quad \text{with} \quad D \in \mathbb{R}^{M \times N}, \quad M \ll N, \quad \text{Rank}(D) = M$$

(1)

where $x \in \mathbb{R}^{N \times 1}$ is a coefficient vector whose nonzero entries determine the linear combination of the atoms in $D$ that reconstruct measurement $y$. Ideally, $x$ should be $K$-sparse with $K = 1$, i.e., all entries to be zero except from the one that associates $y$ with the training sample within $D$.

Since $M \ll N$, (1) is underdetermined and therefore has infinite solutions. Determining the best solution $x_b$ is an optimization problem that is ideally solved using the $l_0$-norm in order to identify the sparsest vector $x_b$ out of the infinite solutions

$$x_b = \arg \min \|x\|_0 \quad \text{subject to} \quad Dx = y$$

(2)

where $\|x\|_0 := \#\{i : x_i \neq 0\} \leq N$, which counts the number of nonzero entries in $x$. Solving (2) is NP-hard, and therefore, CS theory [38] suggests exploiting the sparse
nature of the signal \(y\) (if it fulfills that prerequisite) and
reverses the initial signal by solving the optimization problem

\[
x_b = \arg \min \|x\|_1 \quad \text{subject to} \quad Dx = y.
\]

For 2-D data such as SAR images \(I \in \mathbb{R}^{n \times b}\), these are first remapped from the original \(a \times b\) image basis to a \(c \times d\) feature basis by down sampling \(I\) using bicubic interpolation. It is worth noting that \(I\) is not the complex data representation of a SAR image, but a grayscale 2-D image where the pixel values correspond to the amplitude of the SAR-based reflectivity that is constrained in the 0–255 value range. We down sample \(I\) to reduce its dimensions, and thus decrease the computational demands and increase the robustness of the SC ATR module to noise, resolution variation, and depression angle variation. We examine several down sampling factors to identify the one that presents an optimum performance (see Section III-B1). The reason for exploiting bicubic interpolation rather than other interpolation techniques appropriate for 2-D imagery, in general, is smoothing \(I\), which enhances robustness to nuisance factors, e.g., noise.

Then, the remapped images are converted into an \(m \times 1\) column vector with \(M = c \times d\) [39] and are normalized to have a unit \(l_2\)-norm

\[
I \in \mathbb{R}^{n \times b} \rightarrow I_{\text{sp}} \in \mathbb{R}^{m \times 1}, \quad M = c \times d < a \times b.
\]

Finally, the dictionary is defined as \(D = [D_1, D_2, \ldots, D_J]\) where \(j\) is the number of training classes and each class is defined as \(D_o = [I_{\text{sp}}^{o_1}, I_{\text{sp}}^{o_2}, \ldots, I_{\text{sp}}^{o_k}] \in \mathbb{R}^{m \times k}\), \(o \leq j\) with \(k\) the number of atoms/entries per class \(o\). Hence, we create an overcomplete dictionary \(D \in \mathbb{R}^{M \times N}\) with base elements, the 1-D SAR feature vectors of the corresponding SAR training images as created in (4). In contrast to current SC-based SAR ATR methods [8], [11], [14], we do not create the 1-D SAR feature vectors from preprocessed grayscale SAR images but from the raw grayscale SAR images. The advantage of using directly the grayscale SAR imagery relaxes the complexity, and thus reduces the processing burden of the proposed SC module without though sacrificing its SAR ATR performance (see Section III). It is worth noting that the size of \(D\) has a major influence on the performance of the SC algorithm. Specifically, \(N\) purely depends on the available training images, but the value of \(M\), i.e., 1-D feature vector length, even though fixed it is user-defined, meeting the constraints presented in (1). For this work, we examine several feature lengths such as to optimize the SC SAR ATR performance (see Section III-B1).

SC classification relies on the assumption that a new unknown test image \(I'\) from class \(u\) that is converted into a 1-D feature vector \(I_{\text{sp}}'\) lies within the same subspace with the training atoms of the same class. Thus \(I_{\text{sp}}'\) can be represented by (1) and solved with (3). It is reminded that the test SAR image is not input directly to (3), but we exploit its corresponding 1-D feature vector \(I_{\text{sp}}'\) that is produced according to (4).

Driven by the underlying SAR imagery data structure, we generalize [40] and consider that an \(l_1\)-norm SC is effective for non-Gaussian-type 1-D SAR feature vectors, whereas \(l_2\)-norm for Gaussian type. Therefore, given a test SAR image, we first remap it according to (4) and then analyze its core structure to identify if it is a Gaussian or a non-Gaussian type. Specifically, we analyze the 1-D SAR feature vector \(I_{\text{sp}}'\) as a combination of a two-component Gaussian mixture model (GMM) [41]

\[
p(I_{\text{sp}}') = \sum_{i=1}^{2} \varphi_i N \left( I_{\text{sp}}' | \mu_i, \sigma_i \right) \quad (5)
\]

\[
\varphi_1 + \varphi_2 = 1 \quad (6)
\]

\[
N \left( I_{\text{sp}}' | \mu_i, \sigma_i \right) = \frac{1}{\sigma_i \sqrt{2\pi}} \exp \left( -\frac{(I_{\text{sp}}' - \mu_i)^2}{2\sigma_i^2} \right) \quad (7)
\]

where \(\mu_i, \sigma_i,\) and \(\varphi_i\) are the mean, the variance, and the component weight of the \(i\)th GMM component of the 1-D SAR feature \(I_{\text{sp}}'\).

Then, we substitute (3) with an elastic net regularization technique [42] that is extended to use an adaptive coefficient estimator such as to optimize the regression problem depending on the GMM 1-D SAR feature vector analysis

\[
x_b = \arg \min \left( (1 - a) \|x\|_2^a + a \|x\|_1 \right) \quad \text{subject to} \quad Dx = I_{\text{sp}}' \quad (8)
\]

where \(a\) is the penalty factor that we adaptively define as

\[
a = \left| \frac{1 - \max (\varphi_i)}{0.5} - \varepsilon \right| \quad (9)
\]

such as \(a \rightarrow 1\) when \(\max (\varphi_i) \rightarrow 0.5\) and \(a \rightarrow 0\) when \(\max (\varphi_i) \rightarrow 1\), with \(\varepsilon\) a very small constant (in our trials we use \(\varepsilon = 10^{-5}\) and \(\varphi_i\) the GMM component weight.

We solve (8) using the least angle regression-elastic net (LARS-EN) [42], with a convergence threshold of \(10^{-4}\) for the cyclical coordinate descent [43] that is computed along the regularization path with \(10^5\) maximum iterations. Using the LARS-EN solver implies the penalty factor to be in the range of \((0, 1]\).

It is important to note that in contrast to [40], our extension

1) Does not consider SC classification on 1-D data that are affected by Gaussian and non-Gaussian noise. In our architecture, we solve (5) after analyzing the underlying structure of 2-D SAR imagery and determine whether the core of this structure is governed by a Gaussian or a non-Gaussian distribution.

2) Does not involve a fixed value of the parameter \(\sigma\) that is determined after a tuning process. Instead of that fixed approach, we adaptively estimate \(a\) for each 2-D SAR target image that depends on a GMM-based analysis of the target image. The advantage of this adaptive estimation is that it fully exploits the capabilities of the elastic net solution of (5) as it spans \(a\) to a range of possible values with \(a \in (0, 1]\).
This methodology aims at determining whether a single dominant Gaussian distribution can or cannot describe the 1-D feature $I'_{sp}$ of the SAR image $I'$, and accordingly adapt (9) such as to optimize the elastic net given by (8). Fig. 1 shows two extreme case examples where the 1-D feature $I'_{sp}$ of the SAR image $I'$ (blue curve) is analyzed into a two-component GMM (black and red curve show the Gaussian distribution of each model). Depending on the contribution of each GMM, in Fig. 1(a) we show an example of a 1-D feature vector that has two equally important Gaussian distributions, and thus, in (8) we input $a = 0.922$ ($\max(\phi_i) = 0.538$), while in Fig. 1(b) an example of one dominant Gaussian distribution, and hence, in (8) we input $a = 0.308$ ($\max(\phi_i) = 0.846$). Therefore, in the former case of Fig. 1(a), the SC SAR ATR problem in (8) is solved mostly based on an $l_1$-norm scheme, while for the latter case of Fig. 1(b), the solution of (8) is more affected by the $l_2$-norm contribution.

Fig. 2 shows the $\phi_i$ variation of the dominant Gaussian component and the corresponding penalty factor $a$ over a few example SAR images. From Fig. 2 it is evident that the contribution $\phi_i$ of the dominant GMM varies based on the SAR image reflectivity that affects the 1-D feature vector $I'_{sp}$, which in turn adaptively adjusts the penalty factor $a$ [see (9)] and ultimately influences the elastic net regularization of (8). Fig. 2 also shows the two extreme cases where the 1-D SAR feature vector is a perfect balance of two GMMs, i.e., $\phi_1 = \phi_2 = 0.5$ and thus $a = 1$, and therefore, from (5) the SC ATR problem for that SAR image is solved purely based on $l_1$-norm. Fig. 2 also shows a hypothetical perfect imbalance of the two GMMs with $\phi_1 = 1$ and $\phi_2 = 0$ (or vice versa). In that case, $a = \epsilon$ and from (5) the SC ATR problem for that SAR image is solved based on an $l_2$-norm scheme.

### B. Clustered Convolutional Neural Networks

In the context of SAR ATR, the literature suggests several CNN-based solutions that rely on handcrafted CNNs [5], [7], [8], [12], [13]. A common feature of these CNN architectures is their relatively low depth that varies from six up to nine layers, opposing to the mainstream visual domain CNNs where layers are 23 for AlexNet [32], 16 or 19 for VGG [33] depending on the version, 22 for GoogleNet [34], and 152 for ResNet [35]. This is because visual images have a higher information content per pixel compared to the radar reflections presented in a SAR image. Unarguably, current mainstream CNNs have an exceptional classification capability in the visual domain. A typical way to deviate these CNNs from the dataset these were trained on is by exploiting the transfer learning technique [44]. Nevertheless, this technique is not always effective in steering the weights of the CNN toward a completely different data modality, i.e., from visual to SAR imagery [45]. Additionally, the limited number of publicly available military SAR imagery imposes the SAR ATR CNNs to populate the training images...
TABLE I
Clustered AlexNet Layers

| C-AlexNet layer ID (l) | AlexNet layer ID | Operations involved          |
|-----------------------|------------------|-----------------------------|
| 1                     | 1-2-3-4-5        | Image input → Convolution → ReLU → Normalization → Max pooling |
| 2                     | 6-7-8-9          | Convolution → ReLU → Normalization → Max pooling |
| 3                     | 10-11            | Convolution → ReLU |
| 4                     | 12-13            | Convolution → ReLU |
| 5                     | 14-15-16         | Convolution → ReLU → Max pooling |
| 6                     | 17-18            | Fully connected → ReLU |
| 7                     | 19-20            | Fully connected → ReLU |
| 8                     | 21               | Fully connected |
| 9                     | 22-23            | SoftMax → Classification output |

...either by creating artificial variants, e.g., rotated versions of the existing templates or by sampling patches out of the image. Opposing to that, RGB images are widespread, and thus, the pretrained CNNs [32], [35], [46], [48] for that domain can exploit a massively larger training set.

Driven by the advantages of the RGB pretrained CNNs, we propose a multidiscipline and multimodal architecture that combines the concepts of CNN and multiclass support vector machine (M-SVM) classification [49]. The intention is to transfer the already proven classification capability of the AlexNet [32] from the RGB domain to the X-band SAR without using transfer learning [44]. This is because the combination of the completely different data modalities between SAR and visual imagery along with the lack of SAR training samples imposes a huge constraint to steer the weights of these CNNs toward SAR data and thus offering a moderate classification performance [45].

AlexNet is a 23-layered network that encapsulates from an RGB image features that vary from low-level corners and blobs, in the initial hidden layers, up to high-level RGB-oriented complex features in the last layers. Although AlexNet is powerful, it has been trained on the RGB images of ImageNet [50] that are completely different to SAR imagery. AlexNet is trained on RGB color bands, while SAR images contain radar reflections. Therefore, directly applying AlexNet on SAR imagery is not an optimum solution. Hence, we group the 23 layers of AlexNet into nine clusters l of varying feature description capability, introducing the clustered-AlexNet (C-AlexNet) presented in Table I. Notation l refers to the cluster layer activated with l ∈ {1, 2, 3, 4, 5, 6, 7, 8, 9}. This means, for instance, l = 4 activates up to AlexNet’s clustered layer 4, while the remaining layers {5, 6, 7, 8, 9} are discarded. C-AlexNet uses the same parameters (stride, padding, and convolutional filter sizes) as in the original implementation [32].

This specific clustering scheme is directly related to the position of the convolutional layers within AlexNet, which in turn are directly linked to the complexity of the features extracted from each cluster. That is, the deeper the convolutional layer, the more complex and data specific the detected features. It should be noted that a fully connected layer is a convolutional layer that uses a kernel that has the size of the output of the previous hidden layer [51]. Therefore, the input layer of clusters six to eight is a fully connected rather than a convolutional layer.

Given a SAR image I^{a×b}, \ a, b \in Z^+ and I(s, t) ∈ \{0, 1, ..., 255\} with 1 ≤ s ≤ a and 1 ≤ t ≤ b, we initially remap I into a 3-D tensor to meet the input requirements of AlexNet

\[
I_l = B(I) || B(I) || B(I)
\]

where B(·) is a bicubic interpolation process and ||(·)|| is a 3-D concatenation of a single SAR image in order to replicate the RGB layers that AlexNet requires as an input.

Once I_l is input to the C-AlexNet, it is transformed into a 3-D tensor X^l ∈ \mathbb{R}^{H^l \times W^l \times D^l}, which propagates through the hidden layers until it becomes the output Y^l of the end layer of cluster l. Hence, X^l is the input to cluster l = 1, X^2 is the output of cluster l = 1 and simultaneously the input to l = 2, etc. Notation H^l, W^l, and D^l refer to the height, width, and depth of the tensor at clustered layer l and an element belonging to X^l has an index set of (u^l, v^l, d^l) with 0 ≤ u^l ≤ H^l, 0 ≤ v^l ≤ W^l, 0 ≤ d^l ≤ L^l. Network activations are computed by forward propagating input I_l through the CNN architecture up to the specified layer l. For the feedforward process, we use a mini-batch size of one, i.e., one training instance per iteration, to estimate the gradient of the loss function and estimate the response of the CNN network. The reasoning of choosing a mini-batch size of one is to increase the accuracy of the response.

Three-dimensional tensors X^l and Y^l are stacks of 2-D matrices that highlight features of various complexities in a response map type of representation. As the X^l tensor propagates within the CNN’s activated clusters and ultimately becomes tensor Y^l, the tensor’s size changes based on the size of the convolutional kernel of each layer. That is a kernel size of 11 × 11 × 3 for cluster 1, the height and width of which approximately halves for each subsequent convolution till cluster 3, and thereafter, it stabilizes at a kernel size of 3 × 3 (height × width). Tensors X^l and Y^l can be regarded as a generalized scale-space theory [52] concept where the various scales are envisaged via the subsequent shrinking of the convolutional kernel size and the octaves via the kernel weights that are auto-adjusted by the CNN during the training stage. In computer vision, scale space is an important theory for keypoint detection contributing to the robustness of pattern recognition algorithms. Therefore, by linking tensors X^l, Y^l with scale-space theory, we highlight the importance of these tensors and validate their contribution in regards to pattern recognition tasks as examined in this paper.

As noted in Table I, the features that further propagate in our clustered SAR ATR architecture are the ones provided by the end layer of each clustered layer l that may be a rectified linear unit (ReLU) layer, a max pooling layer, or a fully connected layer. Therefore, it is important to present the operating details of these layers.

1) Rectified Linear Unit (ReLU): This layer increases the nonlinearity of a CNN by applying an individual
truncation process on every \( X^l(u', v', d') \)
\[
Y^l_{u,v,d} = \max \left\{ 0, X^l_{u,v,d} \right\}
\]  
(11)

where \( Y^l_{u,v,d} \) is the output of the \( l \) cluster layer. The advantages of ReLU against the classic tanh activation function are the reduction in training time [32] and incorporating a purely supervised training scheme avoiding the need of unsupervised pretraining [53].

2) Max Pooling: This operation substitutes a subregion \( X^l_s \) of size \( s \times s \), i.e., pooling size, of the tensor \( X^l_{u,v,d} \) with its maximum value

\[
Y^l_{u,v,d} = \max \left( X^l_s \right).
\]  
(12)

\( Y^l_{u,v,d} \) will have a size of \( H^l+1 = H^l/s, \ W^l+1 = W^l/s, \) and \( D^l+1 = D^l \).

3) Fully Connected: Through the fully connected layer, the \( X^l(u', v', d') \) input of size \( H^l \times W^l \times D^l \) is remapped to

\[
y^l = w^l_{u,v,d} X^l + \text{bias}
\]  
(13)

that has size \( H^l \times W^l \times D^l \), where \( w^l_{u,v,d} \) is the weight parameter that the fully connected layer is aiming at tuning and \( H^l \) is the height of \( Y^l \) that is defined during the design of the CNN.

In the suggested architecture, the output tensor \( Y^l_{u,v,d} \) of the \( l \) cluster layer is remapped into a 1-D-feature vector of length \( u' \times v' \times d' \) by undergoing a multifeature fusion process. The latter is implemented via a multidimensional vectorization process defined as

\[
\Theta_{a_{u,v,d}}^{h,W} = \begin{bmatrix} a_{1,1,d}, \ldots, a_{H,1,d}, a_{2,1,d}, \ldots, a_{H,2,d}, \\ a_{1,W,d}, \ldots, a_{H,W,d} \end{bmatrix}^T
\]  
(14)

over dimension \( d \), which is then followed by a vectorization procedure

\[
y^l = \text{vec} \left( \Theta_{a_{u,v,d}}^{h,W} \left( Y^l_{u,v,d} \right) \right)
\]  
(15)

where \( o = \{1, \ldots, d\} \). The advantage of this multifusion process is encompassing both the feature responses and the topology of the features for the entire tensor depth.

4) Multiclass Support Vector Machines (M-SVM): The \( y^l \) feature produced from the C-AlexNet at layer \( l \) is then used to train a \textit{one-vs-all} M-SVM classification scheme. Given \( j \) the number of classes, the \( j \)th class is trained with all the examples in the \( j \)th class having positive labels and the remaining examples having negative labels. For \( h \) training images, the data \( y^l \) versus target class \( Cl \) correlation is \( (y^l_1, Cl_1), \ldots, (y^l_p, Cl_p), \ldots, (y^l_j, Cl_j) \) with \( Cl_p = \{1, \ldots, j\} \) being the class of \( y^l_p \). M-SVM performs multiple binary SVM classification tasks and labels the \( y^l \) feature belonging to the class that gains the highest response. For a detailed analysis on SVM classification, the reader is referred to [54].

C. Decision-Level Fusion

The 1-D vector \( x_b \) obtained from (8) includes responses from all the atoms within \( D \) regardless of the class these belong. Thus, we remap \( x_b \) to facilitate a single response per target class \( j \) given by

\[
r^SC_p = \frac{x_p}{\max(x_p)}
\]  
(16)

with \( x_p \) is a subset of \( x_b \) that includes only the responses of the target class \( p \), \( p \leq j \).

Similarly, the output \( Y^l \) of the activated layer in the clustered CNN module is converted into \( r^CNN_p \) so that each target class has a single response

\[
r^CNN_p = \|y^l\|_\infty.
\]  
(17)

Then, we normalize the response per target class obtained from the suggested SC and C-AlexNet modules, i.e., \( r^SC_p \) and \( r^CNN_p \), respectively, to make them comparable. Normalization is done via the z-score technique and the SAR ATR decision-making function \( \exists \) is based on a weighted winner takes it all concept that is given by

\[
\exists = \arg \max_p \left( \lambda \frac{r^CNN_p - \bar{r}^CNN}{\sigma (r^CNN)} \right) - \left( \frac{r^SC_p - \bar{r}^SC}{\sigma (r^SC)} \right)
\]  
(18)

where \( ||(\cdot)|| \) is a 1-D concatenation process, \( \bar{r}, \sigma (r) \) are the average and standard deviation of the corresponding SAR responses, and \( \lambda \) is a regulating parameter

\[
\lambda = \begin{cases} 
1 & \text{if } |S_t - \bar{S}_\text{template}| < E \cdot \sigma (S_\text{template}) \\
1.25 & \text{otherwise}
\end{cases}
\]  
(19)

with \( S_t \) is the target SAR image entropy, \( E \) is a tuning parameter, while \( \bar{S}_\text{template} \) and \( \sigma (S_\text{template}) \) are the average and standard deviation of the entropy of the templates. The role of parameter \( \lambda \) is to tune finely the decision-making function of (19) depending on the deviation of the target’s SAR image disorder \( S_t \) in comparison to the disorder of the templates. The value of \( \lambda = 1.25 \) is determined experimentally.

Our proposed CNN and SC data fusion architecture named \( l_{1-2}-CCNN \) is presented in Fig. 3.

III. EXPERIMENTS

A. MSTAR Dataset

We evaluate the performance of the proposed architecture on the MSTAR database [55], which includes the ground target classes presented in Fig. 4. Each class contains chips of 15° and 17° depression angles using an X-band SAR sensor, while some classes contain additional 30° and 45° depression angle viewings. All target SAR chips cover a full \( 0-360° \) azimuth orientation. Table II presents the number of targets per type and depression angle used in this paper. To avoid the influence of background, we crop all images by extracting an \( 80 \times 80 \) patch set at the center of the image. For compatibility with current literature, we adopt [55] and establish a training set based on 17°.
### B. Three-Class Problem

We use this experiment to fine-tune the free parameters of our architecture, i.e., the modules of SC, C-Alexnet, and decision-level fusion. The target classes used are the BMP2, T72, and BTR70. For the former two, we use all three variants, namely, the 9563, 9566, and c21; for the T72, the 132, 812, and s7; and for BTR70, the c71, which is the only one included in the dataset. Images captured at 17° depression angle are used as training and images at 15° for testing.

Specifically, our architecture is governed by the feature dimension $m$ of the adaptive $l_1-2$-norm SC [see (8)], the layer $l$ of the C-AlexNet that is activated (see Table I), and the entropy boundary $E$ [see (19)] during the fusion stage. During tuning, we set as baseline values $m = 512$, $l = 2$, and $E = 3$, and evaluate the three-class ATR performance of the suggested technique by altering consecutively one of these three values. For the given baseline parameters, Table III highlights the performance of our architecture compared to current algorithms. It is evident that fusing the SC and CNN techniques under their suggested modified versions can outperform solutions that rely on a single method only. All trials are performed in MATLAB on an Intel i7 with 16GB RAM and an Nvidia Quadro K2200 GPU processor. MatConvNet [56] is used to implement AlexNet. The value of $\lambda = 1.25$ in (19) does not affect the performance of the three-class ATR problem.
TABLE III
Three-Class ATR (%)

|                | CM [57] | BMO [23] | SRF [22] | Huang’s [21] | DFSS [58] | ASC [24] | PCA [59] | 2DPCA [60] | $l_1$-SC only | CCNN only | $l_2$-CCNN |
|----------------|---------|----------|----------|--------------|-----------|---------|---------|-----------|-------------|-----------|-----------|
| BMP2          | 97.28   | 94.89    | 94.38    | 91.65        | 97.27     | 97.44   | 99.15   |             | 94.90      | 98.30     | 98.5      |
| BTR70         | 98.98   | 96.43    | 98.47    | 99.48        | 97.96     | 99.49   | 98.47   |             | 97.40      | 98.48     | 100       |
| T72           | 97.78   | 96.91    | 96.91    | 96.04        | 97.53     | 95.92   | 98.45   |             | 96.90      | 99.14     | 99.50     |
| Avg           | 98.69   | 97.58    | 95.98    | 96.04        | 97.58     | 97.61   | 98.75   |             | 96.40      | 98.64     | 99.33     |

Fig. 5. Tuning parameters. (a) SC feature space dimension. (b) CCNN activation layer. (c) $E$ decision-level fusion regulating value.

1) **Adaptive $L_p$-Norm-Based SC Optimization:** We create and evaluate a dictionary $D \in \mathbb{R}^{d \times 1622}$ of various feature dimensions $d = \{64, 128, 256, 512, 1024\}$. As expected, Fig. 5(a) shows that the larger the feature space dimension, the better the classification performance, but the greater the processing time. Fig. 5(a) shows that for the chosen feature length size of $m = 512$, the total processing time for the fused SAR ATR solution we propose is 800 ms. This is because by increasing the feature space dimension, the SC-based encryption becomes more distinct but (8) requires more processing time to provide a solution.

2) **C-AlexNet Activation Layer Optimization:** During this tuning phase, we vary the activating layer of the CCNN according to Table I. Fig. 5(b) shows that the deeper the activated layer, the more RGB specific the feature response becomes and harder to steer the CNN toward the SAR data domain. Thus, the less capable the M-SVM is to linearly separate the three target classes in the activated feature space. Optimum performance for the suggested fused scheme is identified at $l = 2$ achieving 99.0% target recognition.

3) **Decision-Level Fusion Optimization:** We investigate how the decision-level fusion regulating parameter $E$ affects the overall performance of our proposed SAR ATR architecture. From Fig. 5(c) it is evident that this parameter has a minor role to the overall performance but it can still affect it.

C. **Assessment Against Large Depression Variation**

For this trial, we use three similar targets, namely, the 2S1, the BRDM2, and the ZSU 23-4. Images at 17° depression angle are used for training, while the 15°, and 30° and 45° for testing. Table IV shows that the suggested multidiscipline scheme affords a high performing ATR solution. Depression variation involves a nonlinear feature transformation and since our $l_{1-2}$-norm solution seeks for linear projections from the image space to the feature space, the low performance of the SC module is anticipated [39].

D. **Assessment Against Resolution Variation**

We challenge the robustness of the $l_{1-2}$-CCNN to resolution variations from 0.3 m × 0.3 m (original resolution), down to 0.7 m × 0.7 m. Table V shows a target under these resolutions along with the performance of the suggested technique and the performance of current algorithms.

Table V shows that $l_{1-2}$-CCNN outperforms all competitor solutions, while at the lowest resolution it still manages a 94.77% recognition rate. The robustness of $l_{1-2}$-CCNN originates from the robustness of its individual modules, i.e., the $l_{1-2}$-SC and CCNN, which rely on the low-level abstract features extracted from the $l = 2$ layer of C-AlexNet and the adaptive $l$-norm process of the $l_{1-2}$-SC, as described in Section II-A.

E. **Ten-Class ATR**

Literature suggests various target configurations for the ten-class ATR problem, with commonly used standard operation conditions 1 (SOC-1) and SOC-2. Although both are ten-class ATR subsets, their difference relates to the variants of BMP2 and T72 used. Specifically, SOC-1 for both training and testing includes only serial number 9563 for BMP2 and only serial number 132 for T72. SOC-2 uses all available serial numbers for both targets, for training.
and testing. Both SOC-1 and SOC-2 ATR evaluated based on the target’s class and not its serial number. For both target set configurations, the 17° depression angle is used for training and the 15° for testing.

Tables VI and VII compare the ATR performance of \(l_{1-2}\)-CCNN against current literature for the corresponding SOC-1 and SOC-2 MSTAR subsets. In both cases, the suggested \(l_{1-2}\)-CCNN achieves the top ATR performance, which is 99.86% for SOC-1 and 99.50% for SOC-2. In addition, Fig. 6 shows the corresponding confusion matrix per SOC subset. For better readability, we present only the confusion matrix of \(l_{1-2}\)-CCNN.

### Table VI

| method           | Chen’s [8] | MicC [28] | Bayesian CS [14] | SAE [18] | DNN [15] | A-ConvNet [5, 30] | AdaGrad [7] | SGD [7] | \(l_{1-2}\)-SC only | CCNN only | \(l_{1-2}\)-CCNN |
|------------------|------------|-----------|------------------|---------|---------|-------------------|--------------|---------|---------------------|-----------|------------------|
| avg (%)          | 84.70      | 84.00     | 92.60            | 95.40   | 96.00   | 99.1              | 97.4         | 97.1    | 98.20               | 96.65     | 99.86            |

### Table VII

| method           | DNN [15] | IGT [61] | Morgan’s [15] | BMo [21] | KMo [20] | EFS [24] | Zernike [63] | PCA [59] | NMF [19] | Wagner’s [64] | DCNN [6] | \(l_{1-2}\)-SC only | CCNN only | \(l_{1-2}\)-CCNN |
|------------------|---------|----------|--------------|---------|---------|---------|---------|---------|---------|---------------|---------|---------------------|-----------|------------------|
| avg (%)          | 95.00   | 95.00    | 92.30         | 95.74   | 94.58   | 95.41   | 94.10   | 93.46   | 90.24   | 93.76         | 99.50   | 99.50              | 98.83     | 96.19            |

F. Ten-Class ATR at Various Noise Levels

In this trial, we evaluate the robustness of current proposals to various noise levels. Trials are on the SOC-1 subset and the noise simulation is consistent with [5] and [11], i.e., we randomly select a percentage of pixels in the target scene and replace their values with samples generated from a uniform distribution. It should be noted that template images both for the SC and CNN module are the original ones. Table VIII presents the performance achieved for noise levels varying from 1% up to 15%. From Table VIII it is evident that the \(l_{1-2}\)-norm SC is extremely robust to noise levels due to its adaptive nature. Therefore, the \(l_{1-2}\)-CCNN via its effective decision fusion process takes advantage of the high performing \(l_{1-2}\)-norm SC module and outperforms with a great margin current solutions on SOC-1 with additive noise.

G. Extending to Other CNNs

From all trials it can be concluded that \(l_{1-2}\)-SC and CCNN perform equally well for the three-class and ten-class scenarios that do not have nuisance factors. The advantage of the fused \(l_{1-2}\)-CCNN is apparent because it preserves and even increases in quite a few cases, the robustness of CCNN in the depression angle variation scenario and of \(l_{1-2}\)-SC in the additive noise scenarios.

Driven by the results achieved, we extend our layer-clustering strategy to VGG-16, GoogleNet, and ResNet CNNs by utilizing their MatConvNet implementations. As a reminder, similarly to AlexNet, all three CNNs are pre-trained on ImageNet [50]. The clustering methodology is similar to the one used for C-AlexNet, i.e., we cluster their
layers so that the first layer of a cluster is convolutional and the last layer is either a pooling or a ReLU layer. Based on the tuning process in Section III-B, the optimum activation layer for the clustered-VGG-16 is \( l = 2 \) that ends with the MaxPool_2 layer, while for the clustered-GoogleNet (C-GoogleNet) is \( l = 2 \) that ends with the Pool_2 layer. Finally, the clustered-ResNet (C-ResNet) is \( l = 3 \) that ends with the \( \text{res2a_branch2b} \) layer.

The first comparison among the clustered CNNs is on the SOC-1. Table IX shows that all clustered CNN variants perform equally well with C-VGG offering the lowest processing time per scene image, C-ResNet the highest CCNN ATR performance, and C-AlexNet the smallest template storage requirement. Even though all CNNs perform quite well, C-AlexNet achieves the highest overall ATR performance fully exploiting the SC-CCNN fusion scheme.

We continue our trials by evaluating the ATR performance for the three-class recognition case in Section III. Table X reveals that C-AlexNet outperforms C-VGG, C-GoogleNet, and C-ResNet. This can be explained as follows.

1) Both C-VGG and C-AlexNet have the same internal layer construction up to the activated \( l = 2 \) cluster but with different parameters, i.e., convolutional filter and stride sizes. In fact, C-VGG has two \( 3 \times 3 \) convolutional filters with stride one, while C-AlexNet a \( 11 \times 11 \) filter size with stride four and a \( 5 \times 5 \) with stride two. By comparing the performance on the ten-class SOC-1 and three-class trials, we conclude that the filter size of C-VGG does not capture the intraclass spatial content of the target scenes as it is quite small. Even though the \( 3 \times 3 \) convolutional kernel size is sufficient for RGB imagery because it has high-level features (and where VGG is trained for), our trials show that the SAR-type data and the capability for intraclass ATR as in the

| Gaussian noise level | 0% | 1% | 5% | 10% | 15% |
|----------------------|----|----|----|-----|-----|
| Example              | ![Image](image1.png) | ![Image](image2.png) | ![Image](image3.png) | ![Image](image4.png) | ![Image](image5.png) |
| A-ConvNet [5], [30]  | 99.13 | 91.76 | 88.52 | 75.84 | 54.68 |
| \( l_{SC} \) only    | 98.24 | 95.68 | 95.38 | 95.42 | 94.51 |
| CCNN only            | 99.65 | 95.81 | 92.55 | 77.78 | 60.32 |
| \( l_{SC} \) CCNN    | 99.86 | 98.68 | 96.53 | 92.01 | 87.43 |

| Method               | C-VGG | C-GoogLeNet | C-AlexNet | C-ResNet |
|----------------------|-------|-------------|-----------|----------|
| CCNN storage (KB/template) | 186.6 | 602.1 | 433 | 200.1 |
| CCNN time (ms/image)    | 6.35  | 14.65 | 17.50 | 45.9 |
| CCNN only (%)           | 97.86 | 95.08 | 96.65 | 98.07 |
| \( l_{SC} \) CCNN (%)   | 99.58 | 99.53 | 99.86 | 99.57 |

Table X shows...
three-class ATR problem requires larger receptive filters to provide discriminative responses.

2) GoogleNet mainly uses inception modules rather than a standard deep network construction. The tuning process of C-GoogLeNet provided as optimum cluster the \( l = 2 \) ending with the Pool_2 layer, and thus, a quite shallow part of the original GoogleNet is exploited even before the inception modules are applied. For the activated layer \( l = 2 \), the two convolutional filters involve a \( 7 \times 7 \) and a \( 3 \times 3 \) kernel size, and thus, similar to the C-VGG, these are too small to encapsulate the intraclass SAR imagery information and bridge the original training with the testing modality gap, i.e., visual versus SAR imagery.

3) ResNet uses residual blocks. Each residual block encloses a convolutional filter of \( 3 \times 3 \), which similar to the C-VGG and C-GoogLeNet does not encapsulate efficiently the intraclass target variations.

By extending our architecture to facilitate the mainstream CNNs, we can draw the following conclusions. First, our concept is validated since in the SOC-1 ATR problem all CNNs have a similar performance. Second, the size of the convolutional filter plays an important role in the intraclass ATR performance. This is obvious from the three-class scenario, which highlights that the CNNs with a small filter size fail to classify correctly the target.

IV. CONCLUSION

Deep learning techniques for ATR of SAR imagery aim at extracting deep features that can uniquely describe a target within a SAR image. Instead of a single-discipline solution, we fuse a CNN module with an SC module. For the former, we extend the effectiveness of the AlexNet CNN to operate from the visual to the SAR domain by introducing a layer-clustering concept. In order to bridge the visual-SAR modality gap, the clustered CNN is combined with a multiclass SVM classification scheme. The latter module (SC) extends SC theory to facilitate a proposed adaptive elastic net optimization concept that balances the advantages of \( l_1\)-norm and \( l_2\)-norm optimization based on the scene SAR imagery. Finally, the clustered CNN and the adaptive SC module are innovatively fused under a decision-level scheme that adaptively alters the fusion weights based on the scene characteristics.

Experimental results on the MSTAR data set under various configurations such as the ten-class ATR problem with and without target variants, the three-class ATR problem, and affected by several nuisance factors such as noise, large depression angle variation, and resolution variation, illustrate the effectiveness of our suggested architecture against current ATR techniques. In fact, on the MSTAR dataset, our architecture yields the highest ATR performance reported yet in the literature, which is 99.33% and 99.86% for the three- and ten-class problems, respectively. Finally, we also demonstrate that among current CNNs used by the computer vision community, AlexNet has the unique characteristics to host this data modality extension.

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