Learning from Synthetic Data
Using a Stacked Multichannel Autoencoder

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Abstract—Learning from synthetic data has many important and practical applications. An example of application is photo-sketch recognition. Using synthetic data is challenging due to the differences in feature distributions between synthetic and real data, a phenomenon we term synthetic gap. In this paper, we investigate and formalize a general framework – Stacked Multichannel Autoencoder (SMCAE) that enables bridging the synthetic gap and learning from synthetic data more efficiently. In particular, we show that our SMCAE can not only transform and use synthetic data on the challenging face-sketch recognition task, but that it can also help simulate real images, which can be used for training classifiers for recognition. Preliminary experiments validate the effectiveness of the framework.

I. INTRODUCTION

Modern supervised learning algorithms need plenty of data to help train classifiers. More data with higher quality is always desired in real-world applications; but sometimes, it is beneficial to turn to synthetic data. For example, to help identify criminals, many criminal investigations can only rely on a synthetic face sketch rather than a facial photograph of a suspect which may not be available. Such synthetic face data is normally drawn by an expert based on descriptions of eyewitnesses and/or victim(s). Several photo-sketch examples are shown in Fig. 1. In this application, recognition based on synthetic data is very crucial.

Directly using synthetic data in a learning algorithm is unfortunately very challenging since synthetic data is different from real data at least to some extent, e.g. exaggerated facial shapes in sketch images in Fig. 1 as compared with real images. As a result, the feature distributions of synthetic data may be shifted away from those of real data as illustrated in Fig. 2. We term such shift in distributions as synthetic gap. Synthetic gap is largely caused by the generating process of synthetic data: whereas the synthetic data are generated by replicating principal patterns such as eyes, mouth, nose and hairstyle, rather than replicating every detail of real data. The synthetic gap is a major obstacle in using synthetic data in recognition problems, since synthetic data may fail to simulate potentially useful patterns of real data which are important to a successful recognition. To solve this problem, we associate synthetic data with real data, and jointly learn from them in a Stacked Multichannel Autoencoder (SMCAE) which can help bridge the synthetic gap by transforming characteristics of synthetic data to better simulate real data.

Fig. 2. t-SNE visualization of the distribution of Histogram of Oriented Gradients (HOG) features in the data in CUFSF dataset [31, 33]. Left: synthetic gap is observed between photo and sketch features; Right: the synthetic gap is bridged by our SMCAE.

This paper addresses the problem of learning a mapping from synthetic data to real data. Specifically, we propose a novel framework – SMCAE. The training process of SMCAE facilitates the bridging of the synthetic gap between the real and the synthetic data by learning how to transform: (1) synthetic to real data and (2) real to real data. In (2), the model learns most essential ‘characters’ and ‘patterns’ of real data, while in (1) it learns how to augment the synthetic data to best reproduce the distribution of real data. Because the two tasks are learned simultaneously, with shared parameters, the essential ‘characteristics’ learned in (2) help to regularize results in (1) and vice versa as we will illustrate in the Handwritten Digit experiments.

We highlight two main contributions of this paper: (1) To the best of our knowledge, this is the first attempt to address the problem of synthetic gap, by demonstrating that the synthetic data could be used to improve the performance on a recognition task. (2) We propose a Stacked Multichannel Autoencoder (SMCAE) model to bridge the synthetic gap and jointly learn from both real and synthetic data.
Fig. 1. Examples of face photos and sketches. Data comes from the CUFSF dataset [31], [33].

II. RELATED WORK

Transfer Learning aims to extract the knowledge from one, or more, source tasks and apply it to a target task. Transfer learning can be used in many different applications, such as web page classification [21] and zero-shot classification [15]. A more detailed survey of transfer learning is given by [18]. Our method is a specific form of transfer learning, termed domain adaptation [6], [32], [34]. Nonetheless, different from previous domain adaptation approaches, we assume the the synthetic gap is caused by the shift in feature distribution of synthetic data from real data and so we assume that the main ’characters’ and ’patterns’ strongly co-exist in both the synthetic and real data. Our SMCAE is thus developed based on this assumption.

Autoencoder is a special type of a neural network where the output vectors have the same dimensionality as the input vectors [29]. Autoencoder with its different variants [10], [12], [2], [20] was shown to be successful in learning and transferring shared knowledge among data source from different domains [5], [9], [11], and thus benefit other machine learning tasks. Our framework borrows the idea of autoencoder to jointly learn two different and yet related tasks: mapping synthetic to real data; and real to real data. It is worth noting that in [22], a multimodal autoencoder with structure similar to ours is proposed. Their multimodal autoencoder put two normal autoencoders together by sharing a hidden layer. In their structure, data at input end and output end are fully symmetric and each modal of data occupy one branch of the autoencoder. In contrast to their structure, the proposed SMCAE composes the structure of both normal autoencoder and denoising autoencoder. With this composition, one branch of SMCAE is capable of exploring intrinsic features of data in one domain, and another branch of SMCAE is going to transfer data from one domain to another domain using features discovered from both branches. The structure of SMCAE could be easily expanded to more branches to compensate more complicated multi-task learning problems. Our experiments show that our SMCAE is better than other autoencoders in this regard.

Learning from synthetic templates. Some recent works of learning from synthetic data [26], [27], [4] mostly generate synthetic data either by applying a simple geometric transformation or adding image degradation to real data. To help offline recognition of handwritten text [26], [27], a perturbation model combined with morphological operation is applied to real data. To enhance the quality of degraded document [4], degradation models such as brightness degradation, blurring degradation, noise degradation, and texture-blending degrad-

III. STACKED MULTICHANNEL AUTOENCODER (SMCAE)

We propose the SMACE model to learn a mapping from synthetic and real data. To learn this mapping, the SMCAE model is formulated as a stacked structure of multichannel autoencoders which facilitates an efficient and flexible way of jointly learning from both synthetic and real data. The structure and configuration of the SMCAE is illustrated in Fig. 3. Specifically, we set the left and right tasks in two channels of the SMCAE respectively. The left task, as illustrated in left channel of Fig. 3, takes synthetic data as input and real data as reconstruction target; while the right task of the right channel in Fig. 3 uses real data in both input and reconstruction target. All between-layer connections that are colored in grey are shared by tasks of the two channels. The SMCAE structured in this way attempts to transform synthetic data to real data in left task using representation learned from real data in right task.

Fig. 3. (left) Illustration of the SMCAE: black edges between two layers are linked to and shared by two tasks; red and blue links are separately connected to the left and right task respectively. (right) A zoom-in structure of SMCAE with single hidden layer.
A. Problem setup

We first illustrate the setup of a single layer in each channel of our SMCAE. For a single channel of our SMCAE, we basically an autoencoder [7][28]. Assume an input dataset with $n$ instances $X = \{x_i\}_{i=1}^n$ where $x_i \in \mathbb{R}^m$. To encode the input data, we have $h_e(x_i) = f(W_{e}^j x_i + b_{e}^j)$ where $f(\cdot)$ is a sigmoid function and $\theta_e = \{W_{e}^j, b_{e}^j\}$. $W_{e}^j \in \mathbb{R}^{k \times m}$, $b_{e}^j \in \mathbb{R}^k$ is a set of encoding parameters in $j$-th layer. In contrast, the decoding process is defined as $h_d(x_i) = f(W_{d}^j h_e(x_i) + b_{d}^j)$ with the decoding parameters $\theta_d = \{W_{d}^j, b_{d}^j\}$. $W_{d}^j \in \mathbb{R}^{m \times k}$, $b_{d}^j \in \mathbb{R}^m$ and the encoded representations $h_e(x_i)$.

To minimize the reconstruction error, we have

$$J(\theta_e, \theta_d) = \frac{1}{n} \sum_{i=1}^{n} (h_d(x_i) - x_i)^2 + \lambda W^j$$

where $W^j = (\sum_{k} \sum_{m} (W_{d}^j)^2 + \sum_{m} \sum_{k} (W_{e}^j)^2)/2$ is a weight decay term added to improve generalisation of the autoencoder and $\lambda$ leverages the importance of this term. To avoid the learning identity mapping in the autoencoder, a regularisation term $\Theta = \sum_{k} \sum_{i=1}^n (1 - \delta) \log \frac{1}{\delta_i}$ that penalizes over-activation of the nodes in the hidden layer is added, $\delta_i$ is an averaged activation of all the nodes in the hidden layer and is computed as: $\delta_i = \frac{1}{n} \sum_{i=1}^n h_e(x_i)$. Thus the objective of single channel is updated to:

$$J(\theta_e, \theta_d) = \frac{1}{n} \sum_{i=1}^{n} (h_d(x_i) - x_i)^2 + \lambda W^j + \rho \Theta$$

where $\rho$ controls sparsity of representation in hidden layer.

B. The SMCAE model

The structure of the SMCAE model is extended from an autoencoder so that it can simultaneously deal with tasks in both the left and right channels. Specifically, we use the notation $(i: X, \sigma: X)$ to denote the configuration of input data (short for $i$) and reconstruction target at the output layer (short for $\sigma$) in one channel of SMCAE. We thus label the tasks in the left and right channels of SMCAE as $(i: X_{s}, \sigma: X_{r})^L$ and $(i: X_{s}, \sigma: X_{r})^R$ individually, where $(\cdot)^L$ and $(\cdot)^R$ indicate the left and right channel branch of SMCAE. $X_{s}$, $X_{r}$ stand for synthetic and real data respectively. The tasks in the two channels share the same parameters $\theta_e$ in all hidden layers which enforces the autoencoder to learn common structures of both tasks. At the output layer, we divide the SMCAE into two separate channels with their own parameters $\theta_d^L$ and $\theta_d^R$.

Our target is to minimize the reconstruction error of the two tasks of SMCAE together while taking into account the balance between two channels. The new objective function of SMCAE is thus,

$$E = J^L(\theta_e, \theta_d^L) + J^R(\theta_e, \theta_d^R) + \gamma \Psi$$

We add $\Psi = \frac{1}{2}(J^L(\theta_e, \theta_d^L) - J^R(\theta_e, \theta_d^R))^2$ as a regularisation term to balance the learning rate between the two channels.

The regularization term of $\Psi$ is a novel contribution of our SMCAE. Basically, $\Psi$ penalizes a situation where the difference of learning errors between two channels are large. Since in the configuration of the SMCAE the data at the input and output end of two channels are not symmetric, the learning error resulted by optimizing learning process in two channels are very different. Having $\Psi$ in our objective will prevent from a situation where the optimization of one channel dominates the entire SMCAE so as to help SMCAE to better leverage the learning process and find a compromising balance between two channels. For importance of $\Psi$ in our objective, we show the learning results of setting different $\gamma$ for $\Psi$ in Fig. 7.

The minimization of Eq. 6 is achieved by back propagation and stochastic gradient descent using a Quasi-Newton method – LBFGS. In the SMCAE, with balance regularization added to the objective, the only difference as opposed to sparse autoencoder is the gradient computation of unknown parameters $\theta_e$ and $\theta_d^L, \theta_d^R$. We clarify these differences in the following equations:

$$\nabla_{W_e^j} E = \frac{\partial J^L}{\partial W_e^j} + \frac{\partial J^R}{\partial W_e^j} + \gamma (J^L - J^R)\left(\frac{\partial J^L}{\partial W_e^j} - \frac{\partial J^R}{\partial W_e^j}\right)$$

and

$$\nabla_{W_d^L} E = \frac{\partial J^L}{\partial W_d^L} + \gamma (J^L - J^R)\frac{\partial J^L}{\partial W_d^L}$$

$$\nabla_{W_d^R} E = \frac{\partial J^R}{\partial W_d^R} + \gamma (J^L - J^R)\left(-\frac{\partial J^R}{\partial W_d^R}\right)$$

We train a SMCAE in a greedy manner where one layer gets trained at a time. The configuration for training one layer of SMCAE is shown in Fig. 8(right). The output of a trained layer is then sent as input to the next layer for training. A fine-tuning is implemented to the entire stacked structure once all layers are trained. Thus, after SMCAE has been trained, to transform new synthetic data, the data is sent to the left channel of the SMCAE $(i: X_{s}, \sigma: X_{r})^L$. We take output of this process as transformed synthetic data.

C. Competitors

As shown in Fig. 9 we compare the SMCAE configuration to three alternative configurations: (1) SMCAE-II which places two separate channels on the structure, i.e. $(i: X_{s}, \sigma: X_{r})^L$ and $(i: X_{s}, \sigma: X_{r})^R$. (2) Stacked autoencoder type-I (SAE-I) which merges the tasks in a single channel stacked autoencoder, with the configuration of $(i: X_{s}, \sigma: X_{r})^L$. (3) Stacked autoencoder type-II (SAE-II) which simply transforms source data to target data, and configures as: $(i: X_{s}, \sigma: X_{r})$. 

\[1\] $\delta$ is a sparsity parameter and is empirically set to 0.05 in all our experiments.
Compared with SAE-I and SAE-II, our two channel structures endow more flexibility. Critically, the single channel models force synthetic data to fit real data, which causes synthetic data to lose information and become less useful for recognition. In contrast, SMCAE can explore ‘characters’ and ‘patterns’ common in both synthetic and real data. Intrinsically, SMCAE first encodes both synthetic and real data into common hidden layers which model common information useful for recognition. Then the decoding process transforms the synthetic data to better simulate real data. Although SMCAE-II has the same two branches in the structure, it does not learn such transformation between synthetic data and real data.

Fig. 4. Illustration of the compared configurations: SMCAE, SMCAE-II, SAE-I and SAE-II.

**IV. Experiments and Results**

We first compare SMCAE on the challenging task of face-sketch recognition [31], [33] using the CUFSF dataset. We show that SMCAE is better than alternative configurations. To further validate the efficacy of our framework, we train SMCAE on handwritten digit images and generate synthetic data to simulate real images. We show that the synthetic data can help train classifiers for recognition.

**Dataset.** We conduct our experiments on two different datasets: (1) The CUFSF dataset [31], [33] containing the photos and sketches of 1194 people with lighting variations. We employ the standard split defined in [31], [33] which selects 500 persons as the training set, and the remaining 694 persons as the testing set. (2) handwritten digits dataset [4] (HWDUCI) containing 5620 instances in total in which 3823 samples are used for training and 1917 samples are used for testing. The handwritten digits from 0 to 9 in this dataset are collected from 43 people: 30 contributed to the training set and the other 13 to the test set. For all experiments, we empirically set the number of hidden layers in SMCAE to two and each layer has 1000 nodes. The same settings are used to make SMCAE, SMCAE-II, SAE-I and SAE-II more comparable.

**Evaluation Metrics.** We report the following metrics when they are available: (1) F1-score, which is defined as $F1 = 2 \cdot \frac{\text{Precision} \cdot \text{Recall}}{\text{Precision} + \text{Recall}}$. (2) Receiving Operator Characteristic (ROC) curves and VR@0.1% FAR which is the performance of Verification Rate (VR) at 0.1% False Acceptance Rate (FAR). VR@0.1% FAR is a standard evaluation metric and proposed in [31]. (3) Rank-1 recognition accuracy.

**Features.** Similar to [14], in the CUFSF dataset we use Histogram of Oriented Gradients (HOG). To further reduce the computational cost, the resolution of all photos and sketches is reduced to $50 \times 50$. So the cell size of HOG features is set to 3. (2) The HWDUCI dataset uses HOG features with cell size 3.

**Classifiers.** For CUFSF dataset, nearest-neighbor search with Euclidean metric is used in retrieving the most similar photo to the query sketch. In the handwritten digit classification, a Support Vector Machine (SVM) with RBF kernel [11] is used in the experiments.

**A. Results on the CUFSF dataset**

In all experiments on this dataset, HOG features of sketch images are first transformed by the SMCAE and then used as queries. We first compare the results of photo-sketch matching using HOG feature transformed by SMCAE, SMCAE-II, SAE-I and SAE-II. The results are reported as ROC curve starting with VR@0.1% FAR. The dissimilarity between a photo and a sketch is computed as the Euclidean distance between descriptors.

Fig. 5. Results on CUFSF dataset. Left: ROC curve of different methods; Right: VR@0.1% FAR of different methods.

The ROC curves and VR@0.1% FAR are shown in Fig. 5. Clearly, the proposed SMCAE achieves the highest results on AUC values and VR@0.1% FAR accuracy and significantly outperforms the alternative configurations. Note that we also report the state-of-the-art approaches of VR@0.1% FAR including LFDA [14], CITE [33] and classic eigenfaces (PCA) [24]. It is worth noting that in some of previous works, a better result could be obtained by combining multiple features. For example in [33], multiple CITE features generated by a random forest are used to better matching photos and sketches. Here, to enable a comparison with more fairness, we focus our comparison on matching results obtained by using uncombined feature only.

There are several reasons why our SMCAE outperform the other approaches. First, compared with SMCAE-II, the configuration of SMCAE involves a task that handles the transformation from synthetic to real data, and thus better eliminates the distance between them. Second, compared with SAE-I, rather than merging two tasks in a single channel SMCAE employs two channels to better clarify each task with

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$^2$ collected from UCI machine learning repository (HWDUCI) [4].

$^3$ The parameters are cross-validated.
the aim of reconstructing the main 'characters' and 'patterns' co-existing in both tasks. Thus synthetic data can be more easily transformed to real data with less error. Finally, SMCAE is better than SAE-II as SMCAE learns features of real data in task \( <i: X_r, o: X_r>_R \). These features will better compensate the difference between synthetic data and real data during the transformation.

We further validate the results by using Rank-1 recognition accuracy which is also reported in [13], [30]. The results are shown in Fig. 6. The methods of [13], [30] are comparable to our SMCAE. Method [13] employed a discriminant common subspace to maximize the between-class variations and minimize the within-class variations. Method [30] used a structure composed of two autoencoders. As can be seen Fig. 6 the SMCAE outperforms all other methods.

Parameter Validation in Eq. 6 To validate the significance of \( \Psi \) in Eq. 6 we set \( \gamma \) with different values and report the rank-1 accuracy in Fig. 7. Particularly, when \( \gamma = 0 \), it takes 2 times longer for SMCAE to converge compared with \( \gamma = 50 \) used in this work. Further with \( \gamma = 0 \) the rank-1 accuracy is dropped by more than 2%. This validates the importance of term \( \Psi \) discussed in Sec. 3.2.

Qualitative results. Some qualitative results are shown in Fig. 8. It shows that a sketch HOG transformed by our SMCAE is more similar to the ground truth photo HOG.

B. Handwritten Digit Recognition

Generating synthetic data. A synthetic version of each real character is generated as a variant of a centralized model learned from real characters. The centralized model of digit is shaped by control points \( C = \{c_i\}_{i=1}^n \) settled on the boundary of the digit. A technique called migration is used to locate corresponding control points on each real digit image. A synthetic digit image then could be generated by filling areas closed by the control points [5]. Examples of generated synthetic digits are shown in Fig. 9. To generate more synthetic data which is used to train the classifier once transformed by the trained SMCAE, we assume that locations of the control points follow a multivariate normal distribution \( C \sim N(\mu, \Sigma) \) with \( \mu \) and \( \Sigma \) estimated using control points on the synthetic digit images. For each digit, 3,000 new synthetic images are generated by randomly drawing samples from \( N(\mu, \Sigma) \).

We compare our SMCAE with SMCAE-II, SAE-I, SAE-II, LeNet-5 [16] and the best results [1] reported on this data set. The classification performance is evaluated by F1-score. A Support Vector Machine (SVM) classifier with RBF kernel is used in the experiments. For SMCAE, SMCAE-II, SAE-I and SAE-II in the test, real training data together with transformed synthetic data are used to train the SVM.

As shown in Fig. 10 (left), the SVM classifier with our SMCAE is better than all the alternative methods. This validates the effectiveness of our framework in generating synthetic data to better help training a classifier.

To further demonstrate how transformed synthetic data improve the classification results, we conducted more evaluations by training classifiers using different combinations of training sets in Fig. 10 (right). Particularly, four combinations of training sets are used. First, to have a performance baseline of SVM, we trained the SVM using real data only. To investigate how much improvement we could obtain in classification using

*Please refer to supplementary material for details.*
The number of training synthetic data

V. CONCLUSION

In this paper we identify the synthetic gap problem. To solve this problem, we propose a novel Stacked Multichannel autoencoder (SMCAE) model. SMCAE has multiple channels in its structure and is an extension of a standard autoencoder. We show that SMCAE not only bridges the synthetic gap between real data and synthetic data, but also jointly learns from both real and synthetic data.

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Supplemental Material

VI. OPTIMIZATION OF SMCAE

With two branches in the SMCAE, we target to minimize the reconstruction error of two tasks together while taking into account the balance between two branches. The new objective function is given as:

\[ E = J^L(\theta_e, \theta^L_d) + J^R(\theta_e, \theta^R_d) + \gamma \Psi \]  

where \[ \Psi = \frac{1}{2}(J^L(\theta_e, \theta^L_d) - J^R(\theta_e, \theta^R_d))^2 \]

is a regularization added to balance the learning rate between two branches. In the SMCAE, with balance regularization added to the objective, the only difference as opposed to sparse autoencoder is the gradient computation of unknown parameters \( \theta_e \) and \( \theta^L_d, \theta^R_d \). We clarify these differences in the following equations:

\[ \nabla_{W_e} E = \frac{\partial J^L}{\partial W^L_e} + \frac{\partial J^R}{\partial W^R_e} + \gamma (J^L - J^R) \left( \frac{\partial J^L}{\partial W^L_e} - \frac{\partial J^R}{\partial W^R_e} \right) \]

\[ \nabla_{b_e} E = \frac{\partial J^L}{\partial b^L_e} + \frac{\partial J^R}{\partial b^R_e} + \gamma (J^L - J^R) \left( \frac{\partial J^L}{\partial b^L_e} - \frac{\partial J^R}{\partial b^R_e} \right) \]

and

\[ \nabla_{W_d} E = \frac{\partial J^L}{\partial W^L_d} + \gamma (J^L - J^R) \frac{\partial J^L}{\partial W^L_d} \]

\[ \nabla_{b_d} E = \frac{\partial J^L}{\partial b^L_d} + \gamma (J^L - J^R) \frac{\partial J^L}{\partial b^L_d} \]

\[ \nabla_{W^R_d} E = \frac{\partial J^R}{\partial W^R_d} + \gamma (J^L - J^R) \left( - \frac{\partial J^R}{\partial W^R_d} \right) \]

\[ \nabla_{b^R_d} E = \frac{\partial J^R}{\partial b^R_d} + \gamma (J^L - J^R) \left( - \frac{\partial J^R}{\partial b^R_d} \right) \]

The exact form of gradients of \( \theta_e \) and \( \theta^L_d, \theta^R_d \) varies according to different sparsity regularization \( \Theta \) used in the framework.

VII. GENERATING SYNTHETIC DATA

Synthetic data are created to highlight the potential useful pattern in real images. In the proposed approach, the synthetic data are represented as a parametric model of a set of control points and edges associated to these points in the images. From the control points, the synthetic images could be generated to simulate the real images in terms of having the same structure or a similar appearance. Initially, the control points are selected from a centralized prototype that generalizes all images in the same class. Then the locations of the control points are iteratively optimized until convergence in order to minimize the distance between synthetic images generated by control points and the real image. We annotate the control points and edges associated to them as \( S = \{C,E\} \), where \( C = \{c_i\}_{i=1}^n \) is the set of the control points, and \( E = \{(c_i,c_j)\}, 1 \leq i,j \leq n \) is the set of edges connecting control points. A generalized algorithm of getting the best matching synthetic image is provided in Algorithm 1.

Algorithm 1 Get Matching Synthetic Image.

Input:
- A real image \( U \).
- A set of control points \( S = \{C,E\} \) with all control points \( c_i \in C \) set to their initial positions.
- A prototype image \( V \) generated using the initial \( S \).

1: while \( S \) is not converged do
2: \( S = \) OptimizeControlPoints \( (U, V, S) \).
3: Generate \( V \) using \( S \).
4: end while
5: Generate synthetic image \( I \) using \( S \).
6: return \( I \).

A. Learning Synthetic Prototype from Data

In hand written digit dataset used in this work, we learn a centralized prototype from given data. A digit prototype is generated for all images with the same digit. Congealing algorithm proposed in [17] is employed in this step to produce the synthetic prototypes for digits. In congealing, the project transformations are applied to images to minimize a joint entropy. Thus the prototype is considered to be an average image of all images after congealing, shown in Fig. 12.

Then control points are evenly sampled from the boundary detected from the prototype image. The control points needs to be mapped to each digit image in order to generate a synthetic image. To find this mapping we implement an approach that migrates the control points from the prototype images to destination image.

![Image of control points on a digit image.](image_url)

This point migration algorithm is based on a series of intermediate images generated in between synthetic prototype and destination image. To generate the intermediate images, we binarize all the images and the distance transformed images [9] of the synthetic prototype and the real image are generated. Given the number of steps, an intermediate image then is generated as a binarized image of linear interpolation between two distance transformed images.
images. In each step, the control points are snapped to the closest boundary pixels of the intermediate image. The algorithm of OptimizeControlPoints(U, V, S) in this situation is given in Algorithm 2. We fix the number of steps to 5 in this algorithm. A step by step examples is given in Fig. 14. A zoom in example showing how control points moved from one digit to another is shown in Fig. 15.

Algorithm 2 OptimizeControlPoints(U, V, S)

Input:
- A real image U.
- A prototype of the synthetic image S = {C, E}.
- A synthetic image V.

1: steps = 10.
2: Compute distance transform image of U, V as U', V'.
3: for i = 1 to steps do
4:    I = (1 - \frac{i}{steps})U' + \frac{i}{steps}V'.
5: end for
6: I = Binarizer(I).
7: Update S by snapping to the closest boundary pixel on I.
8: end for
9: Set the status of S to be converged.
10: return S.

To generate more synthetic digit images, we assume the distribution of control points on each digit image follows a multivariate normal distribution that C ∼ N(μ, Σ) where μ and Σ are computed using existing control points. The visualization of the distribution of control points of each digit is then shown in Fig. 16.
Fig. 14. Illustrations of the migration of control points and intermediate synthetic images generated using control points in each step. The distance transform images of the synthetic prototype and real images are shown as the left most and right most images respectively.

Fig. 16. Illustration of distributions of control points on each digit image, where colors from blue to red are used to represent the probability density from low to high.