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(54) PERSONALIZED FORM ERROR CORRECTION PROPAGATION

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G06V 30/14	(2022.01)
G06V 30/262	(2022.01)
G06V 30/414	(2022.01)

(52) **U.S. Cl.**

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(58) **Field of Classification Search**

None

See application file for complete search history.

(56) **References Cited**

U.S. PATENT DOCUMENTS

2004/0181749 A1*	9/2004	Chellapilla	....	G06F 40/174 715/222
2018/0365227 A1*	12/2018	Zheng	....	G06F 40/279

OTHER PUBLICATIONS

Aggarwal, Milan , et al., "Form2Seq : A Framework for Higher-Order Form Structure Extraction", Cornell University arXiv, arXiv.org [retrieved Feb. 20, 2023]. Retrieved from the Internet <https://arxiv.org/pdf/2107.04419.pdf>., Jul. 9, 2021, 11 Pages.

(Continued)

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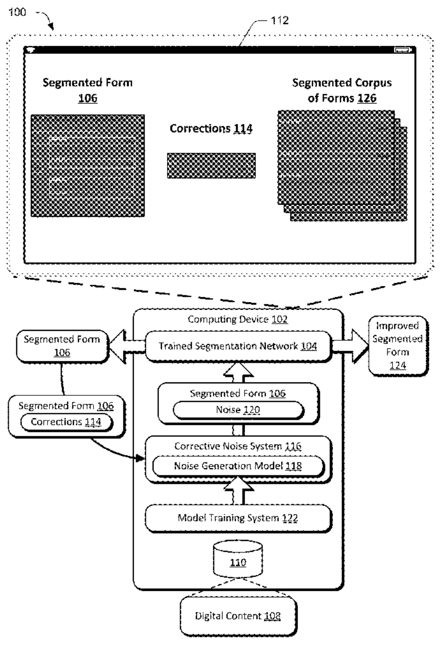
(74) *Attorney, Agent, or Firm* — FIG. 1 Patents

(57) **ABSTRACT**

A corrective noise system receives an electronic version of a fillable form generated by a segmentation network and receives a correction to a segmentation error in the electronic version of the fillable form. The corrective noise system is trained to generate noise that represents the correction and superimpose the noise on the fillable form. The corrective noise system is further trained to identify regions in a corpus of forms that are semantically similar to a region that was subject to the correction. The generated noise is propagated to the semantically similar regions in the corpus of forms and the noisy corpus of forms is provided as input to the segmentation network. The noise causes the segmentation network to accurately identify fillable regions in the corpus of forms and output a segmented version of the corpus of forms having improved fidelity without retraining or otherwise modifying the segmentation network.

20 Claims, 7 Drawing Sheets


100
112
Segmented Form 106
Corrections 114
Segmented Corpus of Forms 126
Computing Device 102
Segmented Form 106
Trained Segmentation Network 104
Improved Segmented Form 124
Segmented Form 106
Noise 120
Segmented Form 106
Corrections 114
Corrective Noise System 116
Noise Generation Model 118
Model Training System 122
110
Digital Content 108

(56) **References Cited**

OTHER PUBLICATIONS

Aggarwal, Milan , et al., "Multi-Modal Association based Grouping for Form Structure Extraction", Cornell University arXiv, arXiv.org [retrieved Feb. 20, 2023]. Retrieved from the Internet <https://arxiv.org/pdf/2107.04396.pdf>., Jul. 9, 2021, 10 Pages.
Akhtar, Naveed , "Advances in adversarial attacks and defenses in computer vision: A survey", Cornell University arXiv, arXiv.org [retrieved Feb. 21, 2023]. Retrieved from the Internet <https://arxiv.org/pdf/2108.00401.pdf>., Sep. 2, 2021, 35 Pages.
Akhtar, Naveed , et al., "Threat of Adversarial Attacks on Deep Learning in Computer Vision: A Survey", Cornell University arXiv, arXiv.org [retrieved Feb. 21, 2023]. Retrieved from the Internet <https://arxiv.org/pdf/1801.00553.pdf>., Feb. 26, 2018, 21 Pages.
Goodfellow, Ian J, et al., "Explaining and Harnessing Adversarial Examples", Cornell University arXiv, arXiv.org [retrieved Feb. 21, 2023]. Retrieved from the Internet <https://arxiv.org/pdf/1412.6572.pdf>., Mar. 20, 2015, 11 Pages.
Hao, Yuying , et al., "EdgeFlow: Achieving Practical Interactive Segmentation with Edge-Guided Flow", Cornell University arXiv, arXiv.org [retrieved Feb. 21, 2023]. Retrieved from the Internet <https://arxiv.org/pdf/2109.09406.pdf>., Oct. 26, 2021, 10 Pages.
Jang, Won-Dong , et al., "Interactive Image Segmentation via Backpropagating Refinement Scheme", IEEE/CVF [retrieved Mar. 15, 2023]. Retrieved from the Internet <https://openaccess.thecvf.com/content_CVPR_2019/papers/Jang_Interactive_Image_Segmentation_via_Backpropagating_Refinement_Scheme_CVPR_2019_paper.pdf>., Jun. 2019, 10 Pages.
Java, Abhinav , et al., "One-Shot Doc Snippet Detection: Powering Search in Document Beyond Text", Cornell University arXiv, arXiv.org [retrieved Feb. 20, 2023]. Retrieved from the Internet <https://arxiv.org/pdf/2209.06584.pdf>., Sep. 12, 2022, 17 Pages.
Jiang, Dalei , et al., "Residual refinement for interactive skin lesion segmentation", Journal of Biomedical Semantics, London vol. 12 [retrieved Feb. 21, 2023]. Retrieved from the Internet <https://media.proquest.com/media/hms/PFT/1/e4EpL?_s=U8O9vZCLBWCTUU%2BbIVKWjJGHKUw%3D>., Dec. 18, 2021, 12 Pages.
Liu, Xin , et al., "Self-Error-Correcting Convolutional Neural Network for Learning with Noisy Labels", IEEE International Conference on Automatic Face & Gesture Recognition [retrieved Feb. 21, 2023]. Retrieved from the Internet <https://ieeexplore.ieee.org/abstract/document/7961730>., May 30, 2017, 7 Pages.
Majumder, Soumajit , et al., "Two-in-One Refinement for Interactive Segmentation", Institute of Computer Science II, University of Bonn, Germany [retrieved Feb. 21, 2023]. Retrieved from the Internet <https://www.bmvc2020-conference.com/assets/papers/0702.pdf>., 2020, 12 Pages.
Sarkar, Mausoom , et al., "Document Structure Extraction using Prior based High Resolution Hierarchical Semantic Segmentation", Cornell University arXiv, arXiv.org [retrieved Feb. 20, 2023]. Retrieved from the Internet <https://arxiv.org/pdf/1911.12170.pdf>., Sep. 17, 2020, 18 Pages.
Sofiiuk, Konstantin , et al., "F-BRS: Rethinking Backpropagating Refinement for Interactive Segmentation", Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition [retrieved Mar. 15, 2023]. Retrieved from the Internet <10.1109/CVPR42600.2020.00865>., Jan. 2020, 10 Pages.
Sofiiuk, Konstantin , et al., "Reviving Iterative Training with Mask Guidance for Interactive Segmentation", Cornell University arXiv, arXiv.org [retrieved Mar. 15, 2023]. Retrieved from the Internet <https://arxiv.org/pdf/2102.06583.pdf>., Feb. 12, 2021, 15 Pages.
Szegedy, Christian , et al., "Intriguing properties of neural networks", Cornell University arXiv, arXiv.org [retrieved Feb. 21, 2023]. Retrieved from the Internet <https://arxiv.org/pdf/1312.6199.pdf>., Feb. 19, 2014, 10 Pages.
Zheng, Haizhong , et al., "Efficient Adversarial Training with Transferable Adversarial Examples", Cornell University arXiv, arXiv.org [retrieved Feb. 21, 2023]. Retrieved from the Internet <https://arxiv.org/pdf/1912.11969.pdf>., Jul. 2, 2020, 14 Pages.
Zhou, Mingyi , et al., "DaST: Data-free Substitute Training for Adversarial Attacks", Cornell University arXiv, arXiv.org [retrieved Feb. 21, 2023]. Retrieved from the Internet <https://arxiv.org/pdf/2003.12703.pdf>., Mar. 31, 2020, 10 Pages.
Zhou, Wen , et al., "Transferable Adversarial Perturbations", Computer Vision ECCV [retrieved Feb. 21, 2023]. Retrieved from the Internet <https://openaccess.thecvf.com/content_ECCV_2018/papers/Bruce_Hou_Transferable_Adversarial_Perturbations_ECCV_2018_paper.pdf>., Sep. 8, 2018, 16 Pages.

* cited by examiner

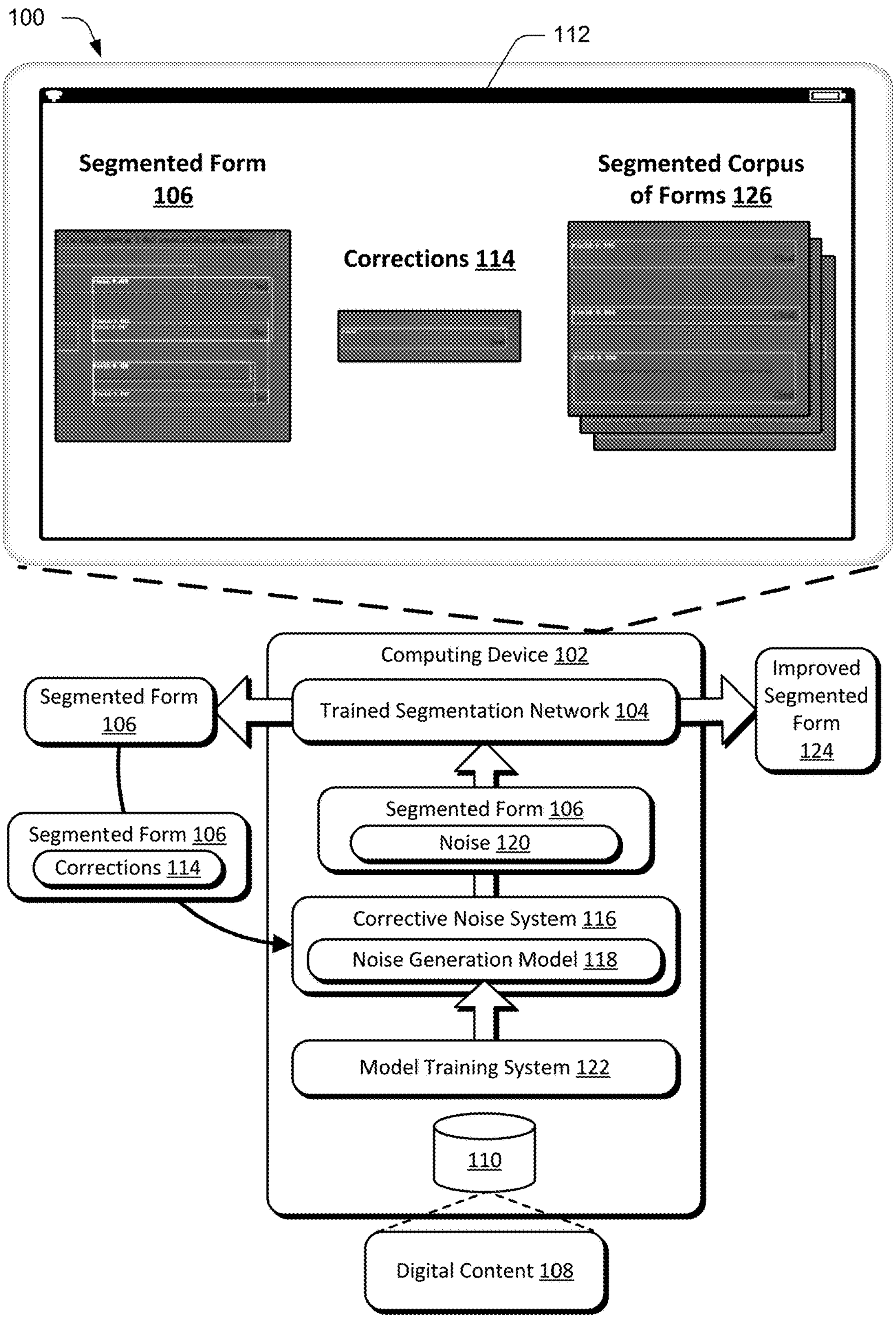

100
112
Segmented Form 106
Corrections 114
Segmented Corpus of Forms 126
Computing Device 102
Segmented Form 106
Trained Segmentation Network 104
Improved Segmented Form 124
Segmented Form 106
Noise 120
Segmented Form 106
Corrections 114
Corrective Noise System 116
Noise Generation Model 118
Model Training System 122
110
Digital Content 108

Fig. 1

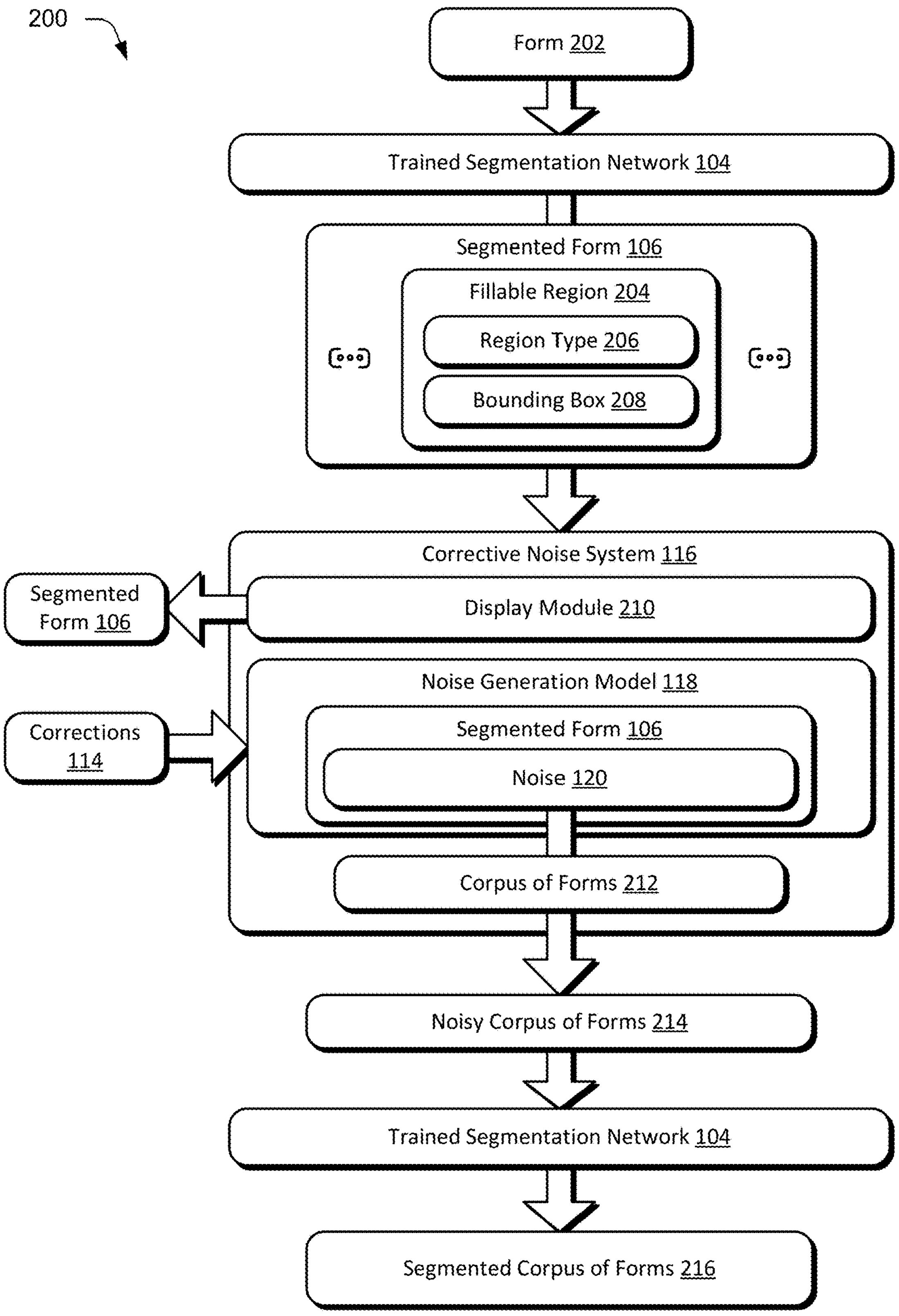

200
Form 202
Trained Segmentation Network 104
Segmented Form 106
Fillable Region 204
Region Type 206
Bounding Box 208
Corrective Noise System 116
Display Module 210
Segmented Form 106
Noise Generation Model 118
Corrections 114
Segmented Form 106
Noise 120
Corpus of Forms 212
Noisy Corpus of Forms 214
Trained Segmentation Network 104
Segmented Corpus of Forms 216

Fig. 2

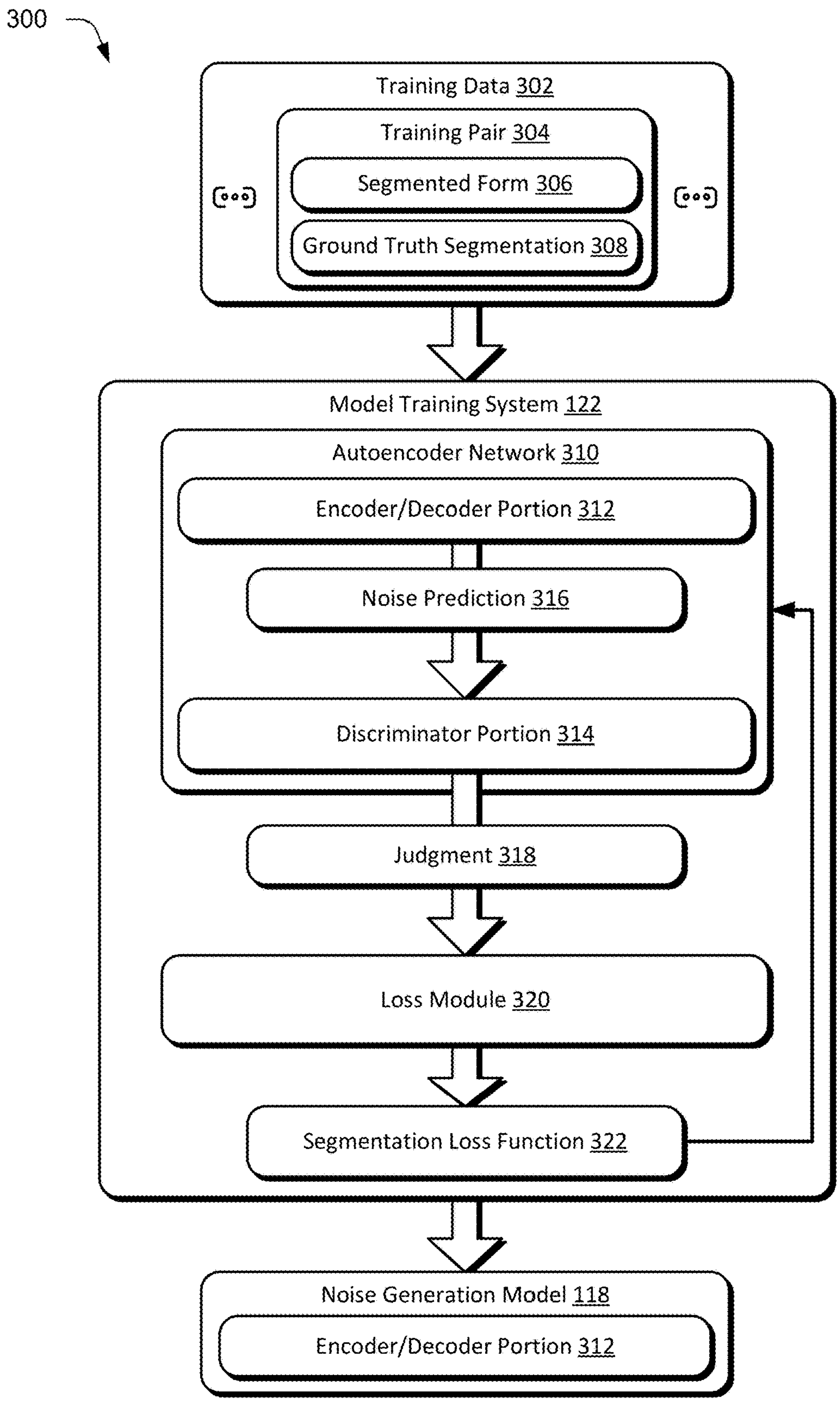
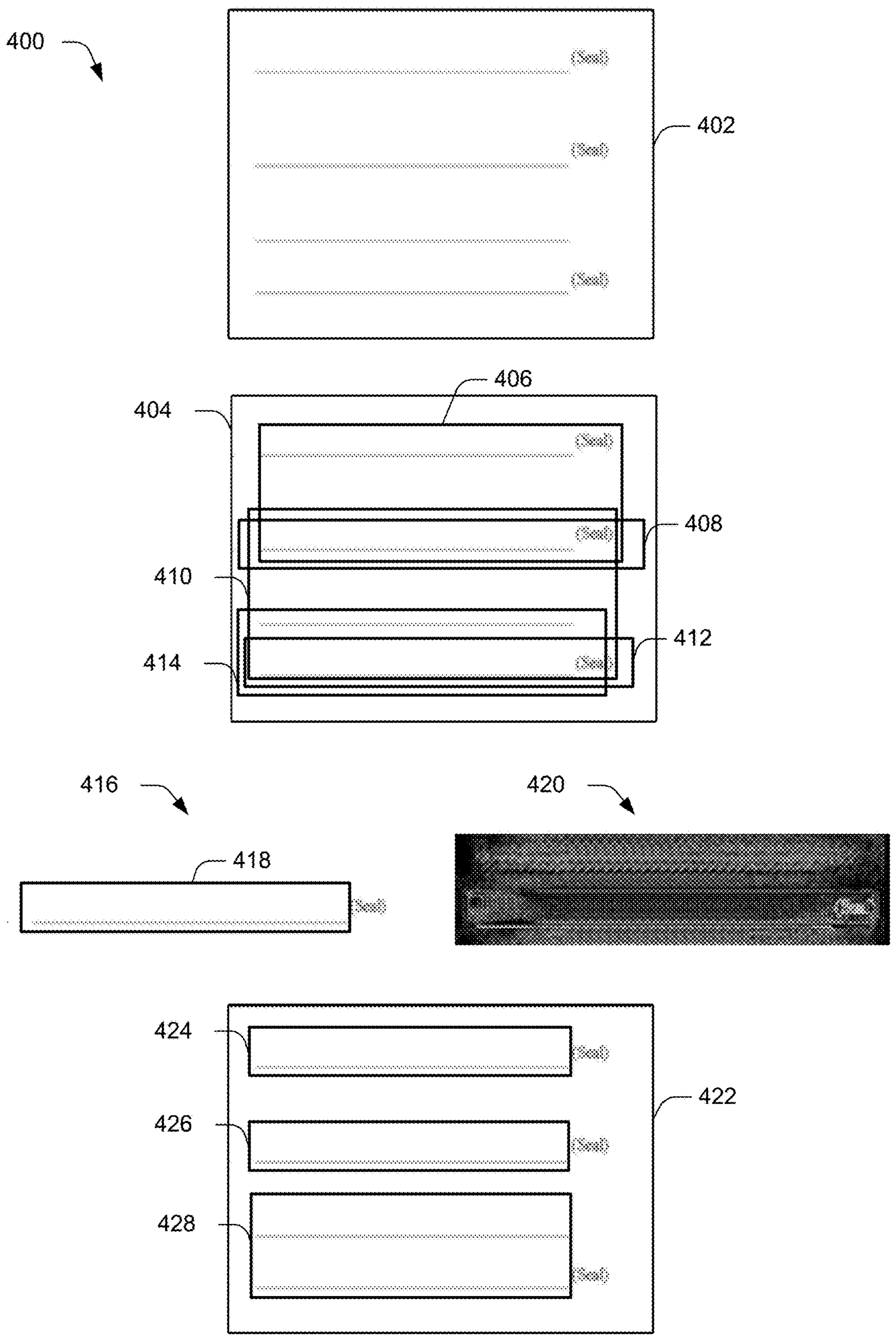

300
Training Data 302
Training Pair 304
Segmented Form 306
Ground Truth Segmentation 308
Model Training System 122
Autoencoder Network 310
Encoder/Decoder Portion 312
Noise Prediction 316
Discriminator Portion 314
Judgment 318
Loss Module 320
Segmentation Loss Function 322
Noise Generation Model 118
Encoder/Decoder Portion 312

Fig. 3


400
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(Seal)
(Seal)
(Seal)
404
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(Seal)
(Seal)
(Seal)
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(Seal)
420
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424
426
428
(Seal)
(Seal)
(Seal)

Fig. 4

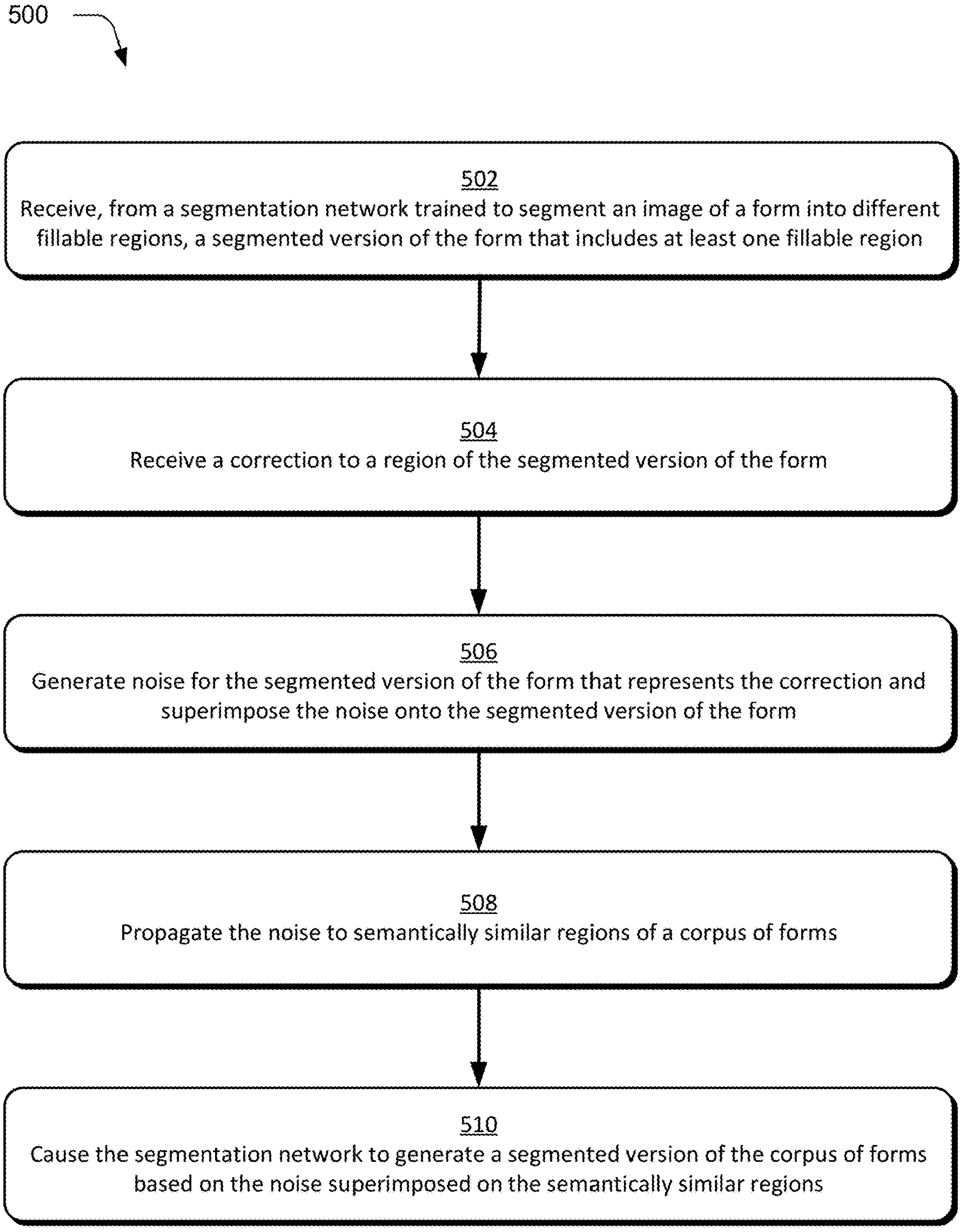
500
502
Receive, from a segmentation network trained to segment an image of a form into different fillable regions, a segmented version of the form that includes at least one fillable region
504
Receive a correction to a region of the segmented version of the form
506
Generate noise for the segmented version of the form that represents the correction and superimpose the noise onto the segmented version of the form
508
Propagate the noise to semantically similar regions of a corpus of forms
510
Cause the segmentation network to generate a segmented version of the corpus of forms based on the noise superimposed on the semantically similar regions

Fig. 5

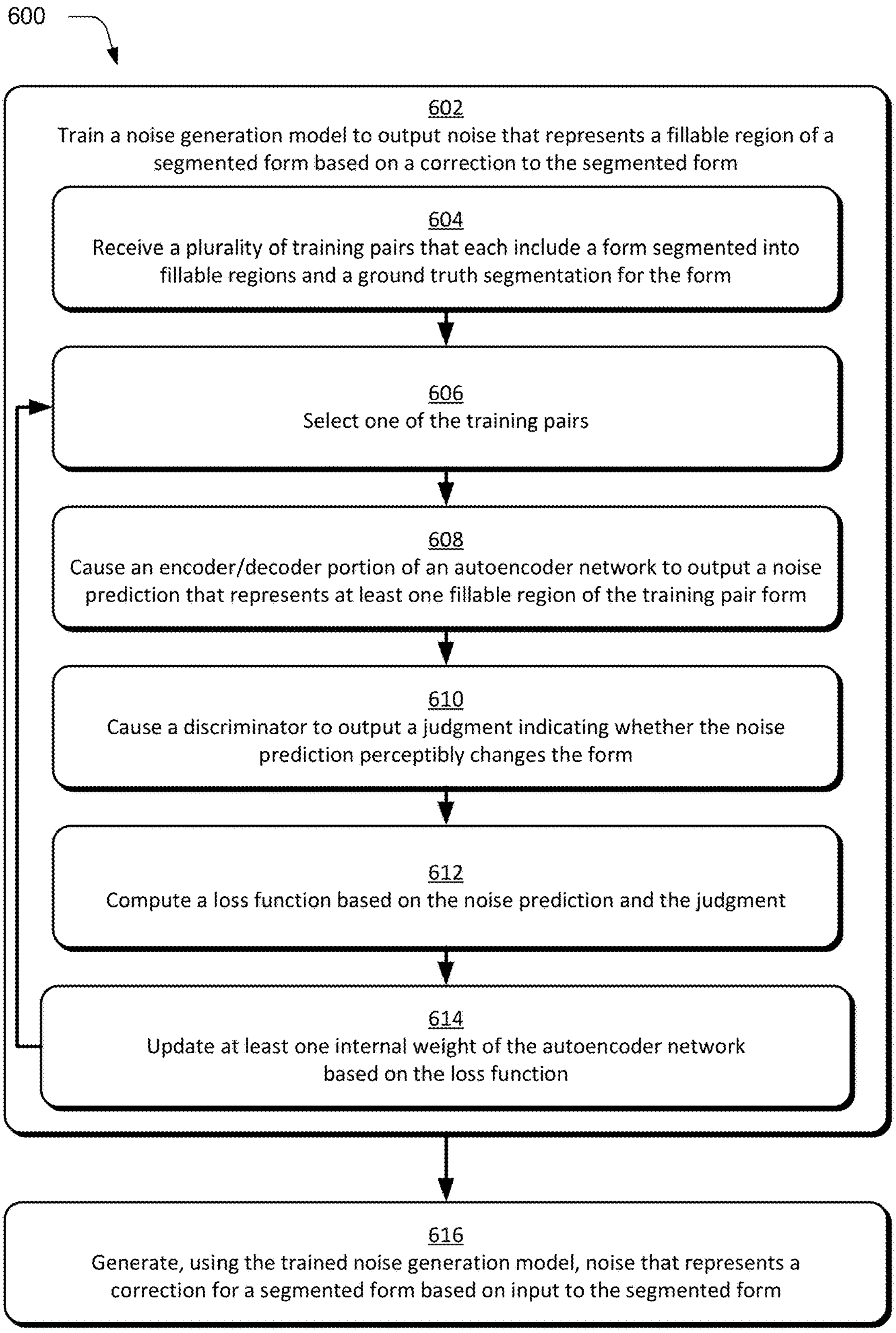
600
602
Train a noise generation model to output noise that represents a fillable region of a segmented form based on a correction to the segmented form
604
Receive a plurality of training pairs that each include a form segmented into fillable regions and a ground truth segmentation for the form
606
Select one of the training pairs
608
Cause an encoder/decoder portion of an autoencoder network to output a noise prediction that represents at least one fillable region of the training pair form
610
Cause a discriminator to output a judgment indicating whether the noise prediction perceptibly changes the form
612
Compute a loss function based on the noise prediction and the judgment
614
Update at least one internal weight of the autoencoder network based on the loss function
616
Generate, using the trained noise generation model, noise that represents a correction for a segmented form based on input to the segmented form

Fig. 6

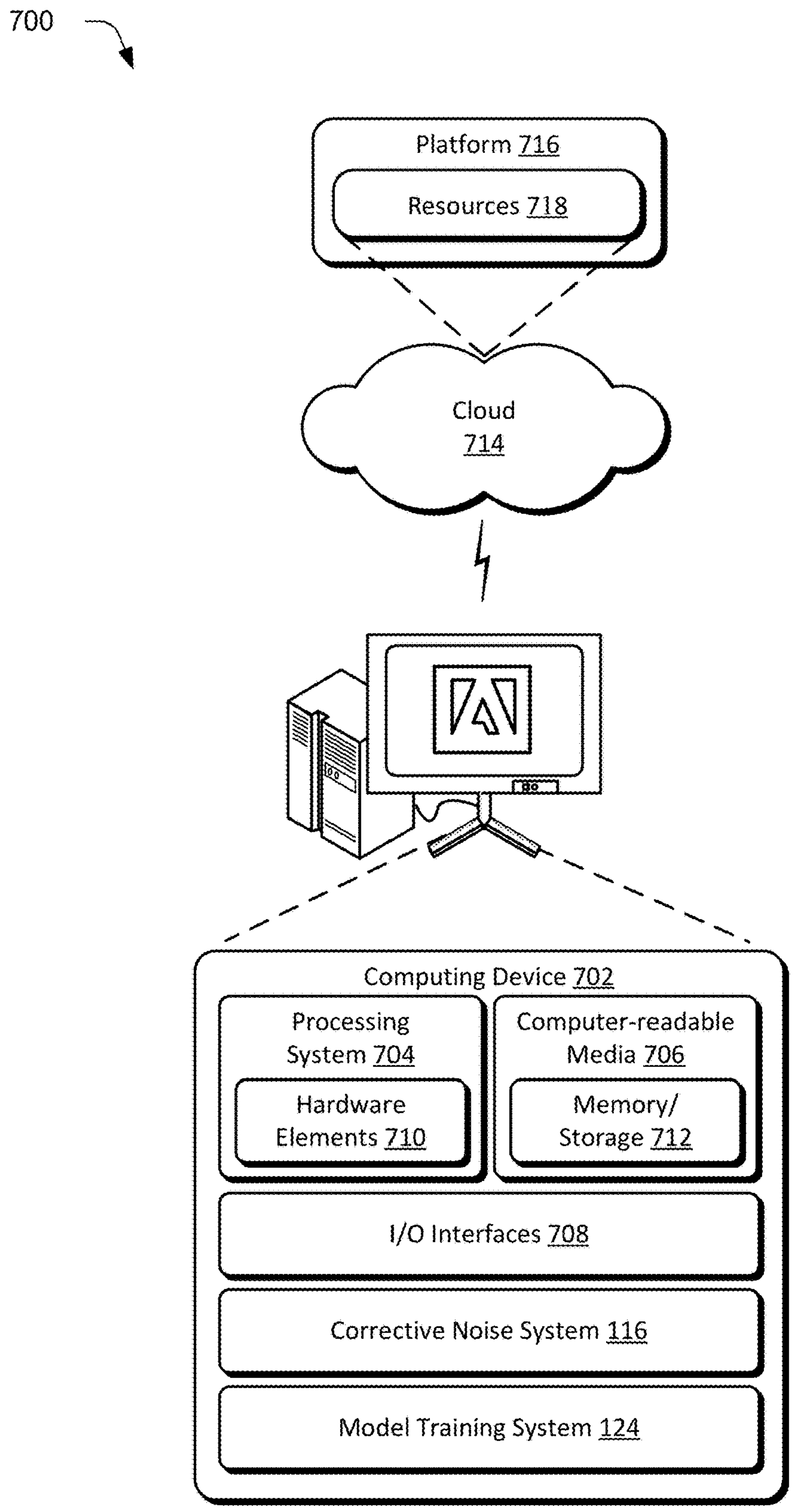
700
Platform 716
Resources 718
Cloud
714
Computing Device 702
Processing System 704
Hardware Elements 710
Computer-readable Media 706
Memory/ Storage 712
I/O Interfaces 708
Corrective Noise System 116
Model Training System 124

Fig. 7

PERSONALIZED FORM ERROR CORRECTION PROPAGATION

BACKGROUND

Fillable form documents are a crucial part of communicating information between entities for many different industries, such as legal forms, banking forms, and so forth. With advances in computing device technology, forms that were previously used only in printed paper copies are now implemented as electronic documents to facilitate information communication, which was previously written via pen and paper, computing devices. With such advances, systems have been developed to automatically convert physical (e.g., paper) forms to electronic versions (e.g., Portable Document Format (PDF) versions of paper forms). However, existing systems for converting physical, paper forms to electronic versions are unable to accurately categorize paper forms and require user input to correct segmentation errors for each form converted to an electronic format.

SUMMARY

A corrective noise system is described that is configured to obtain an electronic version of a fillable form generated by a segmentation network and receive user input correcting one or more errors in the electronic version of the fillable form. The corrective noise system includes a noise generation model, which is trained to generate noise that represents corrections to the segmented version of a fillable form. The corrective noise system is trained to distill, from a segmented form that includes at least one correction, a noise that represents an intended change.

The corrective noise system is further trained to identify a region of a fillable form that includes a correction and propagate noise generated for the region to other regions of a corpus of forms that are semantically similar to the corrected region. Noise generated for one fillable form region is thus automatically propagated to all regions of a corpus of forms that are semantically similar to the corrected region (e.g., noise representing a correction to one check box is propagated to all check box regions in a corpus of forms, noise representing a correction to one text box is propagated to all text box regions in a corpus of forms, and so forth).

Noise representing the correction is then superimposed on the corrected region of the form as well as the semantically similar regions in the corpus of forms. The corpus of forms, with superimposed noise, are input to the segmentation network. The noise causes the segmentation network to accurately identify fillable regions in the corpus of forms and output a segmented version of the corpus of forms having improved fidelity (e.g., relative to a segmented version of the corpus of forms generated without the superimposed noise generated by the corrective noise system).

This Summary introduces a selection of concepts in a simplified form that are further described below in the Detailed Description. As such, this Summary is not intended to identify essential features of the claimed subject matter, nor is it intended to be used as an aid in determining the scope of the claimed subject matter.

BRIEF DESCRIPTION OF THE DRAWINGS

The detailed description is described with reference to the accompanying figures. In some implementations, entities represented in the figures are indicative of one or more

entities and thus reference is made interchangeably to single or plural forms of the entities in the discussion.

FIG. **1** is an illustration of a digital medium environment in an example implementation that is operable to employ a corrective noise system for generating a noisy version of a segmented form and a model training system configured to generate a noise generation model employed by the corrective noise system.

FIG. **2** depicts a digital medium environment showing operation of the corrective noise system of FIG. **1** generating a noisy corpus of forms based on a correction provided to a single form and of a trained segmentation network generating a segmented corpus of forms based on the noisy corpus of forms.

FIG. **3** depicts a digital medium environment showing operation of the model training system of FIG. **1** generating the noise generation model employed by the corrective noise system.

FIG. **4** depicts an example of a segmented form output by a segmentation network, noise representing a correction to the segmented form, and an improved version of the segmented form generated based on the noise.

FIG. **5** is a flow diagram depicting a procedure in an example implementation of generating a segmented version of a corpus of forms based on noise representing a correction to a single form generated by the corrective noise system of FIG. **1**, using the techniques described herein.

FIG. **6** is a flow diagram depicting a procedure in an example implementation of training a noise generation model and using the trained noise generation model to generate noise representing a correction to a segmented form using the techniques described herein.

FIG. **7** illustrates an example system including various components of an example device to implement the techniques described with reference to FIGS. **1-6**.

DETAILED DESCRIPTION

Overview

A fillable form document is a digital or electronic document that is designed with editable fields or sections (e.g., fillable regions) that can be completed or filled in with information (e.g., information input by users based on requests for information or other prompts included in the form). Fillable form documents are commonly used for collecting data or information from multiple individuals or entities in a standardized format. Fillable form documents are configurable as including different types of fillable regions, such as text boxes, checkboxes, dropdown menus, date fields, signature blocks, and so forth, which are individually populatable with relevant information.

Fillable form documents are used for a wide range of purposes, such as job applications, surveys, registration forms, feedback forms, contracts, and more. Fillable form documents provide a convenient mechanism for users to input information in a structured and organized manner, thus presenting information obtained from numerous (e.g., millions) of different users in a standardized manner. After information is input to a fillable form by a user, data representing the information can be submitted electronically, saved for future reference, or printed for physical submission, depending on the form's intended use and requirements.

With advances in computing device technology, forms that were previously configured in physical hard copies (e.g., printed paper forms) are now implemented as electronic documents configured in various formats, such as PDF formats, web-adaptive formats, mobile responsive formats, and so forth. Some conventional approaches to converting traditional hard copy forms into a digital or electronic format leverage segmentation networks to do so. Segmentation networks (e.g., semantic segmentation models) are deep learning algorithms that are trained to convert hard copy fillable forms into a digital format. Conventional processes for training such segmentation networks begin by obtaining a digital image of a hard copy fillable form (e.g., using a scanner, a camera, or other digital imaging device). In some conventional approaches, the digital image is preprocessed (e.g., resized, oriented in a certain manner, and so forth) to prepare the digital image of the form for segmentation network.

The segmentation network is then used to analyze the digital image of the form and identify different regions or segments of the form, such as text fields, checkboxes, signature blocks, and so forth. Generally, the segmentation process involves labeling individual pixels or regions in the image of the digital form with a corresponding class or category. After assigning each pixel or region with a corresponding class or category, post-processing to refine the results (e.g., smoothing edges of segmented regions). After an image of a fillable form has been segmented, the assigned classes or categories are used to designate various regions as “fillable” via user input (e.g., configured as a text box to receive text, configured as a check box to receive a binary selection, and so forth).

Text fields that include prompts for information at various regions of the fillable form are identified using optical character recognition to identify text and other static elements of the fillable form. Data representing the fillable regions and static elements of the fillable form are then used to generate a digital format of the fillable form (e.g., HTML, mobile responsive format, and so forth), which is made available for distribution in a digital format. This digitization enables entities to more efficiently collect information from users in a standardized manner and avoid manual data entry that is otherwise required to input data from a completed hard copy form (e.g., a filled-out paper fillable form) into a computing device.

While such conventional approaches for converting hard copy forms into digital versions represent an improvement over manually processing hard copy forms, these conventional approaches remain deficient. For instance, conventional segmentation networks output digital versions of fillable forms that include numerous errors, such as incorrectly placed and/or dimensioned bounding boxes that represent different fillable regions of a form. Other errors include outputting a digital version of a fillable form that incorrectly represents a single fillable region as multiple fillable regions, or vice versa (e.g., incorrectly representing multiple fillable regions as only a single fillable regions). Further example errors include failing to identify a fillable region, incorrectly classifying a fillable region as an incorrect type (e.g., classifying a check box as a text box), and so forth. To address these common errors, some conventional systems provide user interfaces with tools that enable a user to manually correct a digital version of a fillable form output by a segmentation network. However, these conventional editing systems for correcting segmentation network errors require users to individually edit each form output by the segmentation network, which is time consuming, tedious, and prone to human error, particularly when scaled to processing large corpuses of forms (e.g., a corpus of forms for an entity that includes millions of different forms).

To address these conventional shortcomings, a corrective noise system is described. The corrective noise system is configured to obtain an electronic version of a fillable form generated by a segmentation network, such as a segmentation network used by the conventional approaches described above. The corrective noise system includes a display module that is configured to output a display of the electronic version of the fillable form output by the segmentation network and receive user input correcting one or more errors in the electronic version of the fillable form generated by the segmentation network. For instance, the display module receives input using tools offered by conventional form editing systems to correct common errors (e.g., form editing tools for adjusting boundaries of segmented regions, correcting mislabeled segments by modifying a region type associated with a segmented region, adding fillable regions, removing fillable regions, and so forth).

The corrective noise system includes a noise generation model, which is trained to generate noise that represents user-provided corrections to the segmented version of a fillable form output by the segmentation network. To do so, the corrective noise system is trained to distill, from a segmented form that includes at least one correction, a noise that represents an intended change (e.g., as represented by the correction). The corrective noise system is further trained to identify a region of a fillable form that includes a correction and propagate noise generated for the region to other regions of the same form, a corpus of multiple forms, or a combination thereof, that are semantically similar to the corrected region. Noise generated for one fillable form region is thus automatically propagated to all regions of a corpus of forms that are semantically similar to the corrected region (e.g., noise representing a correction to one check box is propagated to all check box regions in a corpus of forms, noise representing a correction to one text box is propagated to all text box regions in a corpus of forms, and so forth).

The corrective noise system is further trained to superimpose the noise representing a correction to the corrected region of the form as well as semantically similar regions in the corpus of forms. The corpus of forms, with superimposed noise, are then provided as input to the segmentation network. The noise forces the segmentation network to accurately identify fillable regions in the corpus of forms, guided by corrections provided to a single form, and output a segmented version of the corpus of forms having improved fidelity relative to the segmented version of the corpus of forms generated by the segmentation network independent of (e.g., without) the noise generated by the corrective noise system.

Advantageously, by training the corrective noise system independent of training the segmentation network, the underlying machine learning model of the segmentation network is not altered or otherwise modified. This advantage provided by the corrective noise system thus enables a convenient way of efficiently propagating error correction among a corpus of forms without requiring retraining (e.g., changing internal weights) of the segmentation network. This advantage contrasts with conventional approaches to segmenting fillable forms, which require retraining or otherwise modifying the segmentation network, which involves significant computational resources and time to do so. Furthermore, the corrective noise system enables personalization of error correction for a particular entity without destructively altering the underlying segmentation network used to segment a corpus of forms. For instance, corrections made to a segmented fillable form that are particular to one entity’s style of forms may contrast with a different entity’s style of forms. In a conventional scenario where error correction involves retraining the segmentation network to identify corrections made by one entity, such a retraining process biases the segmentation network to the preferences of the entity—resulting in incorrectly propagating the entity's style to segmentation of a different entity's forms. The systems and techniques described herein thus enable personalizing how a corpus of forms are selected on an entity-specific basis, without requiring modification of an underlying segmentation network, thus enabling different entities to leverage the same segmentation network and customize form segmentation corrections as desired.

Term Examples

As used herein, the term "machine learning model" refers to a computer representation that is tunable (e.g., trainable) based on inputs to approximate unknown functions. By way of example, the term "machine learning model" includes a model that utilizes algorithms to learn from, and make predictions on, known data by analyzing the known data to learn to generate outputs that reflect patterns and attributes of the known data. According to various implementations, such a machine learning model uses supervised learning, semi-supervised learning, unsupervised learning, reinforcement learning, and/or transfer learning. For example, the machine learning model is capable of including, but is not limited to, clustering, decision trees, support vector machines, linear regression, logistic regression, Bayesian networks, random forest learning, dimensionality reduction algorithms, boosting algorithms, artificial neural networks (e.g., fully-connected neural networks, deep convolutional neural networks, or recurrent neural networks), deep learning, etc. By way of example, a machine learning model makes high-level abstractions in data by generating data-driven predictions or decisions from the known input data.

As used herein, a "fillable form region" refers to a distinct section or area within a form that is designated for the collection of specific data or information. In the context of digital forms, a fillable form region corresponds to a pre-defined area or field where users can input data, such as text, numbers, or selections, to provide responses or complete the form. Example fillable form regions are designed to capture specific types of information such as name, address, phone number, email address, date, or other relevant data, depending on the purpose and requirements of the form. Fillable form regions are typically delineated by boundaries or outlines to indicate a specific area where data is expected to be entered by users. Example types of fillable form regions include text fields, checkboxes, radio buttons, dropdown menus, or other interactive elements that allow users to input data in a structured manner.

As used herein, a "semantically similar region" of a form, relative to a given fillable form region, refers to regions that have similar or related appearances, content, or combinations thereof. Semantically similar regions thus serve a similar purpose or convey similar information, even in scenarios where a visual appearance or layout of different regions differs. Semantically similar regions may contain similar types of data or have a shared function in the form, such that semantically similar regions are expected (e.g., by an entity that develops the form) to be processed or analyzed in a similar manner.

As used herein, the term "noise" refers to a type of noise that is intentionally added or applied to an image for the purpose of mitigate or reducing an impact of other types of noise or imperfections. An example of noise includes digital image pixels that are selectable to have visual properties (e.g., color, luminance, intensity, etc.) that is similar to or distinct from a background pixel value of digital image content to which the noise is applied, similar to or distinct from adjacent noise to delineate boundaries for fillable form regions, or a combination thereof. "Noise," as used herein, thus refers to corrective noise added to compensate for errors output in a digitally segmented version of a fillable form.

In the following discussion, an example environment is described that is configured to employ the techniques described herein. Example procedures are also described that are configured for performance in the example environment as well as other environments. Consequently, performance of the example procedures is not limited to the example environment and the example environment is not limited to performance of the example procedures.

Example Environment

FIG. **1** is an illustration of a digital medium environment **100** in an example implementation that is operable to employ techniques described herein. As used herein, the term "digital medium environment" refers to the various computing devices and resources utilized to implement the techniques described herein. The digital medium environment **100** includes a computing device **102**, which is configurable in a variety of manners.

The computing device **102**, for instance, is configurable as a desktop computer, a laptop computer, a mobile device (e.g., assuming a handheld or wearable configuration such as a tablet, mobile phone, smartwatch, etc.), and so forth. Thus, the computing device **102** ranges from full resource devices with substantial memory and processor resources (e.g., personal computers, game consoles) to low-resource devices with limited memory and/or processing resources (e.g., mobile devices). Additionally, although a single computing device **102** is shown, the computing device **102** is representative of a plurality of different devices, such as multiple servers utilized by an entity to perform operations "over the cloud."

The computing device **102** is illustrated as including a trained segmentation network **104**. The trained segmentation network **104** is representative of functionality that automatically (e.g., independent of user input) generates an electronic version of a fillable form from an image of a hard copy (e.g., physical, non-digital) version of the fillable form. Example instances of the trained segmentation network **104** include segmentation networks described by Aggarwal et al. in Multi-modal association based grouping for form structure extraction, *Proceedings of the ICEE/CVF Winter Conference on Applications of Computer Vision,* 2020; Aggarwal et al. in Form2seq: A framework for higher-order form structure extraction, arXiv, 2021; and Sarkar, et al. in Document structure extraction using prior based high resolution hierarchical semantic segmentation, *In European Conference on Computer Vision,* 2020, the disclosures of which are hereby incorporated by reference. An example instance of an electronic version of a fillable form output by the trained segmentation network **104** is represented in FIG. **1** as segmented form **106**.

In implementations, the segmented form **106** is generated based on a digital image of a fillable form (e.g., an image of a paper form that does not include digital information identifying different regions of the fillable form), where the digital image of the fillable form is stored as digital content **108** in storage **110** of the computing device **102**. Alternatively or additionally, the digital image of the fillable form is representative of digital content **108** maintained in storage of a different computing device (e.g., a computing device communicatively coupled to the computing device **102**). The storage **110** is further representative of a storage device configured to maintain data useable for a noise generation model that generates noise representing a correction to the segmented form **106**, data representing a corpus of forms to which a correction is propagated, or combinations thereof, as described in further detail below.

The segmented form **106** includes at least one region that is identified by the trained segmentation network **104** as being "fillable" (e.g., configured to receive input specifying information prompted for entry by the form), such as a checkbox that is selectable to provide a binary (e.g., Yes/No) response to a prompt for information, a textbox that receives textual input to a prompt for information, a signature block that receives a signature, and so forth.

In implementations, fillable regions of the segmented form **106** output by the trained segmentation network **104** are formatted based on a respective region type identified by the trained segmentation network **104**. For instance, fillable regions that are identified as prompting a user for input defining a date are output in the segmented form **106** as configured to receive numerical input in a certain format (e.g., MM-DD-YYYY). As another example, fillable regions that are identified as checkboxes prompting a user for selecting an option presented in the form are output in the segmented form **106** as selectable fields that have a first visual appearance when not selected (e.g., an empty box) and a second visual appearance when selected (e.g., a checked box, a filled box, and so forth). Although described with respect to specific examples of region types (e.g., text boxes, checkboxes, signature blocks, etc.), these examples are not limiting and the techniques described herein are extendable to any type or format of fillable form region.

An example instance of the segmented form **106** as output by the trained segmentation network **104** is depicted in FIG. **1** at display **112** of the computing device **102**. Specifically, the display **112** depicts an example of a portion of the segmented form **106** that includes three different signature blocks, where the trained segmentation network **104** has incorrectly identified the three different signature blocks as being five different fillable regions in the segmented form **106**, an example of which is illustrated and described in further detail below with respect to FIG. **4**. The example instance of the segmented form **106** output by the trained segmentation network **104** thus represents how the trained segmentation network **104** often generates errors that incorrectly represent an underlying form from which the segmented form **106** was generated.

To rectify such in the segmented form **106** output by the trained segmentation network **104**, corrections **114** are made to the segmented form **106**. The segmented form **106**, as corrected by the corrections **114**, is useable by a corrective noise system **116** to generate noise that represents the corrections **114**. In some implementations, the corrective noise system **116** is configured to facilitate provision of the corrections **114**, such as by outputting a display of the segmented form **106** in a user interface that includes one or more tools for correcting errors associated with segmented regions identified by the trained segmentation network **104**.

For instance, the corrective noise system **116** offers functionality similar to that provided by Adobe's Automated Forms Conversion Service "Review and Correct Tool." As an example, the corrective noise system **116** is configured to output a display of the segmented form **106** generated by the

trained segmentation network **104** together with a visual indication of each fillable region identified by the trained segmentation network **104** (e.g., a visual display of a size and a position of a bounding box representing a fillable region, information describing a region type of the fillable region as identified by the trained segmentation network **104**, and so forth). Continuing this example, the corrective noise system **116** displays the segmented form **106** in a user interface that includes tools for modifying a fillable region identified by the trained segmentation network **104**, such as drag-and-drop tools that enable modifying a position and/or dimensions of a fillable region bounding box, a properties tool that enables modifying properties such as a region type of a fillable region, a tool to add a fillable region not identified by the trained segmentation network **104**, a tool to delete a fillable region erroneously identified by the trained segmentation network **104**, combinations thereof, and so forth. In FIG. **1**, the display **112** depicts an example of corrections **114** made to one of the signature blocks depicted in the displayed segmented form **106**, where the corrections **114** define appropriate dimensions and a position for a bounding box of a fillable signature block region of the segmented form **106**.

Alternatively or additionally, in some implementations the corrections **114** are made to the segmented form **106** via a computing device, service, or system other than the corrective noise system **116** and the corrective noise system **116** receives the segmented form **106** together with the corrections **114**. The corrective noise system **116** includes a noise generation model **118** that is configured to generate noise **120** representing the corrections **114**. The noise **120** represents digital image pixels generated by the noise generation model **118** that provide semantic structure that is identified by the trained segmentation network **104** as corresponding to fillable form regions.

For instance, in an example implementation where the corrections **114** modify dimensions of a region bounding box included in the segmented form **106**, the noise **120** includes pixels that provide sharp contrast along borders of the bounding box, as corrected by the corrections **114**, such that the trained segmentation network **104** interprets the noise **120** as a clearly defined region for the segmented form. As another example, consider a scenario where the trained segmentation network **104** outputs a segmented form **106** that incorrectly classifies a check box and associated descriptive text for the check box (e.g., "check this box if the answer is yes") as a single fillable region. In this scenario, the corrections **114** specify that only the check box is to be designated as the fillable region (e.g., without the associated descriptive text). The noise **120** generated by the noise generation model **118** thus includes pixels that mask the associated descriptive text (e.g., using a color similar to a background color of the segmented form **106**) and provide sharp borders for boundaries of the check box, thus causing the trained segmentation network **104** to identify only the check box without its associated descriptive text as a fillable region.

The noise **120** thus represents a corrective noise formatted according to a data type that the trained segmentation network **104** is configured to process as input (e.g., digital image data in the form of pixels), such that the trained segmentation network **104** identifies the corrections **114** without requiring retraining or otherwise adapting the trained segmentation network **104** to understand annotated corrections. Training of the noise generation model **118** to generate noise **120** representing corrections **114** to a segmented form **106** is performed by the model training system

122, as described in further detail below with respect to FIG. **3**. Although depicted in the illustrated example of FIG. **1** as being implemented by the computing device **102** to generate the noise generation model **118**, in some implementations the model training system **122** is implemented by a computing device other than the computing device **102** and the noise generation model **118** is received by the computing device **102** from the other computing device.

The corrective noise system **116** is configured to superimpose the noise **120** representing the corrections **114** on the segmented form **106** and provide the segmented form **106** with the superimposed noise **120** as input to the trained segmentation network **104**, which causes the trained segmentation network **104** to output a version of the segmented form **106** that has improved fidelity relative to an original hard copy of the form that was input to the trained segmentation network **104**. Advantageously, the corrective noise system **116** is further configured to automatically (e.g., independent of user input) identify one or more regions of the segmented form **106** that were corrected by the corrections **114** and identify, from a corpus of forms, regions in the corpus of forms that are semantically similar to the region(s) corrected by the corrections **114**.

As described herein, a "semantically similar" region of a fillable form refers to regions that have similar or related appearances, content, or combinations thereof. Semantically similar regions thus serve a similar purpose or convey similar information, even in scenarios where a visual appearance or layout of different regions differs. Semantically similar regions may contain similar types of data or have a shared function in the form, such that semantically similar regions are expected (e.g., by an entity that develops the form) to be processed or analyzed in a similar manner. For example, in a fillable form for a job application, semantically similar regions include fields or sections that collect personal information such as name, address, and contact details for a job applicant. Even though the layout or visual appearance of the regions may differ when perceived by the human eye, they are semantically similar due to serving a common purpose of gathering personal information from the job applicant.

The corrective noise system **116** applies the noise **120** to each semantically similar region identified in a corpus of forms by superimposing the noise onto each semantically similar region. In implementations, applying the noise **120** to semantically similar regions in the corpus of forms includes adjusting the noise **120** to correspond to attributes of a particular semantically similar region, such as by adjusting dimensions of the noise, pixel values of the noise, combinations thereof, and so forth. In this manner, the corrective noise system **116** ensures that the noise is limited to a semantically similar region and does not extend to other portions of a form that are not semantically similar to the region corrected by the corrections **114**. Each form with superimposed noise **120** is then provided as input to the trained segmentation network **104**, which causes the trained segmentation network **104** to output an improved segmented form **124**. The improved segmented form **124** represents an instance of the segmented form **106** that has an improved fidelity relative to a fillable form from which the segmented form **106** was originally generated.

In implementations, the improved segmented form **124** represents one form in a segmented corpus of forms **126** that includes numerous (e.g., millions) of different forms. By propagating the noise **120** to semantically similar regions in a corpus of forms, the techniques described herein cause the trained segmentation network **104** to remedy errors made in

originally segmenting the corpus of forms using corrections **114** made to one or more regions of a single form (e.g., corrections to segmented form **106**). For instance, in the illustrated example of FIG. **1**, display **112** depicts how the corrections **114** pertain to a single signature block region in the segmented form **106**. The display **112** further depicts how that single signature block region, as corrected by the corrections **114**, is propagated to other regions in the segmented corpus of forms **126** that are identified as being semantically similar to the single signature block region (e.g., corrections **114** are propagated to all signature block regions in the segmented corpus of forms **126**).

Having considered an example digital medium environment, consider now a discussion of example systems useable to generate a trained noise generation model, operation of the noise generation model to generate noise representing corrections to a segmented form region and propagate the noise to semantically similar regions in a corpus of forms, and using the noisy version of the corpus of forms to improve an output of the trained segmentation network.

Corrective Noise and Model Training Systems

FIG. **2** depicts a digital medium environment **200** showing operation of the corrective noise system **116** generating a noisy corpus of forms based on a correction provided to a single form and of the trained segmentation network **104** generating a segmented corpus of forms based on the noisy corpus of forms.

FIG. **3** depicts a digital medium environment **300** showing operation of the model training system **122** generating the noise generation model **118**.

FIG. **4** depicts an example **400** of a segmented form output by a segmentation network, noise representing a correction to the segmented form, and an improved version of the segmented form generated based on the noise.

As illustrated in FIG. **2**, the trained segmentation network **104** receives a form **202** as input. The form **202** is representative of a digital image of a hard-copy form (e.g., a form physically printed on paper) that includes one or more regions prompting a user filling out the form to input information (e.g., name, date, signature, check box selection, and so forth). The trained segmentation network **104** is trained to generate, from the form **202**, the segmented form **106**.

The segmented form **106** output by the trained segmentation network **104** includes a fillable region **204** that has associated data describing a region type **206** of the fillable region **204** and a bounding box **208** for the fillable region **204** (e.g., a position and dimensions of the fillable region **204** relative to other regions or an overall layout of the segmented form **106**). The trained segmentation network **104** is configured to output the segmented form **106** as including any number of fillable regions, as indicated by the ellipses adjacent to the fillable region **204** in the illustrated example of FIG. **2**.

The segmented form **106** is then provided as input to the corrective noise system **116**. The corrective noise system **116** includes a display module **210**, which represents functionality of the corrective noise system **116** to output a display of the segmented form **106** (e.g., via display **112**) together with a visual indication of each fillable region **204** and associated information as identified by the trained segmentation network **104**.

For instance, in the illustrated example **400**, portion **402** depicts an area of the form **202** processed by the trained segmentation network **104** to generate the segmented form

106. Specifically, portion **402** corresponds to an area of the form **202** that includes three different regions that are each designed to prompt input of a signature (e.g., as denoted by the text prompting a user filling out the form **202** to enter a "Seal" on an adjacent line). Portion **404** represents an area of the segmented form **106** generated by the trained segmentation network **104** from portion **402** and is depicted as including a plurality of different fillable regions **204**, which are each represented by a different bounding box. Specifically, portion **404** includes bounding box **406**, bounding box **408**, bounding box **410**, bounding box **412**, and bounding box **414**, which represent five different fillable regions identified by the trained segmentation network **104** as being included in the portion **402**.

The display module **210** is configured to output a display of the portion **404**, together with the bounding box **406**, bounding box **408**, bounding box **410**, bounding box **412**, and bounding box **414**, thus conveying to a user of the corrective noise system **116** as to how the trained segmentation network **104** interpreted the portion **402**. Although not depicted, the display module **210** further represents functionality of the corrective noise system **116** to display a user interface that includes controls configured to receive input defining one or more corrections **114** to the segmented form **106** (e.g., one or more controls for tools offered by provided by Adobe's Automated Forms Conversion Service "Review and Correct Tool").

The corrective noise system **116** is further depicted as including the noise generation model **118**, which represents functionality of the corrective noise system **116** to generate noise **120** representing the corrections **114** and apply the noise **120** to the segmented form **106** (e.g., superimpose pixels of the noise **120** onto corresponding regions of the segmented form **106** corrected by the corrections **114**). For instance, as illustrated in FIG. **4**, view **416** depicts an example of a bounding box **418** resulting from corrections **114** made to bounding box **408**. The bounding box **418** thus provides a tight border around a signature block that more accurately represents the middle signature block region in portion **402** relative to the border provided by bounding box **408**.

View **420** depicts an example of noise **120** generated based on the corrections **114** that adjusted a size and position of the bounding box **408** to result in bounding box **418**. As depicted at view **420**, different pixel values (e.g., depicted via different colors in the view **420**) of the noise **120** distinguish pixels of the segmented form **106** that correspond to the corrections **114** represented by bounding box **418** from other pixels that the corrections **114** indicate as being different from a fillable form region. Specifically, the noise **120** depicted in view **420** represents portions of the fillable region using purple pixels and differentiates from other portions of the form **202** using pixels that are blue, green, black, white, and so forth. Notably, the noise **120** depicted at view **420** distinguishes the textual prompt of "(Seal)," which was previously encompassed at least partially in bounding box **406**, bounding box **408**, bounding box **410**, bounding box **412**, and bounding box **414** from an area that should be designated as encompassed by the fillable signature block region of bounding box **418**.

Returning to FIG. **2**, in some implementations the corrective noise system **116** is configured to receive a corpus of forms **212**. The corpus of forms **212** is representative of a collection of forms retrieved, for instance, from storage **110** of the computing device **102**, from a computing device other than computing device **102**, or a combination thereof. In implementations, the corpus of forms **212** represents a

collection of forms that are associated with a same entity as the entity associated with the form **202**. Alternatively, in some implementations the corpus of forms **212** includes forms associated with multiple different entities. The corrective noise system **116** is configured to identify a type of a fillable region **204** that was corrected by the corrections **114** (e.g., a type of the fillable region **204** to which the noise **120** was superimposed) and identify one or more regions in the corpus of forms **212** that are semantically similar to the corrected fillable region **204** of the segmented form **106**. For instance, in some implementations, the corrective noise system **116** is configured to identify regions in the forms **212** that are semantically similar to a fillable region **204** corrected by the corrections **114** using techniques described by Java, et al. in "One-shot doc snippet detection: Powering search in document beyond text," arXiv, 2022, the disclosure of which is hereby incorporated by reference.

In response to identifying one or more regions in the corpus of forms **212** that are semantically similar to the fillable region **204** corrected by the corrections **114**, the corrective noise system **116** generates a noisy corpus of forms **214** by propagating the noise **120** to the semantically similar regions in the corpus of forms **212**. In some implementations, the segmented form **106** is included in the corpus of forms **212**, such that corrections **114** to one fillable region **204** in the segmented form **106** is propagated to other semantically similar regions in the segmented form **106**. In this manner, the corrective noise system **116** enables a user to provide corrections **114** to a single fillable region **204** of a segmented form **106** and is trained to generate noise **120** that represents the corrections **114**, apply the noise **120** to the corrected fillable region **204**, and propagate the noise **120** to other regions in the segmented form **106** or a larger corpus of forms **212** that are semantically similar to the corrected fillable region **204**.

The noise **120** causes the trained segmentation network **104** to output a segmented corpus of forms **216** that each include one or more fillable regions **204** that have improved fidelity to a corresponding form in the corpus of forms **212**, relative to a segmented corpus of forms generated by the trained segmentation network **104** using only the corpus of forms **212** as input (e.g., independent of the noise **120**). For instance, in the illustrated example of FIG. **4**, portion **422** depicts how the corrections **114** represented by bounding box **418** are propagated to other semantically similar regions (e.g., other signature block regions) of the portion **402** to generate an improved segmented form **124**.

For instance, the portion **422** is depicted as including bounding box **424**, bounding box **426**, and bounding box **428**, which respectively represent fillable regions for the three signature blocks included in portion **402**. The bounding box **424**, bounding box **426**, and bounding box **428** represent an improved segmented form **124** relative to the segmented form **106** represented by portion **404** and its bounding boxes **406**, **408**, **410**, **412**, and **414**. Notably, portion **422** represents functionality of the corrective noise system **116** to propagate noise **120** to regions that are semantically similar to, and visually different from, a region corrected by the corrections **114**. For instance, while view **416** depicts how the corrections **114** adjusted a bounding box **418** for a signature block that includes only one line, bounding box **428** in portion **422** represents an improved segmentation of a fillable region for a signature block that includes two lines.

By propagating noise to fillable form regions that are semantically similar to a corrected region and providing the fillable forms with superimposed noise as input to the trained segmentation network **104**, the techniques described herein advantageously enable generation of improved segmented forms without requiring retraining of the trained segmentation network **104**. This enables different entities to leverage the same trained segmentation network **104** and limit error correction propagation to a corpus of forms associated with one entity without destructively altering the trained segmentation network **104** or otherwise biasing the trained segmentation network **104** to favoring corrections that are particular to the style of one entity. For a further description of training the noise generation model used by the corrective noise system **116** to generate noise representing the corrections **114**, consider FIG. **3**.

As depicted in the illustrated example of FIG. **3**, the model training system **122** is configured to train the noise generation model **118** using training data **302**. The training data **302** includes a plurality of training pairs, where each training pair **304** of the plurality of training pairs includes a segmented form **306** and a ground truth segmentation **308** for the segmented form **306**. The segmented form **306** is representative of an instance of a segmented form generated by the trained segmentation network **104**, such as segmented form **106** generated from form **202**. The ground truth segmentation **308** represents a reference or benchmark describing the correct locations, dimensions, and region types of fillable regions included in the segmented form **306**. In some implementations, the ground truth segmentation **308** for a segmented form **306** is manually generated (e.g., via user input defining positions, dimensions, types, etc. of fillable regions included in a form from which the segmented form **306** was generated).

In some implementations, the training data **302** is obtained from storage **110** of a computing device implementing the model training system **122** (e.g., computing device **102**). Alternatively or additionally, the training data **302** is obtained from one or more computing devices other than the computing device implementing the model training system **122**. Using the training data **302**, the model training system **122** is configured to train an autoencoder network **310**, which represents an artificial neural network that includes an encoder/decoder portion **312** and a discriminator portion **314**.

The encoder/decoder portion **312** represents functionality of the autoencoder network **310** to transform input data into a lower-dimensional representation (e.g., a latent representation, a compressed representation, and the like). In the context of training the noise generation model **118**, the encoder/decoder portion **312** is tasked with generating a noise prediction **316** that represents noise predicted by the encoder/decoder portion **312** to define one or more fillable regions in the segmented form **306** of a training pair **304** (e.g., a prediction of noise that would represent actual fillable regions as represented by the ground truth segmentation **308** of the training pair **304**).

In some implementations, the encoder/decoder portion **312** of the autoencoder network **310** is configured with an architecture as described in Table 1:

TABLE 1

Network Layer	Input Resolution	Output Resolution
Conv2d	1 × 28 × 28	8 × 26 × 26
INstanceNorm2d + ReLu	8 × 26 × 26	8 × 26 × 26
Conv2d	8 × 26 × 26	16 × 12 × 12
INstanceNorm2d + ReLu	16 × 12 × 12	16 × 12 × 12
Conv2d	16 × 12 × 12	32 × 5 × 5
INstanceNorm2d + ReLu	32 × 5 × 5	32 × 5 × 5
ResNetBlock × 4	32 × 5 × 5	32 × 5 × 5
ConvTranspose2d	32 × 5 × 5	16 × 11 × 11
INstanceNorm2d + ReLu	16 × 11 × 11	16 × 11 × 11
ConvTranspose2d	16 × 11 × 11	8 × 23 × 23
INstanceNorm2d + ReLu	8 × 23 × 23	8 × 23 × 23
ConvTranspose2d	8 × 23 × 23	1 × 28 × 28
tanh	1 × 28 × 28	1 × 28 × 28

As described in Table 1, in some configurations the encoder/decoder portion **312** architecture includes convolutional layers (Conv2d and ConvTranspose2d), instance normalization (INstanceNorm2d), activation functions (ReLu and tanh), and residual blocks (ResNetBlock). The input image (e.g., an image of the segmented form **306**) has a size of 28×28 pixels with a single channel (e.g., grayscale). The first convolutional layer (Conv2d) applies filters to the input image, creating eight feature maps with a size of 26×26 pixels. Instance normalization and ReLu activation function are applied to the eight feature maps, keeping their size the same (8×26×26).

The second convolutional layer reduces the size of the feature maps to 16 maps with a size of 12×12 pixels. Instance normalization and ReLu activation function are applied again to these 16 feature maps, keeping their size the same (16×12×12). The third convolutional layer further reduces the feature maps to 32 maps with a size of 5×5 pixels. Instance normalization and ReLu activation function are applied once more to these 32 feature maps, keeping their size the same (32×5×5). Four residual blocks (ResNetBlock) are applied to the feature maps, maintaining the same size and number of feature maps (32×5×5). A transposed convolutional layer (ConvTranspose2d) is used to increase the size of the feature maps back to 16 maps with a size of 11×11 pixels.

Instance normalization and ReLu activation function are applied to these 16 feature maps, keeping their size the same (16×11×11). Another transposed convolutional layer increases the size of the feature maps to 8 maps with a size of 23×23 pixels. Instance normalization and ReLu activation function are applied to these 8 feature maps, keeping their size the same (8×23×23). A final transposed convolutional layer is used to generate a single output feature map with a size of 28×28 pixels, the same size as the original input (e.g., the image of segmented form **306**). A tanh activation function is applied to the output feature map to obtain the noise prediction **316**, which has the same size as the input (1×28×28). Such an architecture of the encoder/decoder portion **312** thus enables the autoencoder network **310** to generate a noise prediction **316** for a segmented form **306** of a training pair **304** while retaining an overall structure and size of the segmented form **306**.

The discriminator portion **314** represents functionality of the autoencoder network **310** to process the lower-dimensional representation output by the encoder portion **312** (e.g., the noise prediction **316**) and output a judgment **318** indicating whether the noise prediction **316** output by the encoder portion **312**, when combined with the segmented form **306**, creates a result that remains perceptible as a fillable form. In implementations, an architecture of the discriminator portion **314** is configured as a feedforward neural network (FNN), a convolutional neural network (CNN), a recurrent neural network (RNN), or the like.

The model training system **122** further includes a loss module **320** that is configured to compute a segmentation loss function **322** based on the noise prediction **316** and the judgment **318** output for a training pair **304**. In implementations, the segmentation loss function **322** is expressed as L in Equation 1:

$$L = L_{CE}(\theta_S(x+\delta_x), g) + \log(D(x)) + \log(1 - D(x+\delta_x)) + \|\delta_x\|_2 \quad \text{(Eq. 1)}$$

In Equation 1, x represents the segmented form **306** of a training pair **304**, as generated by a pre-trained structure extraction network θ_S (e.g., the trained segmentation network **104**). δ_x represents the noise prediction **316** generated by the decoder portion **312** for the segmented form **306** and g represents the ground truth segmentation **308** for the training pair **304**, where D represents the discriminator portion **314**. In Equation 1, the first term represents the cross-entropy loss between the prediction of the trained segmentation network **104** and the noise prediction **316** relative to the ground truth segmentation **308**.

The second and third terms in Equation 1 represent adversarial training of the noise generation model **118** using the discriminator portion **314**. For instance, the second term forces the noise generation model **118** to learn the real distribution of segmented regions included in a segmented form **306** and the third term forces the encoder/decoder portion **312** to generate a reasonable noise prediction **316** to fool the discriminator portion **314**. The fourth term penalizes the autoencoder network **310** by minimizing the L_2 norm of the noise prediction **316**.

The segmentation loss function **322** is then applied during training of the autoencoder network **310** to adjust weights and biases of the autoencoder network **310** with an objective of minimizing the segmentation loss function **322**. In this manner, the operations depicted in FIG. **3** represent a single training iteration for generating the noise generation model **118** and the model training system **122** is conf configured to perform the operations described with respect to FIG. **3** for as many training iterations as necessary until the autoencoder network **310** converges (e.g., until the noise prediction **316**, when combined with the segmented form **306**, achieves a threshold difference relative to the ground truth segmentation **308**).

Upon achieving convergence, the encoder/decoder portion **312** of the autoencoder network **310** is output as the trained noise generation model **118** for use by the corrective noise system **116**.

Having considered example systems and techniques, consider now example procedures to illustrate aspects of the techniques described herein.

Example Procedures

The following discussion describes techniques that are configured to be implemented utilizing the previously described systems and devices. Aspects of each of the procedures are configured for implementation in hardware, firmware, software, or a combination thereof. The procedures are shown as a set of blocks that specify operations performed by one or more devices and are not necessarily limited to the orders shown for performing the operations by the respective blocks. In portions of the following discussion, reference is made to FIGS. **1-4**.

FIG. **5** is a flow diagram depicting a procedure **500** in an example implementation of generating a segmented version

of a corpus of forms based on noise representing a correction to a single form generated using the techniques described herein.

To begin, a segmented version of a form that includes at least one fillable region is received from a segmentation network trained to segment an image of the form into different fillable regions (block **502**). The corrective noise system **116**, for instance, receives segmented form **106** from the trained segmentation network **104**.

A correction is received to a region of the segmented version of the form (block **504**). The corrective noise system **116**, for instance, receives corrections **114** that rectify at least one error in the segmented form **106** as output by the trained segmentation network **104**, such as a modification to a position of a bounding box for a fillable region **204**, a modification to one or more dimensions of a fillable region **204**, a modification to a region type **206** of a fillable region, or combinations thereof. In some implementations, the received corrections **114** pertain to multiple different fillable regions of the **106**.

Noise that represents the correction to the segmented version of the form is generated and the noise is superimposed onto the segmented version of the form (block **506**). The corrective noise system **116**, for instances, leverages the noise generation model **118** to generate noise **120** that represents the corrections **114** and superimposes the noise **120** onto the segmented form **106** at corresponding positions of one or more fillable regions corrected by the corrections **114**.

The noise is propagated to semantically similar regions of a corpus of forms (block **5080**. The corrective noise system **116**, for instance, identifies at least one region in the corpus of forms **212** that is semantically similar to a region in the segmented form **106** corrected by the corrections **114** and superimposes the noise **120** onto the semantically similar regions in the corpus of forms **212**, resulting in the noisy corpus of forms **214**.

The segmentation network is then caused to generate a segmented version of the corpus of forms based on the noise superimposed onto the semantically similar regions (block **510**). The noisy corpus of forms **214**, for instance, is input to the trained segmentation network **104**, which causes the trained segmentation network **104** to output the segmented corpus of forms **216** that include fillable regions identified based on the corrections **114**.

FIG. **6** is a flow diagram depicting a procedure **600** in an example implementation of training a noise generation model and using the trained noise generation model to generate noise representing a correction to a segmented form using the techniques described herein.

A noise generation model is trained to output noise that represents a fillable region of a segmented form based on a correction to the segmented form (block **602**). As part of training the noise generation model, a plurality of training pairs are received, where each training pair includes a form segmented into fillable regions and a ground truth segmentation for the form (block **604**). The model training system **122**, for instance, receives training data **302** that includes a plurality of training pairs **304**, where each training pair **304** includes a segmented form **306** and a ground truth segmentation **308** for the segmented form **306**.

One of the training pairs is selected (block **606**). For the selected training pair, an encoder/decoder portion of an autoencoder network is caused to output a noise prediction that represents at least one fillable region of the training pair form (block **608**). The encoder/decoder portion **312** of the autoencoder network **310**, for instance, is caused to generate a noise prediction **316** for the segmented form **306** of the selected training pair **304**.

For the selected training pair, a discriminator is caused to output a judgment indicating whether the noise prediction perceptibly changes the form of the training pair (block **610**). The model training system **122**, for instance, causes the discriminator portion **314** to output a judgment **318** that indicates whether the noise prediction **316**, when combined with the segmented form **306** of the training pair **304**, results in an electronic document that still appears as a fillable form.

A loss function is then computed based on the noise prediction and the judgment (block **612**). The loss module **320**, for instance, computes the segmentation loss function **322** based on the noise prediction **316** and the judgment **318** generated for the training pair **304**. At least one internal weight of the autoencoder network is then updated based on the loss function (block **614**). The model training system **122**, for instance, modifies at least one internal weight of the autoencoder network **310** using the segmentation loss function **322** with an objective of minimizing the segmentation loss function **322** during a subsequent training iteration. Operation of procedure **600** then returns to block **606**, where an additional training pair is selected and the flow of operations from block **606** to block **614** is repeated until the autoencoder network **310** achieves convergence, at which point the encoder/decoder portion **312** is output as the trained noise generation model (e.g., noise generation model **118**).

The trained noise generation model is then used to generate noise that represents a correction for a segmented form based on input to the segmented form (block **616**). The noise generation model **118**, for instance, generates noise **120** based on one or more corrections **114** to the segmented form **106**.

Having described example procedures in accordance with one or more implementations, consider now an example system and device to implement the various techniques described herein.

Example System and Device

FIG. **7** illustrates an example system **700** that includes an example computing device **702**, which is representative of one or more computing systems and/or devices that implement the various techniques described herein. This is illustrated through inclusion of the corrective noise system **116** and the model training system **122**. The computing device **702** is configured, for example, as a service provider server, as a device associated with a client (e.g., a client device), as an on-chip system, and/or as any other suitable computing device or computing system.

The example computing device **702** as illustrated includes a processing system **704**, one or more computer-readable media **706**, and one or more I/O interface **708** that are communicatively coupled, one to another. Although not shown, the computing device **702** is further configured to include a system bus or other data and command transfer system that couples the various components, one to another. A system bus includes any one or combination of different bus structures, such as a memory bus or memory controller, a peripheral bus, a universal serial bus, and/or a processor or local bus that utilizes any of a variety of bus architectures. A variety of other examples are also contemplated, such as control and data lines.

The processing system **704** is representative of functionality to perform one or more operations using hardware. Accordingly, the processing system **704** is illustrated as including hardware element **710** that are configurable as processors, functional blocks, and so forth. For instance, hardware element **710** is implemented in hardware as an application specific integrated circuit or other logic device formed using one or more semiconductors. The hardware elements **710** are not limited by the materials from which they are formed, or the processing mechanisms employed therein. For example, processors are alternatively or additionally comprised of semiconductor(s) and/or transistors (e.g., electronic integrated circuits (ICs)). In such a context, processor-executable instructions are electronically executable instructions.

The computer-readable storage media **706** is illustrated as including memory/storage **712**. The memory/storage **712** represents memory/storage capacity associated with one or more computer-readable media. The memory/storage **712** is representative of volatile media (such as random-access memory (RAM)) and/or nonvolatile media (such as read only memory (ROM), Flash memory, optical disks, magnetic disks, and so forth). The memory/storage **712** is configured to include fixed media (e.g., RAM, ROM, a fixed hard drive, and so on) as well as removable media (e.g., Flash memory, a removable hard drive, an optical disc, and so forth). In certain implementations, the computer-readable media **706** is configured in a variety of other ways as further described below.

Input/output interface(s) **708** are representative of functionality to allow a user to enter commands and information to computing device **702** and allow information to be presented to the user and/or other components or devices using various input/output devices. Examples of input devices include a keyboard, a cursor control device (e.g., a mouse), a microphone, a scanner, touch functionality (e.g., capacitive, or other sensors that are configured to detect physical touch), a camera (e.g., a device configured to employ visible or non-visible wavelengths such as infrared frequencies to recognize movement as gestures that do not involve touch), and so forth. Examples of output devices include a display device (e.g., a monitor or projector), speakers, a printer, a network card, tactile-response device, and so forth. Thus, the computing device **702** is representative of a variety of hardware configurations as further described below to support user interaction.

Various techniques are described herein in the general context of software, hardware elements, or program modules. Generally, such modules include routines, programs, objects, elements, components, data structures, and so forth that perform particular tasks or implement particular data types. The terms "module," "functionality," and "component" as used herein generally represent software, firmware, hardware, or a combination thereof. The features of the techniques described herein are platform-independent, meaning that the techniques are configured for implementation on a variety of commercial computing platforms having a variety of processors.

An implementation of the described modules and techniques are stored on or transmitted across some form of computer-readable media. The computer-readable media include a variety of media that is accessible by the computing device **702**. By way of example, and not limitation, computer-readable media includes "computer-readable storage media" and "computer-readable signal media."

"Computer-readable storage media" refers to media and/or devices that enable persistent and/or non-transitory storage of information in contrast to mere signal transmission, carrier waves, or signals per se. Thus, computer-readable storage media refers to non-signal bearing media. The computer-readable storage media includes hardware such as volatile and non-volatile, removable and non-removable media and/or storage devices implemented in a method or technology suitable for storage of information such as computer readable instructions, data structures, program modules, logic elements/circuits, or other data. Examples of computer-readable storage media include, but are not limited to, RAM, ROM, EEPROM, flash memory or other memory technology, CD-ROM, digital versatile disks (DVD) or other optical storage, hard disks, magnetic cassettes, magnetic tape, magnetic disk storage or other magnetic storage devices, or other storage device, tangible media, or article of manufacture suitable to store the desired information for access by a computer.

"Computer-readable signal media" refers to a signal-bearing medium that is configured to transmit instructions to the hardware of the computing device **702**, such as via a network. Signal media typically embody computer readable instructions, data structures, program modules, or other data in a modulated data signal, such as carrier waves, data signals, or other transport mechanism. Signal media also include any information delivery media. The term "modulated data signal" means a signal that has one or more of its characteristics set or changed in such a manner as to encode information in the signal. By way of example, and not limitation, communication media include wired media such as a wired network or direct-wired connection, and wireless media such as acoustic, RF, infrared, and other wireless media.

As previously described, hardware elements **710** and computer-readable media **706** are representative of modules, programmable device logic and/or fixed device logic implemented in a hardware form that is employed in some embodiments to implement at least some aspects of the techniques described herein, such as to perform one or more instructions. Hardware, in certain implementations, includes components of an integrated circuit or on-chip system, an application-specific integrated circuit (ASIC), a field-programmable gate array (FPGA), a complex programmable logic device (CPLD), and other implementations in silicon or other hardware. In this context, hardware operates as a processing device that performs program tasks defined by instructions and/or logic embodied by the hardware as well as a hardware utilized to store instructions for execution, e.g., the computer-readable storage media described previously.

Combinations of the foregoing are employed to implement various techniques described herein. Accordingly, software, hardware, or executable modules are implemented as one or more instructions and/or logic embodied on some form of computer-readable storage media and/or by one or more hardware elements **710**. The computing device **702** is configured to implement instructions and/or functions corresponding to the software and/or hardware modules. Accordingly, implementation of a module that is executable by the computing device **702** as software is achieved at least partially in hardware, e.g., through use of computer-readable storage media and/or hardware elements **710** of the processing system **704**. The instructions and/or functions are executable/operable by one or more articles of manufacture (for example, one or more computing devices **702** and/or processing systems **704**) to implement techniques, modules, and examples described herein.

The techniques described herein are supported by various configurations of the computing device **702** and are not limited to the specific examples of the techniques described herein. This functionality is further configured to be implemented all or in part through use of a distributed system, such as over a "cloud" **714** via a platform **716** as described below.

The cloud **714** includes and/or is representative of a platform **716** for resources **718**. The platform **716** abstracts underlying functionality of hardware (e.g., servers) and software resources of the cloud **714**. The resources **718** include applications and/or data that is utilized while computer processing is executed on servers that are remote from the computing device **702**. Resources **718** also include services provided over the Internet and/or through a subscriber network, such as a cellular or Wi-Fi network.

The platform **716** is configured to abstract resources and functions to connect the computing device **702** with other computing devices. The platform **716** is further configured to abstract scaling of resources to provide a corresponding level of scale to encountered demand for the resources **718** that are implemented via the platform **716**. Accordingly, in an interconnected device embodiment, implementation of functionality described herein is configured for distribution throughout the system **700**. For example, in some configurations the functionality is implemented in part on the computing device **702** as well as via the platform **716** that abstracts the functionality of the cloud **714**.

Although the invention has been described in language specific to structural features and/or methodological acts, the invention defined in the appended claims is not necessarily limited to the specific features or acts described. Rather, the specific features and acts are disclosed as example forms of implementing the claimed invention.

What is claimed is:

1. A method comprising:

receiving, at a computing device, a segmented version of a form output by a segmentation network trained to segment an image of a form into different fillable regions;

displaying, by the computing device, the segmented version of the form;

receiving, by the computing device, a correction to at least one of the different fillable regions of the segmented version of the form;

generating, by the computing device using a trained noise generation model comprising a convolutional autoencoder network, noise for the segmented version of the form that represents the correction to the at least one of the different fillable regions, the noise comprising digital image pixels having visual properties that are distinct from adjacent pixels of the segmented version of the form;

providing, by the computing device, the segmented version of the form with the noise as input to the segmentation network; and

causing, by the computing device, the segmentation network to generate a segmented version of another form by propagating the correction represented by the noise to at least one other region of the other form.

2. The method of claim **1**, wherein providing the segmented version of the form with the noise as input to the segmentation network and causing the segmentation network to generate the segmented version to the other form is performed independent of modifying internal weights of the segmentation network.

3. The method of claim **1**, wherein the at least one other region of the other form is identified by the segmentation network as being semantically similar to the at least one of the different fillable regions corrected by the correction.

4. The method of claim 1, wherein generating the trained noise generation model is trained to generate noise that represents an area of a form to be represented as a fillable portion of the form with an objective of minimizing generated noise.

5. The method of claim 4, further comprising training, by the computing device, the noise generation model by:

inputting training data comprising a plurality of input pairs to the convolutional autoencoder network, each of the plurality of input pairs comprising a segmented form and a ground truth segmentation of the segmented form that identifies fillable regions of the segmented form; and

tasking the convolutional autoencoder network with predicting, for each training pair, noise that represents one or more fillable regions in the segmented form of the training pair.

6. The method of claim 5, wherein training the generation model further comprises:

computing a cross-entropy loss based on a difference between the noise predicted by the convolutional autoencoder network for a training pair and the ground truth segmentation for the training pair; and

modifying one or more internal weights of the noise generation model using the cross-entropy loss.

7. The method of claim 1, wherein the noise causes the segmentation network to:

identify a region of the form that is corrected by the correction;

identify the at least one other region of the other form as being a semantically similar region to the region of the form that is corrected by the correction; and

designate the semantically similar region as being a fillable portion of the other form.

8. The method of claim 1, wherein the correction indicates that two or more fillable regions of the segmented version of the form should be represented as a single fillable region.

9. The method of claim 1, wherein the correction indicates that one fillable region of the segmented version of the form should be represented as two or more fillable regions.

10. The method of claim 1, wherein the correction includes adjusting a position of a fillable region in the segmented version of the form.

11. The method of claim 1, wherein the correction includes modifying one or more dimensions of a fillable region in the segmented version of the form.

12. The method of claim 1, wherein the correction includes modifying a region type associated with a fillable region in the segmented version of the form.

13. The method of claim 1, further comprising generating, by the computing device, the segmented version of the form by inputting a digital image of the form to the segmentation network.

14. The method of claim 1, wherein providing the segmented version of the form with the noise as input to the segmentation network comprises superimposing the noise onto the segmented version of the form prior to input to the segmentation network.

15. A method comprising:

generating, by a processing device, a trained noise generation model configured to output a segmented form with superimposed noise that represents one or more corrections to a form by:

causing an autoencoder network to predict, for each training pair of a plurality of training pairs that each include a segmented form and a ground truth segmentation of the segmented form that identifies fillable regions of the segmented form, noise that represents the fillable regions of the segmented form;

computing a loss function based on a difference between the noise predicted by the autoencoder network for each training pair and the ground truth segmentation for the training pair; and

modifying at least one internal weight of the autoencoder network based on the loss function; and

outputting the autoencoder network with the at least one internal weight as the trained noise generation model.

16. The method of claim 15, wherein the one or more corrections to the form define at least one fillable region of the form that is configured to receive input defining information requested by the form.

17. The method of claim 15, wherein generating the trained noise generation model further comprises:

causing a discriminator portion of the autoencoder network to generate a discriminator prediction that indicates whether the noise predicted by the autoencoder network, when superimposed on the segmented form of a training pair for which the noise was generated, results in a document that is similar to the segmented form of the training pair for which the noise was generated; and

computing the loss function based on the discriminator prediction.

18. The method of claim 15, further comprising:

receiving a segmented form and a correction to at least one fillable region of the segmented form; and

generating a noisy version of the segmented form by providing the segmented form and the correction to the at least one fillable region as input to the trained noise generation model.

19. The method of claim 18, further comprising causing a segmentation network to segment a corpus of forms based on the noisy version of the segmented form, independent of modifying one or more internal weights of the segmentation network, by inputting the noisy version of the segmented form to the segmentation network.

20. A system comprising:

one or more processors; and

a computer-readable storage medium storing instructions that are executable by the one or more processors to perform operations comprising:

receiving a segmented version of a form generated by a segmentation network that is trained to segment an image of a form into different fillable regions;

receiving user input defining a correction to one of the different fillable regions of the segmented version of the form;

generating, using a trained noise generation model comprising a convolutional autoencoder network, noise for the segmented version of the form that represents the correction to the one of the different fillable regions, the noise comprising digital image pixels having visual properties that are distinct from adjacent pixels of the segmented version of the form;

inputting the noise superimposed on the segmented version of the form to the segmentation network; and

causing the segmentation network to generate, for a form of a plurality of forms, a segmented version of the form based on the noise superimposed on the segmented version of the form.

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