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Burges

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[54] **ELIMINATING INVARIANCES BY PREPROCESSING FOR KERNEL-BASED METHODS**

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[73] Assignee: **Lucent Technologies Inc.**, Murray Hill, N.J.

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[51] **Int. Cl.**⁷ **G06F 1/035; G06F 5/00**

[52] **U.S. Cl.** **706/20**

[58] **Field of Search** 382/159, 181, 382/276; 706/20

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Primary Examiner—Tariq R. Hafiz

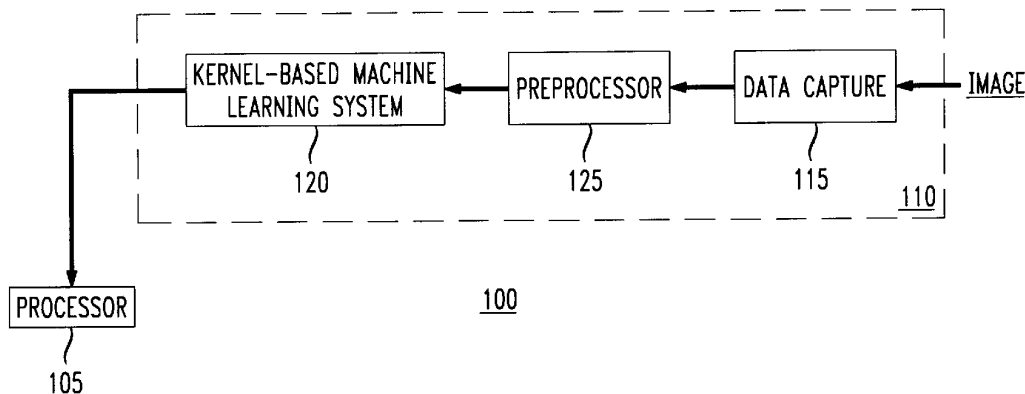
Assistant Examiner—Michael Pender

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[57] **ABSTRACT**

A kernel-based method and apparatus includes a preprocessor, which operates on an input data in such a way as to provide invariance under some symmetry transformation.

14 Claims, 2 Drawing Sheets



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FIG. 1

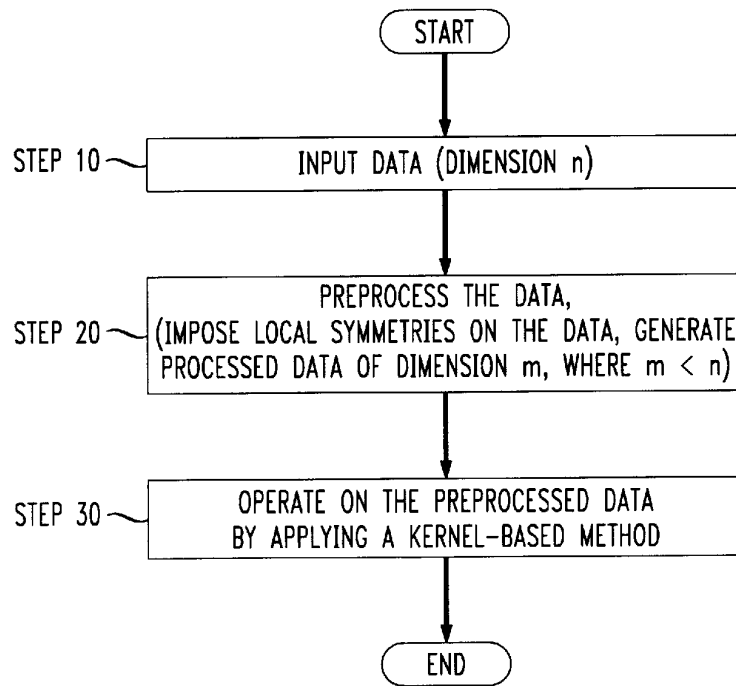


FIG. 2

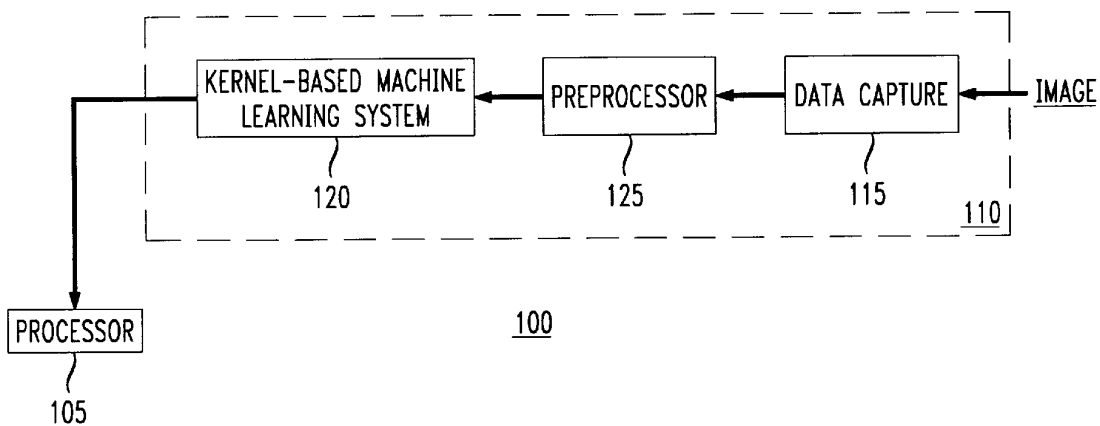


FIG. 3

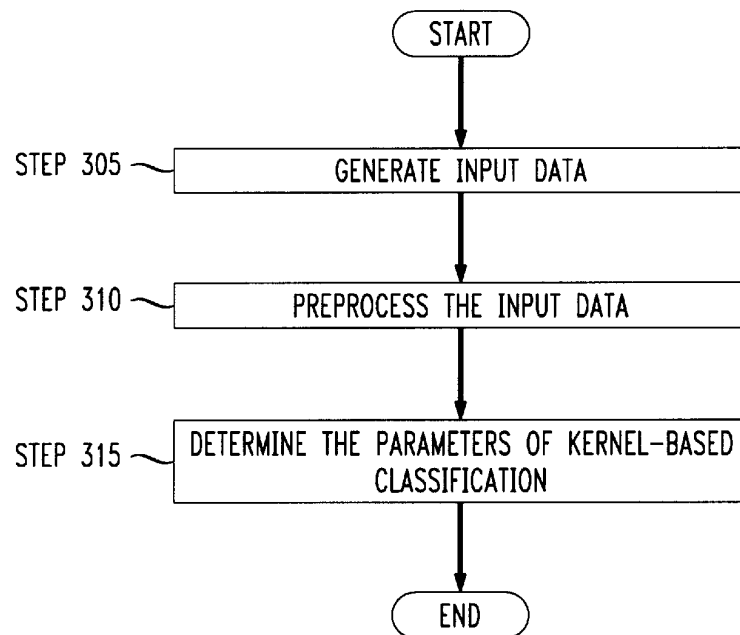
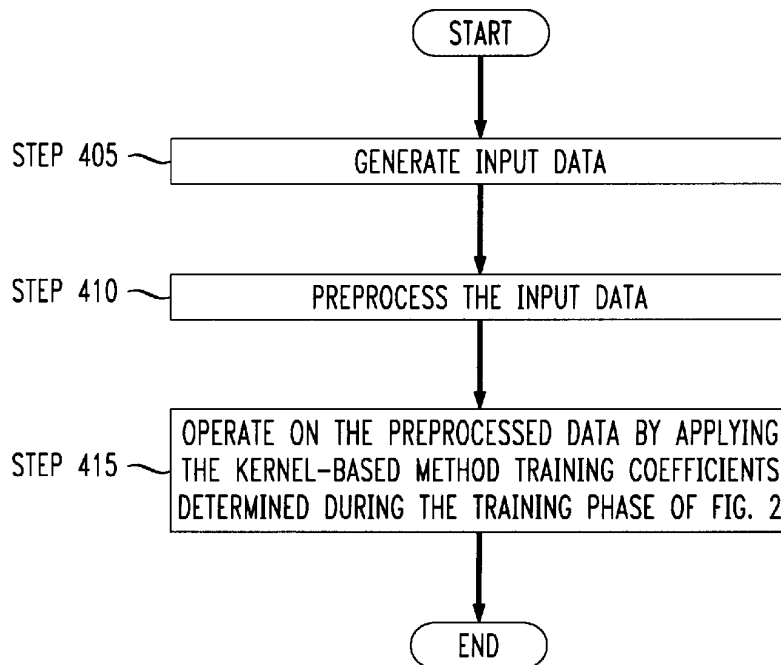


FIG. 4



ELIMINATING INVARIANCES BY PREPROCESSING FOR KERNEL-BASED METHODS

FIELD OF THE INVENTION

This invention relates generally to a class of problems falling within what is known as “kernel-based methods.”

BACKGROUND OF THE INVENTION

Pattern recognition, regression estimates, density estimation are a few examples of a class of problems that are analyzed using kernel-based methods. The latter are illustratively described herein in the context of pattern recognition. However, it should be noted that the inventive concept (described below) is not limited to pattern recognition and is applicable to kernel-based methods in general (of which support-vector-machines are an example).

In pattern recognition, it is known in the art to use a recognizer having a support-vector-machine (SVM) architecture. The SVM is viewed as mapping an input image onto a decision plane. The output of the SVM is typically a numerical result, the value of which is associated with whether, or not, the input image has been recognized as a particular type of image.

As a very general example, consider a 16 pixel by 16 pixel image of a tree. In this context, an SVM recognition system is first “trained” with a set of known images of a tree. For example, the SVM system could be trained on 1000 different tree images, each image represented by 256 pixels. Subsequently, during operation, or testing, the SVM system classifies input images using the training data generated from the 1000 known tree images. The SVM system indicates classification of an input image as the desired tree if, e.g., the output, or result, of the SVM is a positive number.

Unfortunately, in the above example, the recognizer may have to deal not only with a particular type of tree image, but also with translates of that tree image. For example, a tree image that is shifted in the vertical direction—but is still the same tree. To some extent this kind of translation can be dealt with by using tree images that represent such a vertical shift. However, the SVM system is still trained to predefined images, it’s just that some of these predefined images are used to represent translations of the image (as opposed to, e.g., different types of trees).

SUMMARY OF THE INVENTION

A kernel-based method and apparatus includes a preprocessor, which operates on an input data in such a way as to provide invariance under some symmetry transformation.

In an embodiment of the invention, a pattern recognizer includes a preprocessor and a support vector machine (SVM). The latter is trained to recognize a particular set of images. The preprocessor operates on an input image in such a way as to provide local translation invariance. In particular, the preprocessor maps a particular input image, and its translate, to two points in the decision plane of the SVM, whose difference is independent of the original data. As a result, the recognizer has built-in local invariance and does not require training the SVM to translated versions of the images.

In accordance with a feature of the invention, the size of the preprocessed image is less than the size of the original image. In other words, the SVM operates on less data than required in the prior art. Thus, the inventive concept enables

the SVM to operate more efficiently in terms of, e.g., memory size, and training time, yet classify more patterns than in the prior art for a given-size SVM.

BRIEF DESCRIPTION OF THE DRAWING

FIG. 1 shows an illustrative flow chart in accordance with the principles of the invention;

FIG. 2 shows a block diagram of a portion of a recognition system embodying the principles of the invention;

FIG. 3 shows an illustrative method for training the system of FIG. 2 in accordance with the principles of the invention; and

FIG. 4 shown an illustrative method for operating the system of FIG. 2 in accordance with the principles of the invention.

DETAILED DESCRIPTION

Before describing an illustrative embodiment of the invention, the inventive concept itself is described. (Other than the inventive concept, it is assumed that the reader is familiar with mathematical notation used to generally represent kernel-based methods as known in the art.) Also, the inventive concept is illustratively described in the context of pattern recognition. However, the inventive concept is applicable to all kernel-based methods. Some examples of the classes of problems covered by kernel-based methods are: regression estimates, density estimation, etc.

Introduction

As used herein, “kernel-based methods” means methods which approximate an unknown function $G(x)$ by $F(x)$, where $F(x)$ has the form:

$$F(x) = \sum_q a_q K(p_q, x) + b, \quad a_q, b \in \mathbb{R}^1, \quad x \in \mathbb{R}^n, \quad p_q \in \mathbb{R}^{n'} \quad (1)$$

and where a_q , b , and $P_{q'}$ are parameters that are to be determined from empirical data by a training procedure, and K is a kernel function, whose form is usually chosen in advance. Additive models (e.g., see T. J. Hastie and R. J. Tibshirani, *Generalized Additive Models*, Chapman and Hall, 1st edition, 1990), Radial Basis Functions (e.g., see M. J. D. Powell, Radial basis functions for multivariable interpolation: A review, In *Algorithms for Approximation*, J. C. Mason and M. G. Cox (Eds.), pages 143–167, Oxford Clarendon Press, 1987; F. Girosi, M. Jones, and T. Poggio, Regularization theory and neural networks architectures, *Neural Computation*, 7(2):219–269, 1995; and C. M. Bishop, *Neural Networks for Pattern Recognition*, Clarendon Press, Oxford, 1995; and Support Vector Machines (e.g., see C. Cortes and V. Vapnik, Support vector networks, *Machine Learning*, 20:273–297, 1995; and V. Vapnik, *The Nature of Statistical Learning Theory*, Springer Verlag, New York 1995) are examples of such methods. Pattern recognition, regression estimation, density estimation, and operator inversion are examples of problems tackled with these approaches (e.g., see A. Smola, V. Vapnik, S. Golowich, Support vector method for function approximation, regression estimation, and signal processing, *Advances in Neural Information Processing Systems*, 9, 1996). Thus for example in the density estimation case, x is a point (in a vector space) at which the probability density is required, and $F(x)$ is the approximation to that density; for the classification case, x is a test pattern to be classified, and $\text{sgn}(F(x))$ gives the corresponding label. Similarly, for pattern recognition, an SVM is first trained to recognize a target

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