plus infinity. A desired function is learned while a deviation between a desired output value and an actual output value is reduced using a back-propagation algorithm.

[0089] When a signal output from a sensor is input to nodes on an input layer of the artificial neural network **1100**, the signal is changed in each node and then transmitted to a medium layer. In the same manner, the signal is transmitted to the final layer, which outputs a score of each motion pattern. Intensity of connection between nodes (hereinafter, referred to as "node connection intensity") is adjusted such that a difference between activation values output from the artificial neural network **1100** and activation values defined for individual patterns during learning is reduced. In addition, according to a delta learning rule, a lower layer adjusts a node connection intensity based on a result of back-propagation on an upper layer to minimize an error. According to the delta learning rule, the node connection intensity is adjusted such that an input/output function minimizes the sum of squares of errors between a target output and outputs obtained from all individual input patterns in a network including nonlinear neurons.

[0090] After learning all of the designated motion patterns through the above-described leaning process, the artificial neural network **1100** receives a motion signal from the sensing unit **210** (**FIG. 2**) sensing a user's motion and recognizes the motion signal as one of the designated motion patterns.

[0091] The artificial neural network **1100** may be operated to relearn motion patterns according to a user's selection when necessary. For example, when a user selects a motion pattern to be relearned and makes a motion corresponding to the selected motion pattern a plurality of times, the artificial neural network **1100** may relearn the motion pattern reflecting the motion made by the user.

[0092] Alternatively, a user's motion pattern may be recognized using an SVM (Support Vector Machine). Here, N-dimensional vector space is formed from N-dimensional features of motion signals. After an appropriate hyperplane is found based on learning data, patterns can be classified using the hyperplane. Each of the patterns can be defined by Equation 2.

$$\text{class}=1 \text{ if } W^T X+b \geqq 0$$
$$\text{class}=0 \text{ if } W^T X+b<0 \tag{2}$$

where W is a weight matrix, X is an input vector, and "b" is an offset.

[0093] Alternatively, a motion pattern may be recognized using template matching. Here, after template data with which patterns are classified is selected from learning data, a template data item closest to a current input is found and the current input is classified into a pattern corresponding to the template data item. In other words, with respect to input data $X=P(x_1, \ldots x_n)$ and an i-th data item $Y_i=P(y_1, \ldots y_n)$ among the learning data, Y* can be defined by Equation 3.

$$Y^*=\min_i \text{Distance}(X, Y_i) \tag{3}$$

[0094] Distance (X, Y) in Equation 3 can be calculated using Equation 4.

$$\text{Distance}(X, Y) = \|X - Y\| = \sqrt{\sum_{i=1}^{n} (x_i - y_i)^2} \tag{4}$$

[0095] According to Equations 3 and 4, the input X is classified into a pattern to which data Y* belongs.

[0096] Alternatively, a motion pattern may be recognized using a hidden Markov model. The hidden Markov model is a set of states connected via transitions and output functions associated with each state. A model is composed of two kinds of probability: a transition probability needed for transition and an output probability indicating a conditional probability of observing an output symbol included in finite alphabet at each state. Since temporal-spatial change is represented with probabilities in a state and a transition, it is not necessary to additionally consider the temporal-spatial change in the reference pattern during a matching process.

[0097] Besides the above-described pattern recognition algorithms, it is to be understood that other diverse pattern recognition algorithms may be used in the present invention.

[0098] The above-described embodiments of the invention can also be embodied as computer readable codes on a computer readable recording medium. The computer readable recording medium is any data storage device that can store data which can be thereafter read by a computer system. Examples of the computer readable recording medium include read-only memory (ROM), random-access memory (RAM), CD-ROMs, magnetic tapes, floppy disks, optical data storage devices, and carrier waves (such as data transmission through the Internet). The computer readable recording medium can also be distributed over network coupled computer systems so that the computer readable code is stored and executed in a distributed fashion.

[0099] According to the above-described embodiments of the present invention, a character is entered by combining a user's key input and motion, thereby increasing character input speed. In addition, more than a combinable number of characters or functions can be entered with a limited number of character input buttons, and therefore, a user is provided with convenience.

[0100] Although a few embodiments of the present invention have been shown and described, the present invention is not limited to the described embodiments. Instead, it would be appreciated by those skilled in the art that changes may be made to these embodiments without departing from the principles and spirit of the invention, the scope of which is defined by the claims and their equivalents.

What is claimed is:

1. A method of executing a function in a communication terminal, the method comprising:

receiving a key input from a user;

sensing a motion of the user using a sensor;

recognizing a pattern of the sensed motion; and

executing a function corresponding to a combination of the key input and the recognized motion pattern.