

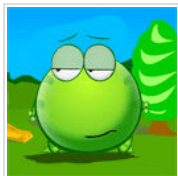
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fengbingchun



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卷积神经网络(CNN)代码实现(MNIST)解析

2016-12-03 16:09

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在<http://blog.csdn.net/fengbingchun/article/details/50814710>中给出了CNN的简单实现，这里对每一步的实现作个说明：

共7层：依次为输入层、C1层、S2层、C3层、S4层、C5层、输出层，C代表卷积层(特征提取)，S代表降采样层或池化层(Pooling)，输出层为全连接层。

1. 各层权值、偏置(阈值)初始化：

各层权值、偏置个数计算如下：

(1)、输入层：预处理后的32*32图像数据，无权值和偏置；

(2)、C1层：卷积窗大小5*5，输出特征图数量6，卷积窗种类1*6=6，输出特征图大小28*28，因此可训练参数(权值+偏置)：(5*5*1)*6+6=150+6；

(3)、S2层：卷积窗大小2*2，输出下采样图数量6，卷积窗种类6，输出下采样图大小14*14，因此可训练参数(权值+偏置)：1*6+6=6+6；

(4)、C3层：卷积窗大小5*5，输出特征图数量16，卷积窗种类6*16=96，输出特征图大小10*10，因此可训练参数(权值+偏置)：(5*5*6)*16+16=2400+16；

(5)、S4层：卷积窗大小2*2，输出下采样图数量16，卷积窗种类16，输出下采样图大小5*5，因此可训练参数(权值+偏置)：1*16+16=16+16；

(6)、C5层：卷积窗大小5*5，输出特征图数量120，卷积窗种类16*120=1920，输出特征图大小1*1，因此可训练参数(权值+偏置)：(5*5*16)*120+120=48000+120；

(7)、输出层：卷积窗大小1*1，输出特征图数量10，卷积窗种类120*10=1200，输出特征图大小1*1，因此可训练参数(权值+偏置)：(1*120)*10+10=1200+10。

代码段如下：

```
[cpp]
01. #define num_map_input_CNN      1 //输入层map个数
02. #define num_map_C1_CNN        6 //C1层map个数
03. #define num_map_S2_CNN        6 //S2层map个数
04. #define num_map_C3_CNN        16 //C3层map个数
05. #define num_map_S4_CNN        16 //S4层map个数
06. #define num_map_C5_CNN        120 //C5层map个数
07. #define num_map_output_CNN    10 //输出层map个数
08.
09. #define len_weight_C1_CNN      150 //C1层权值数，(5*5*1)*6=150
10. #define len_bias_C1_CNN        6 //C1层偏置数，6
```

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oschina

```
11. #define len_weight_S2_CNN      6 //S2层权值数,1*6=6
12. #define len_bias_S2_CNN        6 //S2层阈值数,6
13. #define len_weight_C3_CNN      2400 //C3层权值数,(5*5*6)*16=2400
14. #define len_bias_C3_CNN        16 //C3层阈值数,16
15. #define len_weight_S4_CNN      16 //S4层权值数,1*16=16
16. #define len_bias_S4_CNN        16 //S4层阈值数,16
17. #define len_weight_C5_CNN      48000 //C5层权值数,(5*5*16)*120=48000
18. #define len_bias_C5_CNN        120 //C5层阈值数,120
19. #define len_weight_output_CNN  1200 //输出层权值数,(1*120)*10=1200
20. #define len_bias_output_CNN    10 //输出层阈值数,10
21.
22. #define num_neuron_input_CNN    1024 //输入层神经元数,(32*32)*1=1024
23. #define num_neuron_C1_CNN       4704 //C1层神经元数,(28*28)*6=4704
24. #define num_neuron_S2_CNN       1176 //S2层神经元数,(14*14)*6=1176
25. #define num_neuron_C3_CNN       1600 //C3层神经元数,(10*10)*16=1600
26. #define num_neuron_S4_CNN       400 //S4层神经元数,(5*5)*16=400
27. #define num_neuron_C5_CNN       120 //C5层神经元数,(1*1)*120=120
28. #define num_neuron_output_CNN  10 //输出层神经元数,(1*1)*10=10
```

权值、偏置初始化：

(1)、权值使用函数uniform_real_distribution均匀分布初始化，tiny-cnn中每次初始化权值数值都相同，这里作了调整，使每次初始化的权值均不同。每层权值初始化大小范围都不一样；

(2)、所有层的偏置均初始化为0。

代码段如下：

```
[cpp]
01. double CNN::uniform_rand(double min, double max)
02. {
03.     //static std::mt19937 gen(1);
04.     std::random_device rd;
05.     std::mt19937 gen(rd());
06.     std::uniform_real_distribution<double> dst(min, max);
07.     return dst(gen);
08. }
09.
10. bool CNN::uniform_rand(double* src, int len, double min, double max)
11. {
12.     for (int i = 0; i < len; i++) {
13.         src[i] = uniform_rand(min, max);
14.     }
15.
16.     return true;
17. }
18.
19. bool CNN::initWeightThreshold()
20. {
21.     srand(time(0) + rand());
22.     const double scale = 6.0;
23.
24.     double min_ = -std::sqrt(scale / (25.0 + 150.0));
25.     double max_ = std::sqrt(scale / (25.0 + 150.0));
26.     uniform_rand(weight_C1, len_weight_C1_CNN, min_, max_);
27.     for (int i = 0; i < len_bias_C1_CNN; i++) {
28.         bias_C1[i] = 0.0;
29.     }
30.
31.     min_ = -std::sqrt(scale / (4.0 + 1.0));
32.     max_ = std::sqrt(scale / (4.0 + 1.0));
33.     uniform_rand(weight_S2, len_weight_S2_CNN, min_, max_);
34.     for (int i = 0; i < len_bias_S2_CNN; i++) {
35.         bias_S2[i] = 0.0;
36.     }
37.
38.     min_ = -std::sqrt(scale / (150.0 + 400.0));
39.     max_ = std::sqrt(scale / (150.0 + 400.0));
40.     uniform_rand(weight_C3, len_weight_C3_CNN, min_, max_);
41.     for (int i = 0; i < len_bias_C3_CNN; i++) {
42.         bias_C3[i] = 0.0;
43.     }
44.
45.     min_ = -std::sqrt(scale / (4.0 + 1.0));
46.     max_ = std::sqrt(scale / (4.0 + 1.0));
47.     uniform_rand(weight_S4, len_weight_S4_CNN, min_, max_);
48.     for (int i = 0; i < len_bias_S4_CNN; i++) {
```

关闭

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sift
TiRG
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Friendly Link

OpenCL
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Open Computer Vision Library
CImage
ImageMagick
ImageMagick China
OpenCV_China
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```
49.         bias_S4[i] = 0.0;
50.     }
51.
52.     min_ = -std::sqrt(scale / (400.0 + 3000.0));
53.     max_ = std::sqrt(scale / (400.0 + 3000.0));
54.     uniform_rand(weight_C5, len_weight_C5_CNN, min_, max_);
55.     for (int i = 0; i < len_bias_C5_CNN; i++) {
56.         bias_C5[i] = 0.0;
57.     }
58.
59.     min_ = -std::sqrt(scale / (120.0 + 10.0));
60.     max_ = std::sqrt(scale / (120.0 + 10.0));
61.     uniform_rand(weight_output, len_weight_output_CNN, min_, max_);
62.     for (int i = 0; i < len_bias_output_CNN; i++) {
63.         bias_output[i] = 0.0;
64.     }
65.
66.     return true;
67. }
```

2. 加载MNIST数据：

关于MNIST的介绍可以参考：<http://blog.csdn.net/fengbingchun/article/details/49611549>

使用MNIST库作为训练集和测试集，训练样本集为60000个，测试样本集为10000个。

(1)、MNIST库中图像原始大小为28*28，这里缩放为32*32，数据取值范围为[-1,1]，扩充值均取-1，作为输入层输入数据。

代码段如下：

```
[cpp]
01. static void readMnistImages(std::string filename, double* data_dst, int num_image)
02. {
03.     const int width_src_image = 28;
04.     const int height_src_image = 28;
05.     const int x_padding = 2;
06.     const int y_padding = 2;
07.     const double scale_min = -1;
08.     const double scale_max = 1;
09.
10.     std::ifstream file(filename, std::ios::binary);
11.     assert(file.is_open());
12.
13.     int magic_number = 0;
14.     int number_of_images = 0;
15.     int n_rows = 0;
16.     int n_cols = 0;
17.     file.read((char*)&magic_number, sizeof(magic_number));
18.     magic_number = reverseInt(magic_number);
19.     file.read((char*)&number_of_images, sizeof(number_of_images));
20.     number_of_images = reverseInt(number_of_images);
21.     assert(number_of_images == num_image);
22.     file.read((char*)&n_rows, sizeof(n_rows));
23.     n_rows = reverseInt(n_rows);
24.     file.read((char*)&n_cols, sizeof(n_cols));
25.     n_cols = reverseInt(n_cols);
26.     assert(n_rows == height_src_image && n_cols == width_src_image);
27.
28.     int size_single_image = width_image_input_CNN * height_image_input_CNN;
29.
30.     for (int i = 0; i < number_of_images; ++i) {
31.         int addr = size_single_image * i;
32.
33.         for (int r = 0; r < n_rows; ++r) {
34.             for (int c = 0; c < n_cols; ++c) {
35.                 unsigned char temp = 0;
36.                 file.read((char*)&temp, sizeof(temp));
37.                 data_dst[addr + width_image_input_CNN * (r + y_padding) + c + x_padding] =
38.             }
39.         }
40.     }
41. }
```

关闭

(2)、对于Label,输出层有10个节点，对应位置的节点值设为0.8，其它节点设为-0.8，作为输出层数据。

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卷积神经网络(CNN)的简单实现(
fengbingchun: @hugl950123: NN中一共有四个工程, 它们之间没有任何关系, 都是独立的, 如果要运行这篇文章的...

代码段如下:

```
[cpp] C P
01. static void readMnistLabels(std::string filename, double* data_dst, int num_image)
02. {
03.     const double scale_max = 0.8;
04.
05.     std::ifstream file(filename, std::ios::binary);
06.     assert(file.is_open());
07.
08.     int magic_number = 0;
09.     int number_of_images = 0;
10.     file.read((char*)&magic_number, sizeof(magic_number));
11.     magic_number = reverseInt(magic_number);
12.     file.read((char*)&number_of_images, sizeof(number_of_images));
13.     number_of_images = reverseInt(number_of_images);
14.     assert(number_of_images == num_image);
15.
16.     for (int i = 0; i < number_of_images; ++i) {
17.         unsigned char temp = 0;
18.         file.read((char*)&temp, sizeof(temp));
19.         data_dst[i * num_map_output_CNN + temp] = scale_max;
20.     }
21. } static void readMnistLabels(std::string filename, double* data_dst, int num_image)
22. {
23.     const double scale_max = 0.8;
24.
25.     std::ifstream file(filename, std::ios::binary);
26.     assert(file.is_open());
27.
28.     int magic_number = 0;
29.     int number_of_images = 0;
30.     file.read((char*)&magic_number, sizeof(magic_number));
31.     magic_number = reverseInt(magic_number);
32.     file.read((char*)&number_of_images, sizeof(number_of_images));
33.     number_of_images = reverseInt(number_of_images);
34.     assert(number_of_images == num_image);
35.
36.     for (int i = 0; i < number_of_images; ++i) {
37.         unsigned char temp = 0;
38.         file.read((char*)&temp, sizeof(temp));
39.         data_dst[i * num_map_output_CNN + temp] = scale_max;
40.     }
41. }
```

3. 前向传播: 主要计算每层的神经元值; 其中C1层、C3层、C5层操作过程相同; S2层、S4层操作过程相同。

(1)、输入层: 神经元数为 $(32*32)*1=1024$ 。

(2)、C1层: 神经元数为 $(28*28)*6=4704$, 分别用每一个 $5*5$ 的卷积图像去乘以 $32*32$ 的图像, 获得一个 $28*28$ 的图像, 即对应位置相加再求和, stride长度为1; 一共6个 $5*5$ 的卷积图像, 然后对每一个神经元加上一个阈值, 最后再通过tanh激活函数对每一神经元进行运算得到最终每一个神经元的结果。

激活函数的作用: 它是用来加入非线性因素的, 解决线性模型所不能解决的问题, 提供网络的非线性建模能力。如果没有激活函数, 那么该网络仅能够表达线性映射, 此时即便有再多的隐藏层, 其整个网络跟单层神经网络也是等价的。因此也可以认为, 只有加入了激活函数之后, 深度神经网络才具备了分层的非线性映射学习能力。

代码段如下:

```
[cpp] C P
01. double CNN::activation_function_tanh(double x)
02. {
03.     double ep = std::exp(x);
04.     double em = std::exp(-x);
05.
06.     return (ep - em) / (ep + em);
07. }
08.
09. bool CNN::Forward_C1()
10. {
11.     init_variable(neuron_C1, 0.0, num_neuron_C1_CNN);
12. }
```

关闭

卷积神经网络(CNN)的简单实现([hugl950123: @fengbingchun](#):下的是新的,我在CNN.cpp文件中每个函数都设置了断点,还是没有变化=...

卷积神经网络(CNN)的简单实现([fengbingchun: @hugl950123](#):你用的是GitHub上最新的吗?既然能编译过,在Debug下设断点,应该很快...

卷积神经网络(CNN)的简单实现([hugl950123](#): 博主,请问我按照您的代码成功编译后执行结果窗口一闪而过,并且里面什么内容也没有,应该如何解决,能不能...

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展开



碧桂园森林城市



```
13.     for (int o = 0; o < num_map_C1_CNN; o++) {
14.         for (int inc = 0; inc < num_map_input_CNN; inc++) {
15.             int addr1 = get_index(0, 0, num_map_input_CNN * o + inc, width_kernel_conv_CNN);
16.             int addr2 = get_index(0, 0, inc, width_image_input_CNN, height_image_input_CNN);
17.             int addr3 = get_index(0, 0, 0, width_image_C1_CNN, height_image_C1_CNN, num_map_C1_CNN);
18.
19.             const double* pw = &weight_C1[0] + addr1;
20.             const double* pi = data_single_image + addr2;
21.             double* pa = &neuron_C1[0] + addr3;
22.
23.             for (int y = 0; y < height_image_C1_CNN; y++) {
24.                 for (int x = 0; x < width_image_C1_CNN; x++) {
25.                     const double* ppw = pw;
26.                     const double* ppi = pi + y * width_image_input_CNN + x;
27.                     double sum = 0.0;
28.
29.                     for (int wy = 0; wy < height_kernel_conv_CNN; wy++) {
30.                         for (int wx = 0; wx < width_kernel_conv_CNN; wx++) {
31.                             sum += *ppw++ * ppi[wy * width_image_input_CNN + wx];
32.                         }
33.                     }
34.
35.                     pa[y * width_image_C1_CNN + x] += sum;
36.                 }
37.             }
38.         }
39.     }
40.
41.     int addr3 = get_index(0, 0, 0, width_image_C1_CNN, height_image_C1_CNN, num_map_C1_CNN);
42.     double* pa = &neuron_C1[0] + addr3;
43.     double b = bias_C1[0];
44.     for (int y = 0; y < height_image_C1_CNN; y++) {
45.         for (int x = 0; x < width_image_C1_CNN; x++) {
46.             pa[y * width_image_C1_CNN + x] += b;
47.         }
48.     }
49.
50.     for (int i = 0; i < num_neuron_C1_CNN; i++) {
51.         neuron_C1[i] = activation_function_tanh(neuron_C1[i]);
52.     }
53.
54.     return true;
55. }
```

(3)、S2层: 神经元数为 $(14*14)*6=1176$, 对C1中6个 $28*28$ 的特征图生成6个 $14*14$ 的下采样图, 相邻四个神经元分别乘以同一个权重再进行相加求和, 再求均值即除以4, 然后再加上一个阈值, 最后再通过tanh激活函数对每一个神经元进行运算得到最终每一个神经元的结果。

代码段如下:

```
[cpp]
01. bool CNN::Forward_S2()
02. {
03.     init_variable(neuron_S2, 0.0, num_neuron_S2_CNN);
04.     double scale_factor = 1.0 / (width_kernel_pooling_CNN * height_kernel_pooling_CNN);
05.
06.     assert(out2wi_S2.size() == num_neuron_S2_CNN);
07.     assert(out2bias_S2.size() == num_neuron_S2_CNN);
08.
09.     for (int i = 0; i < num_neuron_S2_CNN; i++) {
10.         const wi_connections& connections = out2wi_S2[i];
11.         neuron_S2[i] = 0;
12.
13.         for (int index = 0; index < connections.size(); index++) {
14.             neuron_S2[i] += weight_S2[connections[index].first] * neuron_C1[connections[index].second];
15.         }
16.
17.         neuron_S2[i] *= scale_factor;
18.         neuron_S2[i] += bias_S2[out2bias_S2[i]];
19.     }
20.
21.     for (int i = 0; i < num_neuron_S2_CNN; i++) {
22.         neuron_S2[i] = activation_function_tanh(neuron_S2[i]);
23.     }
24.
25.     return true;
26. }
```

关闭

(4)、C3层：神经元数为 $(10 \times 10) \times 16 = 1600$ ，C3层实现方式与C1层完全相同，由S2中的6个 14×14 下采样图生成16个 10×10 特征图，对于生成的每一个 10×10 的特征图，是由6个 5×5 的卷积图像去乘以6个 14×14 的下采样图，然后对应位置相加求和，然后对每一个神经元加上一个阈值，最后再通过tanh激活函数对每一神经元进行运算得到最终每一个神经元的结果。

也可按照Y.Lecun给出的表进行计算，即对于生成的每一个 10×10 的特征图，是由n个 5×5 的卷积图像去乘以n个 14×14 的下采样图，其中n是小于6的，即不完全连接。这样做的原因：第一，不完全的连接机制将连接的数量保持在合理的范围内。第二，也是最重要的，其破坏了网络的对称性。由于不同的特征图有不同的输入，所以迫使他们抽取不同的特征。

代码段如下：

```
[cpp]
// connection table [Y.Lecun, 1998 Table.1]
#define 0 true
#define X false
static const bool tbl[6][16] = {
    0, X, X, X, 0, 0, 0, X, X, 0, 0, 0, 0, X, 0, 0,
    0, 0, X, X, X, 0, 0, 0, X, X, 0, 0, 0, 0, X, 0,
    0, 0, 0, X, X, X, 0, 0, 0, X, X, 0, X, 0, 0, 0,
    X, 0, 0, 0, X, X, 0, 0, 0, 0, X, X, 0, X, 0, 0,
    X, X, 0, 0, 0, X, X, 0, 0, 0, 0, X, 0, 0, X, 0,
    X, X, X, 0, 0, 0, X, X, 0, 0, 0, 0, X, 0, 0, 0
};
#undef 0
#undef X

bool CNN::Forward_C3()
{
    init_variable(neuron_C3, 0.0, num_neuron_C3_CNN);

    for (int o = 0; o < num_map_C3_CNN; o++) {
        for (int inc = 0; inc < num_map_S2_CNN; inc++) {
            if (!tbl[inc][o]) continue;

            int addr1 = get_index(0, 0, num_map_S2_CNN * o + inc, width_kernel_conv_CNN, height_kernel_conv_CNN);
            int addr2 = get_index(0, 0, inc, width_image_S2_CNN, height_image_S2_CNN, num_map_S2_CNN);
            int addr3 = get_index(0, 0, o, width_image_C3_CNN, height_image_C3_CNN, num_neuron_C3_CNN);

            const double* pw = &weight_C3[0] + addr1;
            const double* pi = &neuron_S2[0] + addr2;
            double* pa = &neuron_C3[0] + addr3;

            for (int y = 0; y < height_image_C3_CNN; y++) {
                for (int x = 0; x < width_image_C3_CNN; x++) {
                    const double* ppw = pw;
                    const double* ppi = pi + y * width_image_S2_CNN + x;
                    double sum = 0.0;

                    for (int wy = 0; wy < height_kernel_conv_CNN; wy++) {
                        for (int wx = 0; wx < width_kernel_conv_CNN; wx++) {
                            sum += *ppw++ * ppi[wy * width_image_S2_CNN + wx];
                        }
                    }

                    pa[y * width_image_C3_CNN + x] += sum;
                }
            }

            int addr3 = get_index(0, 0, o, width_image_C3_CNN, height_image_C3_CNN, num_neuron_C3_CNN);
            double* pa = &neuron_C3[0] + addr3;
            double b = bias_C3[o];
            for (int y = 0; y < height_image_C3_CNN; y++) {
                for (int x = 0; x < width_image_C3_CNN; x++) {
                    pa[y * width_image_C3_CNN + x] += b;
                }
            }
        }
    }

    for (int i = 0; i < num_neuron_C3_CNN; i++) {
        neuron_C3[i] = activation_function_tanh(neuron_C3[i]);
    }

    return true;
}
```

关闭

63. }

(5)、S4层：神经元数为 $(5*5)*16=400$ ，S4层实现方式与S2层完全相同，由C3中16个 $10*10$ 的特征图生成16个 $5*5$ 下采样图，相邻四个神经元分别乘以同一个权值再进行相加求和，再求均值即除以4，然后再加上一个阈值，最后再通过tanh激活函数对每一神经元进行运算得到最终每一个神经元的结果。

代码段如下：

```
[cpp] C
01. bool CNN::Forward_S4()
02. {
03.     double scale_factor = 1.0 / (width_kernel_pooling_CNN * height_kernel_pooling_CNN);
04.     init_variable(neuron_S4, 0.0, num_neuron_S4_CNN);
05.
06.     assert(out2wi_S4.size() == num_neuron_S4_CNN);
07.     assert(out2bias_S4.size() == num_neuron_S4_CNN);
08.
09.     for (int i = 0; i < num_neuron_S4_CNN; i++) {
10.         const wi_connections& connections = out2wi_S4[i];
11.         neuron_S4[i] = 0.0;
12.
13.         for (int index = 0; index < connections.size(); index++) {
14.             neuron_S4[i] += weight_S4[connections[index].first] * neuron_C3[connections[index].second];
15.         }
16.
17.         neuron_S4[i] *= scale_factor;
18.         neuron_S4[i] += bias_S4[out2bias_S4[i]];
19.     }
20.
21.     for (int i = 0; i < num_neuron_S4_CNN; i++) {
22.         neuron_S4[i] = activation_function_tanh(neuron_S4[i]);
23.     }
24.
25.     return true;
26. }
```

(6)、C5层：神经元数为 $(1*1)*120=120$ ，也可视为全连接层，C5层实现方式与C1、C3层完全相同，由S4中16个 $5*5$ 下采样图生成120个 $1*1$ 特征图，对于生成的每一个 $1*1$ 的特征图，是由16个 $5*5$ 的卷积图像去乘以16个 $5*5$ 的下采样图，然后相加求和，然后对每一个神经元加上一个阈值，最后再通过tanh激活函数对每一神经元进行运算得到最终每一个神经元的结果。

代码段如下：

```
[cpp] C
01. bool CNN::Forward_C5()
02. {
03.     init_variable(neuron_C5, 0.0, num_neuron_C5_CNN);
04.
05.     for (int o = 0; o < num_map_C5_CNN; o++) {
06.         for (int inc = 0; inc < num_map_S4_CNN; inc++) {
07.             int addr1 = get_index(0, 0, num_map_S4_CNN * o + inc, width_kernel_conv_CNN, height_kernel_conv_CNN);
08.             int addr2 = get_index(0, 0, inc, width_image_S4_CNN, height_image_S4_CNN, num_map_S4_CNN);
09.             int addr3 = get_index(0, 0, o, width_image_C5_CNN, height_image_C5_CNN, num_map_C5_CNN);
10.
11.             const double *pw = &weight_C5[0] + addr1;
12.             const double *pi = &neuron_S4[0] + addr2;
13.             double *pa = &neuron_C5[0] + addr3;
14.
15.             for (int y = 0; y < height_image_C5_CNN; y++) {
16.                 for (int x = 0; x < width_image_C5_CNN; x++) {
17.                     const double *ppw = pw;
18.                     const double *ppi = pi + y * width_image_S4_CNN + x;
19.                     double sum = 0.0;
20.
21.                     for (int wy = 0; wy < height_kernel_conv_CNN; wy++) {
22.                         for (int wx = 0; wx < width_kernel_conv_CNN; wx++) {
23.                             sum += *ppw++ * ppi[wy * width_image_S4_CNN + wx];
24.                         }
25.                     }
26.
27.                     pa[y * width_image_C5_CNN + x] += sum;
28.                 }
29.             }
30.         }
31.     }
```

关闭


```
31.
32.     int addr3 = get_index(0, 0, 0, width_image_C5_CNN, height_image_C5_CNN, num_map_C5_CNN, 0);
33.     double *pa = &neuron_C5[0] + addr3;
34.     double b = bias_C5[0];
35.     for (int y = 0; y < height_image_C5_CNN; y++) {
36.         for (int x = 0; x < width_image_C5_CNN; x++) {
37.             pa[y * width_image_C5_CNN + x] += b;
38.         }
39.     }
40. }
41.
42. for (int i = 0; i < num_neuron_C5_CNN; i++) {
43.     neuron_C5[i] = activation_function_tanh(neuron_C5[i]);
44. }
45.
46. return true;
47. }
```

(7)、输出层：神经元数为 $(1*1)*10=10$ ，为全连接层，输出层中的每一个神经元均是由C5层中的120个神经元乘以相对应的权值，然后相加求和；然后对每一个神经元加上一个阈值，最后再通过tanh激活函数对每一神经元进行运算得到最终每一个神经元的结果。

代码段如下：

```
[cpp] C
01. bool CNN::Forward_output()
02. {
03.     init_variable(neuron_output, 0.0, num_neuron_output_CNN);
04.
05.     for (int i = 0; i < num_neuron_output_CNN; i++) {
06.         neuron_output[i] = 0.0;
07.
08.         for (int c = 0; c < num_neuron_C5_CNN; c++) {
09.             neuron_output[i] += weight_output[c * num_neuron_output_CNN + i] * neuron_C5[c];
10.         }
11.
12.         neuron_output[i] += bias_output[i];
13.     }
14.
15.     for (int i = 0; i < num_neuron_output_CNN; i++) {
16.         neuron_output[i] = activation_function_tanh(neuron_output[i]);
17.     }
18.
19.     return true;
20. }
```

4. 反向传播：主要计算每层权值和偏置的误差以及每层神经元的误差；其中输入层、S2层、S4层操作过程相同；C1层、C3层操作过程相同。

(1)、输出层：计算输出层神经元误差；通过mse损失函数的导数函数和tanh激活函数的导数函数来计算输出层神经元误差，即a、已计算出的输出层神经元值减去对应label值，b、1.0减去输出层神经元值的平方，c、a与c的乘积和。

损失函数作用：在统计学中损失函数是一种衡量损失和错误(这种损失与“错误地”估计有关)程度的函数。损失函数在实践中最重要的运用，在于协助我们通过过程的改善而持续减少目标值的变异，并非仅仅追求符合逻辑。在深度学习中，对于损失函数的收敛特性，我们期望是当误差越大的时候，收敛(学习)速度应该越快。成为损失函数需要满足两点要求：非负性；预测值和期望值接近时，函数值趋于0。

代码段如下：

```
[cpp] C
01. double CNN::loss_function_mse_derivative(double y, double t)
02. {
03.     return (y - t);
04. }
05.
06. void CNN::loss_function_gradient(const double* y, const double* t, double* dst, int len)
07. {
08.     for (int i = 0; i < len; i++) {
09.         dst[i] = loss_function_mse_derivative(y[i], t[i]);
10.     }
11. }
```

关闭


```

12.
13. double CNN::activation_function_tanh_derivative(double x)
14. {
15.     return (1.0 - x * x);
16. }
17.
18. double CNN::dot_product(const double* s1, const double* s2, int len)
19. {
20.     double result = 0.0;
21.
22.     for (int i = 0; i < len; i++) {
23.         result += s1[i] * s2[i];
24.     }
25.
26.     return result;
27. }
28.
29. bool CNN::Backward_output()
30. {
31.     init_variable(delta_neuron_output, 0.0, num_neuron_output_CNN);
32.
33.     double dE_dy[num_neuron_output_CNN];
34.     init_variable(dE_dy, 0.0, num_neuron_output_CNN);
35.     loss_function_gradient(neuron_output, data_single_label, dE_dy, num_neuron_output_CNN);
36.     // 失函数: mean squared error(均方差)
37.     // delta = dE/da = (dE/dy) * (dy/da)
38.     for (int i = 0; i < num_neuron_output_CNN; i++) {
39.         double dy_da[num_neuron_output_CNN];
40.         init_variable(dy_da, 0.0, num_neuron_output_CNN);
41.
42.         dy_da[i] = activation_function_tanh_derivative(neuron_output[i]);
43.         delta_neuron_output[i] = dot_product(dE_dy, dy_da, num_neuron_output_CNN);
44.     }
45.
46.     return true;
47. }

```

(2)、C5层：计算C5层神经元误差、输出层权值误差、输出层偏置误差；通过输出层神经元误差乘以输出层权值，求和，结果再乘以C5层神经元的tanh激活函数的导数(即1-C5层神经元值的平方)，获得C5层每一个神经元误差；通过输出层神经元误差乘以C5层神经元获得输出层权值误差；输出层偏置误差即为输出层神经元误差。

代码段如下：

```

[cpp]
10. bool CNN::muladd(const double* src, double c, int len, double* dst)
11. {
12.     for (int i = 0; i < len; i++) {
13.         dst[i] += (src[i] * c);
14.     }
15.
16.     return true;
17. }
18.
19. bool CNN::Backward_C5()
20. {
21.     init_variable(delta_neuron_C5, 0.0, num_neuron_C5_CNN);
22.     init_variable(delta_weight_output, 0.0, len_weight_output_CNN);
23.     init_variable(delta_bias_output, 0.0, len_bias_output_CNN);
24.
25.     for (int c = 0; c < num_neuron_C5_CNN; c++) {
26.         // propagate delta to previous layer
27.         // prev_delta[c] += current_delta[r] * W[c * out_size + r]
28.         delta_neuron_C5[c] = dot_product(&
29. delta_neuron_output[0], &weight_output[c * num_neuron_output_CNN], num_neuron_output_CNN);
30.         delta_neuron_C5[c] *= activation_function_tanh_derivative(neuron_C5[c]);
31.     }
32.
33.     // accumulate weight-step using delta
34.     // dw[c * out_size + i] += current_delta[i] * prev_out[c]
35.     for (int c = 0; c < num_neuron_C5_CNN; c++) {
36.         muladd(&delta_neuron_output[0], neuron_C5[c], num_neuron_output_CNN, &delta_weight_output[c * len_weight_output_CNN]);
37.     }
38.
39.     for (int i = 0; i < len_bias_output_CNN; i++) {
40.         delta_bias_output[i] += delta_neuron_output[i];
41.     }
42. }

```

关闭

```
32.
33.     return true;
34. }
```

(3)、S4层：计算S4层神经元误差、C5层权值误差、C5层偏置误差；通过C5层权值乘以C5层神经元误差，求和，结果再乘以S4层神经元的tanh激活函数的导数(即1-S4神经元的平方)，获得S4层每一个神经元误差；通过S4层神经元乘以C5层神经元误差，求和，获得C5层权值误差；C5层偏置误差即为C5层神经元误差。

代码段如下：

```
[cpp]
31. bool CNN::Backward_S4()
32. {
33.     init_variable(delta_neuron_S4, 0.0, num_neuron_S4_CNN);
34.     init_variable(delta_weight_C5, 0.0, len_weight_C5_CNN);
35.     init_variable(delta_bias_C5, 0.0, len_bias_C5_CNN);
36.
37.     // propagate delta to previous layer
38.     for (int inc = 0; inc < num_map_S4_CNN; inc++) {
39.         for (int outc = 0; outc < num_map_C5_CNN; outc++) {
40.             int addr1 = get_index(0, 0, num_map_S4_CNN * outc + inc, width_ke
41.             int addr2 = get_index(0, 0, outc, width_image_C5_CNN, height_image_C5_CNN, num
42.             int addr3 = get_index(0, 0, inc, width_image_S4_CNN, height_image_S4_CNN, num
43.
44.             const double* pw = &weight_C5[0] + addr1;
45.             const double* pdelta_src = &delta_neuron_C5[0] + addr2;
46.             double* pdelta_dst = &delta_neuron_S4[0] + addr3;
47.
48.             for (int y = 0; y < height_image_C5_CNN; y++) {
49.                 for (int x = 0; x < width_image_C5_CNN; x++) {
50.                     const double* ppw = pw;
51.                     const double pdelta_src = pdelta_src[y * width_image_C5_CNN + x];
52.                     double* pppdelta_dst = pdelta_dst + y * width_image_S4_CNN + x;
53.
54.                     for (int wy = 0; wy < height_kernel_conv_CNN; wy++) {
55.                         for (int wx = 0; wx < width_kernel_conv_CNN; wx++) {
56.                             pppdelta_dst[wy * width_image_S4_CNN + wx] += *ppw++ * pppdelta
57.                         }
58.                     }
59.                 }
60.             }
61.         }
62.     }
63.
64.     for (int i = 0; i < num_neuron_S4_CNN; i++) {
65.         delta_neuron_S4[i] *= activation_function_tanh_derivative(neuron_S4[i]);
66.     }
67.
68.     // accumulate dw
69.     for (int inc = 0; inc < num_map_S4_CNN; inc++) {
70.         for (int outc = 0; outc < num_map_C5_CNN; outc++) {
71.             for (int wy = 0; wy < height_kernel_conv_CNN; wy++) {
72.                 for (int wx = 0; wx < width_kernel_conv_CNN; wx++) {
73.                     int addr1 = get_index(wx, wy, inc, width_image_S4_CNN, height_image_S4
74.                     int addr2 = get_index(0, 0, outc, width_image_C5_CNN, height_image_C5
75.                     int addr3 = get_index(wx, wy, num_map_S4_CNN * outc + inc, width_kerne
76.
77.                     double dst = 0.0;
78.                     const double* prevo = &neuron_S4[0] + addr1;
79.                     const double* delta = &delta_neuron_C5[0] + addr2;
80.
81.                     for (int y = 0; y < height_image_C5_CNN; y++) {
82.                         dst += dot_product(prevo + y * width_image_S4_CNN, delta + y * width_image_C5_CNN);
83.                     }
84.
85.                     delta_weight_C5[addr3] += dst;
86.                 }
87.             }
88.         }
89.     }
90.
91.     // accumulate db
92.     for (int outc = 0; outc < num_map_C5_CNN; outc++) {
93.         int addr2 = get_index(0, 0, outc, width_image_C5_CNN, height_image_C5_CNN, num_ma
94.         const double* delta = &delta_neuron_C5[0] + addr2;
95.
96.         for (int y = 0; y < height_image_C5_CNN; y++) {
```

关闭

```

67.         for (int x = 0; x < width_image_C5_CNN; x++) {
68.             delta_bias_C5[outc] += delta[y * width_image_C5_CNN + x];
69.         }
70.     }
71. }
72.
73. return true;
74. }

```

(4)、C3层：计算C3层神经元误差、S4层权值误差、S4层偏置误差；通过S4层权值乘以S4层神经元误差，求和，结果再乘以C3层神经元的tanh激活函数的导数(即1-S4神经元的平方)，然后再乘以1/4，获得C3层每一个神经元误差；通过C3层神经元乘以S4神经元误差，求和，再乘以1/4，获得S4层权值误差；通过S4层神经元误差求和，来获得S4层偏置误差。

代码段如下：

```

[cpp]
01. bool CNN::Backward_C3()
02. {
03.     init_variable(delta_neuron_C3, 0.0, num_neuron_C3_CNN);
04.     init_variable(delta_weight_S4, 0.0, len_weight_S4_CNN);
05.     init_variable(delta_bias_S4, 0.0, len_bias_S4_CNN);
06.
07.     double scale_factor = 1.0 / (width_kernel_pooling_CNN * height_kernel_pooling_CNN);
08.
09.     assert(in2wo_C3.size() == num_neuron_C3_CNN);
10.     assert(weight2io_C3.size() == len_weight_S4_CNN);
11.     assert(bias2out_C3.size() == len_bias_S4_CNN);
12.
13.     for (int i = 0; i < num_neuron_C3_CNN; i++) {
14.         const wo_connections& connections = in2wo_C3[i];
15.         double delta = 0.0;
16.
17.         for (int j = 0; j < connections.size(); j++) {
18.             delta += weight_S4[connections[j].first] * delta_neuron_S4[connections[j].second];
19.         }
20.
21.         delta_neuron_C3[i] = delta * scale_factor * activation_function_tanh_derivative(neuron_C3[i]);
22.     }
23.
24.     for (int i = 0; i < len_weight_S4_CNN; i++) {
25.         const io_connections& connections = weight2io_C3[i];
26.         double diff = 0;
27.
28.         for (int j = 0; j < connections.size(); j++) {
29.             diff += neuron_C3[connections[j].first] * delta_neuron_S4[connections[j].second];
30.         }
31.
32.         delta_weight_S4[i] += diff * scale_factor;
33.     }
34.
35.     for (int i = 0; i < len_bias_S4_CNN; i++) {
36.         const std::vector<int>& outs = bias2out_C3[i];
37.         double diff = 0;
38.
39.         for (int o = 0; o < outs.size(); o++) {
40.             diff += delta_neuron_S4[outs[o]];
41.         }
42.
43.         delta_bias_S4[i] += diff;
44.     }
45.
46.     return true;
47. }

```

关闭

(5)、S2层：计算S2层神经元误差、C3层权值误差、C3层偏置误差；通过C3层权值乘以C3层神经元误差，求和，结果再乘以S2层神经元的tanh激活函数的导数(即1-S2神经元的平方)，获得S2层每一个神经元误差；通过S2层神经元乘以C3层神经元误差，求和，获得C3层权值误差；C3层偏置误差即为C3层神经元误差和。

代码段如下：

```

[cpp]
01. bool CNN::Backward_S2()
02. {

```

```

03.     init_variable(delta_neuron_S2, 0.0, num_neuron_S2_CNN);
04.     init_variable(delta_weight_C3, 0.0, len_weight_C3_CNN);
05.     init_variable(delta_bias_C3, 0.0, len_bias_C3_CNN);
06.
07.     // propagate delta to previous layer
08.     for (int inc = 0; inc < num_map_S2_CNN; inc++) {
09.         for (int outc = 0; outc < num_map_C3_CNN; outc++) {
10.             if (!tbl[inc][outc]) continue;
11.
12.             int addr1 = get_index(0, 0, num_map_S2_CNN * outc + inc, width_kernel_conv_CNI
13.             int addr2 = get_index(0, 0, outc, width_image_C3_CNN, height_image_C3_CNN, num
14.             int addr3 = get_index(0, 0, inc, width_image_S2_CNN, height_image_S2_CNN, num
15.
16.             const double *pw = &weight_C3[0] + addr1;
17.             const double *pdelta_src = &delta_neuron_C3[0] + addr2;
18.             double* pdelta_dst = &delta_neuron_S2[0] + addr3;
19.
20.             for (int y = 0; y < height_image_C3_CNN; y++) {
21.                 for (int x = 0; x < width_image_C3_CNN; x++) {
22.                     const double* ppw = pw;
23.                     const double ppdelta_src = pdelta_src[y * width_image_C3_CNN + x];
24.                     double* ppdelta_dst = pdelta_dst + y * width_image_S2_CNN + x;
25.
26.                     for (int wy = 0; wy < height_kernel_conv_CNN; wy++) {
27.                         for (int wx = 0; wx < width_kernel_conv_CNN; wx++) {
28.                             ppdelta_dst[wy * width_image_S2_CNN + wx] += *ppw++ * ppdelta
29.                         }
30.                     }
31.                 }
32.             }
33.         }
34.     }
35.
36.     for (int i = 0; i < num_neuron_S2_CNN; i++) {
37.         delta_neuron_S2[i] *= activation_function_tanh_derivative(neuron_S2[i]);
38.     }
39.
40.     // accumulate dw
41.     for (int inc = 0; inc < num_map_S2_CNN; inc++) {
42.         for (int outc = 0; outc < num_map_C3_CNN; outc++) {
43.             if (!tbl[inc][outc]) continue;
44.
45.             for (int wy = 0; wy < height_kernel_conv_CNN; wy++) {
46.                 for (int wx = 0; wx < width_kernel_conv_CNN; wx++) {
47.                     int addr1 = get_index(wx, wy, inc, width_image_S2_CNN, height_image_S
48.                     int addr2 = get_index(0, 0, outc, width_image_C3_CNN, height_image_C3
49.                     int addr3 = get_index(wx, wy, num_map_S2_CNN * outc + inc, width_kern
50.
51.                     double dst = 0.0;
52.                     const double* prevo = &neuron_S2[0] + addr1;
53.                     const double* delta = &delta_neuron_C3[0] + addr2;
54.
55.                     for (int y = 0; y < height_image_C3_CNN; y++) {
56.                         dst += dot_product(prevo + y * width_image_S2_CNN, delta + y * wi
57.                     }
58.
59.                     delta_weight_C3[addr3] += dst;
60.                 }
61.             }
62.         }
63.     }
64.
65.     // accumulate db
66.     for (int outc = 0; outc < len_bias_C3_CNN; outc++) {
67.         int addr1 = get_index(0, 0, outc, width_image_C3_CNN, height_image_C3_CNN, num_ma
68.         const double* delta = &delta_neuron_C3[0] + ai
69.
70.         for (int y = 0; y < height_image_C3_CNN; y++) {
71.             for (int x = 0; x < width_image_C3_CNN; x++) {
72.                 delta_bias_C3[outc] += delta[y * width_image_C3_CNN + x];
73.             }
74.         }
75.     }
76.
77.     return true;
78. }

```

关闭

(6)、C1层：计算C1层神经元误差、S2层权值误差、S2层偏置误差；通过S2层权值乘以S2层神经元误差，求

和，结果再乘以C1层神经元的tanh激活函数的导数(即1-C1神经元的平方)，然后再乘以1/4，获得C1层每一个神经元误差；通过C1层神经元乘以S2神经元误差，求和，再乘以1/4，获得S2层权值误差；通过S2层神经元误差求和，来获得S4层偏置误差。

代码段如下：

```
[cpp]
01. bool CNN::Backward_C1()
02. {
03.     init_variable(delta_neuron_C1, 0.0, num_neuron_C1_CNN);
04.     init_variable(delta_weight_S2, 0.0, len_weight_S2_CNN);
05.     init_variable(delta_bias_S2, 0.0, len_bias_S2_CNN);
06.
07.     double scale_factor = 1.0 / (width_kernel_pooling_CNN * height_kernel_pooling_CNN);
08.
09.     assert(in2wo_C1.size() == num_neuron_C1_CNN);
10.     assert(weight2io_C1.size() == len_weight_S2_CNN);
11.     assert(bias2out_C1.size() == len_bias_S2_CNN);
12.
13.     for (int i = 0; i < num_neuron_C1_CNN; i++) {
14.         const wo_connections& connections = in2wo_C1[i];
15.         double delta = 0.0;
16.
17.         for (int j = 0; j < connections.size(); j++) {
18.             delta += weight_S2[connections[j].first] * delta_neuron_S2[connections[j].second];
19.         }
20.
21.         delta_neuron_C1[i] = delta * scale_factor * activation_function_tanh_derivative(neuron_C1[i]);
22.     }
23.
24.     for (int i = 0; i < len_weight_S2_CNN; i++) {
25.         const io_connections& connections = weight2io_C1[i];
26.         double diff = 0.0;
27.
28.         for (int j = 0; j < connections.size(); j++) {
29.             diff += neuron_C1[connections[j].first] * delta_neuron_S2[connections[j].second];
30.         }
31.
32.         delta_weight_S2[i] += diff * scale_factor;
33.     }
34.
35.     for (int i = 0; i < len_bias_S2_CNN; i++) {
36.         const std::vector<int>& outs = bias2out_C1[i];
37.         double diff = 0;
38.
39.         for (int o = 0; o < outs.size(); o++) {
40.             diff += delta_neuron_S2[outs[o]];
41.         }
42.
43.         delta_bias_S2[i] += diff;
44.     }
45.
46.     return true;
47. }
```

(7)、输入层：计算输入层神经元误差、C1层权值误差、C1层偏置误差；通过C1层权值乘以C1层神经元误差，求和，结果再乘以输入层神经元的tanh激活函数的导数(即1-输入层神经元的平方)，获得输入层每一个神经元误差；通过输入层神经元乘以C1层神经元误差，求和，获得C1层权值误差；C1层偏置误差即为C1层神经元误差和。

```
[cpp]
01. bool CNN::Backward_input()
02. {
03.     init_variable(delta_neuron_input, 0.0, num_neuron_input_CNN);
04.     init_variable(delta_weight_C1, 0.0, len_weight_C1_CNN);
05.     init_variable(delta_bias_C1, 0.0, len_bias_C1_CNN);
06.
07.     // propagate delta to previous layer
08.     for (int inc = 0; inc < num_map_input_CNN; inc++) {
09.         for (int outc = 0; outc < num_map_C1_CNN; outc++) {
10.             int addr1 = get_index(0, 0, num_map_input_CNN * outc + inc, width_kernel_conv);
11.             int addr2 = get_index(0, 0, outc, width_image_C1_CNN, height_image_C1_CNN, num_map_C1_CNN);
12.             int addr3 = get_index(0, 0, inc, width_image_input_CNN, height_image_input_CNN, num_map_input_CNN);
13.
14.             const double* pw = &weight_C1[0] + addr1;
```

关闭

```

15.         const double* pdelta_src = &delta_neuron_C1[0] + addr2;
16.         double* pdelta_dst = &delta_neuron_input[0] + addr3;
17.
18.         for (int y = 0; y < height_image_C1_CNN; y++) {
19.             for (int x = 0; x < width_image_C1_CNN; x++) {
20.                 const double* ppw = pw;
21.                 const double pdelta_src = pdelta_src[y * width_image_C1_CNN + x];
22.                 double* pdelta_dst = pdelta_dst + y * width_image_input_CNN + x;
23.
24.                 for (int wy = 0; wy < height_kernel_conv_CNN; wy++) {
25.                     for (int wx = 0; wx < width_kernel_conv_CNN; wx++) {
26.                         pdelta_dst[wy * width_image_input_CNN + wx] += *ppw++ * pde;
27.                     }
28.                 }
29.             }
30.         }
31.     }
32. }
33.
34. for (int i = 0; i < num_neuron_input_CNN; i++) {
35.     delta_neuron_input[i] *= activation_function_identity_derivative(data_single_image);
36. }
37.
38. // accumulate dw
39. for (int inc = 0; inc < num_map_input_CNN; inc++) {
40.     for (int outc = 0; outc < num_map_C1_CNN; outc++) {
41.         for (int wy = 0; wy < height_kernel_conv_CNN; wy++) {
42.             for (int wx = 0; wx < width_kernel_conv_CNN; wx++) {
43.                 int addr1 = get_index(wx, wy, inc, width_image_input_CNN, height_image_C1_CNN);
44.                 int addr2 = get_index(0, 0, outc, width_image_C1_CNN, height_image_C1_CNN);
45.                 int addr3 = get_index(wx, wy, num_map_input_CNN * outc + inc, width_image_C1_CNN, height_image_C1_CNN);
46.
47.                 double dst = 0.0;
48.                 const double* prevo = data_single_image + addr1; // &neuron_input[0]
49.                 const double* delta = &delta_neuron_C1[0] + addr2;
50.
51.                 for (int y = 0; y < height_image_C1_CNN; y++) {
52.                     dst += dot_product(prevo + y * width_image_input_CNN, delta + y * width_image_C1_CNN);
53.                 }
54.
55.                 delta_weight_C1[addr3] += dst;
56.             }
57.         }
58.     }
59. }
60.
61. // accumulate db
62. for (int outc = 0; outc < len_bias_C1_CNN; outc++) {
63.     int addr1 = get_index(0, 0, outc, width_image_C1_CNN, height_image_C1_CNN, num_map_C1_CNN);
64.     const double* delta = &delta_neuron_C1[0] + addr1;
65.
66.     for (int y = 0; y < height_image_C1_CNN; y++) {
67.         for (int x = 0; x < width_image_C1_CNN; x++) {
68.             delta_bias_C1[outc] += delta[y * width_image_C1_CNN + x];
69.         }
70.     }
71. }
72.
73. return true;
74. }

```

5. 更新各层权值、偏置：通过之前计算的各层权值、各层权值误差；各层偏置、各层偏置误差以及学习率来更新各层权值和偏置。

代码段如下：

关闭

```

[cpp]
1. void CNN::update_weights_bias(const double* delta, double* e_weight, double* weight, int len) {
2.     for (int i = 0; i < len; i++) {
3.         e_weight[i] += delta[i] * delta[i];
4.         weight[i] -= learning_rate_CNN * delta[i] / (std::sqrt(e_weight[i]) + eps_CNN);
5.     }
6. }
7.
8. bool CNN::UpdateWeights()
9. {
10.

```

```

11.         update_weights_bias(delta_weight_C1, E_weight_C1, weight_C1, len_weight_C1_CNN);
12.         update_weights_bias(delta_bias_C1, E_bias_C1, bias_C1, len_bias_C1_CNN);
13.
14.         update_weights_bias(delta_weight_S2, E_weight_S2, weight_S2, len_weight_S2_CNN);
15.         update_weights_bias(delta_bias_S2, E_bias_S2, bias_S2, len_bias_S2_CNN);
16.
17.         update_weights_bias(delta_weight_C3, E_weight_C3, weight_C3, len_weight_C3_CNN);
18.         update_weights_bias(delta_bias_C3, E_bias_C3, bias_C3, len_bias_C3_CNN);
19.
20.         update_weights_bias(delta_weight_S4, E_weight_S4, weight_S4, len_weight_S4_CNN);
21.         update_weights_bias(delta_bias_S4, E_bias_S4, bias_S4, len_bias_S4_CNN);
22.
23.         update_weights_bias(delta_weight_C5, E_weight_C5, weight_C5, len_weight_C5_CNN);
24.         update_weights_bias(delta_bias_C5, E_bias_C5, bias_C5, len_bias_C5_CNN);
25.
26.         update_weights_bias(delta_weight_output, E_weight_output, weight_output, len_weight_output_CNN);
27.         update_weights_bias(delta_bias_output, E_bias_output, bias_output, len_bias_output_CNN);
28.
29.         return true;
30.     }

```

6. 测试准确率是否达到要求或已达到循环次数：依次循环3至5中操作，根据训练集数量，每循环60000次时，通过计算的权值和偏置，来对10000个测试集进行测试，如果准确率达到0.985或者达到迭代次数时，保存权值和偏置。

代码段如下：

```

[cpp]
01. bool CNN::train()
02. {
03.     out2wi_S2.clear();
04.     out2bias_S2.clear();
05.     out2wi_S4.clear();
06.     out2bias_S4.clear();
07.     in2wo_C3.clear();
08.     weight2io_C3.clear();
09.     bias2out_C3.clear();
10.     in2wo_C1.clear();
11.     weight2io_C1.clear();
12.     bias2out_C1.clear();
13.
14.     calc_out2wi(width_image_C1_CNN, height_image_C1_CNN, width_image_S2_CNN, height_image_S2_CNN, num_map_S2_CNN, out2bias_S2);
15.     calc_out2wi(width_image_S2_CNN, height_image_S2_CNN, width_image_S4_CNN, height_image_S4_CNN, num_map_S4_CNN, out2bias_S4);
16.     calc_out2wi(width_image_C3_CNN, height_image_C3_CNN, width_image_S4_CNN, height_image_S4_CNN, num_map_S4_CNN, out2bias_S4);
17.     calc_out2bias(width_image_S4_CNN, height_image_S4_CNN, num_map_S4_CNN, out2bias_S4);
18.     calc_in2wo(width_image_C3_CNN, height_image_C3_CNN, width_image_S4_CNN, height_image_S4_CNN, num_map_S4_CNN, in2wo_C3);
19.     calc_weight2io(width_image_C3_CNN, height_image_C3_CNN, width_image_S4_CNN, height_image_S4_CNN, num_map_S4_CNN, weight2io_C3);
20.     calc_bias2out(width_image_C3_CNN, height_image_C3_CNN, width_image_S4_CNN, height_image_S4_CNN, num_map_S4_CNN, bias2out_C3);
21.     calc_in2wo(width_image_C1_CNN, height_image_C1_CNN, width_image_S2_CNN, height_image_S2_CNN, num_map_S2_CNN, in2wo_C1);
22.     calc_weight2io(width_image_C1_CNN, height_image_C1_CNN, width_image_S2_CNN, height_image_S2_CNN, num_map_S2_CNN, weight2io_C1);
23.     calc_bias2out(width_image_C1_CNN, height_image_C1_CNN, width_image_S2_CNN, height_image_S2_CNN, num_map_S2_CNN, bias2out_C1);
24.
25.     int iter = 0;
26.     for (iter = 0; iter < num_epochs_CNN; iter++) {
27.         std::cout << "epoch: " << iter + 1;
28.
29.         for (int i = 0; i < num_patterns_train_CNN; i++) {
30.             data_single_image = data_input_train + i * num_neuron_input_CNN;
31.             data_single_label = data_output_train + i * num_neuron_output_CNN;
32.
33.             Forward_C1();
34.             Forward_S2();
35.             Forward_C3();
36.             Forward_S4();
37.             Forward_C5();
38.             Forward_output();
39.
40.             Backward_output();
41.             Backward_C5();
42.             Backward_S4();
43.             Backward_C3();
44.             Backward_S2();
45.             Backward_C1();
46.             Backward_input();
47.
48.             UpdateWeights();
49.         }

```

关闭


```

50.
51.     double accuracyRate = test();
52.     std::cout << "    accuray rate: " << accuracyRate << std::endl;
53.     if (accuracyRate > accuracy_rate_CNN) {
54.         saveModelFile("E:/GitCode/NN_Test/data/cnn.model");
55.         std::cout << "generate cnn model" << std::endl;
56.         break;
57.     }
58. }
59.
60. if (iter == num_epochs_CNN) {
61.     saveModelFile("E:/GitCode/NN_Test/data/cnn.model");
62.     std::cout << "generate cnn model" << std::endl;
63. }
64.
65. return true;
66. }
67.
68. double CNN::test()
69. {
70.     int count_accuracy = 0;
71.
72.     for (int num = 0; num < num_patterns_test_CNN; num++) {
73.         data_single_image = data_input_test + num * num_neuron_input_CNN;
74.         data_single_label = data_output_test + num * num_neuron_output_CNN;
75.
76.         Forward_C1();
77.         Forward_S2();
78.         Forward_C3();
79.         Forward_S4();
80.         Forward_C5();
81.         Forward_output();
82.
83.         int pos_t = -1;
84.         int pos_y = -2;
85.         double max_value_t = -9999.0;
86.         double max_value_y = -9999.0;
87.
88.         for (int i = 0; i < num_neuron_output_CNN; i++) {
89.             if (neuron_output[i] > max_value_y) {
90.                 max_value_y = neuron_output[i];
91.                 pos_y = i;
92.             }
93.
94.             if (data_single_label[i] > max_value_t) {
95.                 max_value_t = data_single_label[i];
96.                 pos_t = i;
97.             }
98.         }
99.
100.        if (pos_y == pos_t) {
101.            ++count_accuracy;
102.        }
103.
104.        Sleep(1);
105.    }
106.
107.    return (count_accuracy * 1.0 / num_patterns_test_CNN);
108. }

```

7. 对输入的图像数据进行识别：载入已保存的权值和偏置，对输入的数据进行识别，过程相当于前向传播。

代码如下：

关闭

```

[cpp] C P
01. int CNN::predict(const unsigned char* data, int width, int height)
02. {
03.     assert(data && width == width_image_input_CNN && height == height_image_input_CNN);
04.
05.     const double scale_min = -1;
06.     const double scale_max = 1;
07.
08.     double tmp[width_image_input_CNN * height_image_input_CNN];
09.     for (int y = 0; y < height; y++) {
10.         for (int x = 0; x < width; x++) {
11.             tmp[y * width + x] = (data[y * width + x] / 255.0) * (scale_max - scale_min) *

```

```
12.         }
13.     }
14.
15.     data_single_image = &tmp[0];
16.
17.     Forward_C1();
18.     Forward_S2();
19.     Forward_C3();
20.     Forward_S4();
21.     Forward_C5();
22.     Forward_output();
23.
24.     int pos = -1;
25.     double max_value = -9999.0;
26.
27.     for (int i = 0; i < num_neuron_output_CNN; i++) {
28.         if (neuron_output[i] > max_value) {
29.             max_value = neuron_output[i];
30.             pos = i;
31.         }
32.     }
33.
34.     return pos;
35. }
```

GitHub : https://github.com/fengbingchun/NN_Test

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