In [1]:
```
import torch
import numpy as np
import torch.nn as nn
from torchvision import transforms, utils, datasets
import matplotlib.pyplot as plt


transform = transforms.Compose([
    transforms.ToTensor(),
    transforms.Normalize((0.1307,),(0.3081,)),  # mean value = 0.1307, standard deviation value = 0.3081
])

data_path = './MNIST'

train_data = datasets.MNIST(root = data_path, train= True, download=True, transform= transform)
test_data = datasets.MNIST(root = data_path, train= False, download=True, transform= transform)

device = torch.device("cuda:0" if torch.cuda.is_available() else "cpu")
print(device)
```

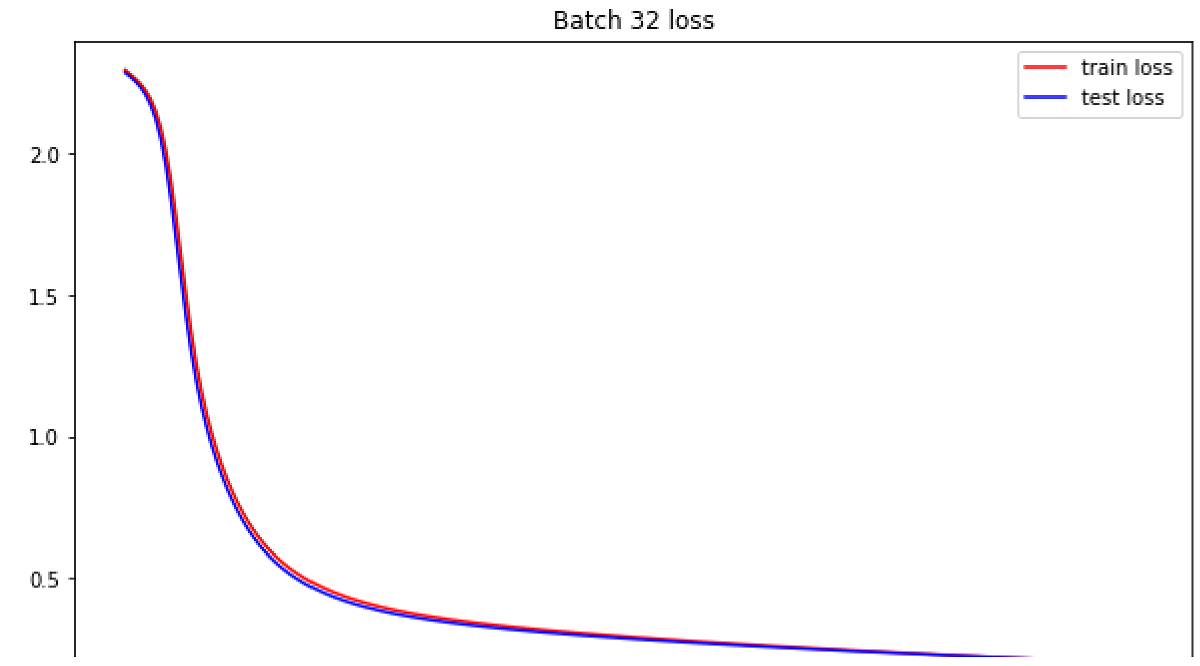
```
cuda:0
```

In [2]:
```
 class Classification(nn.Module):
    def __init__(self):
        super(Classification, self).__init__()

        # construct layers for a neural network
        self.classifier1 = nn.Sequential(
            nn.Linear(in_features=28*28, out_features=20*20),
            nn.Sigmoid(),
        )
        self.classifier2 = nn.Sequential(
            nn.Linear(in_features=20*20, out_features=10*10),
            nn.Sigmoid(),
        )
        self.classifier3 = nn.Sequential(
            nn.Linear(in_features=10*10, out_features=10),
            nn.LogSoftmax(dim=1),
        )


    def forward(self, inputs):                 # [batchSize, 1, 28, 28]
        x = inputs.view(inputs.size(0), -1)    # [batchSize, 28*28]
        x = self.classifier1(x)                # [batchSize, 20*20]
        x = self.classifier2(x)                # [batchSize, 10*10]
        out = self.classifier3(x)              # [batchSize, 10]

        return out
```

In [3]:
```
lr=0.001

criterion = nn.NLLLoss()
classification = Classification().to(device)
optimizer = torch.optim.SGD(classification.parameters(), lr=lr)
```

In [4]:
```
def run_epoch (train_data, test_data):

    tr_loss = 0
    tr_acc = 0
    iter = len(train_data)

    for img_i, label_i in train_data: #{
        img_i, label_i = img_i.to(device), label_i.to(device)

        optimizer.zero_grad()
        # Forward
        y_pred = classification.forward(img_i.view(-1, 28*28))
        ps = torch.exp(y_pred)
        correct = (label_i == ps.max(dim=1)[1])
        # Loss computation
        loss  = criterion(y_pred, label_i)
        # Backward
        loss.backward()
        # Optimize for img_i
        optimizer.step()
        tr_loss += loss.item()
        tr_acc += correct.type(torch.FloatTensor).mean()
    #}
    tr_loss /= iter
    tr_acc /= iter

    test_loss = 0
    test_acc = 0
    iter_test = len(test_data)

    for img_j, label_j in test_data:
        img_j, label_j = img_j.to(device), label_j.to(device)
        correct = 0
        with torch.autograd.no_grad():
            predicted = classification.forward(img_j.view(-1, 28*28))
            ps = torch.exp(predicted)
            correct = (label_j == ps.max(dim=1)[1])
            test_loss += criterion(predicted, label_j).item()
            test_acc += correct.type(torch.FloatTensor).mean()

    test_loss /= iter_test
    test_acc /= iter_test
    return tr_loss, tr_acc, test_loss, test_acc


final_train_loss = []
final_test_loss = []
final_train_acc = []
final_test_acc = []

def run(batch_size, epochs): #{
  lr=0.001
  global classification, optimizer, criterion
  criterion = nn.NLLLoss()
  classification = Classification().to(device)
  optimizer = torch.optim.SGD(classification.parameters(), lr=lr)

  global final_train_loss, final_test_loss, final_train_acc, final_test_acc
  train_data_loader = torch.utils.data.DataLoader(train_data, batch_size, shuffle=False)
  test_data_loader  = torch.utils.data.DataLoader(test_data, batch_size, shuffle=False)
  mini_batch_data, mini_batch_label  = next(iter(train_data_loader))

  train_loss = []
  test_loss = []
  train_acc = []
  test_acc = []

  for epoch in range(epochs): #{
    tr_loss, tr_acc, te_loss, te_acc = run_epoch(train_data_loader, test_data_loader)
    train_loss.append(tr_loss)
    train_acc.append(tr_acc)
    test_loss.append(te_loss)
    test_acc.append(te_acc)
  #}

  final_train_loss.append(train_loss[-1])
  final_test_loss.append(test_loss[-1])
  final_train_acc.append(train_acc[-1])
  final_test_acc.append(test_acc[-1])

  return train_loss, test_loss, train_acc, test_acc

#}

train_loss_32, test_loss_32, train_acc_32, test_acc_32 = run(32, 200)
train_loss_64, test_loss_64, train_acc_64, test_acc_64 = run(64, 300)
train_loss_128, test_loss_128, train_acc_128, test_acc_128 = run(128, 400)

# Plot image
plt.figure(0, figsize=(10,6))
plt.plot(train_loss_32, label='train loss', c='r')
plt.plot(test_loss_32, label='test loss', c='b')
plt.title(f'Batch 32 loss')
plt.legend()
plt.show()

plt.figure(1, figsize=(10,6))
plt.plot(train_acc_32, label='train accuracy', c='r')
plt.plot(test_acc_32, label='test accuracy', c='b')
plt.title(f'Batch 32 accuracy')
plt.legend()
plt.show()

plt.figure(2, figsize=(10,6))
plt.plot(train_loss_64, label='train loss', c='r')
plt.plot(test_loss_64, label='test loss', c='b')
plt.title(f'Batch 64 loss')
plt.legend()
plt.show()

plt.figure(3, figsize=(10,6))
plt.plot(train_acc_64, label='train accuracy', c='r')
plt.plot(test_acc_64, label='test accuracy', c='b')
plt.title(f'Batch 64 accuracy')
plt.legend()
plt.show()

plt.figure(4, figsize=(10,6))
plt.plot(train_loss_128, label='train loss', c='r')
plt.plot(test_loss_128, label='test loss', c='b')
plt.title(f'Batch 128 loss')
plt.legend()
plt.show()

plt.figure(5, figsize=(10,6))
plt.plot(train_acc_128, label='train accuracy', c='r')
```

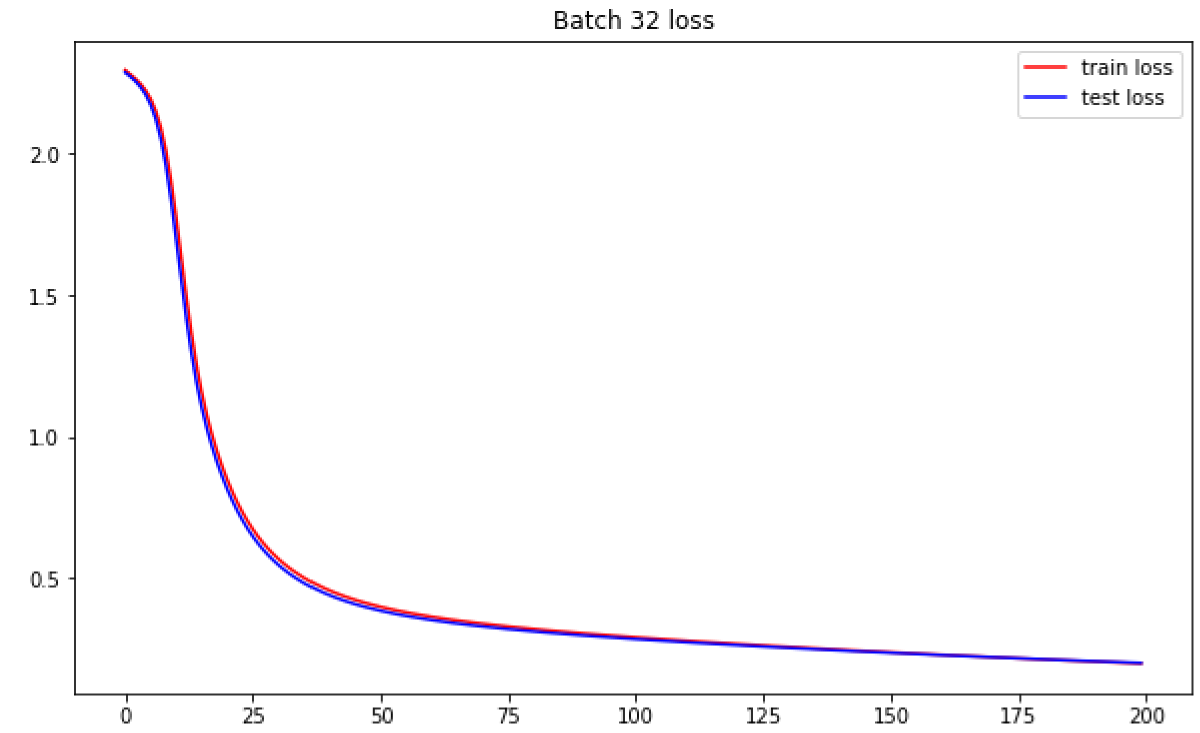
```
plt.plot(test_acc_128, label='test accuracy', c='b')
plt.title(f'Batch 128 accuracy')
plt.legend()
plt.show()


# Print final loss
print("mini batch size  32  64  128")
print(f"training loss   {final_train_loss[0]}   {final_train_loss[1]}  {final_train_loss[2]}")
print(f"testing loss     {final_test_loss[0]}  {final_test_loss[1]}  {final_test_loss[2]}")

print("mini batch size  32  64  128")
print(f"training acc   {final_train_acc[0]}   {final_train_acc[1]}  {final_train_acc[2]}")
print(f"testing acc     {final_test_acc[0]}  {final_test_acc[1]}  {final_test_acc[2]}")
```



Output using the dataset

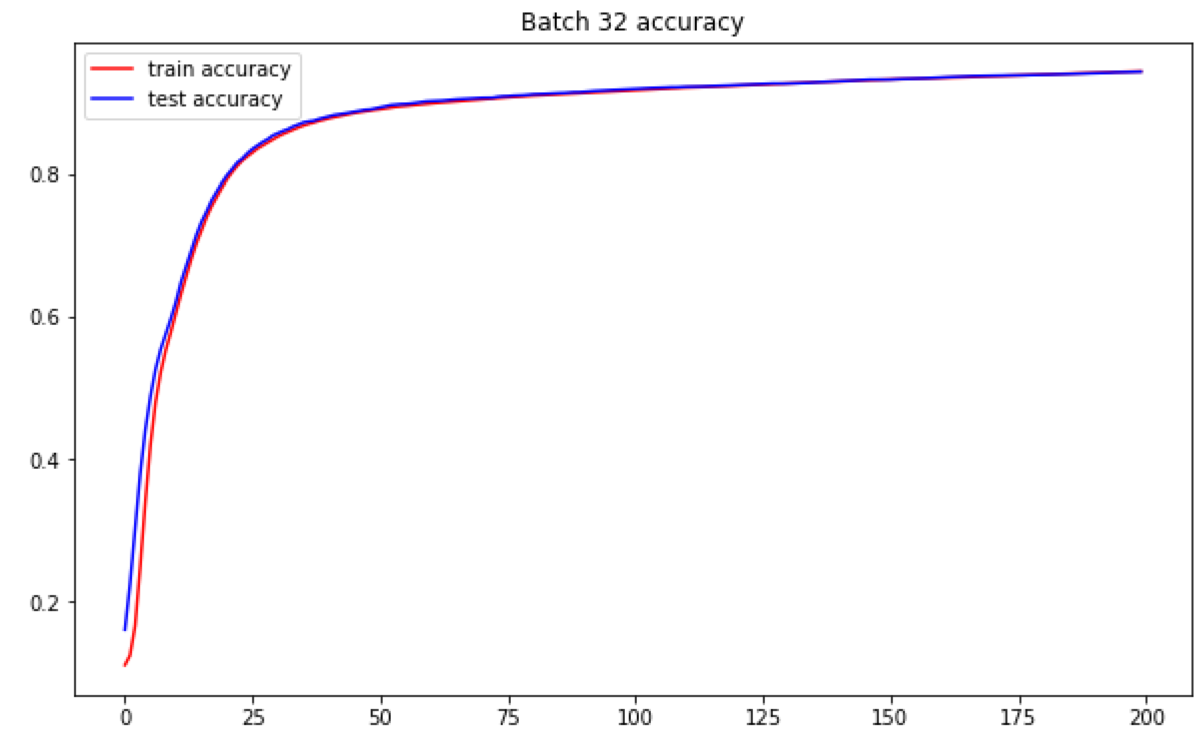
1. Plot the training and testing losses with a batch size of 32

In [5]:
```
plt.figure(0, figsize=(10,6))
plt.plot(train_loss_32, label='train loss', c='r')
plt.plot(test_loss_32, label='test loss', c='b')
plt.title(f'Batch 32 loss')
plt.legend()
plt.show()
```



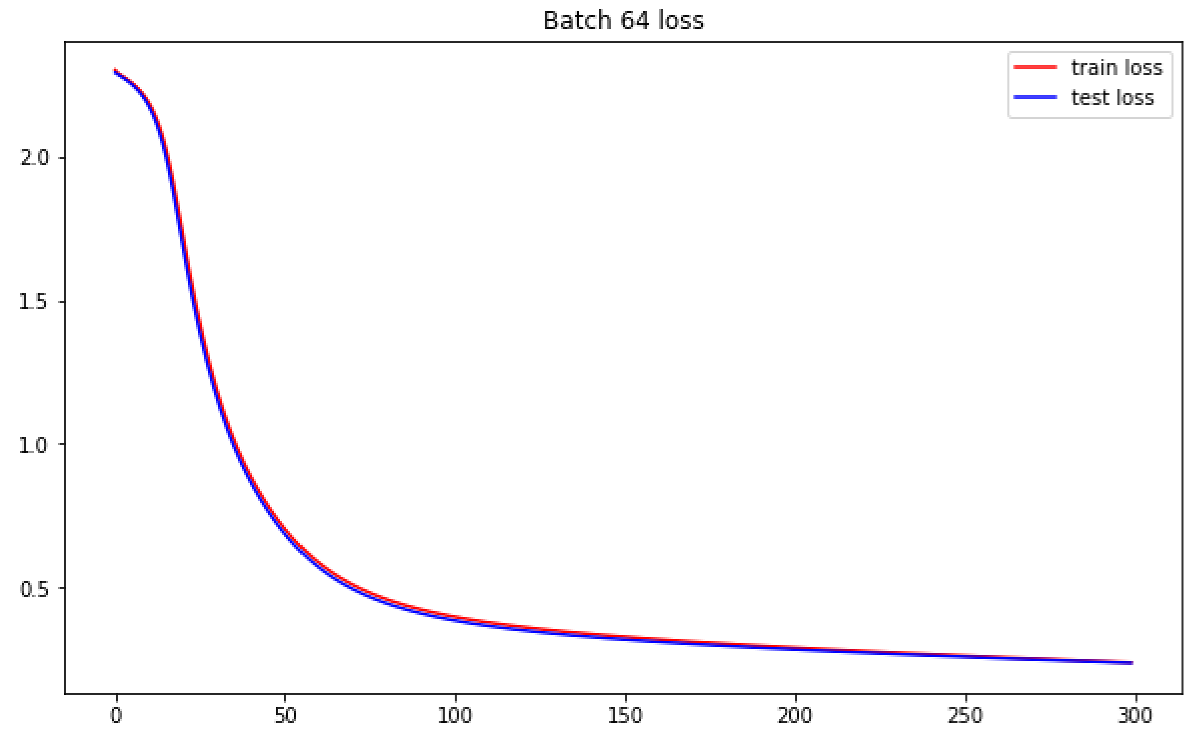
2. Plot the training and testing accuracies with a batch size of 32

In [6]:
```
plt.figure(1, figsize=(10,6))
plt.plot(train_acc_32, label='train accuracy', c='r')
plt.plot(test_acc_32, label='test accuracy', c='b')
plt.title(f'Batch 32 accuracy')
plt.legend()
plt.show()
```



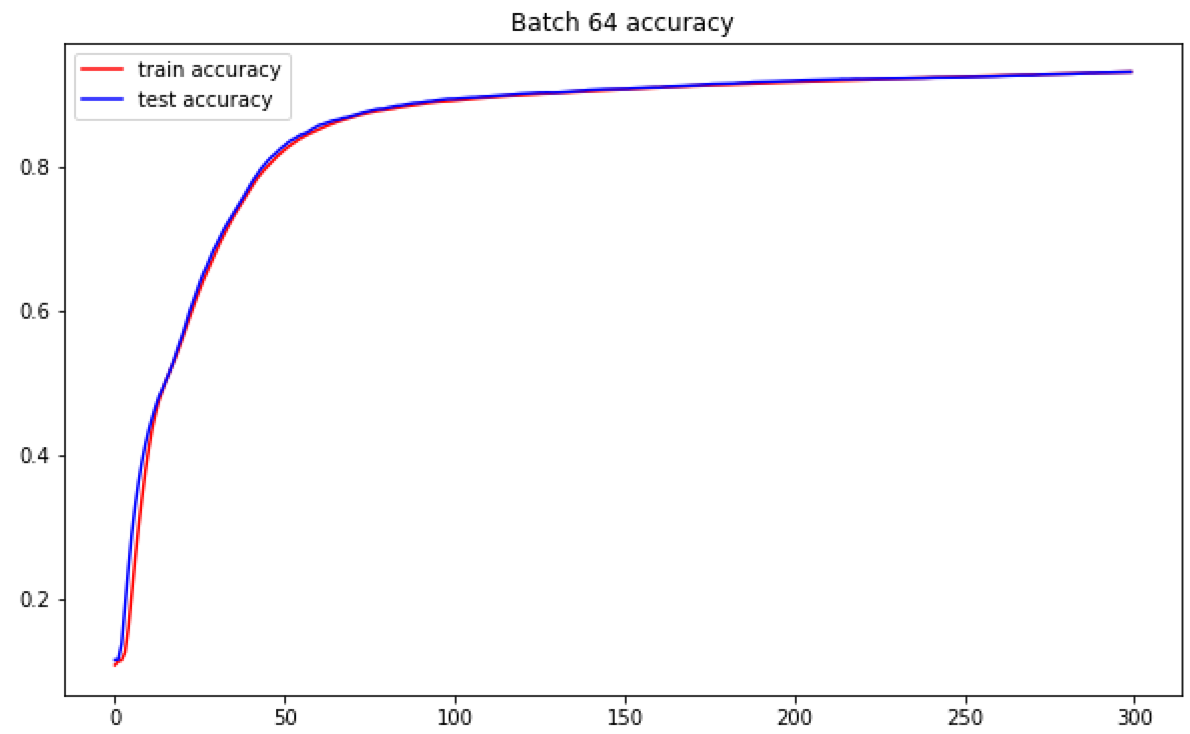
3. Plot the training and testing losses with a batch size of 64

In [7]:
```
plt.figure(2, figsize=(10,6))
plt.plot(train_loss_64, label='train loss', c='r')
plt.plot(test_loss_64, label='test loss', c='b')
plt.title(f'Batch 64 loss')
plt.legend()
plt.show()
```



4. Plot the training and testing accuracies with a batch size of 64

In [8]:
```
plt.figure(3, figsize=(10,6))
plt.plot(train_acc_64, label='train accuracy', c='r')
plt.plot(test_acc_64, label='test accuracy', c='b')
plt.title(f'Batch 64 accuracy')
plt.legend()
plt.show()
```

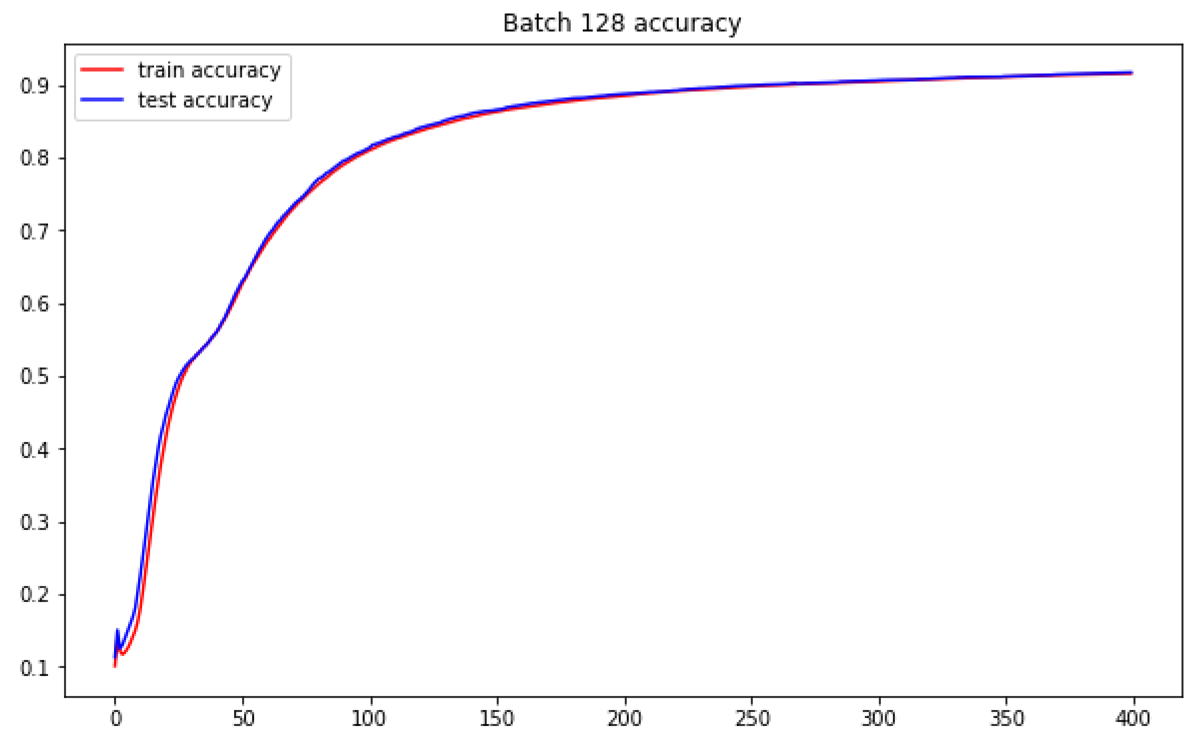


5. Plot the training and testing losses with a batch size of 128

In [9]:
```
plt.figure(4, figsize=(10,6))
plt.plot(train_loss_128, label='train loss', c='r')
plt.plot(test_loss_128, label='test loss', c='b')
plt.title(f'Batch 128 loss')
plt.legend()
plt.show()
```

6. Plot the training and testing accuracies with a batch size of 128

In [10]:
```
plt.figure(5, figsize=(10,6))
plt.plot(train_acc_128, label='train accuracy', c='r')
plt.plot(test_acc_128, label='test accuracy', c='b')
plt.title(f'Batch 128 accuracy')
plt.legend()
plt.show()
```



7. Print the loss at convergence with different mini-batch sizes

In [11]:
```
print("mini batch size  32                64               128")
print(f"training loss   {final_train_loss[0]}   {final_train_loss[1]}  {final_train_loss[2]}")
print(f"testing loss     {final_test_loss[0]}  {final_test_loss[1]}  {final_test_loss[2]}")
```

```
mini batch size  32                64               128
training loss   0.19790151994625726   0.23820224191262715  0.2947566736735769
testing loss     0.19945244435161447  0.2366508606014548  0.287505313282526
```

8. Print the accuracy at convergence with different mini-batch sizes

In [12]:
```
print("mini batch size  32                64               128")
print(f"training acc   {final_train_acc[0]}   {final_train_acc[1]}  {final_train_acc[2]}")
print(f"testing acc     {final_test_acc[0]}  {final_test_acc[1]}  {final_test_acc[2]}")
```

```
mini batch size  32                64               128
training acc   0.9431166648864746   0.9313366413116455  0.9156061410903931
testing acc     0.9426916837692261  0.931329607963562  0.9169303774833679
```