Theoretical algorithm for traffic decorrelation in Fog computing

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ПГУТИ

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Abstract

Given that the presence of correlations in traffic can have a significant impact on the values of service quality parameters, which must be taken into account in the design of services, especially services that are critically dependent on these parameters, the need to develop methods and algorithms for processing correlated traffic increases. This paper presents a theoretical method for decorrelation of network traffic for the purpose of reducing latency in the transmission and processing of video traffic in fog computing. An algorithm and implementation concept for implementing the decorrelation is also given. The method is based on the use of Haar wavelets.

Introduction

Currently, the cloud is virtually the only solution available for healthcare IoT connectivity [1]. However, the cloud has its own limitations with respect to medical IoT devices. Due to the increasing volumes of data being transmitted and processed, response times in cloud computing increasing. A critical requirement for IoT in healthcare is minimum latency [5].

In 2012, a solution to the problem of high latency and bandwidth consumption between IoTs and the cloud was proposed in the form of the concept of fog computing (FC) [6].

This study proposes a model to eliminate the correlation in the network traffic and consequently reduce the network delay.

In addition, various studies on video traffic classification are based on detectable correlation patterns and multifractals, which also indirectly indicate the presence of correlation in video traffic received by terminal devices [10, 11, 12].

So, two tasks follow from these facts:

1) Development of a technique to represent correlated traffic by a sequence of non-correlated random variables.

2) Development of device that decorrelate the traffic in real time at the output of the information source.

Analysis properties of traffic using discrete wavelet transform

Considered the wavelet transform for constructing non-correlated coordinates of traffic sequences.

The correlation properties of the sequence are characterized by the counts of the correlation coefficient according to the definition of self-similarity of the sequence properties, i.e., in the form:

$$R(k) = \frac{\sigma^2}{2}\left[(k+1)^{2H} - 2k^{2H} + (k-1)^{2H}\right], \ (1)$$

where H is the Hurst coefficient with values from the interval $0{,}5 < H < 1$.

The problem is to find a set of coefficients d and c_{ij}, $0 \le j \le 2^i - 1$, $i = 0, \ \dots, k-1$ for a given function $f = \{f_s\}$, $0 \le s \le 2^k - 1$. The wavelet coefficients are calculated using the formulas:

$$d = \int_0^1 f(x)dx = \frac{1}{2^k}\sum_{s=0}^{2^k-1} f_s, \ (2)$$

$$c_{ij} = \int_0^1 f(x)\psi_{ji}(x)dx = \frac{1}{2^k}\sum_{s=0}^{2^k-1} f_s\,\psi_{ji}(x), \ (3)$$

After this transformation, the statistical properties of the "equivalent" traffic are determined by the properties of the coefficients (3).

Let us expand the sum in expression (3) for a given k:

$$c_{ij} = \frac{1}{8}\left[f(0)\psi_{ji}(0) + f(1)\psi_{ji}\left(\frac{1}{8}\right) + \ \cdots \ + f(7)\psi_{ji}\left(\frac{7}{8}\right)\right], \ (4)$$

$$j = 0, \ \dots, \ 2^i - 1, \ \ i = 0, \ \dots, \ k-1$$

given that the function $f = \{f_s\}$, $0 \le s \le 2^k - 1$ has correlation properties defined by formula (1) it is easy to obtain:

$$E(c_{21} \cdot c_{22}) = \frac{\sigma^2}{16}[3R(2) - R(0) - R(4)] = -\,0{,}0036\sigma^2 << R(1),$$

where E is an averaging symbol.

The obtained expression means that the neighboring coefficients *c21* and *c22* can be considered as non-correlated if the correlation of neighboring samples of the original traffic function is significant.

Further, it is easy to obtain $c_{23} = \frac{1}{4}\left[f\left(\frac{6}{8}\right) - f\left(\frac{7}{8}\right)\right]$, and:

$$E(c_{21} \cdot c_{23}) = \frac{\sigma^2}{16}[2R(3) - R(2) - R(5)] = 0{,}00019\sigma^2 << R(2).$$

The last result suggests coefficients c_{ij}, which are two positions apart, are also practically uncorrelated.

Methods decorrelation

The paper considers decorrelation methods based on the Karhunen-Loev decomposition, discrete cosine transform, wavelet transform.

The disadvantage of first method is a very large number of operations, which must be performed by the computing device. Implementation of such volume of calculations for traffic decorrelation can lead to unacceptably high delay of transaction units in a computing device, which will lead to loss of communication network capacity.

The computational complexity of secondmethod is also quite high, which makes it difficult to perform calculations in real time without a significant delay of the transaction unit block in the memory of the calculator.

The proposed variant of decorrelation of time interval sequences between transaction units is aimed to decrease the computational complexity of the decorrelation process by applying a wavelet transform instead of the known methods such as Karhunen-Loeve transform or discrete-cosine transform.

Wavelet-based decorrelation

The implementation of this algorithm in practice is carried out with the device shown in Fig. 1.

Through the input switch 1 transaction units from the network come to the free decorrelation block 8. The number of block is sending to the output switch 7. In the decorrelation block 8 transaction units enter register 3 until completely filling it. The sniffer 2 measures the time intervals between incoming transaction units and writes these values to a register 4 of the decorrelation block 8.

After filling register 3 with transaction units processor 5 changing the input switch 1 to another free decorrelation unit 8.

The number of block is sending to the output switch 7.

In the new decorrelation block 8 the processor 5 calculates the values of the decorrelated time intervals between transaction units, which are recorded in register 6, using a wavelet transform. After calculating the decorrelated time intervals between transaction units the processor 5 turns on the output switch 7 giving to the network transaction units from register 3 intervals stored in register 6.

Similar processes continue in another free decorrelation blocks 8.

Determine the correlation properties of the coefficients of c_{ij}, $0 \le j \le 2^i - 1$, $i = 0, \ \dots, k-1$.

Let us expand the sum in expression (3) for a given k, and use expression (4):

$$c_{ij} = \frac{1}{8}\left[f(0)\psi_{ji}(0) + f(1)\psi_{ji}(\frac{1}{8}) + \ \cdots \ + f(7)\psi_{ji}(\frac{7}{8})\right]$$

where$j = 0, \ \dots, \ 2^i - 1, \ \ i = 0, \ \dots, \ k-1.$

Let us define, for example, the correlation of c_{10} andc_{20},, c_{10}andc_{11}.

$$R_{c_{10},c_{20}} = E(c_{10} \cdot c_{20}) = \frac{1}{8\sqrt{2}}E(f_0^2 - f_0 f_1 + f_0 f_1 - f_1^2 - f_0 f_2 + f_1 f_2 - f_0 f_3 + f_1 f_3)$$

Since $E(f_k f_{k+m}) = R(m)$, using the values of the correlation coefficients of the self-similar sequence considered above, we finally obtain $R_{c_{10},c_{20}} = 0{,}015\sigma^2$.

Doing the same for $R_{c_{10},c_{11}}$ we can get $R_{c_{10},c_{11}} = -\,0{,}029\sigma^2$.

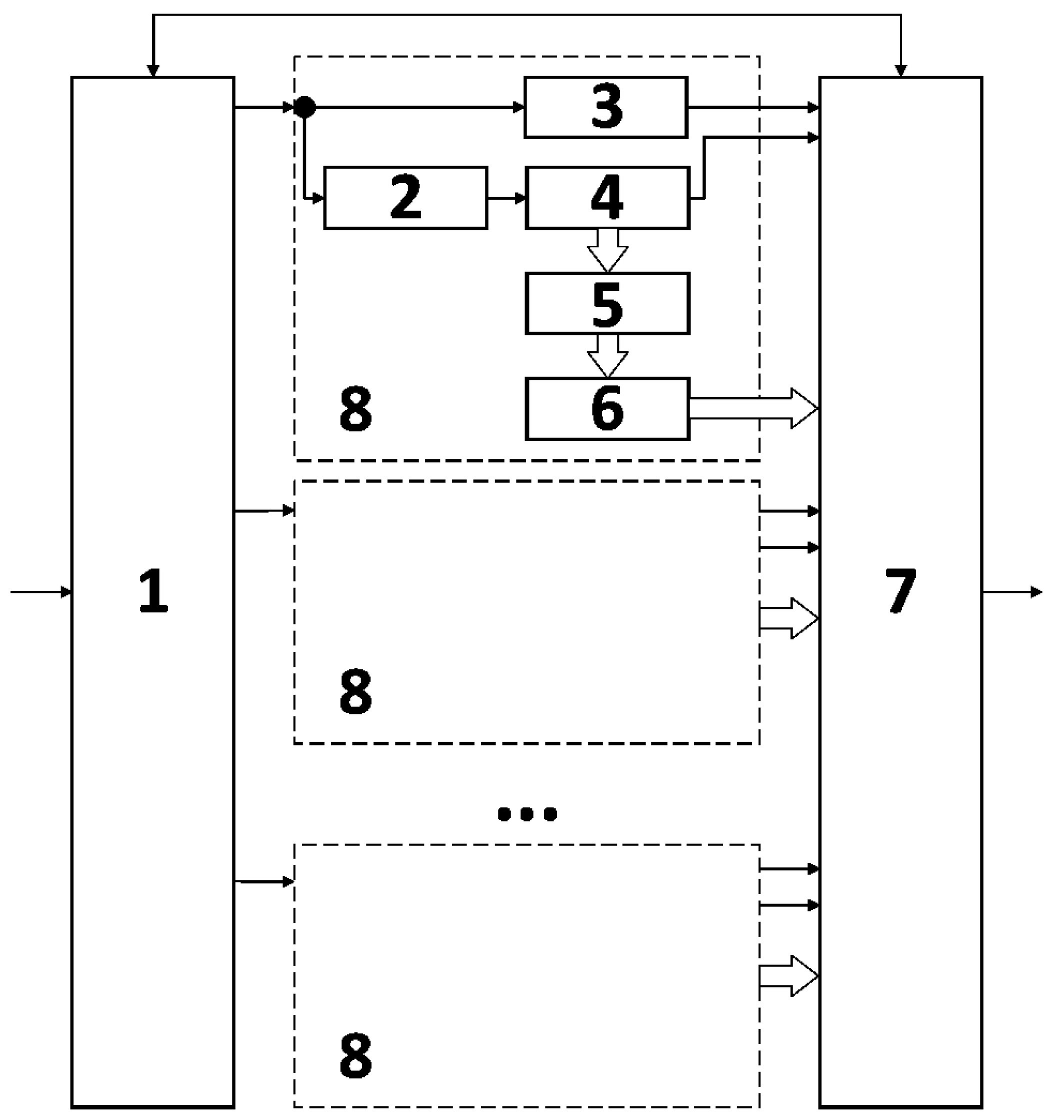

Figure 1. Decorrellating device: 1 - input switch, 2 - time interval measuring device (sniffer), 3 - register 1, 4 - register 2, 5 - processor, 6 - register 3, 7 - output switch, 8 - decorrelation block

Results

Analyzing the residual correlation of new time intervals between transaction units and comparing it with the original one, we can say that such a small residual correlation in practice will not affect the quality characteristics of transaction unit flow processing in any network device. Moreover, the analysis shows that with increasing the parameter k of this wavelet transform (i.e., in practice, with a multiple increase in the used registers), the correlation of new time intervals decreases even more.

Thus, analysis confirms the effectiveness of the considered method of traffic decorrelation.

Conclusions

A real-time, orthogonal-transform-based method for decorrelation of a sequence of correlated time intervals was developed, using Haar wavelets to reduce the time cost. This is especially important for time-critical services like IoT healthcare. This paper shows that a device that performs interval sequence decorrelation can be implemented based on the use of Karhunen-Loeve transform, discrete-cosine transform, wavelet transform. It is also shown that it is reasonable to implement decorrelation of the sequence of time intervals between applications to save computational resource using the Haar wavelet transform which is critical for fog computing.

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