# Classification of the Type of Finger Using a Touch interfaces 

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#### Abstract

Nowadays, touch interface has become popular.It features an easy-to-use intuitive user interface, however touching using different finger is treated as the same touch. Touch interface's having a few amount of input element is one of operability issues. In this study, our method which classifies kinds of fingers touching the touch interface using information on the touch screen and values from an acceleration sensor. This study enables touch interface to increase the amount of input element. In addition, we expect to use identification the ind ividual, operation without viewing the touch screen. We conducted experiments to collect operation logs for each finger by 19 participants. As a result, we confirmed that our method showed classification rate $69.8 \backslash \%$ of the kinds of fingers operating swipe up. In this paper, we describe consideration about the result, and the relation between existing a purpose during operation and classification rate,.


Keywords: machine learning,interface,classifier

## 1. INTRODUCTION

Smartphone which has a high computing power and highspeed communications technology, and high sensitivity rapidly sensor, expand to the masses. Smartphone is equipped with the OS of the general-purpose type. Therefor Smartphone has characteristic in that user who has advanced technique not only they who don't have is possible to add wide variety of application later. Because smartphone rapidly expand around the world in furtherance of many applications, further spread smartphone is expected in the future, for example, game used advanced technique in mobile portable device and social networking service that can easily communicate. The most significant feature in smartphone is touch screen which enables operation by touching the screen with a finger. Touch screen enables intuitive operation as compared with the conventional input device. Touch interfaces which rapidly expand by the towing of smartphone and excellent operability is terminal that is equipped with a touch screen.

Touch interfaces do not have many kinds of input
elements because it has missing in the number of input elements than conventional input devices. For example, general mouse has a left-click to make a decision and a rightclick to view the options menu, a wheel to scroll the page we're viewing to the up, down, left and right. Besides, input element of mouse can be increased by adding a button or wheel, so it can be said that the information that can be entered with a single mouse is a great deal. On the other hand, it can be said that input element of touch interface is only two value that between "Finger touches the screen," and "Finger away from the screen." Shortage of the number of input elements in touch interfaces is feared to force an extra operation to the user and to lead to adverse effects, such as stress increase. As a countermeasure against, there are "multi-touch" recognizing a plurality of finger touching the screen or "pressure-sensitivetouch" sensing a pressure applied finger touching the screen in pressure-sensitive sensor mounted on Liquid crystal display.
In this study, we focus on the type of the finger. We identify a finger touching the screen from 10 fingers in both hand. We will consider the possibility of solving this problem by adding
the difference of the finger as one of the input element of touch interfaces from perspective that is different from the traditional one.

## 2. HEADING

We investigated the studies that identifies the type of the finger, including the studies that attempted to identify using means other than the touch interfaces. In study which attempts to identify the type of the finger using the image processing, and the identification of the type of the finger by determining the angle of each finger from the central axis of the hand. However, they were not able to confirm the accuracy. In study which identifies the type of the finger by photographing a color markers painted on each finger by table top of the camera, because in special circumstances equipment is aligned, and the user must paint to their all fingers, it was suggested that such a large burden on the user. However, by showing an example of an application that assumes actual use, they showed the potential and future possibilities of interaction techniques for the touch interfaces to be used as an input the difference between the fingers.

Moreover, in study which recognize the hand shape by using an infrared camera as a security input device, they successfully identified the type of the finger in approximately $90 \%$ by identifying the closing distance and thickness of the finger as a parameter. Further, devices that can operate by hand gestures called Leap Motion Controller are available from Leap Motion Inc., as those using an infrared camera. It can be determined the position of the hand or finger in 3D space, the type of the finger by shooting 2 groups of the hands and fingers that were illuminated by the infrared LED light in the infrared camera.
As a result of investigation of related research, it was found that it is high identification of the type of finger accuracy by using an infrared finger.

## 3. THE PURPOSE AND EFFECTIVENESS

In this study, we aimed to identify the type of the finger on the touch interface without requiring special equipment. Therefore, it is considered to have novelty in that user does not require special equipment compared to the related research. Also, because the touch interface is a versatile terminal, it can be said that identifying the type of the finger using only the touch interface is superior in terms of versatility. Against a problem in that multi touch operation is not comfortable in the small touch screen, it can be said that can be solved by the identification of the type of finger. This study does not exist studies similar in the past. As mentioned in two chapters, studies of identifying each finger of the types of fingers by founding differences in the characteristics of the motion from the information obtained from the touch interface. In this study,
we propose a method never before to identify the type of the finger touching the screen using only the touch interface, through the experiment, how accurately you can identify the type of the finger, also how much of the kind clarify whether can be identified or the like.

There are three effectiveness by adding a kind of finger as the input information. The first one is the improvement of convenience due to the assignment of function to each finger. The finger that does not usually used in the operation of the interface, it is possible to perform an immediate operation by assigning time-consuming operation processes. It is possible to perform an immediate operation by assigning time-consuming operation. to the finger that does not usually used in the operation of the interface. For example, it is possible to perform immediately operations that require multiple process, such as that user will place a immediate call to frequently used to taxi company by touching with non-dominant hand of the little finger on the touch interface, and user will adjust the illuminance of the touch screen by moving up and down on the touch screen in the dominant hand ring finger. The second is perfuming the operation without viewing the display. The assignment of functions to each finger as described above, it is possible to perform the operation by touching the touch screen without viewing the display. For example, even in a state which the device is in bag or pocket or when user driving, it is possible to perform an operation without viewing the display when the simple operation. The third is a personal authentication. If there are individual differences in the characteristics of each finger, it can also be applied as a method of a new personal authentication.

## 4.PROPOSED METHOD

In this study identifies the kind of finger to machin e learning the information that can be obtained fro m the touch interface learning

### 4.1 OPERATIONS TO TARGET

Operation identifying the kind of finger is directed to the three types described below except for the multi-touch touching with a plurality of fingers.

1) Tap (Touching the screen with your finger, an d releasing immediately)
2) Swipe up (Touching the screen, and releasing a fter finger move on a few centimeters)
3) Swipe down (Touching the screen, and releasin g after finger move down a few centimeters)
We have selected these operations the typical operat ions in manipulating touch interface seems relativel y familiar, for the unfamiliar subject to the use of the machine
using data mining tool Weka [2] with the data set of the feature quantity and identify the type of the

| $\begin{array}{\|c} \hline \text { Inde } \\ \mathrm{x} \\ \hline \end{array}$ | Feature Quantity | Sensor | Method of Calculation | Dimension |
| :---: | :---: | :---: | :---: | :---: |
| (1) | Distance[point] | Touch screen | Distance between the start point and the end point | 1 |
| (2) | Time[s] | " | The time difference between the start and en d | 1 |
| (3) | Speed[point/s] | " | Divide the distance by the time | 1 |
| (4) | Angle[radian] | " | The angle of the horizontal axis and the end point | 1 |
| (5) | Acceleration(average)[mG] | acceleration sensor | HPF processing, average | 3(x,y,z,axis) |
| (6) | " (standard deviation)[mG] | " | HPF processing, standard deviation | 3(x,y,z,axis) |
| (7) | Gravity (average)[mG] | " | LPF processing, average | $3(\mathrm{x}, \mathrm{y}, \mathrm{z}, \mathrm{xis}$ ) |
| (8) | " (standard deviation)[mG] | " | LPF processing, standard deviation | 3(x,y,z,axis) |
| (9) | Angular velocity (average)[mG] | Gyroscope | Average | 3(x,y,z, axis) |
| (10) | " (standard deviation)[mG] | " | Standard deviation | 3(x,y,z,axis) |
| (11) | Pressure value (average) | pressure sensor | Average | 1 |
| (12) | " (standard deviation) | " | Standard deviation | 1 |
| (13) | Touch coordinates(covariance) | Touch screen | Covariance | 1 |
| (14) | " (correlation function) | " | Correlation function | 1 |
| (15) | p-type Fourier descriptor | " | Amplitude spectrum | 31 |

Table 1 Feature quantities and these information

### 4.2 TOUCH INTERFACE TO TARGET

Touch interfaces present study is intended equipped with touch screen which is capacitive system for de tecting the position of the finger on the screen touc hed, and with the three-axis acceleration sensor, a gyroscope, pressure sensor. Using these sensors, we get dimensional touch coordinates and the time, acc eleration values (ternary), gravity component acceler ation values (ternary), the angular velocity values ( t ernary), the pressure value

### 4.3 OPERATIONS TO TARGET

We shows Table 1 on the next page, which summa rize feature quantities (1) to (15) obtained from the values of the sensors on the touch interface and $t$ he sensors used to determine the respective feature quantity, the calculation methods, the dimension of the feature quantity. We perform machine learning
finger.

### 4.4 COVARIANCE,CORRELATION FUNCTION, P-TYPE FOURIER DESCRIPTOR

We replace the data of swipe up and swipe down $t$ $\mathrm{o} i$ of sets of bivariate ( $\mathrm{Xi}, \mathrm{Yi}$ ) obtained from appro ximate curve by least-square method. And we repla ce the average value of $X$ and $Y$ to $X$ and $Y$. Feat ure quantities (13) to (15) is obtained from mathem atical formula (1) to (4). Feature quantities (13) an d (15) are covariance and correlation function that represent the relationship of the points in the curve.
Covariance Sxy is obtained from mathematical for mula (1), and correlation function is obtained from mathematical formula (2). Feature quantities(15), p-t ype fourier descriptor is a way to express an overv iew of the curve by describe a curve on the plane in the frequency domain. We show a formula to det ermine the p -type fourier descriptor below. Appro ximate curve is approximated to a polygonal line fi
gure. X axis and Y axis is captured to the real axi $s$ and to the imaginary axis in the complex plane, and a polygonal line represent $i$ of complex Zi . Tot al curvature function is defines by using the angle of the two vectors on a polygonal line. Equation 3 is a complex number of substitutions Wi by using total curvature function. This curve is referred to as $p$ representation. Complex function performed this p representation at discrete fourier-transform is equa tion 4. It is called p-type Fourier descriptor. Numbe $r$ of terms was set to 31 as the optimal number $o$ f software to work comfortable at the time of the experiment. We calculated the amount of the amplit ude spectrum of the p-type fourier descriptor and $h$ ave set it in the feature. ak and bk in equ ation is a real term coefficient and an ima ginary term coefficient of p-type fourier de scriptor.

$$
\begin{gather*}
S_{x y}=\frac{1}{n} \sum_{i=1}\left(X_{i}-\bar{X}\right)\left(Y_{i}-\bar{Y}\right)  \tag{2}\\
R_{x y}=\frac{\frac{1}{n} \sum_{i=1}^{n}\left(X_{i}-\bar{X}\right)\left(Y_{i}-\bar{Y}\right)}{\sqrt{\frac{1}{n} \sum_{i=1}^{n}\left(X_{i}-\bar{X}\right)^{2}} \sqrt{\frac{1}{n} \sum_{i=1}^{n}\left(Y_{i}-\bar{Y}\right)^{2}}}  \tag{3}\\
W_{i}=e^{j \theta_{i}}=\frac{Z_{i+1}-Z_{i}}{\left|Z_{i+1}-Z_{i}\right|}  \tag{4}\\
C_{k}=\frac{\bar{N}}{N} \sum_{i=1} W_{i} e^{\prime}  \tag{5}\\
p_{k}=\sqrt{\left(a_{k}^{2}+b_{k}^{2}\right)}
\end{gather*}
$$

### 4.5 IDENTIFICATION BYMACHINE LEARNING

We carry out a machine learning based on a feature quantity in Chapter 4.4 with data mining tool Weka[3], and identify 10 kinds of finger to each operation. In this study, we distinguish between a feature quantity to be used for each operation because there is a bias in the amount of information obtained for each operation. It has determined that there is no meaning to use covariance, and correlation function, p-type fourier descriptor as feature quantities because tap has the only coordinate information. Therefor, feature quantities of tap is (1) $\sim(12)$ in the table. Feature quantities of swipe up and swipe down are $(1) \sim(15)$ in the table because they have variety of coordinate information. Data on the identification is obtained
by experiment described in Chapter 5.

## 5. EXPERIMENT

In this capture, we describe the experiment to get t he touch interfaces of the operation data. The reaso n is to investigate the possibility of identification o $f$ the type of finger by using feature quantity descri bed in Chapter 4.

### 5.1 EXPERIMENT ENVIRONMENT

The experiment was target healthy college students 19 people (man: 15 people, woman: 4 people) in $t$ heir 19s who consent to participate with an underst anding of the spirit of the present experiment. Abo ut level of experience touch interface of the subject s, 17 subjects have and routinely used smartphone for more than three years, and 2 subjects don't hav e touch interface and have a little experience using it. Before starting the experiment, we instructed to sit in a chair and to have device to the subjects. We did not limit special attitude to them for reason to enhance the versatility of the study. In this exp eriment target of touch interface is smartphone. The smartphone that subject used in this experiment ar e all the same. The smartphone was installed applic ation for the experiment. The smartphone for the e xperiment was Apple's "iPhone 6S 16GB".

### 5.2 CONTENTS OF EACH SECTION

The experiment was carried out over the three secti ons while recording operation $\log$ for making datas et. The main flow of the experiment was the order that instructions on the finger to use and first secti on and second section and third section. During thi s series of flow, subject must operate smartphone with a indicated finger. When the subject perform s ame experiment in all of the finger, the experiment ends. The flow of indicated fingers are the order th at right thumb and right index finger and right mid dle finger and right ring finger and right little fing er and left thumb and left index finger and left mi ddle finger and left ring finger and left little finger. *First section
This section "Operating basic section" is that subjec $t$ perform tap and swipe up, swipe down in accor dance with the image to be displayed on the rando m order and the random position in display. From Figure 1 to Figure 3 shows the screen of the devic $e$ as an example of first section. The number of op erations with a finger is four per type of operation.

Before starting first section, the tutorial of the exp eriment is displayed. Then subjects is able to practi ce until they can understand the flow and the conte nt of the experimental. Thanks to this tutorial, subj ects who do not have usually a smart phone were able to also smoothly experiment. After finishing o perate four times tap and swipe up and swipe dow n with an indicated finger, first section screen is s witched to the second section screen.
*Second section
This section "Reading sentence section" is that subj ect read long sentence. Subjects can proceed to rea d the statement by scrolling the screen to the top. In Figure 4 shows the screen of the device as an e xample of second section. In order to encourage to read the sentence, we instructed the subject to ans wer the question to determine the contents after rea ding the sentence. The subjects read the sentence b y scrolling the sentence to the top with an indicate d finger, and they answer the question to determine the contents after reading. After that, second sectio n screen is switched to the third section screen. *Third section
This section "Browsing web section" is that subject research find out answer for the question on the int ernet. In Figure 5 shows the screen of the device a $s$ an example of third section. We record tap to ac cess web page, and swipe up and down to scroll web page. we do not record to operate of input ch aracter. After finding out answer for the question in dicated on the internet, subjects input it on next sc reen. After that, third section screen is switched to the first screen., and next finger is instructed on th e screen. The subject repeat the experiment of first section to third section with all finger. After that, s creen finishing experiment is displayed on the scree n , and experiment finish.


Figure 1 Swipe up


Figure2 Swipe down


Figure3 Tap


Figure5 Web Browsing

### 5.3 ASSOCIATION WITH TARGET

The subjects perform these three section of the exp eriment with all fingers. The main goal of this exp eriment is the acquisition data of operation with all fingers but, another goal is two types of data that between "operation with a purpose" and "operation with no purpose". In the first section, the subject $p$ erforms the instructed operation with no purpose acc ording to the image to be displayed on the screen. But in the second screen and third screen, the subj ects tap the button in the screen and scroll the scre en to the top and down, with a purpose to read se ntence and to take a next action. We analyze recog nition type of the finger in every three operation of the experiment in next capture. We also consider i nfluence whether with or without purpose of subjec
ts.

## 6. RESULT AND CONSIDERATIO 6.1 EVALUATION METHOD

We created a data set of feature quantities calculate d data obtained in experiment. We perform machine learning by data mining tool "Weka" for recognitio $n$ type of the fingers. Discriminator is Random For est[1] because it has ability of learning and identifi cation of high-speed and potential to estimate the i mportance of the explanatory variables for the obje ctive variable. Random Forest is the ensemble learn ing algorithm to build a multi-class classifier havin $g$ a plurality of determiner structure. Also it created learning a lot of the decision tree, and takes a vo te to correct answer that each of the decision tree was calculated, and identifies by classifying the cla ss has many vote. Evaluation method for data of al 1 subjects is 10 -fold cross-validation ( 10 fold-CV) an d Leave-One-Subject-Out-cross-validation(LOSO-C). Another for data of each subject is 10 fold-CV. 10 fold CV is evaluation method that takes the averag e of 10 times the estimated results. The method de als with the sample dividing into 10 as 9 learning data and 1 evaluation data. On the other hand, LO $\mathrm{SO}-\mathrm{CV}$ is evaluation method that repeats the estima tion for all cases to become the target of a evaluat ion as learning data of other subjects and evaluati on data of one subject. Evaluation index is F-meas ure. It is calculated by Equation 6 with precision $t$ hat indicates include how much correct answer in t he search results and recall that indicates how muc $h$ search results in the correct answer.

### 6.2 EVALUATION RESULT

Table 2 is the F-measures of 10 fold-CV and LOS O-CV against data of all subjects, 10 fold-CV agai nst data of each subject. Kind of the F-measures is tap and swipe up and swipe down. Table from 3 to 5 are three cross table of tap and swipe up and swipe down on LOSO-CV against data of each sub ject. In table2, identification result shows the most high identification accuracy swipe up for all of the evaluation method. It seems that there may be vali dity of the identification of the kind of finger in th e frequently operation because it is the operation to scroll the page by the upper swipe is most often done with a touch interface. Its examples are that t he contents can not be displayed is displayed under the screen in the web page, and contents posted i $n$ the past on SNS is displayed under the screen. It
is higher identification accuracy against data of ea ch subject than data of all subjects. Therefore by a cquiring the operation data for each finger to the $u$ ser previously, it is expected that can provide a hig $h$ identification accuracy system. Further, it can be said that identification fingers either of the right or left are generally successful from the results of the cross table from 3 to 5 . However, it can be seen $t$ hat there is misidentification finger to close fingers as finger s next. In addition, since the identification of the same type of finger to the left and right, Rather than the feature is the difference in the five types of thumb, index finger, middle finger, ring fi nger, little finger, it can also be seen that the featu res is the difference in the 10 types of the right th umb, right index finger, right middle finger, right ri ng finger, right little finger, left thumb, left index $f$ inger, left middle finger, left ring finger, left little f inger.

Table 2 F-measure of each evaluation method

|  | 10fold-CV | LOSO-CV | Each-sbject |
| :--- | :---: | :---: | :---: |
| Swipe up | 0.709 | 0.698 | 0.828 |
| Swipe down | 0.475 | 0.431 | 0.629 |
| Tap | 0.568 | 0.529 | 0.636 |

Table 3 Cross table of swipe up

| a | b | C | d | e | f | g | h | i | j |  |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| 758 | 31 | 13 | 11 | 6 | 3 | 1 | 3 | 0 | 1 | a |
| 83 | 409 | 72 | 45 | 12 | 2 | 1 | 2 | 0 | 0 | b |
| 41 | 61 | 491 | 97 | 29 | 5 | 4 | 3 | 0 | 1 | c |
| 26 | 45 | 90 | 618 | 38 | 1 | 1 | 2 | 1 | 1 | d |
| 6 | 28 | 41 | 94 | 396 | 2 | 6 | 5 | 2 | 1 | e |
| 8 | 2 | 3 | 5 | 3 | 140 | 51 | 40 | 14 | 16 | f |
| 7 | 5 | 5 | 16 | 11 | 17 | 511 | 81 | 10 | 14 | g |
| 7 | 2 | 6 | 0 | 3 | 12 | 99 | 500 | 32 | 18 | h |
| 1 | 1 | 4 | 1 | 3 | 6 | 62 | 81 | 244 | 44 | i |
| 11 | 0 | 3 | 4 | 1 | 5 | 28 | 32 | 42 | 228 | j |

Table 4 Cross table of swipe down

| a | b | C | d | e | f | g | h | i | j |  |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| 257 | 23 | 2 | 11 | 0 | 0 | 9 | 4 | 0 | 2 | a |


| 45 | 142 | 7 | 46 | 6 | 0 | 7 | 0 | 1 | 1 | b |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| 16 | 38 | 22 | 75 | 7 | 1 | 10 | 1 | 0 | 4 | c |
| 23 | 42 | 8 | 216 | 9 | 1 | 4 | 6 | 0 | 0 | d |
| 6 | 19 | 11 | 92 | 53 | 0 | 4 | 3 | 1 | 3 | e |
| 6 | 4 | 1 | 28 | 6 | 27 | 18 | 17 | 6 | 17 | f |
| 17 | 5 | 3 | 18 | 5 | 2 | 163 | 35 | 9 | 7 | g |
| 12 | 3 | 0 | 17 | 2 | 6 | 56 | 127 | 7 | 14 | h |
| 3 | 3 | 0 | 8 | 5 | 6 | 32 | 48 | 34 | 21 | i |
| 16 | 0 | 0 | 14 | 3 | 5 | 16 | 35 | 12 | 60 | j |

Table 5 Cross table of tap

| a | b | C | d | e | f | g | h | i | j |  |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| 240 | 24 | 7 | 9 | 3 | 1 | 2 | 1 | 2 | 4 | a |
| 42 | 159 | 22 | 33 | 8 | 0 | 4 | 5 | 0 | 0 | b |
| 24 | 48 | 69 | 57 | 12 | 3 | 5 | 2 | 0 | 1 | c |
| 18 | 27 | 23 | 312 | 18 | 5 | 0 | 5 | 1 | 3 | d |
| 4 | 10 | 12 | 73 | 102 | 1 | 3 | 4 | 2 | 4 | e |
| 1 | 6 | 5 | 12 | 3 | 69 | 18 | 10 | 17 | 9 | f |
| 2 | 5 | 2 | 4 | 4 | 8 | 122 | 38 | 16 | 5 | g |
| 1 | 1 | 2 | 5 | 6 | 12 | 38 | 105 | 25 | 16 | h |
| 0 | 2 | 0 | 5 | 0 | 13 | 22 | 39 | 82 | 21 | i |
| 9 | 0 | 0 | 7 | 3 | 5 | 14 | 21 | 20 | 79 | j |
| $\begin{aligned} & \text { 6.3 EVALUATION } \\ & \text { EXPERIMENT } \end{aligned}$ |  |  |  |  |  |  |  |  |  |  |

Table 6 shows the F-measure of 10 fold-CV in another three of the experimental section against the data of swipe up identifying accuracy highly by both 10 -fold CV and LOSO-CV. It is much higher identification accuracy in second and third section than in first section. From this fact, than swipe up with no purpose, it is expected to identify the kind of finger in swipe up with purpose as swipe up in order to see the information below the current page.

Table 6 F-measure 10 fold-CV in three section

|  | First section | Second section | Third section |
| :---: | :---: | :---: | :---: |
| F-measure | 0.473 | 0.781 | 0.753 |

Finally, table 7 shows the average $F$ value of the result of the 10 fold-CV against data of each subject in three of the experimental section. It is identification rate over $90 \%$ in second and third section. Especially it is identification rate about $100 \%$ in second section. From this result, perfectly identifying the type of the finger is possible by using only the touch interface by swipe up with purpose in a state of being learned self data.

Table7 F-measure average in three section with data of each subject

|  | First section | Second section | Third section |
| :---: | :---: | :---: | :---: |
| F average | 0.702 | 0.985 | 0.931 |

## 7 CONCLUSION

In this study, for the purpose of increase of the input element on the touch interface, it was investigated possibility of identifying the type of the finger touching the touch screen by using only the touch interface. As a result of the identification with data for each and data of all subjects, so there is generality(identification rate about $70 \%$ )of the characteristics of each finger and there is a large difference individually. In addition, as a result of the identification to use the data in different situation, it was found that the presence or absence of purpose at the time of operation is affected to identify the type of the finger. From these newly obtained findings, it is possibility of identifying the type of the finger by using only the touch interface by swipe up with purpose in a state of being learned self data. In the future, we will investigate features quantity that affect the identification accuracy and features quantity that doesn't affect the identification accuracy. And we will try to improve the identification accuracy.

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