Workload Based Model of Large Scale 1:N Biometrics Multi-Step Narrowing Down Process

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***Abstract*— The use of 1:N identification, which can be easily used with free of hands, for large-scale is expanding. For example, 1:N identification where N=100,000 or more is needed for large companies or nationwide payment systems. To realize a large-scale 1:N identification, the processing time is a key factor. Multi-step narrowing down is an effective method for speeding up. The multi-step narrowing achieves high speed by combining high-precision features (low speed) and low precision features (high speed), appropriately. However, a major disadvantage of multi-step narrowing down is that it is difficult to find the optimal setting. The possible combinations of features and the narrowing down rate is enormous, and usually the brute-force search was necessary in the past.**

In this paper, we propose a model that represents the multi-step narrowing down and report the optimal multi-step narrowing down setting based on the model. As experiments, we evaluated the validity of the model using face data. As a result, our proposed model was confirmed valid as an overall tendency. The evaluation of two-step narrowing down shows the optimum total processing time was realized when the processing time of each step was equal or close, as the model predicted.

I. Introduction

A. Biometrics

Biometrics are technologies that identify individuals based on their physical or behavioral characteristics. Fingerprint, face, iris, vein authentication and voice recognition are known as typical biometrics. Biometrics are currently used in wide variety of areas such as bank ATMs, entry and exit controls, and to lock smartphones and so on[1, 2, 3, 4].

Passwords, ID cards, and other forms of authentication that use memory and possession have long been used. But authentication based on user's memory or possession has risks of forgetting, lending, or losing. On the other hand, since biometrics use bio-specific information for authentication, such risks are very low and secure authentication can be achieved.

B. 1: N Identification

Biometric authentication methods can be roughly divided into 1:1 authentication and 1:N identification. The 1:1 authentication is a method for performing authentication after specifying a template to be compared by inputting ID information in advance. The biometric authentication is executed as a confirmation method for the input ID. On the other hand, 1: N identification is a method of identifying an individual by biometric information only. Here, N represents the number of registered biometrics data and can take various values depending on the system. Since the user does not need to input their ID, the convenience is enhanced. On the other hand, since matching with all registered data is needed for the 1: N identification, higher authentication accuracy and faster matching process are required. As for the processing time, generally N times the processing time is required, therefore, the speeding up is an important factor for realizing a large-scale 1: N identification system.

C. 1: N identification narrowing down process

In the 1: N identification, "narrowing down process" is generally used to select the candidates of the user with high speed. The narrowing down process is usually performed by a matching method which has low accuracy but can be executed at high speed. A small number of candidates are selected from the N registrations by narrowing down process. After that, highly accurate but takes a long-time matching process is applied, and finally identifies one person. Here, the ratio of narrowing is referred to as "narrowing down rate". For example, when N = 1,000 and the candidate is narrowed down to 10, the narrowing rate is 1% (10/1,000). In addition, the narrowing down is not 100% correct, and the genuine data may be mistakenly excluded from the candidates. The rate at which such an error occurs is called the narrowing down error rate.

Various types of matching data can be used as the narrowing down data. For example, many methods that generate index data for fingerprint data have been proposed [5, 6, 7, 8, 9, 10]. In these methods, index data which can be processed at high speed is generated based on the minutia of the fingerprint and so on. By using index data, the candidates can be narrowed down quickly. However, in many cases, the indexing method has somewhat degradation on the accuracy. Further, since it is necessary to generate index data for exclusively used for narrowing down, the system management becomes complicated.

There is another method of narrowing down using the attribute of the biological data [11, 12, 13]. For example, the attribute of a face, such as gender, age and wearing eyeglasses, is estimated, and clustering method is applied to narrow down the candidates. However, this attribute-based method's accuracy is not sufficient for large-scale 1:N identification, it is difficult to perform enough narrowing down.

On the other hand, the multi-step narrowing down process proposed in this paper uses the "reduced" feature data for narrowing down. The multi-step narrowing down is a generic method that achieves high speed by appropriately combining high-precision (low speed) features and low precision (high speed)features. However, a major disadvantage of multi-step narrowing down is that it is difficult to find out the optimal setting because the possible combinations are enormous. As a result, the brute-force search was needed and that was a very burden process conventionally.

The contents of this report are as follows. Section 3 examines the components that determine the processing time for 1: N identification narrowing down process. Next, the "workload" that represents the calculation amount of the narrowing down process is assumed and the optimal narrowing down process when the workload works as a variable is reported in Section 4. Here, the workload is a variable that represents a trade-off relationship between the processing time and the accuracy of the narrowing down process. Section 5 verifies the proposed model and method using face authentication data as experiments. Section 6 summarizes the conclusion of this paper.

II. Multi-Step Narrowing Down

Hereinafter, the multi-step narrowing process [14] will be described. Figure 1 schematically illustrates the process of multi-step narrowing down that uses 512 dimensions feature. First, as the first step narrowing down process, reduced feature (128 dimensions out of 512 dimensions) is used for narrowing down. Apparent imposters are excluded by this step with reduced feature that can be processed very fast. Then, the second narrowing down step with more precise whole features of 512 dimensions is performed and the final narrowed down candidates are given.

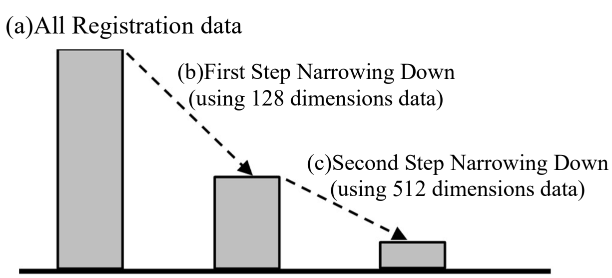


Figure 1 Multi-step narrowing down process.
This figure illustrates the process of multi-step narrow down. (a)shows all data registered at the start of identification. (b)shows the narrowed down data by the first step. (c)shows the final narrowed down data by the second step.

Various types of reduced feature other than reduced dimension can be used as narrowing down data. In a case where a plurality of feature points is used, narrowing down process can be performed by skipping the feature points. Further, when the alignment is applied at the matching process, narrowing down can be realized by reducing the search space for alignment.

With the narrowing down parameters appropriately set, proposed method shows little accuracy deterioration and achieves high performance. It should be noted that the proposed multi-step narrowing down method does not conflict with the index methods mentioned above and may be used in combination. For example, it is possible to narrow down the candidate by the indexing method first, and then apply the proposed method of multi-step narrowing down.

High-speed narrowing down process can be realized by multi-step narrowing down. On the other hand, a major disadvantage of multi-step narrowing down is that it is difficult to find the optimal parameter configuration. An enormous number of combinations of feature quantities and the narrowing down rate are available and required to be set properly. In the example mentioned above, various choices of the first step dimensions such as 8, 16, 32, 64, 128... are available. It is also necessary to set the narrowing down rate of each step appropriately. Conventionally, brute-force evaluation was needed for setting up the multi-step narrowing down.

In this paper, we focus on the processing time of 1:N identification and report the result of examination of the narrowing down process for realizing an efficient system. First, we propose a model that represents multi-step narrowing down process and report the construction of an optimal multi-step narrowing down system based on this model. Finally, a verification result using real face data is reported.

III. Processing Time for Multi-Step Narrowing Down Process

The purpose of this paper is to propose a model for constructing efficient multi-step narrowing down system. In this section, we examine the factors for the multi-step narrowing down processing time. Specifically, by deriving the processing time for the case of (A)single step narrowing down and the case of (B)two-step narrowing down, the problem of model construction is clarified.

A. Case of Single-Step Narrowing Down

Let the number of database registrations = N and let t_p be the narrowing down process time required for each template. Then, the total narrowing down time is simply calculated as follows.

$$T = Nt_p \tag{1}$$

The narrowing down time is simply proportional to the number of registrations N. The narrowing down rate (Percentage of reduced candidates) is defined as α_p. α_p is a value smaller than 1.0, for example, when the candidate is narrowed down to half, $\alpha_p = 0.50$. By performing the narrowing processing above, the candidate is reduced from N to $\alpha_p N$.

B. Case of Two-Step Narrowing Down

One narrowing down process is added to the model above. The first and second narrowing down process times are defined as t_{p1} and t_{p2}, respectively. The narrowing rates are α_{p1} and α_{p2}, respectively. The total narrowing time of this case is calculated as follows.

$$T = Nt_{p1} + \alpha_{p1}Nt_{p2} = N(t_{p1} + \alpha_{p1}t_{p2}) \quad (2)$$

The first term is the time required for the first step narrowing down process. The second term shows the time required to perform the second step narrowing down process on the data after narrowed down (α_{p1}N cases). In this case, the total processing time is proportional to the registered number N, too. By applying this narrowing down process, the number of candidates can be reduced from N to α_{p2}N. The total time of the two-step narrowing down is not simply determined by the process time of each step but is also greatly affected by the narrowing down rate α_{p1}. For example, a very fast but low accuracy narrowing down process is applied to the first step. As a result, the process time of the first step will be very short. However, since it is not possible to sufficiently narrow down the candidates in the first step, the subsequent second step processing time will increase.

There is a trade-off between the processing time and the narrowing rate, and it is necessary to determine an appropriate setting within this trade-off relationship. In the following section, optimizing the multi-step narrowing processing is considered where such a trade-off exists by applying a model.

IV. Multi-Step Narrowing Down Process Model

A. *Workload of the narrowing down process*

In the following, we examine what kind of narrowing down method is required for constructing an efficient multi-step narrowing down system. Specifically, how to set the narrowing down process time and the narrowing rate (t_p, α_p) appropriately is examined. Generally, the high precision process can narrow down the candidates more efficiently but requires a more processing time. On the other hand, the low precision process performed at a high speed but cannot narrow down the candidates sufficiently. To optimize the total processing time, it is necessary to select an appropriate narrowing down process. In the following, a model of a narrowing process is proposed and optimization using this model is examined.

There could be various implementation methods of the narrowing down process, and it is difficult to construct a generalized model. Our model discussed below is based on the following assumptions. The narrowing down processing time t_{pi} and the narrowing down rate α_{pi} of the i-th narrowing down step are assumed to be determined by the processing *workload* w_{pi}. Here, the workload w_{pi} is a variable that represent the calculation amount of the narrowing down process and is required to be tuned in multi-step narrowing down process. For example, when a feature vector is applied to multi-step narrowing down, it is necessary to tune the dimension of the feature vector to be used. In the proposed method, the dimension of the feature vector is set as workload and optimization is executed. The larger the workload w_{pi}, the more accurate the authentication, but the longer the processing time. Conversely, if the workload w_{pi} is small, the authentication accuracy is low, but the processing is fast.

The narrowing down process time and the narrowing down rate are assumed to be expressed as follows by using the workload w_{pi}.

$$\begin{cases} t_{pi}(w_{pi}) = w_{pi}t \\ \alpha_{pi}(w_{pi}) = \frac{\alpha}{w_{pi}} \end{cases} \quad (3)$$

Here, t and α are proportional constants representing processing time and narrowing down rate according to the workload. The t and α are depend on the algorithm, modality, etc. Figure 2 illustrate this model schematically. The narrowing down process time and the narrowing down rate for real data represented by the workload are presented in the experimental chapter.

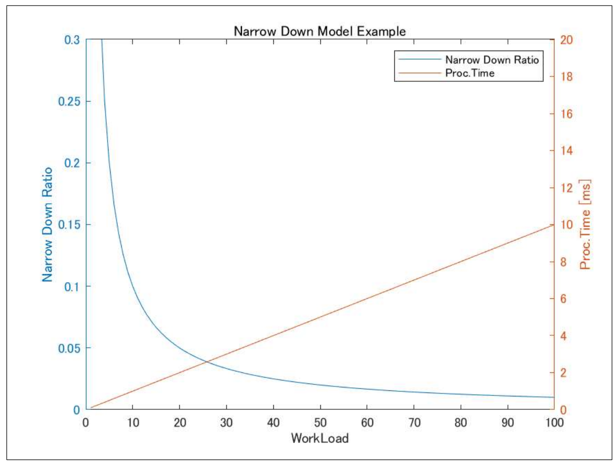


Figure 2 Proposed narrowing down model.
Narrowing down rate is inversely proportional to the workload(left axis).
Possessing time is proportional to the workload(right axis).

Workload w_{pi} is a variable representing a calculation amount, and optimization of the narrowing processing is performed by adjusting the variable w_{pi}. Specifically, workload w_{pi} is corresponded to the alignment search space, the dimensions of the feature vectors, the number of feature points, etc. The optimization of the 1: N narrowing down process time is discussed below based on the model.

B. *Narrowing Down Error and Narrowing Down Rate*

In our model, the total narrowing down error rate is assumed to be set in advance. For example, the total narrowing down error rate is set to 1% in advance and the narrowing down process is optimized with the workload w_{pi} as a variable based on the model that gives the total narrowing down error. In the multi-step narrowing, a plurality of narrowing processes is applied. As an idea, the narrowing down error in each narrowing down step could be independent each other. In other words, it is assumed that the errors in each step could be accumulated and result in a total narrowing down error. However, the proposed narrowing down method assumes that the reduced feature is used for narrowing down. Therefore, there is a high possibility that the data which becomes an error in a narrowing down step also becomes an error in another step. In other words, the correlation of narrowing down error in each step is very high. Therefore, the error in the each of narrowing down process is not supposed to be added. As a result, it is sufficient to set the narrowing down rate of each of the narrowing down step the value corresponding to the total narrowing down error rate.

Case of Two-Step Narrowing Down

First, two-step narrowing down is examined. It is assumed that the narrowing down process time and the narrowing down rate are determined by the workload w_{p1} of the narrowing down process as described above. Also, it is assumed that the time of the second processing is determined by the workload w_{p2}. The total narrowing down time of the two-step process can be expressed as follows.

$$\begin{aligned} T_2(w_{p1}, w_{p2}) &= N \cdot (t_{p1} + \alpha_{p1} t_{p2}) \\ &= N\left((t w_{p1}) + \left(\frac{\alpha}{w_{p1}}\right)(t \cdot w_{p2})\right) \\ &= Nt\left(w_{p1} + \alpha \frac{w_{p2}}{w_{p1}}\right) \end{aligned} \quad (4)$$

The workload w_{p1} that minimizing the total processing time T_2 (w_{p1}, w_{p2}) is derived by partial differentiating of w_{p1} and set it equal to 0.

$$\frac{\partial T_2(w_{p1}, w_{p2})}{\partial w_{p1}} = Nt\left(1 - \alpha \frac{w_{p2}}{w_{p1}^2}\right) = 0 \quad (5)$$

The workload w_{p1} that satisfy the above conditions is obtained as follows.

$$w_{p1} = \sqrt{\alpha w_{p2}} \quad (6)$$

Substituting the obtained optimum narrowing down process workload w_{p1}, the optimized total narrowing down process time T_2 is obtained as follows.

$$\begin{aligned} T_2(w_{p1}, w_{p2}) &= N t_{p1} + N \alpha_{p1} t_{p2} \\ &= N\sqrt{\alpha w_{p2}}\, t + N \frac{\alpha}{\sqrt{\alpha w_{p2}}} w_{p2} t \\ &= \underbrace{Nt\sqrt{\alpha w_{p2}}}_{\text{First Step processing Time}} + \underbrace{Nt\sqrt{\alpha w_{p2}}}_{\text{Second Step processing Time}} \end{aligned} \quad (7)$$

It can be seen from the above equation that the total processing time becomes shortest when the processing time of the first step is equal to the second step. The first and second narrowing times are represented by the common workload w_{p2}. This result is derived from the condition that the total processing time is minimized. This corresponds to the equal distribution of processing loads in the narrowing process

D. Case of Three-Step Narrowing Down

In the same way as above, the case of three-step narrowing down is examined. The processing time T_3 (w_{p1}, w_{p2}, w_{p3}) is shown as follows. Here, w_{p1}, w_{p2} and w_{p3} are workloads of each steps of the narrowing down process, respectively.

$$\begin{aligned} & T_3(w_{p1}, w_{p2}, w_{p3}) \\ &= N t_{p1} + N \alpha_{p1} t_{p2} + N \alpha_{p2} t_3 \\ &= Nt\left(w_{p1} + \alpha \frac{w_{p2}}{w_{p1}} + \alpha \frac{w_{p3}}{w_{p2}}\right) \end{aligned} \quad (8)$$

We need to find the workload w_{p1} and w_{p2} that minimize T_3. The optimal total time is obtained by applying partial differentiation of each workload and set it equal to 0.

$$\left\{ \begin{aligned} \frac{\partial T_3}{\partial w_{p1}} &= Nt - Nt\alpha \frac{w_{p2}}{w_{p1}^2} = 0 \\ \frac{\partial T_3}{\partial w_{p2}} &= Nt\alpha \frac{1}{w_{p1}} - Nt\alpha \frac{w_{p3}}{w_{p2}^2} = 0 \end{aligned} \right. \quad (9)$$

The workloads w_{p1} and w_{p2} that satisfy the above conditions are obtained as follows.

$$\left\{ \begin{aligned} w_{p1} &= \sqrt[3]{\alpha^2 w_{p3}} \\ w_{p2} &= \sqrt[3]{\alpha w_{p3}^2} \end{aligned} \right. \quad (10)$$

From this, the optimum total processing time in the case of the three-step narrowing down process is obtained as follows.

$$\begin{aligned} & T_3(w_{p1}, w_{p2}, w_{p3}) \\ &= \underbrace{Nt\sqrt[3]{\alpha^2 w_{p3}}}_{\text{First Step processing Time}} + \underbrace{Nt\sqrt[3]{\alpha^2 w_{p3}}}_{\text{Second Step processing Time}} + \underbrace{Nt\sqrt[3]{\alpha^2 w_{p3}}}_{\text{Third Step processing Time}} \end{aligned} \quad (11)$$

As same in this case, the optimum total time is obtained when the processing times of each steps are equal.

E. Case of n-Step Narrowing Down

In this section, we consider the general case of n steps of narrowing down. The processing time T_n in the n-step narrowing down is as follows. Here, w_{pi} represents the workload of the i-step narrowing down process.

$$\begin{aligned} & T_n(w_{p1}, w_{p2}, \dots, w_{pn}) \\ &= N t_{p1} + N \alpha_{p1} t_{p2} .. + \alpha_{pn-1} t_{pn} \\ &= Nt\left(w_{p1} + \alpha \frac{w_{p2}}{w_{p1}} \dots + \alpha \frac{w_{pn}}{w_{pn-1}}\right) \end{aligned} \quad (12)$$

A workload w_{pi} which minimizes the above is calculated as the same way above. Since this calculation is complicated, only the result is shown.

$$
\begin{aligned}
&T_n(w_{p1}, w_{p2}, \dots, w_{pn}) \\
&= \mathrm{Nt}\sqrt[n+1]{\alpha^n w_n} + \mathrm{Nt}\sqrt[n+1]{\alpha^n w_n} \dots \mathrm{Nt}\sqrt[n+1]{\alpha^n w_n}
\end{aligned} \tag{13}
$$

In the general case of n-step narrowing down, the total time is optimized when the processing time of each step is equal as described above.

V. Experiments

In this section, the evaluation using face data was carried out as a verification of the proposed model. Data and evaluation environments used for this assessment are shown in Table 1.

Facial images detected by MTCNN[15] were used for feature extraction by inception ResNet v1 (training dataset: VGGFace2) of FaceNet[16]. The extracted features are stored as 512 dimensions float data.

Table 1 Data and Evaluation Environment.

Evaluation Data	CASIA-WebFace(10,256IDs)
Evaluation Tool	FaceNet (Inception ResNet v1 Trained on VGGFace2) L2 norm was used as score
Evaluation Machine	Windows 8.1 Pro. Intel Xeon CPU E5-2620 2.40GHz

The dimension of feature vector was used as the workload in the proposed model. In the matching processing, L2 norm of gallery and probe data is calculated as score. We used CASIA-WebFace database for our verification [17]. This database contains 10,256 individual IDs, so 1:10,256 identification was processed. Two images for each IDs were used for the gallery and the probe respectively.

The following two evaluations were carried out.

A. Validation of the Proposed Model

It was verified whether the processing time and narrowing down rate agreed with our model (equation (3)).

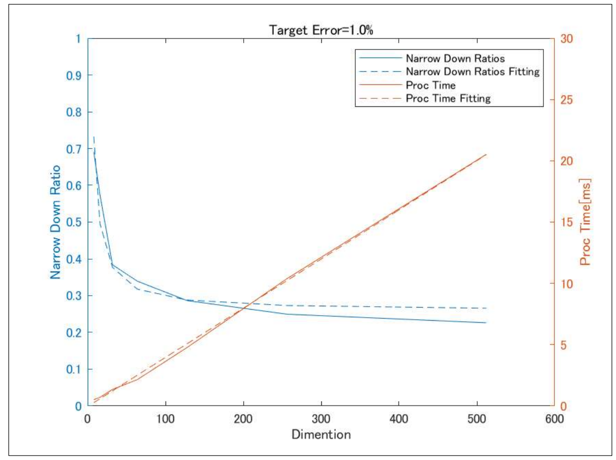
B. Verification of Optimal Total Time

In our proposed model, the optimal total processing time is realized when the processing times of each step are equal. Whether this is correct was verified using actual face data.

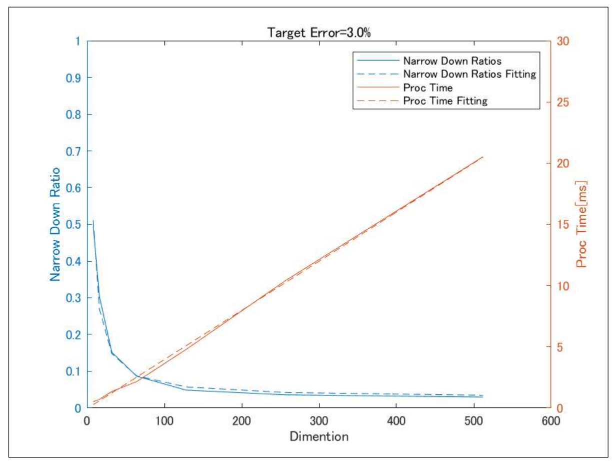
The details of the evaluation are shown below.

A. Validation of the Proposed Model

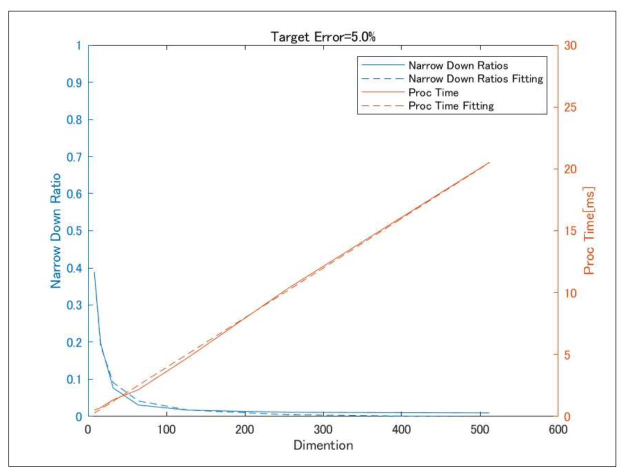
The validity of our proposed model was verified by face data. In the evaluation, the validity of the model was evaluated by setting some total narrowing down error rates. As explained in the previous chapter, our proposed model assumes the narrowing down error rate in advance and optimize the total processing time with workload. In the following, we call the narrowing down error rate set in advance as the target error rate.



(a)Target Error = 1.0%



(b)Target Error = 3.0%



(c)Target Error = 5.0%

Figure 3 Validation of the Proposed Model
(a), (b) and (c) correspond to the target error rates of 1%, 3% and 5%, respectively.

The measured results are shown in Figure 3. In Figure 3, (a), (b) and (c) correspond to the target error rates of 1%, 3% and 5%, respectively. The horizontal axis of the figure represents the dimension of the feature data and is a value corresponding to the workload. The figure shows the narrowing down ratio (left axis) and processing time (right axis) corresponding to the workload. The narrowing down rate represents the narrowing down rate when the feature data corresponding to the workload provides the target error rate shown above. The dotted lines show the results of least squares fitting the workload in inverse and direct proportion, respectively to verify the validity of equation (3).

Figure 3 shows processing time is almost linearly proportional to the workload. On the other hand, the narrowing down rate has some discrepancy with the fitting data. Especially when the target error rate is 1%, the discrepancy tends to be relatively large. However, although there exist some errors, the figure shows our proposed model equation (3) is overall appropriated.

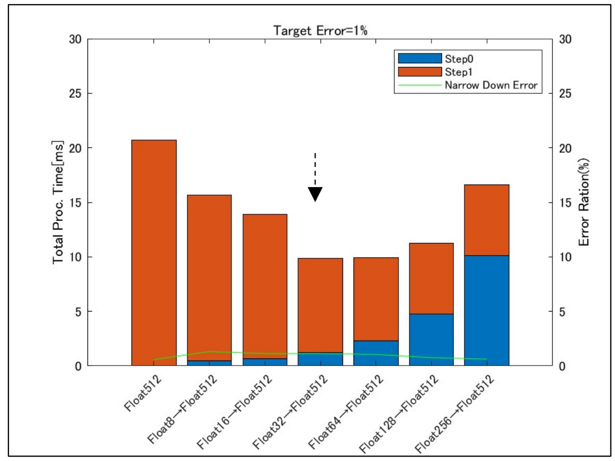
B. Verification of Optimal Total Time

The hypothesis that the optimum total time is obtained when the processing time of each step is equal was examined. Simulations were carried out for target total error rates of 1%, 3% and 5% same as in the above evaluation. As evaluation, two-step narrowing down of the reduced dimension data and 512 dimensions was carried out (Figure 4).

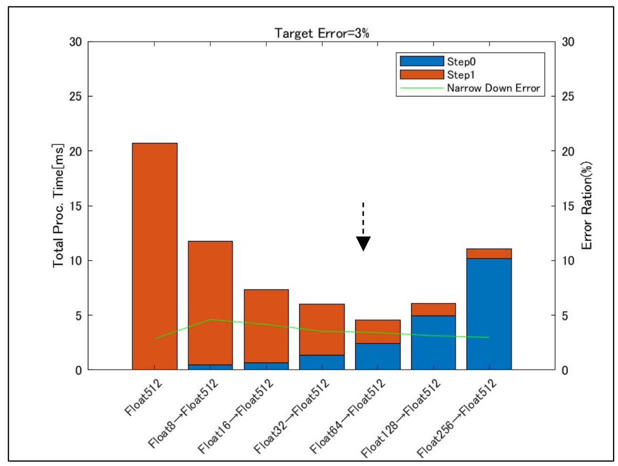
Figure 4 shows the total processing time (left axis) of the two-step narrowing down when the first step narrowing down feature dimension is set to 8, 16, 32, 64, 128, and 256, respectively. The right axis shows the total narrowing down error rate at the corresponding feature dimension. Focusing on the total processing time in Figure 4, effectiveness of the multi-step narrowing down can be easily confirmed. The application of multi-step narrowing can achieve speedups of (a) 2.1-fold, (b) 4.6-fold, and (c) 7.0-fold, for each of the target total narrowing down error respectively.

When the target error rate is set to 3% or 5% (Figure 4 (b), (c)), the processing times of the first and second steps at the minimum total processing time (dotted arrow) are nearly equal or close. On the other hand, when the targe error rate is set to 1% (Figure 4 (a)), the discrepancy of the processing time from the hypothesis becomes large. We think this is because the narrowing down rate shows some discrepancy from our proposed model as shown in Figure 3 (a). Improvement of this point is an issue to be discussed in the future and rethinking of the model is considered necessary.

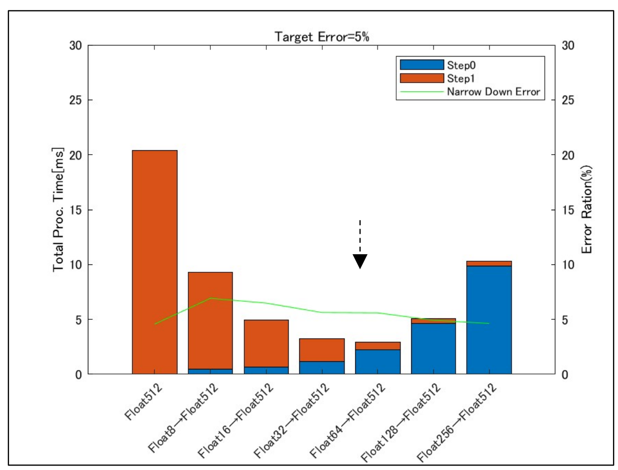
And the total narrowing down error rates are approximately equal or close to the preset target error rates. This shows that the model is appropriate for narrowing down error. Specifically, narrowing down errors in each step are not independent and indicating a high correlation.



(a)Target Error = 1.0%



(b)Target Error = 3.0%



(c)Target Error = 5.0%

Figure 4 Verification of Optimal Total Time
(a), (b) and (c) correspond to the target error rates of 1%, 3% and 5%, respectively.

VI. Conclusions

We proposed and evaluated a multi-step narrowing down model that is helpful for constructing the large-scale 1:N biometrics identification system efficiently.

A workload variable w_p for the narrowing down process is assumed and a model in which the processing time and the narrowing down rate have a trade-off relation is proposed. In the proposed model, it was found that the total processing time is optimized when the processing time of each step becomes equal. This result gives a practical guideline for constructing an large-scale multi-step narrowing down biometrics system effectively. When the processing time of a certain step is longer than others, the optimal system is obtained by reducing the calculation amount of the corresponding step and tuning it to approach the other step processing time. This process is much effective than conventional brute-force searching.

The proposed model is evaluated by using face data. As a result, it was confirmed that the proposed model was valid as an overall tendency although there was some discrepancy. As a result of evaluation using the two-step narrowing down, it was confirmed that the optimum total processing time was realized when the processing time of each step was equal or close.

As the use of biometrics spreads, the need for large-scale 1: N identification is expected to increase in the future because of its usability. We believe this study will contribute the realization of such a large-scale 1:N identification system.

On the other hand, there exist some error between the proposed model and the measured real face data, and the improvement of the accuracy of the model is an issue to be discussed in the future. And in this paper, a single modality biometrics is assumed and examined. But the use of multimodal biometrics systems combining different kind of biometrics is expected to increase in the future, and the expansion of the model to multimodal systems is also an issue to be studied.

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