# Erratum to: Appearance-based bidirectional representation for palmprint recognition 

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## Erratum to: Multimed Tools Appl <br> DOI 10.1007/s11042-014-1887-4

The authors have found errors with their original proposed method.
The authors used the BRBPC method for face recognition across pose in Ref. [34]. The palmprint recognition is different for face recognition as the database is larger. For example, for PolyU 2D and 3D palmprint database, the database contains a total of 8000 samples collected from 400 different palms. So for palmprint recognition, the test sample class should be expressed by class not by training samples one by one. The expression has been modified by class, as well as the formula (1)-(7) of the BRBPC method.
Suppose that there are $m$ class training samples and each class provides $n_{i}$ training samples. Let $X_{i}$ be $n_{i}$ training samples from the $i_{t h}$ class $(i=1, \ldots, m)$. Let $y$ be the test sample.
Step 1 . We assume that the test sample can be represented by the training samples class by class. Let $X_{i}$ be $n$ training samples from the $i_{t h}$ class $(i=1, \ldots, m)$, so we can write the first step of the NBR method by

$$
\begin{equation*}
y=\sum_{j=1}^{n_{i}} w_{j}^{i} x_{j}^{i}+\varepsilon_{i}=X_{i} w_{i}+\varepsilon_{i} \tag{2}
\end{equation*}
$$

where $X_{i}=\left[x_{1}^{i}, \ldots, x_{n}^{i}\right], w_{i}=\left[w_{1}^{i}, \ldots, w_{n}^{i}\right]^{T}$. Here, $w_{i}$ denotes the coefficient of the $i_{t h}$ class training samples. We can calculate it by using

[^0]\[

$$
\begin{equation*}
w_{i}=\left(X_{i}^{T} X_{i}+\mu I\right)^{-1} X_{i}^{T} y \tag{3}
\end{equation*}
$$

\]

where $\mu$ is a positive constant and $I$ is the identity matrix.
The deviation between the test sample and each class is calculated using Eq. (4)

$$
\begin{equation*}
d e v_{i}=\left\|\varepsilon_{i}\right\|=\left\|y-X_{i} w_{i}\right\|(i=1, \ldots, m) \tag{4}
\end{equation*}
$$

Step 2. In the second step, we express a training sample by the test sample, as well as the training samples that belongs to the same class with this training sample, i.e.

$$
\begin{equation*}
x_{j}^{i}=w_{0} y+\overline{X_{j}^{i}} w_{i}+\xi_{j}^{i} \tag{5}
\end{equation*}
$$

where $x_{j}^{i}$ is the $j_{t h}$ training sample from the $i_{t h}$ class, $\overline{X_{j}^{i}}$ denotes all of the samples from the $i_{t h}$ class except $x_{j}^{i}$, and $\xi_{j}^{i}$ is the residue. In this way, each training sample is associated with a residue.
Let $H_{j}^{i}=\left[\begin{array}{ll}y & x_{1}^{i}, \ldots, x_{j-1}^{i}, x_{j+1}^{i}, \ldots, x_{m}^{i}\end{array}\right], W_{j}^{i}=\left[\begin{array}{ll}w_{0} & w_{1}^{i}, \ldots, w_{j-1}^{i}, w_{j+1}^{i}, \ldots, w_{m}^{i}\end{array}\right]$, then we can calculate $W_{j}^{i}$ as follows

$$
\begin{equation*}
W_{j}^{i}=\left(\left(H_{j}^{i}\right)^{T} H_{j}^{i}+\mu I\right)^{-1}\left(H_{j}^{i}\right)^{T} X_{i} \tag{6}
\end{equation*}
$$

With $W_{j}^{i}$, we can obtain the complimentary deviation for $x_{j}^{i}$ by

$$
\begin{equation*}
\operatorname{com}_{j}^{i}=\left\|\xi_{j}^{i}\right\|=\left\|x_{j}^{i}-H_{j}^{i}\left(W_{j}^{i}\right)^{T}\right\|=\left\|x_{j}^{i}-w_{0} y+\overline{X_{j}^{i}} w_{i}\right\| \tag{7}
\end{equation*}
$$

1. Corrected tables of experimental results appear below. Corrections are marked with a bold, italic typeface.

Table 1. Classification accuracy rates of different methods on Green channel.

| Methods | Classification accuracy rates |
| :--- | :--- |
| PCA(150) | 0.9333 |
| 2DPCA | 0.8050 |
| LDA | 0.9683 |
| 2DLDA | 0.9483 |
| 2DLPP[36] | 0.9576 |
| SRC[24] | 0.9820 |
| LRC[37] | 0.9310 |
| The proposed method | $\mathbf{0 . 9 9 3 3}$ |

Table 2. Classification accuracy rates of different methods on Red channel.

| Methods | Classification accuracy rates |
| :--- | :--- |
| PCA(200) | 0.9600 |
| 2DPCA | 0.8500 |
| LDA | 0.9750 |
| 2DLDA | 0.9667 |
| 2DLPP[36] | 0.9790 |
| SRC[24] | 0.9590 |
| LRC[37] | 0.9600 |
| The proposed method | $\mathbf{0 . 9 8 6 6}$ |

Table 3. Classification accuracy rates of different methods on Blue channel.

| Methods | Classification accuracy rates |
| :--- | :--- |
| PCA(250) | 0.9700 |
| 2DPCA | 0.8683 |
| LDA | 0.9700 |
| 2DLDA | 0.9833 |
| 2DLPP[36] | 0.9742 |
| SRC[24] | 0.9900 |
| LRC[37] | 0.9510 |
| The proposed method | $\mathbf{0 . 9 9 3 3}$ |

Table 4. Classification accuracy rates of different methods on Near-Infrared channel.

| Methods | Classification accuracy rates |
| :--- | :--- |
| PCA(250) | 0.9583 |
| 2DPCA | 0.8383 |
| LDA | 0.9667 |
| 2DLDA | 0.9550 |
| 2DLPP[36] | 0.9653 |
| SRC[24] | 0.9650 |
| LRC[37] | 0.9610 |
| The proposed method | $\mathbf{0 . 9 8 8 8}$ |

Table 5. Classification accuracy rates of different methods on 2D palmprint images.

| Methods | Classification accuracy rates |
| :--- | :--- |
| PCA(200) | 0.9460 |
| 2DPCA | 0.8520 |
| LDA | 0.9760 |
| 2DLDA | 0.9880 |
| 2DLPP[36] | 0.9785 |
| SRC[24] | 0.9883 |
| LRC[37] | 0.9590 |
| The proposed method | $\mathbf{0 . 9 9 7 8}$ |

Table 6. Classification accuracy rates of different methods on MCI.

| Methods | Classification accuracy rates |
| :--- | :--- |
| PCA(250) | 0.9900 |
| 2DPCA | 0.9800 |
| LDA | 0.9840 |
| 2DLDA | 0.9900 |
| 2DLPP[36] | 0.9863 |
| SRC[24] | 0.9857 |
| LRC[37] | 0.9860 |
| The proposed method | $\mathbf{0 . 9 9 6 6}$ |


[^0]:    The online version of the original article can be found at http://dx.doi.org/10.1007/s11042-014-1887-4.

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