Malaysian Journal of Computer, Vol. 9 No. 2, December 1996, pp. 71-78

PIN SIGNATURE VERIFICATION USING WAVELET TRANSFORM

Elok Robert Tee
Jabatan Sains Komputer
Universiti Pertanian Malaysia
43400 UPM Serdang
email: robert@fsas.upm.edu.my

Selvanathan N.
Fakulti Sains Komputer & Teknologi Maklumat
Universiti Malaya
50603 Kuala Lumpur
email: selva@fsktm.um.edu.my

ABSTRACT

*The personal identification number signature (**PIN signature**) is a method of remembering and typing the PIN using the **de facto** standard numeric keypad format. The PIN signature affords a second level security in that it enhances the PIN with additional information on the user, i.e. the profile of its input. The PIN signature reference profile can be viewed as a signal vector and can thus be enhanced and verified as to its physiological characteristics using wavelet transform. The result of this analysis is presented.*

Keywords: ***Keystroke characteristics recognition, PIN, PIN signature, Artificial neural networks, Wavelets***

1.0 INTRODUCTION

The security of a computer system depends on its ability to verify the identity of its authorised users. Common security measures include the use of artifacts such as magnetic cards and passwords, both of which have inherent limitations. Additional precautions may incorporate biometrics that is safe, easy to use and yet difficult if not impossible to fraud.

The action of typing the PIN can be empirically analysed with respect to its physiological characteristics. The latency time between successive keystrokes, keystroke pressure, key displacement and key displaced-duration are some of the quantifiable components. [1].

The PIN signature reference profile of a user can be viewed as a signal that has transient properties and is different from other user profiles. These transient properties can be classified and used for verification. Frequency analysis methods such as the Fourier transform and wavelet transform can be applied to isolate specific regions of interest. An impostor may be able to produce a PIN signature which has a pattern similar to the authentic signature. This indicates a need to identify unidentical obscured regions of the signal. The wavelet transform, as compared with the Fourier transform, can better represent transient abnormalities of the signature pattern for classification [2, 3, 4].

1.1 Keystroke Characteristics Recognition

It was documented that telegraph operators were able to identify typists from incoming telegraph signals by listening to streams of dots and dashes. Since then various methods have been devised to verify the identity of typists from the physiological characteristics of their keyboard input [5]. These methods include dynamic verification of continuous keystrokes and keystroke characteristics from typing names. [5, 6, 7]

1.2 The PIN Signature

The PIN signature is reproduced by remembering and typing the PIN sequence as a series of continuous digits with pauses between digits. For example, the PIN sequence *738831* can be memorized as "*seven-three, eight-eight-three-one*" or as "*seven-three-eight, eight-three-one*". The keys are consequently pressed in this manner, somewhat like playing a tune on a musical instrument.

The PIN signature pattern, similar to the written signature, is not always consistent and may be slightly different each time it is typed. As such, a method of typing the PIN sequence was devised to ensure minimal measurable deviation.

Consistent input requires the mapping of the fingers with respect to the numeric keypad. This includes consistent placement of the favored-hand and limiting each finger to press only a specific set of numeric keys. The *de facto* standard numeric keypad format was proposed.

It was suggested that the PIN signature profile varies with different individuals and thus can be used as a basis for biometrics identification. [1, 8, 9].

1.3 Wavelet Transform

The Fourier transform expands a signal as orthonormal basis functions of sine and cosine functions which are infinite in duration. The coefficients of the transformed function can only poorly represent transient components such as sharp alteration in the frequency signal. Wavelets are basis functions that are independent of the sine and cosine approach yet offer infinite sets of possible basis functions providing a large base for signal analysis.

Wavelet transform provides *compact support*, in that wavelets are localised both in frequency and time [3, 10]. This is among the important features that enable analysis of frequencies at different resolutions on the time-frequency plane.

The Quadrature Mirror Filter (QMF) *decomposes* the input frequency signal into *detail* and *approximate* coefficients at different levels of the scale. The output from the QMF process is decimated by a factor of 2 and the low-pass filter output is repeated on the QMF process (Fig. 1). The different levels enable the signal to be analysed for its frequency content on different scales.

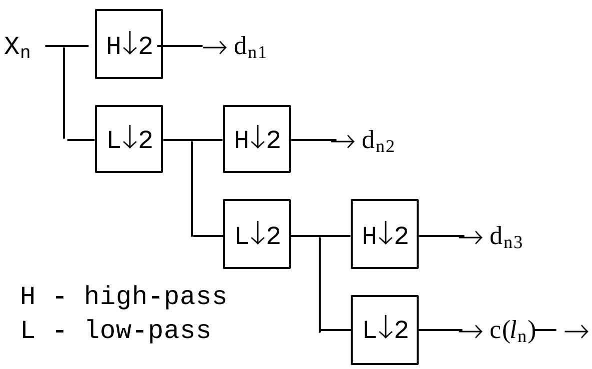

Fig. 1: QMF *filter* process

The wavelet transform exemplified for scaling and translation, known as the *analysing wavelet* or *mother function* takes the form:

$$\Phi_{(s,i)}(x) = 2^{-(s/2)}\,\Phi(2^{-s}.x-i)$$

The variables s (width) and i (location index of s) are integers that scale and dilate the mother function $\Phi(x)$ to generate wavelets. The basic function $W(x)$:

$$W(x) = \sum_{k=-1}^{N-2} (-1)^k\, c_{k+1}\, \Phi(2x+k)$$

where c_k is the wavelet coefficient of the mother function. The wavelet coefficient must satisfy the conditions of linearity and quadratic constraints [2, 3, 10, 11, 12, 13].

The Daubechies scaling and filter functions adopted for this experiment were gleaned from Daubechies [11, 12]. Introduction to and further discussion on wavelet transform can be found in papers by Graps, Cody and Jawerth *et al*. [2, 3, 4, 10].

2.0 METHOD

A multilayer perceptron (MLP) artificial neural network employing the *backpropagation* algorithm was used to classify users. The configuration adopted utilised momentum term to train the MLP (Fig. 2) [14].

The reference profiles of 4 individuals were created after familiarisation with the typing procedure [1]. Each profile consisted of 20 latency time sets sampled at random. A test profile was created after a week with 5 samples recorded from each individual. Impostor samples were also included in the test profile. These include impostors given the same PIN-memory patterns as the genuine owners.

Eight sets consisting of 5 latency times each were taken at random from the reference profiles to train the MLP. The training data included 4 sets of 6 fictitious keystroke pressure values (a touch sensitive keyboard was unavailable for this experiment).

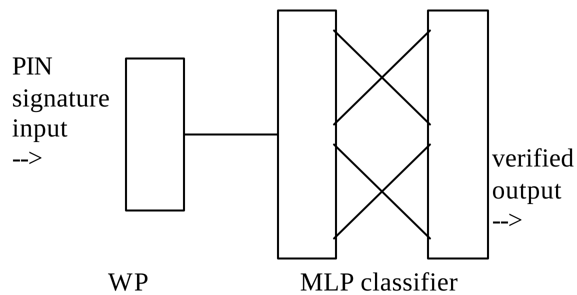

Fig. 2: WP-MLP classifier

A simple MLP implementation will verify impostors producing similar patterns as correct [9]. The MLP will have to be trained to recognise potential impostors. Without such training data, the limits for variation of an input pattern can be set on the reference profile.

This can be achieved by identifying potential transient “spots” from the reference profile. These spots can be parameterised to permit fluctuation of input signals at the local region while constraints can be imposed on steady signal regions. The MLP can be trained to recognise these parameters using decomposed signal data at different resolutions, thus controlling the degree and location of variation of the PIN signature pattern input.

For this experiment, the margins for variation were arbitrarily set at 80%, 60% and 40% across all levels of the scale. A comparison of using wavelet verification was made against the results obtained from just using the MLP without decomposition.

3.0 FINDINGS

The results from running test profiles on the WP-MLP and plain MLP are tabulated below as Table 1 and 2.

Table 1: Acceptance rate % - PIN signature verified by the WP-MLP classifier as correct.

tolerance	genuine users	impostors similar patterns	impostors dissimilar patterns
80%	100	35	5
60%	100	25	5
40%	75	*n/a*	*n/a*
var.	14.43	11.18	1.67
avg.	91.67	10.0	3.33

Indecisive results occur when more than one output neuron fires with a high degree of certainty - indicated as *n/a*. The results from the 40% tolerance window for impostors with similar and dissimilar patterns were inconclusive while 75% of genuine PIN signature samples were verified as correct.

The results indicated that when the tolerance window was increased from 40% to 60%, the acceptance rate of impostor samples with similar patterns deteriorated from 25% to 35%.

Table 2: Acceptance rate % - comparison between the WP-MLP classifier at 60% tolerance and using a plain MLP classifier.

	genuine users	impostors similar patterns	impostors dissimilar patterns
WP-MLP	100	25	5
MLP	100	100	0
diff.	0	75	(5)

Results from tests on the MLP (without WP) produced a 100% false acceptance rate (FAR) of impostors with similar PIN signature patterns. This is due to the similarity of the general pattern forms.

The 5% FAR of dissimilar patterns from the WP-MLP was likely due to similarity in minute pattern forms which were ‘"exposed’" and would thus be classified by the network as correct.

4.0 SUMMARY

The findings presented herein indicate that it may be possible to distinguish general pattern form through WP decomposition to highlight obscured features of a PIN signature signal. It is thus feasible to explore the use of the PIN signature verification method using WP for its application.

The WP-MLP classifier has indicated that it is possible to vary its tolerance in verifying users. Greater restriction placed on the verification may produce false rejection, and reduce the acceptance rate of genuine users. The degree of acceptable false acceptance and rejection rates would depend on the context of its use.

Increasing the number of parameters employed should strenghten the verification by adding complexity to the PIN signature pattern. This needs to be looked into.

Like the written signature, the PIN signature should produce a fairly consistent pattern over time. However, certain factors may affect the PIN signature during input and should be considered. These include:

- Handedness: The typical numeric keypad was apparently designed for right-hand use. The location of the *Enter* and *0* keys may not be suitable for those who are left-handed.
- Typing: Comparison between one-finger, multiple-fingers, two-hand typists and hand placement.
- Age and gender differences.
- Accomplished typists and musicians: very fast execution may be difficult to measure.
- Physical disability such as deformities of the hand.
- Temporary disability such as caused by injuries and illnesses.

Besides the above, variations of the PIN sequence in relation to the mechanics of executing the PIN signature should warrant further exploration. This should also include testing with the masses and exploring hardware feasibility before the PIN signature concept can be commercially introduced.

Among the verification methods that have been explored for the PIN signature verification include:

- neural-fuzzy application using fuzzy-rule matrix tables [8]
- plain latency time sampling using multilevel perceptron network and sampling with additional parameters such as keystroke pressure [9]

REFERENCES

[1] E. R. Tee and N. Selvanathan, "PIN Signature: A New Approach to Signature Identification". accepted and revised: *Journal of Information Technology*, 1996.

[2] Amara. Graps, "An Introduction to Wavelets". *IEEE Computational Science and Engineering*, vol. 2 num. 2. Summer 1995.

[3] M. A. Cody, "The Fast Wavelet Transform: Beyond Fourier Transforms". *Dr. Dobb's Journal*, April 1992.

[4] M. A. Cody, "The Wavelet Packet Transform: Extending the Wavelet Transform". *Dr. Dobb's Journal*, April 1994.

[5] J. Leggett, G. Williams, M. Usnick and M. Longnecker. "Dynamic identity via keystroke characteristics". *International Journal of Man-Machine Studies* 35: 859-870, 1991.

[6] M. Brown and S. J. Rogers, "User identification via keystroke characteristics of typed names using neural networks". *International Journal of Man-Machine Studies* 39: 999-1014, 1993.

[7] J. Rogers, "Neural Network User Authentication". *AI Expert*: 29-33, June 1995.

[8] E. R. Tee and N. Selvanathan, "Enhancing The Personal Identification Number Input As A Means Of Identification Signature", *Malaysian Journal of Computer Science*, vol. 9 num. 1: 49-55, June 1996.

[9] E. R. Tee and N. Selvanathan, "PIN Signature: A Multilevel Perceptron Implementation", *Journal of Information Technology*, vol. 8 num. 1: 48-57, June 1996.

[10] B. Jawerth and W. Sweldens, "An Overview of Wavelet Based Multiresolution Analyses". *Dept. of Mathematics, University of South Carolina*, 1995.

[11] I. Daubechies, "Ten lectures on wavelets". *SIAM*, 1992.

[12] I. Daubechies, "Orthonormal bases of compactly supported wavelets". *Communication Pure Applied Maths*, vol. 4.1: 909-996, Nov. 1995.

[13] N. Selvanathan, "Wavelet Packets as Features for Segmentation & Classification". (refer) *FSKTM Universiti Malaya*, 1995.

[14] L. Fausett, *Fundamentals of Neural Networks: architectures, algorithms, and applications*. Prentice Hall International Editions, 1994.

BIOGRAPHY

Elok Robert Tee is a Tutor at Universiti Pertanian Malaysia currently enrolling for his Ph.D.

Selvanathan N. is the Deputy Dean of the Faculty of Computer Science and Information Technology, Universiti Malaya. His current interests are biomedical image processing, ANN and wavelets.

ACKNOWLEDGMENT

To Universiti Pertanian Malaysia for funding this research. This paper was submitted as partial fulfillment for the degree of Master of Computer Science.

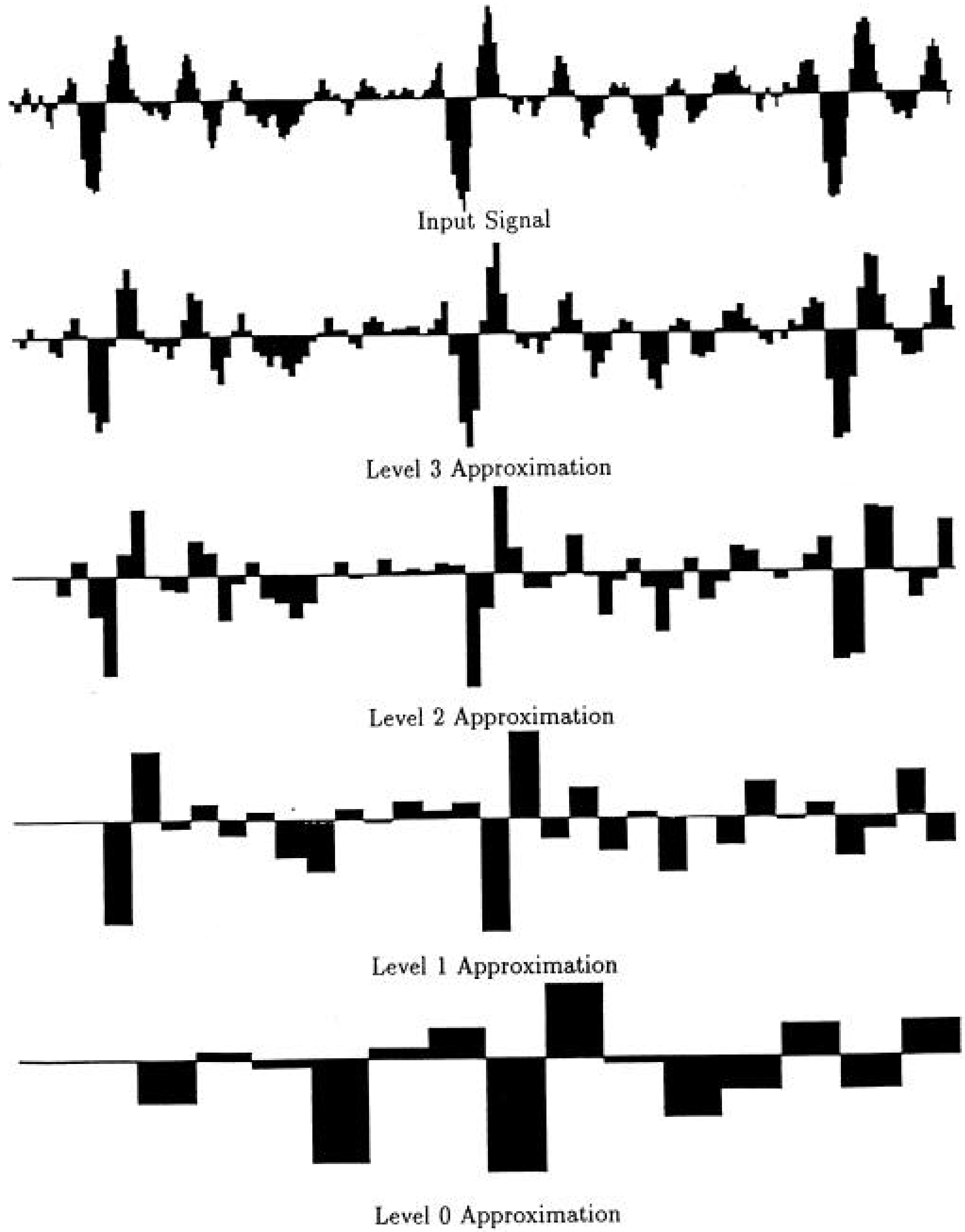

Fig. 3: **Decomposed** ***approximation*** Cody, M.A. [3, 4]

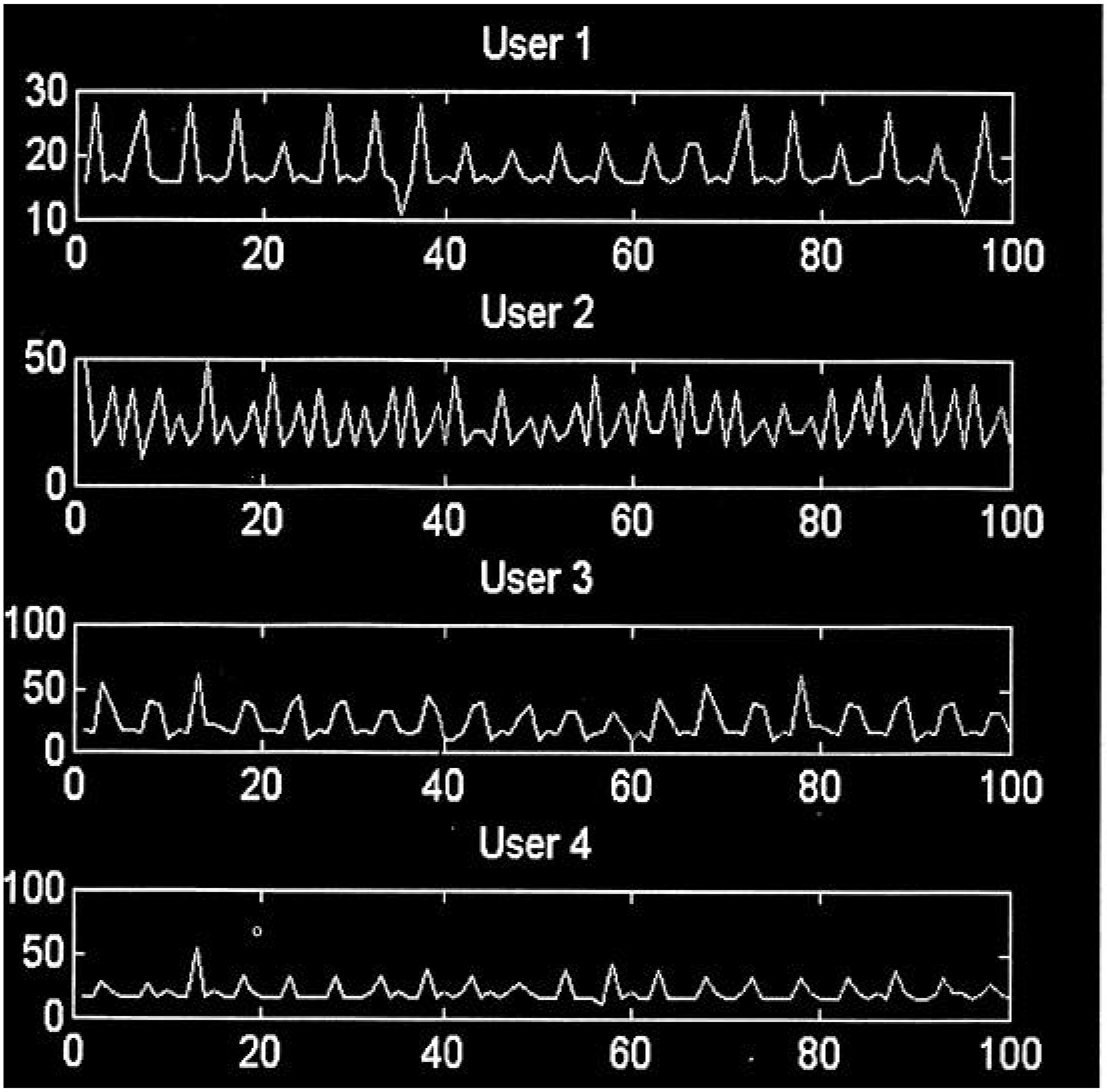

Fig. 4: **Reference profile of genuine users**
Chart shows keystroke latency time samples (20 sets @ 6 keystrokes)
Peaks indicates fraction of a second

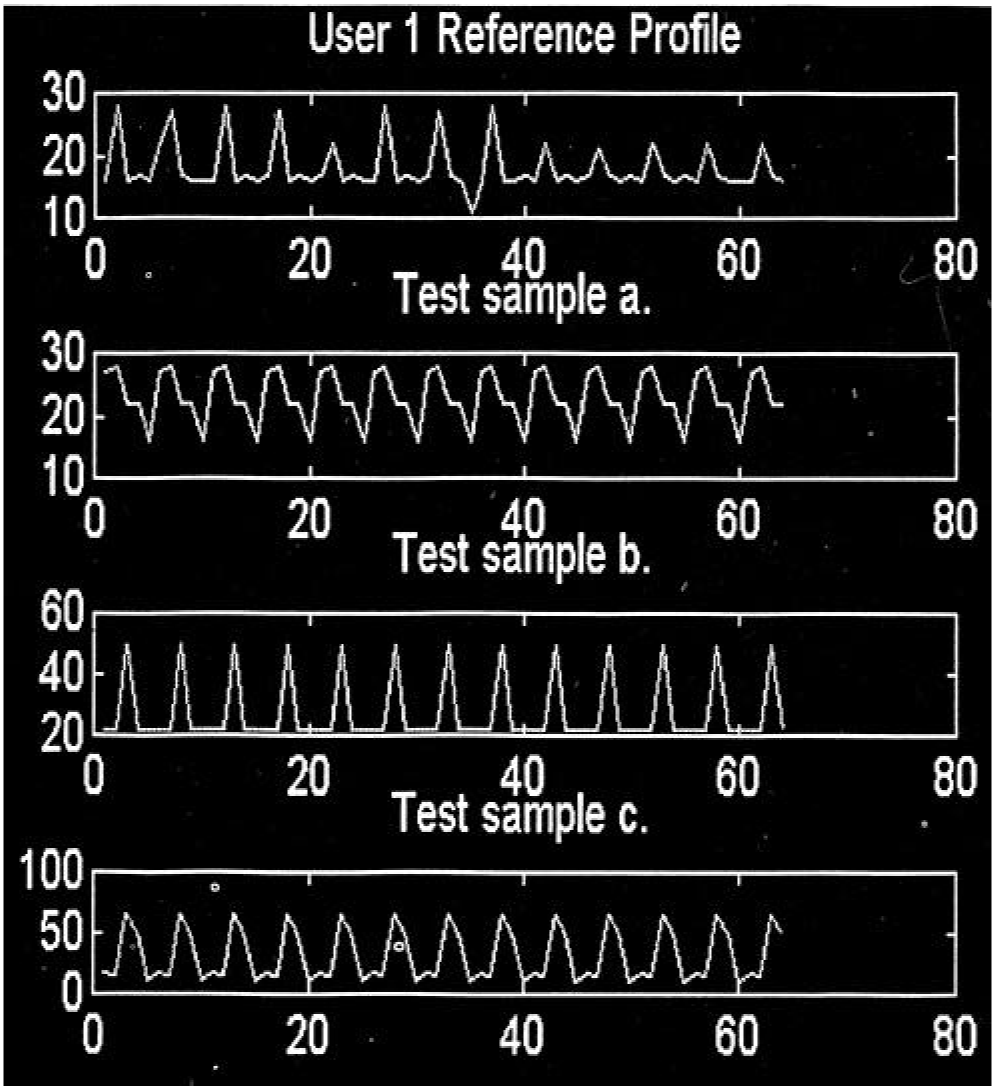

Fig. 5: **General form reference and test profiles compared**
Chart comparing actual profile (in part) with 3 test samples
Peaks indicates fraction of a second

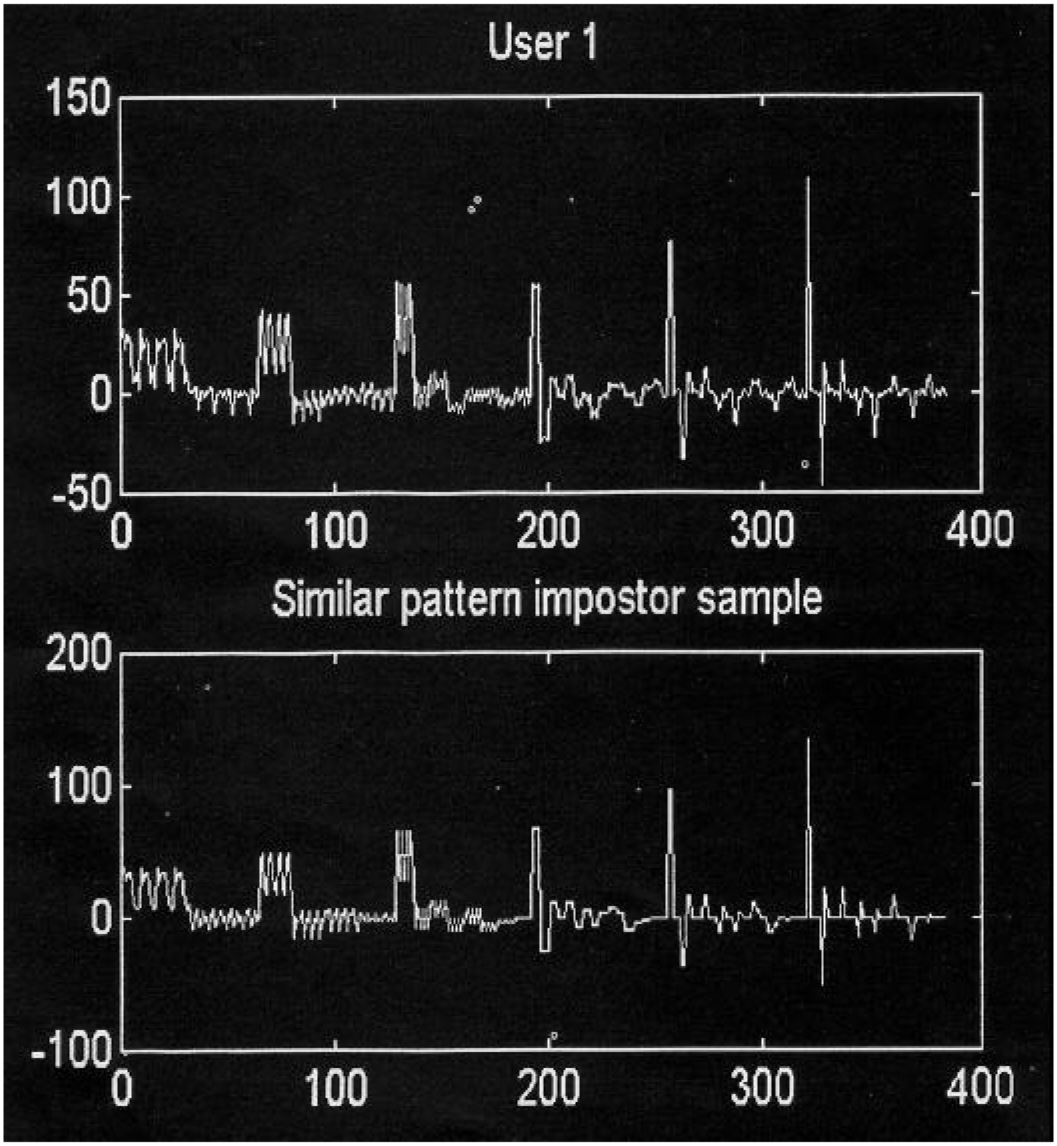

Fig. 6: **WP decomposed reference and test profiles compared**
Chart comparing different resolution stages