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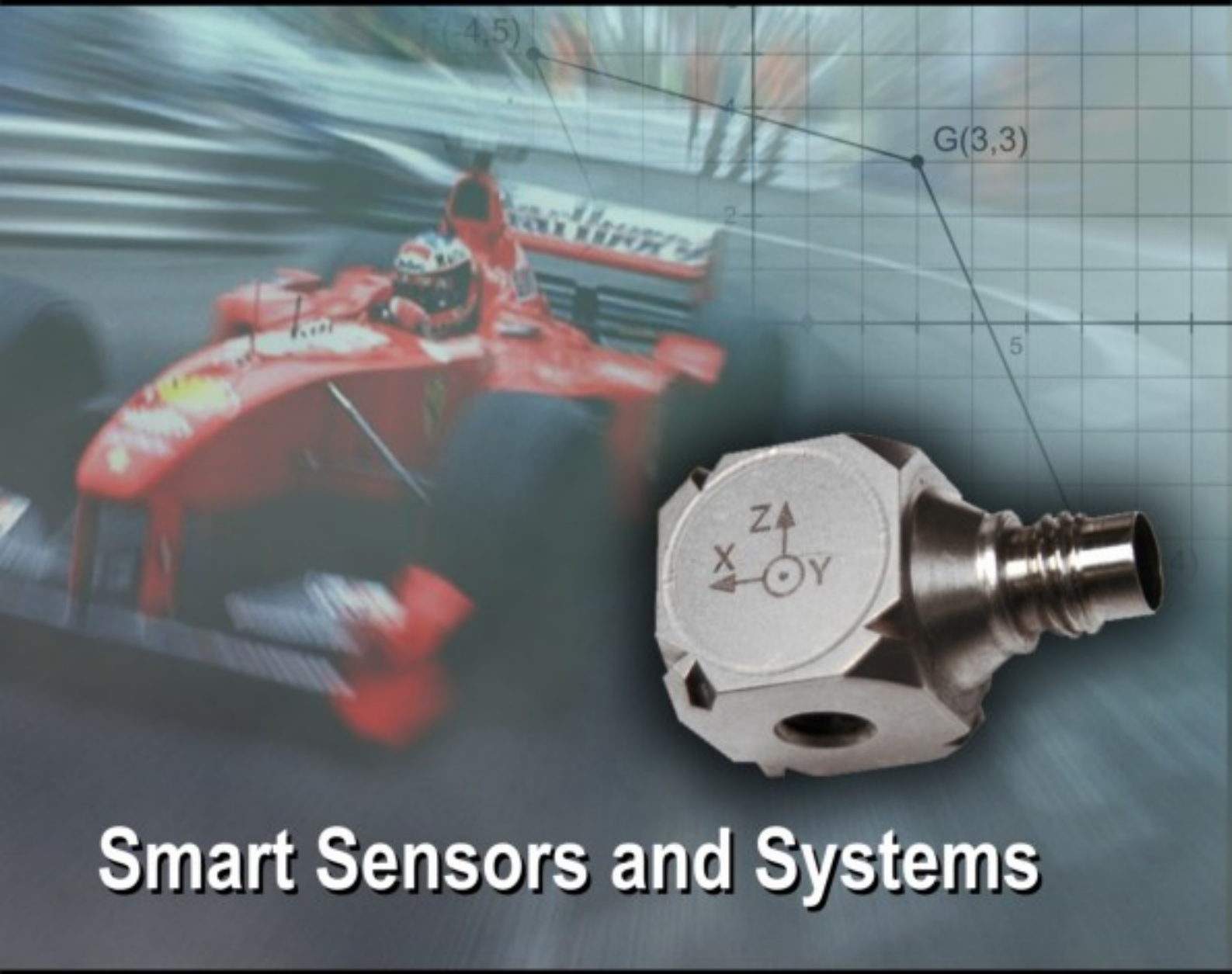

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Type Identification of Unknown Thermocouple Using Principle Component Analysis

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Abstract: Here a general method is proposed for type identification of unknown thermocouple. The thermo e.m.f. vs. temperature characteristic data of different known types and unknown type of thermocouple sensors are complied to form feature matrix. The Principle component analysis method is applied to this feature matrix to reduce the dimension of feature variables of each type. The outcome of this PCA is PCA score data of dimensions (n×2), where n being the total of types. From the score plot and minimum distance classification method the similarity of the unknown type to any of the known class types is determined. *Copyright © 2010 IFSA.*

Keywords: PCA, Minimum-distance

1. Introduction

The classification of thermocouple sensor is required for various purposes such as operating temperature range selection in process control and measurement, sensitivity of temperature measurement, response time of measurement. The conventional method is to perform thermocouple calibration process with the help of calibrator, which is a 5 time consuming task. The classification is based on the material composition of thermocouple and is designated by the type letter (e.g. J, K, R, B etc.). A Novel method may be devised for type identification of a given thermocouple, whose type is unknown. The thermo e.m.f.s of all standard types of thermocouple for selected temperature ranges are collected from standard thermocouple data base. Thermo e.m.f. data set actually represent the typical

features of different types of thermocouple, which can be best observed by its corresponding thermo e.m.f. vs. temperature plot. The mathematical feature (e.g. slope of the curve) can be discriminated well using principle component analysis, an important deterministic method in multivariate statistics. This discrimination method provides the classification of different types of thermocouple.

2. Principle Component Analysis

One of the most commonly used method in multivariate data analysis is the unsupervised method called Principal Component Analysis (PCA). The advantage of PCA is that the dimensionality of the data is dramatically reduced, typically to two or three dimensions. The drawbacks are that the new variables often have no physical meaning and the user has a little control over the loss of information. PCA decomposes the original data space, X, to a much lower dimension. This lower dimension is defined as a hyper plane describing the maximum of variances in the data set. Projections of measurements onto this hyper plane give new co-ordinates known as scores. In this lower dimension and variables is easy to detect significant feature of unknown variable from a group of variables. Let us briefly present the basics of PCA. Generally, this is a mathematical transform used to find correlations and explain variance in a data set. The goal is to map the raw data vector E onto vectors S, where, the vector x can be represented as a linear combination of a set of m orthonormal vectors *i u*

$$x = \sum_{i=1}^{m} z_i u_i \quad ,$$

where the coefficients z_i can be found from the following equation: $z_i = u_i^T x$

This corresponds to a rotation of the coordinate system from the original x to a new set of coordinates given by z. To reduce the dimensions of the data set only a subset ($k < m$) of the basic vectors is preserved. The remaining coefficients are replaced by constants b_i and each vector x is then approximated as

$$\widetilde{x} = \sum_{i=1}^{M} z_i u_i + \sum_{i=1}^{d} b_i u_i$$

The basic vectors u_i, is called principal components which are equal to the eigenvectors of the covariance matrix of the data set. The coefficients b_i and the principal components should be chosen such that the best approximation of the original vector x on average is obtained. However, the reduction of dimensionality from *m* to *k* causes an approximation error. The sum of squares of the errors over the whole data set is minimized if we select the vectors *i u* that correspond to the largest eigen values of the covariance matrix. As a result of the PCA transformation, the original data set is represented in fewer dimensions (typically 2-3) and the measurements can be plotted in the same coordinate system. This plot shows the relation between different observations or experiments. Grouping of data points in this plot suggest some common properties and can be used for classification. As an example, let us suppose that we have a number of liquid samples with different features/properties (e.g. best, good, fair, poor and bad etc.). We have performed measurements of these samples with the electronic tongue. Part of the available measurements can be used as a training set to define the classes, while the rest will be kept out for validation purposes. Assume that n measurements are used for training and p for validation. The training data is organized in a single matrix of the following form

$$X = \begin{bmatrix} x_{11}\, x_{12} \ldots\ldots\ldots\ x_{1m} \\ x_{21}\, x_{22} \ldots\ldots\ldots\ x_{2m} \\ \\ \\ x_{n1}\, x_{n2} \ldots\ldots\ldots\ x_{nm} \\ \\ \end{bmatrix}$$

where, each row in x represents one measurement and the number of columns m is equal to the length of the measurement sequence. Since the original data dimensionality is rather high, we apply principal component analysis to obtain a new data set of lower dimension. Following the steps described above, we compute the covariance matrix $C = \mathrm{cov}(X)$, its eigen values λ and its eigenvectors u_i from an orthonormal basis $U = [u_1 u_2 \ldots\ldots u_m]$. That is $U^T U = 1$.

The original data set can be represented in the new basis using the relation: $Z = U^T X$

After this transformation, we can construct a new data matrix of reduced dimension with the help of eigen values of the matrix C. This is done by selecting the highest values λ since they correspond to the principal components with highest significance. The number PCs to be included should be high enough to ensure good separation between the classes. Principal components with low contribution (low values of I λ) should be neglected. Let us assume that we select the first k PCs as new features and neglect the remaining (m-k) principal components. In this way we obtain the new data matrix D of dimension $n \times k$.

The original data x_{ij} is now represented by new feature z_{ij} as given by [1]

$$D = \begin{bmatrix} z_{11} z_{12} \ldots\ldots z_{1k} \\ z_{21} z_{22} \ldots\ldots z_{2k} \\ \\ \\ z_{n1} z_{n2} \ldots\ldots z_{nk} \end{bmatrix}.$$

With the matrix D defined, we can proceed to the next step for classification of substances. The matrix U will be used during the validation and also play a key role in the online implementation of the classification algorithm. The PCA score data sets are grouped into m no. of classes following the rule of nearest neighborhood clustering algorithm. The above reduced data matrix is utilized for construction of class prototypes. Let $[C]_{i=1\ldots m}$ denote m pattern classes in R^n, represented by the single prototype vector $y, y, y \ldots\ldots y$ respectively.

Hence

$$\begin{bmatrix} C_1 \\ C_2 \\ \ldots\ldots \\ C_n \end{bmatrix} = \begin{bmatrix} z_{11} z_{12} z_{13} \ldots\ldots z_{1k} \\ z_{21} z_{22} z_{23} \ldots\ldots z_{2k} \\ \ldots\ldots\ldots\ldots\ldots\ldots \\ z_{n1} z_{n2} z_{n3} \ldots\ldots\ldots z_{nk}. \end{bmatrix}$$

and

$$[y_i]_{i=1....m}$$

vectors and the mean or class centroids having m no. of classes, each of which represents unique feature in reduced dimension space. The distance between an incoming pattern x and the prototype vectors are $\|x - y_i\|, 1 \le i \le m$. The minimum distance classifier will classify x at C_j (x or y_i), for which D_j is minimum, i.e. $D_j = \min\|x - y_i\|, 1 \le i \le m$.

For online system, it may be inferred that the incoming patter represented by unknown type has similarity with the one of the j-th class of known types.

3. Measurement and Data Analysis

3.1. Case Studies

Here the objects variables are considered as Thermo e.m.f.s in mV of 7 types of thermocouples (e.g. J, K, S, T, R, N, and E types) are considered. The composition and range of operating temperature of different thermocouples are shown in Table 1. The entire data for different type thermocouples are compiled from internet online ITS-90 thermocouple reference table according to NIST (National Institute of Standard & Technology) standard. Instead of considering whole operating ranges of all thermocouples, only selected temperature range (i.e. -40 °C to 400 °C with interval of 2 °C) of all thermocouples are considered for the reason that variation of plot of thermo e.m.f vs. temperature within this range are quite discriminable for all thermocouples. As shown in Table 2. Hence no. of dimensions of the variables is high [i.e. (400-(-40))/2+1=221]. The no. of known types is 7. So the input data matrix becomes 7×440. Now type classification one known type among 7 classes (e.g.) is taken at a time and is combined to input data matrix, which forms the dimension of resultant data matrix as 8×440. The input data matrix is transposed and Principle Components are derived from input. The outputs of the PCS are covariance matrix of order 8×8 in descending order of eigen vectors. Only the 1st two eigen vectors (i.e. 1st two columns) are considered. The PCA score data are obtained also, which is a matrix of order 8×2. The score data are plotted on 2 dimension plot, called PCA score plot. It may be seen that each coordinate value on score plot represents a single class type. Thus all types of thermocouple are represented by each score coordinates. It is observed that the coordinates are well separated from each other since the types are of different classes. The coordinate of unknown class type, whose type is to be classified, may come close to any one of the seven classes as seen by the Fig. 2(a-g). Based of minimum distance classification method, the type of the unknown thermocouple can be identified as one the J, K, S, T, N, E and R types. The results are shown in Table 3.

Table 1. Thermocouple Types.

Type	Composition	Temp. Range (°C)
B	Pt-30% Rh vs. Pt-6% , Rh	0 to 1820
E	Ni-Cr Alloy vs. Cu-Ni alloy	-270 to 1000
J	Fe vs. Cu-Ni alloy	-210 to 1200
K	Ni-Cr alloy vs. Ni-Al alloy	-270 to 1372
N	Ni-Cr-Si alloy vs. Ni-Si-Mg alloy	-270 to 1300
R	Pt-13% , Rh vs. Pt	-50 to 1768
S	Pt-10% , Rh vs. Pt	-50 to 1768
T	Cu vs. Cu-Ni alloy	-270 to 400

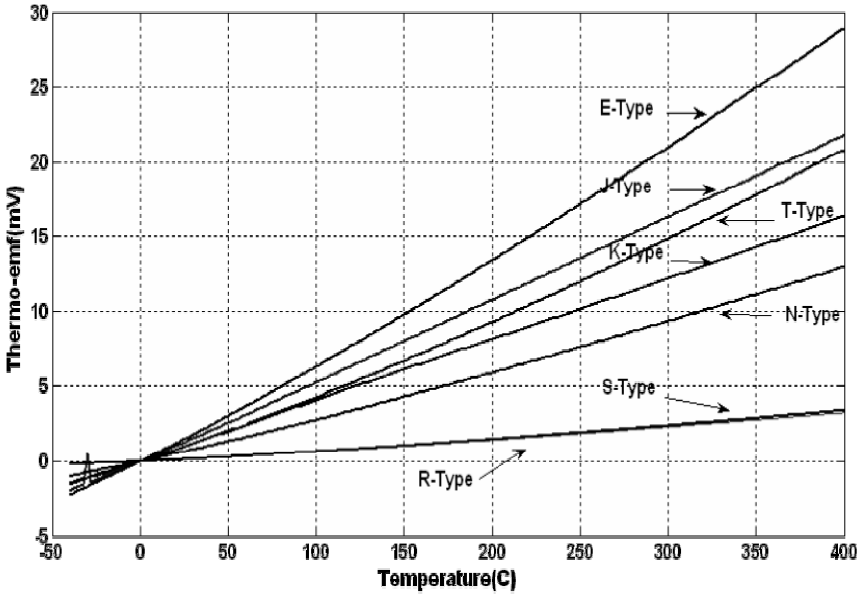

Fig. 1. Thermo e.m.f. vs. temperature plot of all types of thermocouple.

Table 2. Thermocouple Data Base.

Sl No.	Thermo e.m.f.						
	X1	X2	X3	X4	X5	X6	X7
1	-1.961	-1.5270	-0.1940	-1.4750	-1.0230	-0.1880	-2.2550
2	-1.8650	-1.4530	-0.1860	-1.4050	-0.9730	-0.1800	-2.1470
3	-1.7700	-1.3800	-0.1770	-1.3350	-0.9230	-0.1710	-2.0380
4	-1.6740	-1.3050	-0.1680	-1.2640	-0.8730	-0.1630	-1.9290
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215	21.1860	15.8910	3.1450	20.1320	12.5290	3.2840	27.9860
216	21.2970	15.9750	3.1640	20.2550	12.6030	3.3040	28.1460
217	21.4070	16.0590	3.1830	20.3780	12.6770	3.3250	28.3060
218	21.5170	16.1440	3.2020	20.5020	12.7510	3.3460	28.466
219	21.6270	16.2280	3.2210	20.6250	12.8250	3.3660	28.6260
220	21.7380	16.3130	3.2400	20.7480	12.8990	3.3870	28.7860
221	21.8480	16.3970	3.2590	20.8720	12.9740	3.4080	28.9460

3.2. Results

The thermocouple data base consist of 440 rows representing temperature values from -40°C to 400°C with interval of 2°C and eight columns, 7 out of which representing thermo e.m.f. values of known types and the 8-th column, representing the same of unknown type. It should be noted that component

analysis are done for 7 times. For each time, one unknown type is selected from 7 known types. Thus in total seven PCA score plots are generated which are shown in Fig. 2(a) to Fig. 2(g) From score data set, the statistical distances between all known type and unknown types are computed, which are listed in Table 3. From the score plot and Table 3, it is found that characteristic feature of 7 different unknown types are closely matched with corresponding 7 known types of thermocouples following minimum distance classification rule discussed above.

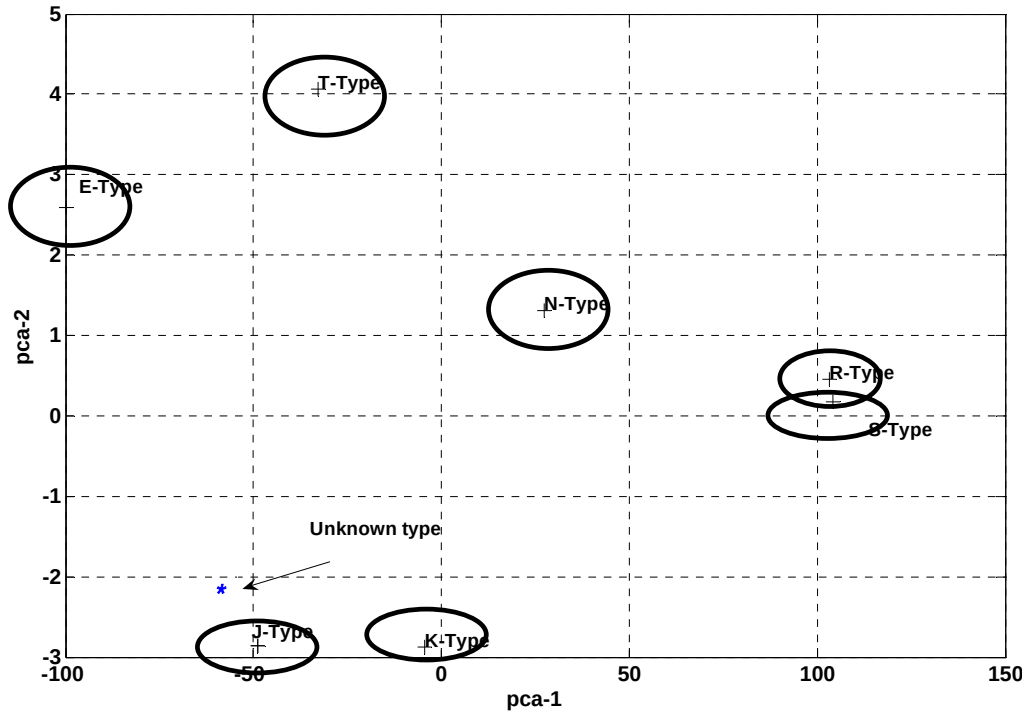

Fig. 2(a). Unknown thermocouple: J-Type.

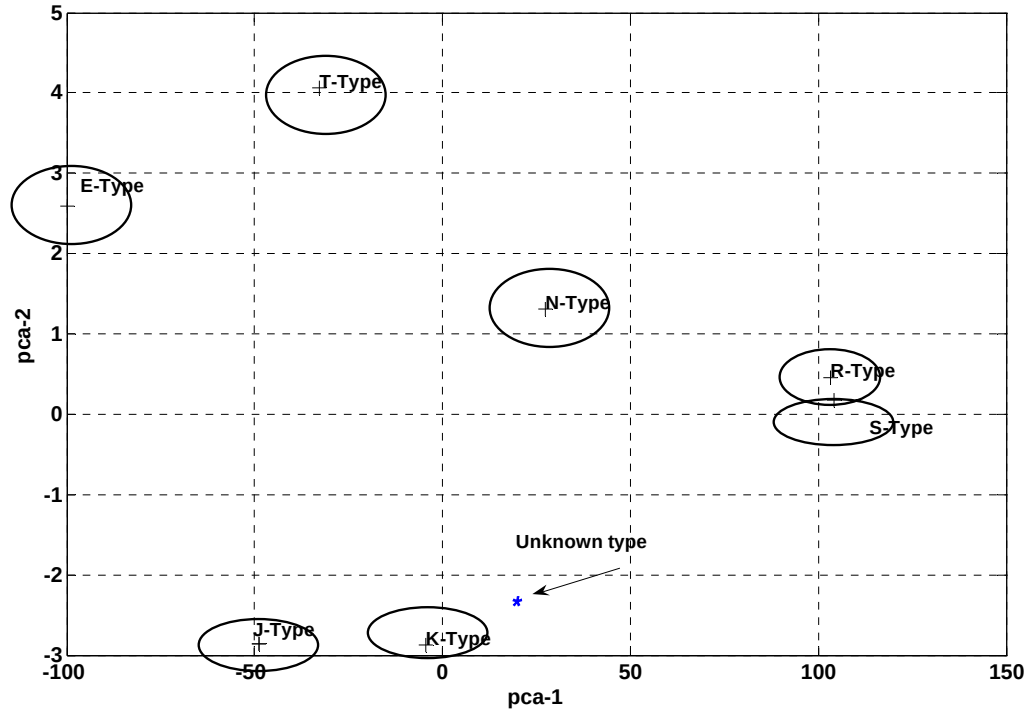

Fig. 2(b). Unknown thermocouple: K-Type.

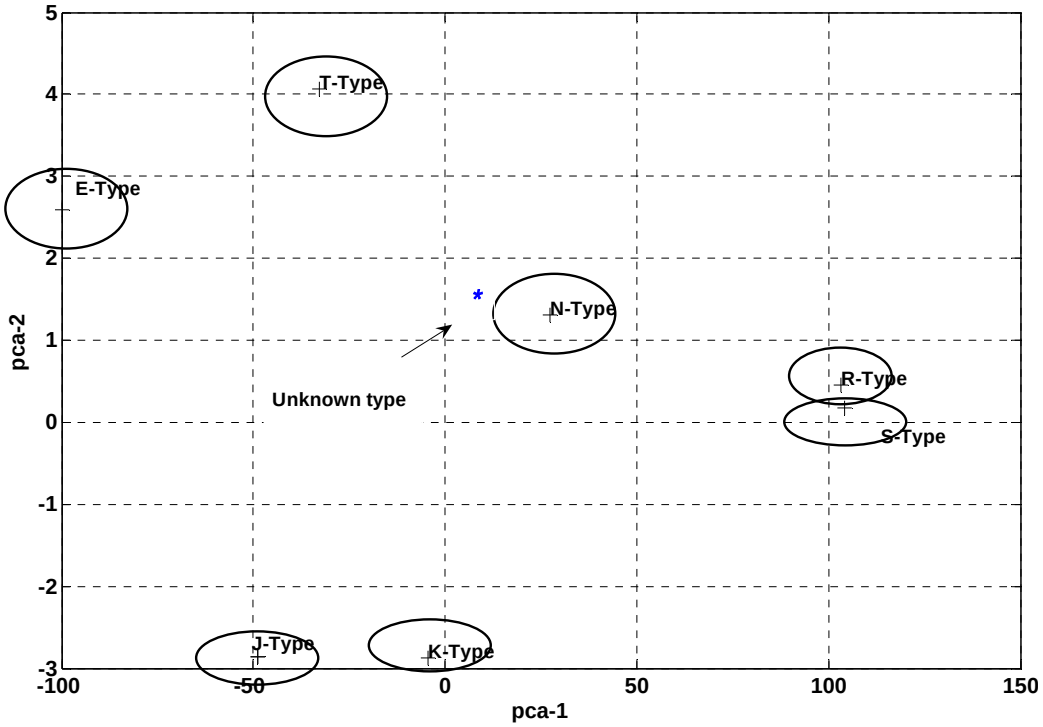

Fig. 2(c). Unknown thermocouple: N-Type.

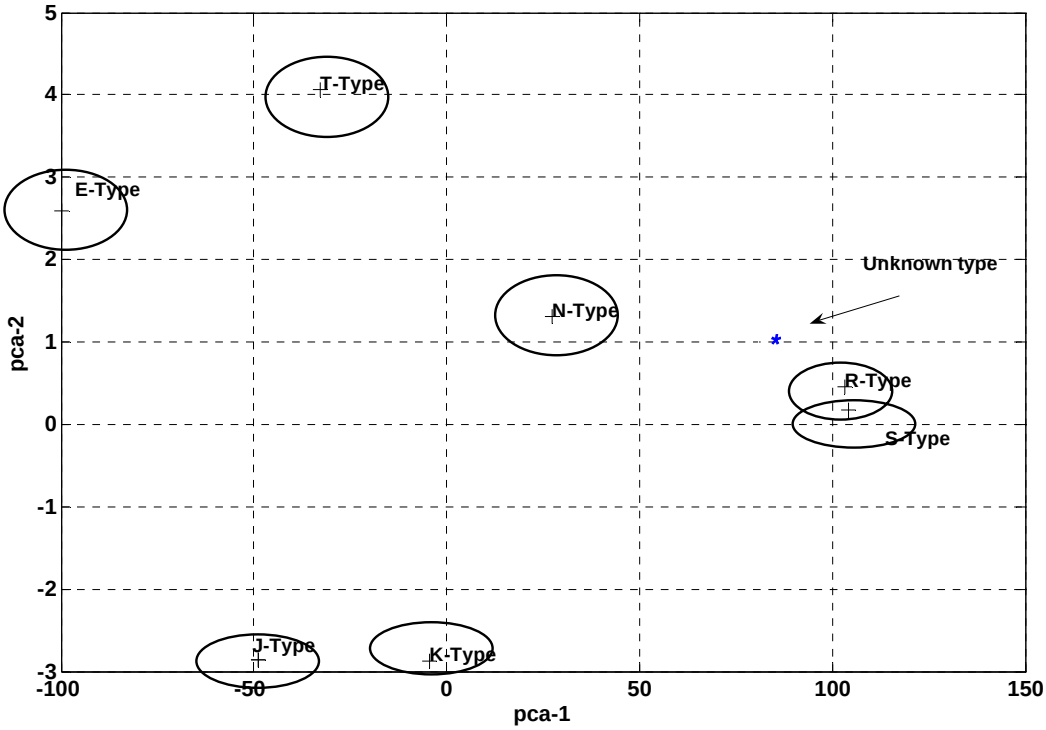

Fig. 2(d). Unknown thermocouple: R-Type.

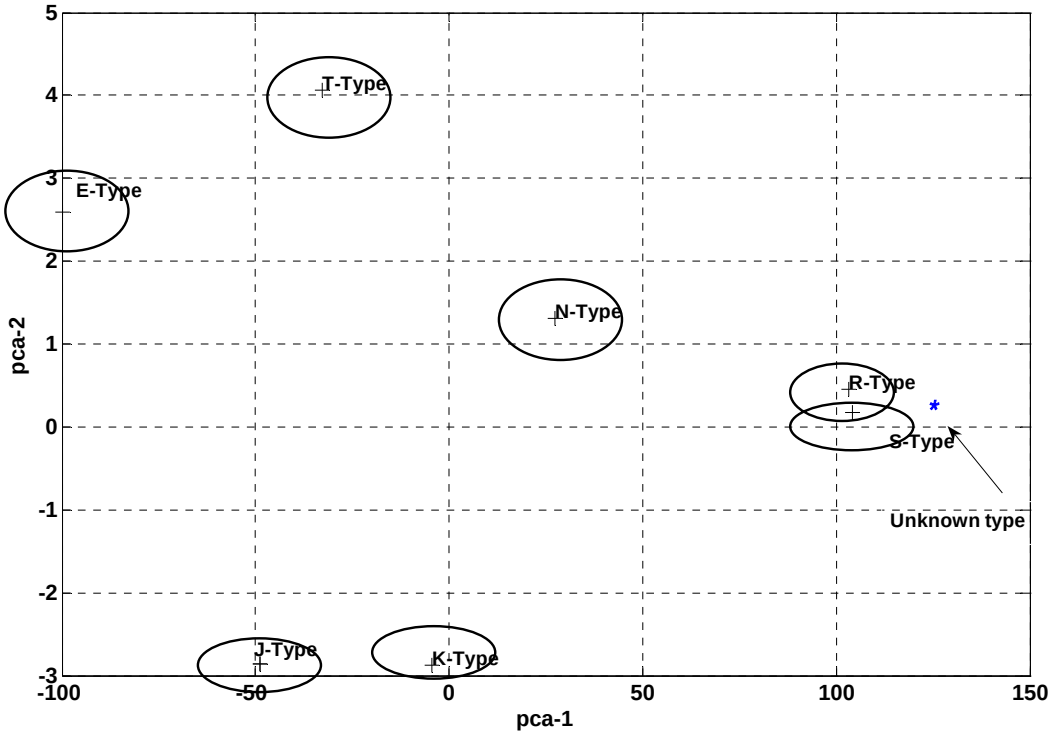

Fig. 2(e). Unknown thermocouple: S-Type.

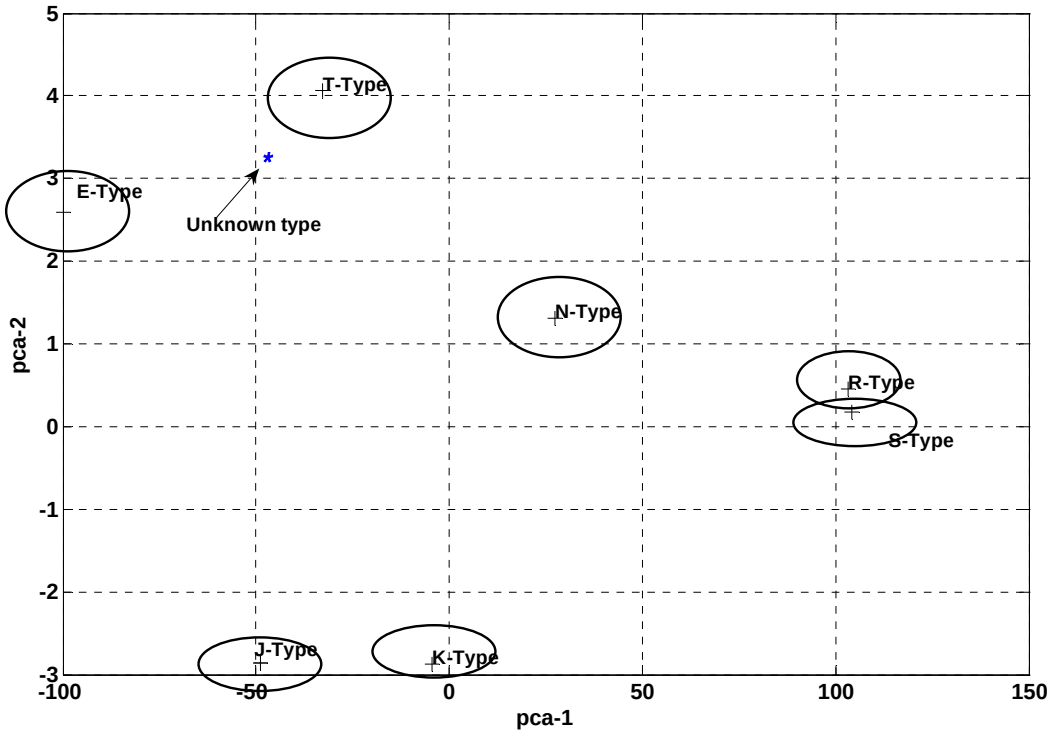

Fig. 2(f). Unknown thermocouple: T-Type.

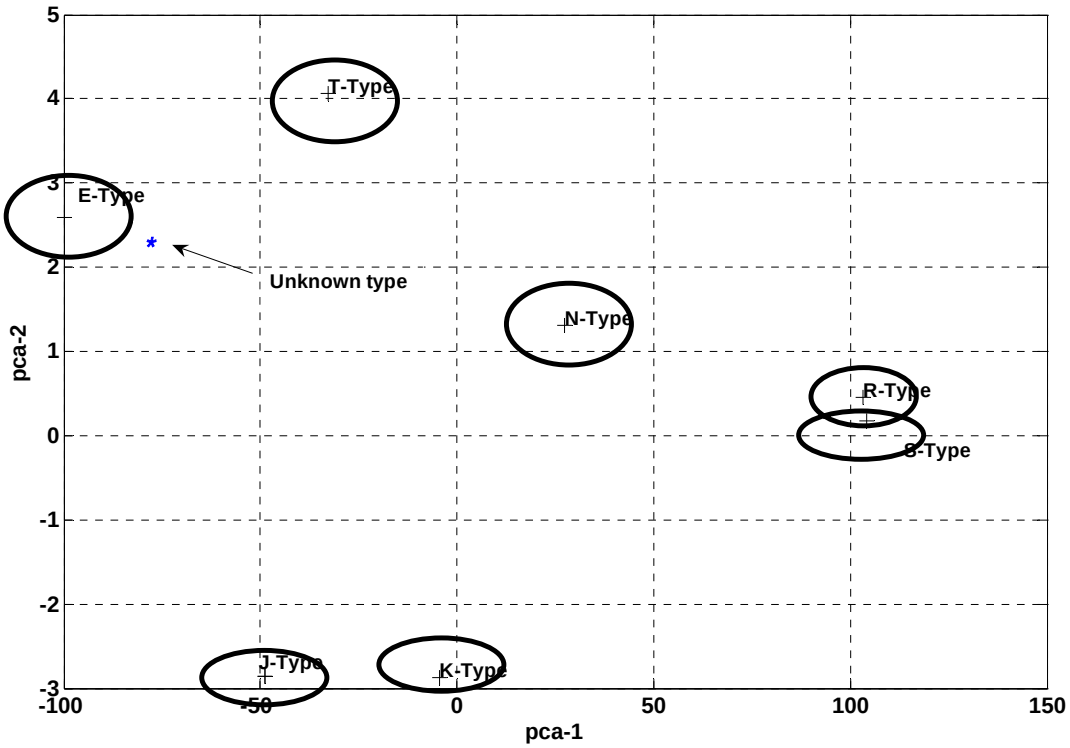

Fig. 2(g). Unknown thermocouple: E-Type.

Table 3. Distance between unknown thermocouple type and known type.

Distance		Known Type						
		J	**K**	**T**	**S**	**N**	**R**	**E**
Unknown Type	**J**	**0**	44.3239	152.8407	17.3645	76.2681	151.9986	51.5246
	K	44.3239	**0**	108.5294	29.2367	32.1038	107.6899	95.7155
	T	152.8407	108.5294	**0**	136.9434	76.6652	0.8930	204.0607
	S	17.3645	29.2367	136.9434	**0**	60.2943	136.0879	67.1748
	N	76.2681	32.1038	76.6652	60.2943	**0**	75.8135	127.396
	R	151.9986	107.6899	0.8930	136.0879	75.8135	**0**	203.2095
	E	51.5246	95.7155	204.0607	67.1748	127.396	203.2095	**0**

4. Discussion

Sometimes the class boundaries are not sharply distinguished by the PCA score plot as seen in the result. In that case HPCA (PCA) method may be applied. At different ambient temperature, the thermo e.m.f. data set of different known type thermocouples is collected over a same temperature range. For each ambient temperatures PCA are done such that different set of PCA data matrix are obtained. The PCA data set for all types are merged together to increase the more feature variables (e.g. for three different ambient temperatures, the dimensions of the input data matrix becomes 8×24). Finally PCA method is applied again to obtain PCA score data set. Following this HPCA method, separation among the coordinates for different types may be increased or in other words better discrimination can be obtained.

References

[1]. Susanne Holman, Per Spangeus, Christina Krantz Rulcker, Fredrik Winquist, Compression of electronic tongue data based on voltametry-comparative study, *Sensors and Actuators, B,* 76, 2001, pp. 455-464.
[2]. Kundu P., Sarkar G, Type Identification of Unknown Thermocouple using Probabilistic Neural Network, in *Proceeding of International Conference MS'07*, India, 3-5 December, 2007.
[3]. Harinder P. Singh, Ravi K. Gulati and Ranjan Gupta, Steller spectral classification using principle component analysis and artificial neural network, *Mon. Not. R. Aston. Soc.,* 295, 1998, pp. 321-318.
[4]. Boyko Lliev, Malin Lindquist, Linn Robertson, Peter Wide, A fuzzy technique for food and water quality assessment with an electronic tongue, *Fuzzy Sets and Systems,* 157, 2006, pp. 1155-1168.
[5]. Menahem Friedman, Abraham Kandel; Introduction to Pattern Recognition – Statistical, structural, Neural and Fuzzy logic approaches, *Machine Perception and Artificial Intelligence,* Vol. 32.

Guide for Contributors

Aims and Scope

Sensors & Transducers Journal (ISSN 1726-5479) provides an advanced forum for the science and technology of physical, chemical sensors and biosensors. It publishes state-of-the-art reviews, regular research and application specific papers, short notes, letters to Editor and sensors related books reviews as well as academic, practical and commercial information of interest to its readership. Because it is an open access, peer review international journal, papers rapidly published in *Sensors & Transducers Journal* will receive a very high publicity. The journal is published monthly as twelve issues per annual by International Frequency Association (IFSA). In additional, some special sponsored and conference issues published annually. *Sensors & Transducers Journal* is indexed and abstracted very quickly by Chemical Abstracts, IndexCopernicus Journals Master List, Open J-Gate, Google Scholar, etc.

Topics Covered

Contributions are invited on all aspects of research, development and application of the science and technology of sensors, transducers and sensor instrumentations. Topics include, but are not restricted to:

- Physical, chemical and biosensors;
- Digital, frequency, period, duty-cycle, time interval, PWM, pulse number output sensors and transducers;
- Theory, principles, effects, design, standardization and modeling;
- Smart sensors and systems;
- Sensor instrumentation;
- Virtual instruments;
- Sensors interfaces, buses and networks;
- Signal processing;
- Frequency (period, duty-cycle)-to-digital converters, ADC;
- Technologies and materials;
- Nanosensors;
- Microsystems;
- Applications.

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Articles should be written in English. Authors are invited to submit by e-mail editor@sensorsportal.com 8-14 pages article (including abstract, illustrations (color or grayscale), photos and references) in both: MS Word (doc) and Acrobat (pdf) formats. Detailed preparation instructions, paper example and template of manuscript are available from the journal's webpage: http://www.sensorsportal.com/HTML/DIGEST/Submition.htm Authors must follow the instructions strictly when submitting their manuscripts.

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