USING ARTIFICIAL NEURAL NETWORK FOR THE KICK TECHNIQUES CLASSIFICATION – AN INITIAL STUDY

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ABSTRACT

In this initial study it is investigated the possibility of using simple artificial neural network for classification of kick techniques based on their specific force course profile. The aim is to investigate whether the neural networks could be a suitable tool for such task and can be possibly used in following research that will deal with classification of punch techniques and also the striker's gender and level of training.

INTRODUCTION
The kick techniques are (apart from punching techniques) the most important and effective techniques in unarmed professional defense with significant force delivery. Various kick techniques are the subject of research investigation mostly for the needs of martial arts. (Liu et al. 2000, Pieter and Pieter 1995).
This paper presents initial results of analysis of two different kick techniques: the direct kick and the round kick (Liu et al. 2000). The aim was to find out whether it is possible to distinguish these two techniques from a kick impact force profile.
In this long-term research the participants were asked to perform a set of different punch and kick techniques on a measuring station. The impact force profiles were stored for further analysis. To uncover whether there are certain unique characteristics for the two kick techniques mentioned above the artificial neural network (ANN) was chosen as a suitable classifier.
Firstly, kick techniques are explained. In the following paragraph, measuring devices, the method of data storage and experiment setup for measurement are described. Artificial neural network theory is depicted in the next section. Problem definition and consequent analysis are followed by result section. The conclusion summarizes the kick techniques classification.

KICK TECHNIQUES
In this study two different kick techniques are distinguished - the direct kick (Fig. 1) and the round kick (Fig. 2). In professional defense, these kicks are used to stop and keep the attacker in distance where the attacker cannot touch us. The second way of use is destabilization of attacker.
During the direct kick a sole or a heel are the hit areas. This kick is made directly and by the shortest way to the target. During the round kick an instep together with part of shank are hit areas. The direct kick is considered to be stronger than the round kick.

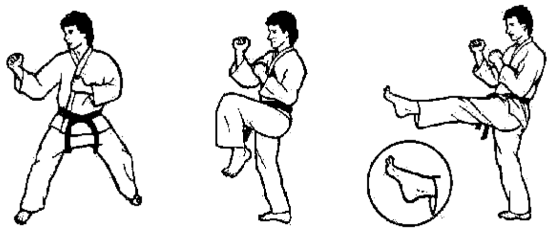

Figure 1: Direct kick

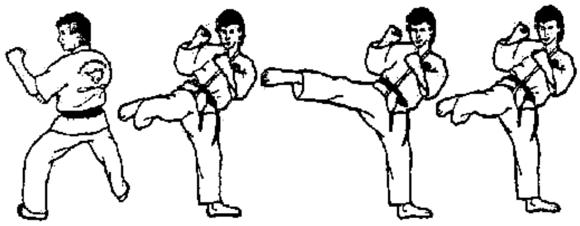

Figure 2: Round kick

MEASURING DEVICES
The strain gauge sensor L6E-C3-300kg (Fig. 3.) works as unilaterally cantilever bending beam. During force delivery the biggest deformation of sensor is in places with the thinnest walls – there are metal film strain gauges which change their electrical resistance depending on deformation. Strain gauges are plugged in Wheatstone bridge and this way is possible to convert difference of resistance to electrical signal which we can process.

Figure 3: Strain gauge sensor L6E-C3-300kg

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The sensor is connected to the computer, which is used for data storage, through the strain gauge. The strain gauge type TENZ2334 is an electronic appliance that converts the signals to data that is stored in memory. The core of the appliance is a single-chip microcomputer that controls all of the activities. The strain gauge sensor is connected to this appliance via four-pole connector XLR by four conductors. The number of values measured by the sensor averages around 600 measurements per second while the data is immediately stored in the memory of a device with a capacity of 512 kB (Lapkova et al., 2012).
The mentioned above strain gauge sensor was placed on the measuring station according to the following schematic (Fig. 4):

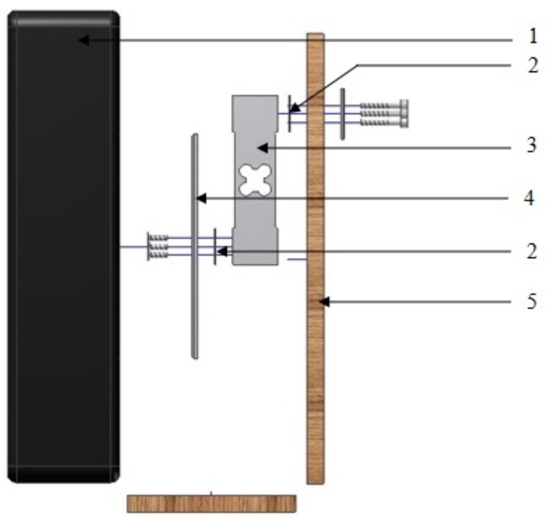

Figure 4: Measuring station schematic

1 – punching bag (made from hardened vinyl filled with foam)
2 –template
3 – strain gauge sensor L6E-C3-300kg
4 – board (200 x 200 x 5 mm)
5 – punching bag base

EXPERIMENT SETUP

The total of 103 participants took part in the experiment; men and women. All participants were in the age from 19 to 28. Based on previous training and experience the participants were divided into following groups:

- No training – These persons have never done any combat sport, martial art or combat system. They have no theoretical knowledge of the striking technique. The technique was presented to these persons before the experiment for safety reasons. Noted further as M1 (for men) and W1 (for women).
- Mid-trained - These persons have the theoretical knowledge of striking techniques and do attend the Special physical training course for at least six months. The course is focused on self-defense and professional defense. Noted further as M2 (only men).
- Person who play football are in separate category due to their too specific kicking technique. Noted further as M3 (only men).

The exact numbers of participants in each group are given in Table 1.

Table 1: The number of participants in groups

Group	Number of participants
M1	44
M2	32
M3	18
W1	9

Due to the number of participants in each category the research was focused on male participants. The W1 group was used only for basic comparison between genders.

During the measurement the target was positioned in such manner that the center of the tensometric sensor was in the height of 70cm. The person was made to stay at the same place for the whole experiment. Any unnecessary movement (e. g. lunge etc.) would lead to data distortion.

ARTIFICIAL NEURAL NETWORKS

Artificial neural networks are inspired in the biological neural nets and are used for complex and difficult tasks (Hertz et al., 1991), (Wasserman, 1980), (Gurney, 1997), (Fausset, 2003). The most often usage is classification of objects as also in this case. ANNs are capable of generalization and hence the classification is natural for them. Some other possibilities are in pattern recognition, control, filtering of signals and also data approximation and others.
There are several kinds of ANN. Simulations were performed with feedforward net with supervision and Levenberg-Marquardt training algorithm (Fausset, 2003). ANN needs a training set of known solutions to be learned on them. Supervised ANN has to have input and also required output. ANN with unsupervised learning exists and there a capability of selforganization is applied.
The neural network works so that suitable inputs in numbers have to be given on the input vector. These inputs are multiplied by weights which are adjusted during the training. In the neuron the sum of inputs multiplied by weights are transferred through mathematical function like sigmoid, linear, hyperbolic tangent etc. to the output from a neuron unit - node.
These single nodes (Fig. 5) are connected to different structures to obtain different structures of ANN (e.g. Fig. 6 and Fig. 7), where $\sum \delta = TF[\sum (w_i x_i + bw_b)]$ and

$\sum = TF[\sum(w_i x_i + bw_b)]$; TF means transfer function and logistic sigmoid function is used in this case.

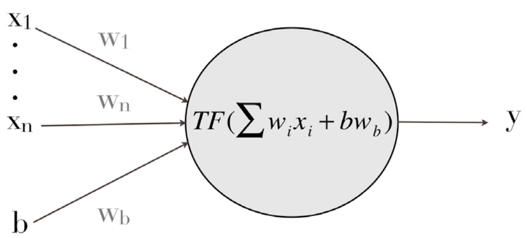

Figure 5: A node model, where TF (transfer function like sigmoid), x_1 - x_n (inputs to neural network), b – bias (usually equal to 1), $w_1 - w_n$, w_b – weights, y – output

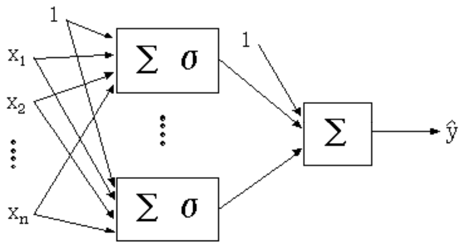

Figure 6: ANN models with one hidden layer

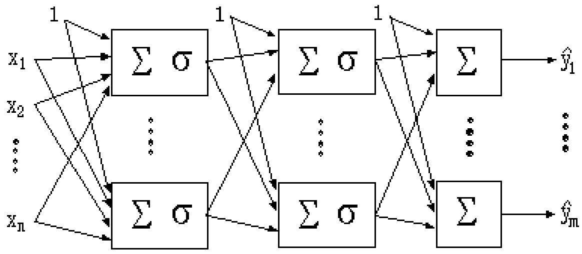

Figure 7: ANN models with two hidden layers and more outputs

The example of relation between inputs and output can be described as a mathematical form (1). It represents the case of only one node and logistic sigmoid function as a transfer function.

$$y = \frac{1}{1 + e^{-(x_1 w_1 + x_2 w_2)}}, \qquad (1)$$

where: y – output

x_1, x_2 – inputs

w_1, w_2 – weights.

PROBLEM DEFINITION AND ANALYSIS

During the experiments on the measuring station ten force profiles for each participant and each kick technique were collected. As an example the mean force profiles for the W1 group are depicted in Fig. 8. The similarities of the main peak are clearly visible. However the mean value may prove very misleading. In Fig. 9 all collected force profiles for the Round kick (W1 group) are depicted. There is high variety in the force profiles that makes the possibility of simple classification much harder. To improve the chance of successful classification a basic signal processing was applied.

A set of statistical values was used to represent each force profile for the classification. Three different spectral sequences were derived from the force profiles. The first was in the range from 3N to 53N with the bandwidth 10N. The second was in range from 73N to 133N with the bandwidth 20N. Finally the third starting at 201N and ending at 801N with the bandwidth of 200N. By this approach eleven integer number inputs for classification were obtained for each force profile. As last (twelfth) input the rounded median value was used. Mean values of these twelve inputs for W1 group are depicted in figure 10. The aim was to highlight the differences in the signals of different kick techniques.

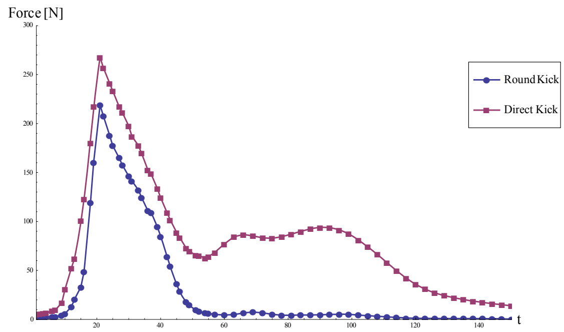

Figure 8: Mean force profiles – Group W1

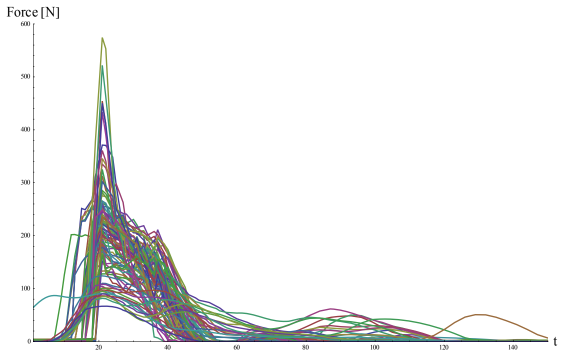

Figure 9: Force profiles – Round kick - Group W1.

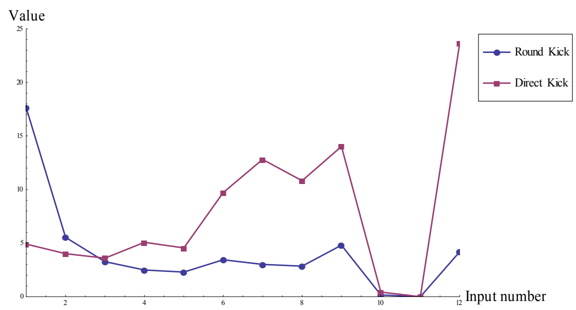

Figure 10: Mean classification input values - Group W1

The example of input values for all force profile samples in group W1 is given in Fig. 11 (Round kick) and in Fig. 12 (Direct kick).

As mentioned previously the simulations were performed with feedforward net with supervision and Levenberg-Marquardt training algorithm. Two different methods of preparing the training and testing set were applied. Typically the set of samples was halved for this purpose. One halve was used as a training set. The other halve served as testing set. In the first approach (noted "a") all ten samples for halve of the participants in the group were used as the training set. The remaining samples were used for testing set. In the second approach (note "b") five samples for each participant served as training set and other five as the testing set.

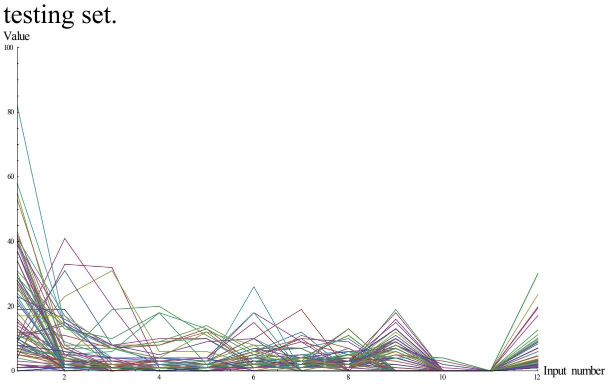

Figure 11: Classification input values – Round kick – Group W1

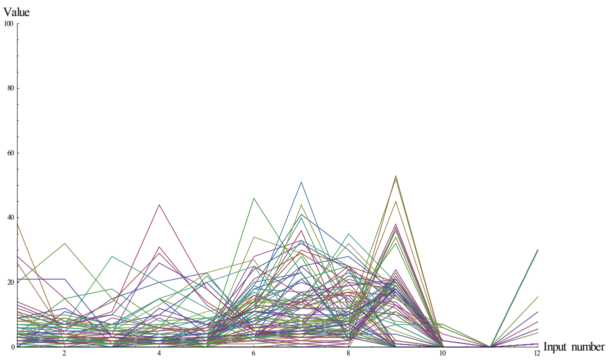

Figure 12: Classification input values – Direct kick – Group W1

Different settings of the number of iterations and number of neurons in the hidden layer were tested. The goal was a higher than 85% rate of successfully classified samples from the testing set. In this initial study the 15% fail rate was taken as acceptable mainly due to errors that occur during the physical measuring. However the aim for future research is to improve the success rate significantly (up to 95% if possible).

The best results obtained for each group are presented in following section.

RESULTS

In this section, the results of neural network based classification of different kick techniques are presented. In Table 2 the final neural network setting for each training set is given alongside with root mean square error (RMSE) that is a typical measure of the quality of training process.

Table 2: Final neural network setting and RMSE

Group	RMSE	Nodes in hidden layer	Iterations
M1a	0.197889	3	60
M1b	0.202538	3	60
M2a	0.172885	2	60
M2b	0.189389	3	20
M3a	2.02E-15	3	40
M3b	0.127763	2	40
W1a	0.255196	7	60
W1b	0.246739	2	30

Furthermore an example of the RMSE shape during the training is given in Fig. 13 for the W1a training set.

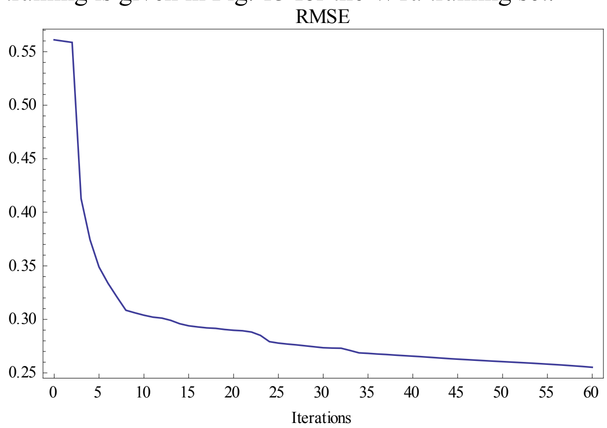

Figure 13: The RMSE shape – W1a training set

In Table 3 the numbers of successfully classified samples (corresponding to results in Table 2) are given.

Table 3: The number of successfully classified samples

Group	N_1/N_2	RMSE	N_3	N_3 %	N_4	N_4 %
M1a	440	0.197	422	95.909	399	90.681
M1b	440	0.202	418	95	407	92.5
M2a	320	0.172	310	96.875	287	89.687
M2b	320	0.189	308	96.25	285	89.062
M3a	180	2.02E-15	180	100	165	91.666
M3b	180	0.127	177	98.333	170	94.444
W1a	80 / 100	0.255	76	95	91	91
W1b	90	0.246	83	92.222	74	82.222

Where:
N_1 – number of samples in the training set.
N_2 – number of samples in the testing set.
Note: Except W1a it applies that $N_1=N_2$.
N_3 – number of successfully classified samples from the training set.
N_4 – number of successfully classified samples from the testing set.

As can be visible from the Table 3, the results achieved at least 89 % which is higher than the specified goal.

CONCLUSION

In this paper an artificial neural network was designed and tested in the task of different kick techniques force profile classification. The goal of 85% successful classification rate was accomplished (in male categories). There have been however several difficulties during the training process. The first was the data preparation issue that was described and solved by employing the spectral analysis. Secondly, the neural network exhibited very strong tendency to over fit, meaning that the higher success rate for training set lead to significantly worse success rate for the testing set. The finding of the balance between these two was the main issue during the neural network designing and learning process. The results presented in previous section are very promising and encourage further research of neural network based classification of force profiles. In the following research the neural networks will be tested on more complex tasks e.g. the classification of participant's gender, training level or for classification of higher number of different kick and striking techniques.

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